Identifying Human Trafficking Networks in Louisiana by Using Authorship Attribution and Network Modeling

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IDENTIFYING HUMAN TRAFFICKING NETWORKS IN LOUISIANA BY USING AUTHORSHIP ATTRIBUTION AND NETWORK MODELING

A Dissertation

Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Doctor of Philosophy

in

The Stephenson Department of Entrepreneurship and Information Systems (SDEIS)

by

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Very special thanks are due to my wife and my children, to whom I dedicate my research. I am so grateful to my wife who kept the family intact during my many days and nights of absence and to my children who sacrificed much during my period of study.
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ABSTRACT

Human trafficking or modern slavery is a problem that has plagued every U.S. state, in both urban and rural areas. During the past decades, online advertisements for sex trafficking have rapidly increased in numbers. The advancement of the Internet and smart phones have made it easier for sex traffickers to contact and recruit their victims and advertise and sell them online. Also, they have made it more difficult for law enforcement to trace the victims and identify the traffickers. Sadly, more than fifty percent of the victims of sex trafficking are children, many of which are exploited through the Internet.

The first step for preventing and fighting human trafficking is to identify the traffickers. The primary goal of this study is to identify potential organized sex trafficking networks in Louisiana by analyzing the ads posted online in Louisiana and its five neighboring states. The secondary goal of this study is to examine the possibility of using authorship attribution techniques (in addition to phone numbers and ad IDs) to group together the online advertisements that may have been posted by the same entity.

The data used in this study was collected from the website Backpage for a time period of ten months. After cleaning the data set, we were left with 123,436 ads from 47 cities in the specified area. Through the application of network analysis, we found many entities that are potentially such networks, all of which posted a large number of ads with many phone numbers in different cities. Also, we identified the time period that each phone number was used in and the cities and states that each entity posted ads for, which shows how these entities moved around between different cities and states.

The four supervised machine learning methods that we used to classify the collected advertisements are Support Vector Machines (SVMs), the Naïve Bayesian classifier, Logistic
Regression, and Neural Networks. We calculated 40 accuracy rates, 35 of which were over 90% for classifying any number of ads per entity, as long as each entity (or author) posted more than 10 ads.
CHAPTER I
INTRODUCTION

1.1. Human Trafficking

Human trafficking is a local, national, and international problem, incidents of which have been reported in every U.S. state, in both urban and rural areas (Godoy, 2016; Davis, 2017). Sex trafficking is “the fastest growing business of organized crime and the third-largest criminal enterprise in the world” (Weitzer, 2014). After Germany, the United States has the largest commercial sex industry and is an ultimate point for many women and children that are victims of sex trafficking (Schauer and Wheaton, 2006).

There are more than 40 million victims of human trafficking worldwide, with around 16 million people in labor forced trafficking, 15.4 million in forced marriage, and 4.8 million people in commercial sex trafficking (ILO, 2017).

It is estimated that only 0.04 percent of human trafficking victims are found around the world, which means most victims of human trafficking go unidentified. Therefore, the magnitude of human trafficking is much larger than one would think (DoSomething.org, 2019).

The victims of human trafficking are mainly women, where the share of women and girls in trafficked people is 71 percent and the other 29 percent are men and young boys (ILO, 2017). It is estimated that for every 1000 adults and every 1000 children, there are 5.9 adult victims and 4.4 underage victims, respectively (ILO, 2017). Around 79 percent of all detected human trafficking cases are sex exploitation cases (Van der Laan et al., 2011).

Every year in the United States, between 244 thousand and 325 thousand minors are at risk of being sexually abused, and approximately 199 thousand are actually exploited (Clawson et al., 2009). In the United States, the average age of starting to work in the commercial sex industry for girls and boys is 11 to 13 years and 12 to 14 years, respectively (Hachey and
Phillippi, 2017). According to the 2018 Federal Human Trafficking Report, the victims of more than half of the sex trafficking identified cases in 2018 were children (Currier and Feehs, 2019). In fact, the number of cases involving children only (51.6%) were more than thrice the number of cases involving adults only (16.3%) (Currier and Feehs, 2019). In an FBI Cross Country operation in 2013, they found minors who were victims of sex trafficking in more than 70 U.S. cities, and 60 percent of them were living in foster care or group homes during the exploitation (Godoy et al., 2016).

In 2018, the National Human Trafficking Hotline (NHTH) received 41,088 reports that resulted in 10,949 human trafficking cases (Polaris, 2020). In this year, 14,701 high indicator victims (victims with “a high level of indicators of human trafficking”) and 21,864 moderate indicator victims (victims with “several indicators of human trafficking, but lack core details of force, fraud, or coercion”) were identified (Polaris, 2020). These cases resulted in the arrests of those who trafficked and sexually exploited minors in all U.S. states except Alaska, Hawaii, West Virginia, and Wyoming. Texas (1000 cases) and Florida (768 cases) ranked second and third after California with the highest number of reported human trafficking cases among all U.S. states (Polaris, 2020). Louisiana, with 149 reported cases, ranked twenty first, being above 29 other states (Polaris, 2020). Louisiana, Alabama, Arkansas, Florida, Mississippi, and Texas altogether had 2,176 total reported human trafficking cases in 2018, which was approximately one fifth of all reported cases throughout the country (Polaris, 2020).

The International Labor Organization projected that human trafficking creates annual unlawful profits of $150 billion, two thirds of which ($99 billion) is created by sex trafficking while the rest is created by labor trafficking (ILO, 2014).
The Internet has had a “revolutionary” influence on commercial sex trafficking to the point where it has “reshaped, expanded, and repackaged the availability of all types of sexual services over the past decade” (Janson et al., 2013). As an example, based on an AIM Group report, Backpage, an online classified advertising website, was responsible for 80 percent of child sex trafficking (Riviera et al., 2016).

The development of technology over the past few years:

- has made trafficking much easier for pimps
- has changed the place of selling sex from streets to places like “massage parlors, residential brothels, hotels, strip club[s] and gentlemen’s club[s]” (Cardenas, 2017)
- has enabled pimps to cover more areas by advertising in more places, spreading their business and raising the demand for their victims
- has provided greater concealment for traffickers from law enforcement
- has enabled pimps to use classified ads, social media and social websites to recruit children
- has created an unidentified network of support for criminals to share information, legitimize their actions and guide less experienced traffickers
- has enabled less successful pimps to advertise the few females that they control and more successful pimps to sell live sex displays and online prostitution with women from any location around the world (Hughes, 2003).

The low risk of being detected by law enforcement along with obtaining large profits has stimulated many crime syndicates to engage in sex trafficking activities (Dank et al., 2014). Also, it has resulted in the creation of new professional crime networks in sex trafficking. In this regard, scattered groups have been combined into complicated organized networks that include
recruiters, transporters, and pimps (Monzini, 2004). Bertone classifies traffickers in three different network groups (Schauer and Wheaton, 2006):

1. Very large networks that receive help from political and financial figures that act as links between sex trafficking source countries and terminal countries
2. Medium-sized networks that operate in only one country
3. Small networks that only have one or a couple of women.

Detecting human trafficking crimes is still a big challenge to federal investigators and prosecutors. Organized crime groups that are involved in sex trafficking activities use many complicated techniques to keep themselves concealed and safe from law enforcement as well as dangerous buyers. They use different strategies such as “setting up illegal enterprises, bribing law enforcement officers, posting ‘beware’ on websites, and using aliases, burn phones, and code words” (Bouché, 2017).

Dank, et al. reports that “the networks of erotic massage parlors, escort services and beach clubs are thought to be transnational, involving Chinese and Eastern European organized crime, respectively” (Dank, et al., 2014). But, due to the limited resources for investigation, it is very hard to identify these networks and therefore we do not have enough information about them (Dank et al., 2014).

1.2. General Approach

A few studies tried to use available data to find organized crime groups involved in sex trafficking. Ibanez and Suthers applied network analysis techniques to Backpage ads to investigate U.S. domestic human trafficking in a virtual environment in order to detect trafficking paths (Ibanez and Suthers, 2014). Cockbain et al. aimed to explore the advantage of using social network analysis as an instrument to assist in the examination of domestic child sex trafficking in the UK (Cockbain et al., 2011). They claimed that social network analysis is a
useful tool that helps make successful strategies in several ways, including helping to make efficient policies, finding the key actors in a network, and detecting significant ties that can be used to create a multi-agency cooperation (Cockbain et al., 2011).

Mancuso also used social network analysis and found that madams play a critical role in sex trafficking networks in Nigeria (Mancuso, 2014). “Madams” are Nigerian women that were formerly sex trafficking victims who became sex traffickers themselves after paying off their debts. They play an important role in the buying of women and girls and turning them into sex slaves.

All of this research illustrates that collecting and analyzing classified sex provider ads could help us identify potential organized groups that could be behind some of these ads. However, doing this presents a few challenges:

- How to group the ads from an entity that has different phone numbers
- What features of ads can be used to group them
- What models should be applied to the chosen features to achieve a good performance in the grouping process

1.3. Objectives of this Study

Every month, two to three thousand ads are posted by adult service providers in Louisiana. Law enforcement does not have enough personal and resources to go through all of these ads and to investigate them one by one. This study aims to create a model so that we can find potential organized sex trafficking groups that post online ads by grouping different ones that could belong to the same entity through using ad IDs and the textual contents of the ads. This study also aims to use network analysis to visualize identified potential organized sex trafficking groups to find individuals who are more central in the group and could potentially be
traffickers or pimps. In this way, law enforcement can use their limited resources to focus on key central phone numbers in identified sex trafficking networks. This can help law enforcement agencies use their available resources more efficiently when it comes to combating these criminal groups.

1.4. Research Questions

This study is descriptive, data-driven, and aims to create a foundation that could be used in future research. We want to find out what is going on in these online classified ads and how we can differentiate between individual advertisers and criminal group advertisers.

Social network analysis has received substantial attention in criminology after the work of Sparrow, which illustrated the advantage of using this method in criminology related studies (Morselli et al., 2007). Social network analysis has been used to explain the general pattern of criminal networks, detect subsets, and find people in high ranking positions. Such descriptive analysis can show us the strengths and weaknesses of criminal networks and help the authorities target and pull apart criminal organizations.

However, only a few recent studies have applied these models to relatively small data sets to study organized sex trafficking groups. Because of the lack of information and the absence of an extensive body of knowledge pertaining to these concepts, we are not in a position to be able to set up hypothesis driven research questions in the field. As an example, there is no precisely defined boundary that separates individual sex advertisers and organized group sex advertisers. The only information that we can get from the current body of knowledge is that organized groups tend to move their victims between different cities and change their phone numbers frequently to reduce the risk of being identified by law enforcement. However, individual service providers also may change their phone numbers from time to time and work in
more than one city. Therefore, there is no clear required minimum number of phone numbers, number of cities, or distance between cities for an entity to be recognized as an organized sex trafficking group. In this regard, our study can be used as a pilot for law enforcement agencies to do similar analysis and find out which uncovered potential groups are actually criminal organizations. Doing this will produce enough knowledge and information in the field that would establish an appropriate amount of background information for future researchers to be able to draw some hypotheses and test them. We cannot have a hypothesis before having enough knowledge to set boundaries that differentiate individual sex providers from organized groups.

In this research, the ultimate goal is to visualize networks of advertisers that hide themselves behind classified ads, the likes of which will help us identify potential criminal organizations.

Every day, adult service providers post new online ads on classified websites. These ads can have the same ad ID and phone number, different ad IDs and phone numbers, same ad ID but different phone numbers, or same phone number but different ad IDs. They could be posted by the same entity (individual or organized group) or by different entities. If the ads that come from the same entity always use the same ad ID and/or phone number, the people behind the ads could be identified easily. However, these ads, even if they are posted by the same entities, typically have different ad IDs and/or phone numbers, making it difficult to track the advertiser.

We use ad IDs and the textual contents of ads to group different phone numbers and find the unique entity that posted these ads with different ad IDs and/or phone numbers. We use two different models (network analysis and authorship identification) to find out if we can identify any potential organized networks behind the posted adult service provider ads. It will also help us find the geographical locations that they work in.
To make a clear roadmap for this research, we specify the questions that we want to answer. These questions are as follows:

1. Is there evidence of sex trafficking organizations and networks?
2. Is there evidence that sex trafficking organizations operate in multiple cities and states?
3. Is there evidence showing key members of sex trafficking networks?
4. Is the difference between the life expectancy of phone numbers used by individual providers and organized providers statistically significant?
5. Is the difference between the average ages of individual adult service providers and organized adult service providers statistically significant?
6. What is the minimum number of ads per entity (threshold) needed to classify the ads into organizations?
7. Are classification methods equally accurate for identifying the organization associated with an ad for escort services?

1.5. Outline of Dissertation

This dissertation contains five chapters. Chapter two reviews the current literature relating to human trafficking, network analysis, authorship attribution issues, and other concepts in this study. We investigate how network analysis techniques have been used by researchers to examine crime organizations and illegal activities. In chapter three, we go through the details of the network analysis framework and authorship attribution methods that have been used to analyze the data and extract the information in this research. Chapter four has three components, the first of which provides an explanatory picture of the collected data before the application of network analysis. The second part is allocated to the achieved results after applying the text classification and network analysis to the collected data. The third part is dedicated to the
authorship classification of the short online messages in ads posted by sex providers on Backpage. The results of the analysis are also used to answer the research questions in chapter four. Chapter five summarizes the study and concludes the work.
CHAPTER II
LITERATURE REVIEW

2.1. Human Trafficking

Human trafficking has always been a huge problem for many generations, but it was not viewed as such until more recent years (Weitzer, 2014). Trafficking is defined as moving a person into a circumstance where they undergo exploitation. It can be in the form of “forced labor, marriage, prostitution, and organ removal” (Modern Slavery Fact Sheet, 2019). Human trafficking has also been given other names, including “trafficking of persons and modern slavery,” which are all often used by the U.S. Department of State (Modern Slavery Fact Sheet, 2019).

Because of the underground characteristics of human trafficking activities, it is very hard, if not impossible, to measure the full scope of human trafficking operations (ILO, 2018). It is estimated that only 0.04 percent of human trafficking victims are found around the world, which means most victims of human trafficking go unidentified. Therefore, the magnitude of human trafficking activities is much larger than one would think (DoSomething.org, 2019).

According to the U.S. Department of Justice, human trafficking experiences one of the highest rates of increase among all types of crime (Davis, 2017). In fact, it is considered the fastest growing crime around the world (Weitzer, 2014).

Box 2.1 illustrates different types of human trafficking, including forced labor trafficking, sex trafficking, and organ trafficking. Between 2012 and 2016, 89 million individuals were the victim of some type of modern slavery for a time period that could span from just a few days to an entire five years (ILO, 2017).

The share trafficking victims that are adult women is 71 percent (ILO, 2017) and 79 percent of human trafficking cases are detected as sex exploitation (Van der Laan et al., 2011). It is
estimated that for every 1000 adults and every 1000 children, there are 5.9 adult victims and 4.4 child victims, respectively (ILO, 2017). Based on the United Nations Office on Drugs and Crime report in 2012, human trafficking victims consisted of 136 different nationalities and were trafficked in 118 countries, which shows how large the scope of the problem is (Greenbaum, 2014).

Box 2.1. Different types of Trafficking in Persons
Source: Hachey and Phillippi, 2017
As Table 2.1 illustrates, the number of victims of human trafficking around the world is more than 40 million, with around 16 million people in forced labor trafficking, 15.4 million in forced marriage, and 4.8 million people in commercial sex trafficking.

Table 2.1. World human trafficking and its subcategories

<table>
<thead>
<tr>
<th>Forced labour sub-categories</th>
<th>Total forced labour</th>
<th>Forced marriage</th>
<th>Modern slavery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forced exploitation</td>
<td>24,850</td>
<td>15,442</td>
<td>40,293</td>
</tr>
<tr>
<td>State-imposed forced labour</td>
<td>24,850</td>
<td>15,442</td>
<td>40,293</td>
</tr>
</tbody>
</table>

**Source:** ILO, 2017.

“The United Nations Protocol to Prevent, Suppress and Punish Trafficking in Persons, known as the Palermo Protocol”, which ensued from a United Nations (UN) convention, defined the term “trafficking in persons” as (Panigabutra-Roberts, 2012): “The recruitment, transportation, transfer, harboring or receipt of persons, by means of the threat or use of force or other forms of coercion, of abduction, of fraud, of deception, of the abuse of power or of a position of vulnerability or of the giving or receiving of payments or benefits to achieve the consent of a person having control over another person, for the purpose of exploitation. Exploitation shall include, at a minimum, the exploitation of the prostitution of others or other forms of sexual exploitation, forced labour or services, slavery or practices similar to slavery, servitude or the removal of organs” (Panigabutra-Roberts, 2012). The United States endorsed the
UN Protocol in the same year and passed the “Trafficking Victims Protection Act of 2000”, known as TVPA.

Based on the TVPA, human trafficking is “the recruitment, harboring, transportation, provision, or obtaining, patronizing, or soliciting of a person for one of three purposes:

1. Labor or services, through the use of force, fraud, or coercion for the purpose of subjection to involuntary servitude, peonage, debt bondage, or slavery
2. A commercial sex act through the use of force, fraud, or coercion
3. Any commercial sex act, if the person is under 18 years of age, regardless of whether any form of coercion is involved” (Johnson, 2016).

The number of people trafficked to the United States is estimated at 50 thousand victims per year, and most of which come from Mexico and the Philippines (DoSomething.org, 2019).

2.1.2. Sex Trafficking

Sex trafficking is not just a local, national, or a regional problem; it is a problem all around the world. Traffickers may recruit a young woman in Nigeria, sell her in Italy to “get her trained” and send her to the Netherlands to work as a sex provider.

Many people think that slavery and human trafficking mostly occur in undeveloped countries. One example of how this common belief is just a myth is the case of Shaniya Davis, who was sold by her mother in North Carolina in 2012 to buy drugs (Jayson, 2013). In fact, Germany, the United States, Italy, the Netherlands, Japan, Greece, India, Thailand, and Australia have the largest commercial sex industries in the world, in that exact order (Schauer and Wheaton, 2006).

The United States is identified as “a source, transit, and destination country for men, women, and children subjected to sex trafficking, debt bondage, involuntary servitude, and
forced labor” (U.S. Department of State, 2013). Foreigners are not the only victims of sex trafficking in the United States. Based on a Venkatraman study, no place is safe “when it comes to human trafficking”; U.S. citizens have the same risk of being trafficked as migrants do (Venkatraman, 2003).

Traffickers create and use social networks around the country to collect information regarding local law enforcement movements, transfer their victims around, and make themselves familiar with new locations (Godoy et al., 2016). Various tactics including fear, manipulation, lies, and debt bondage are used by sex traffickers to force adults and minors into commercial sex activities. These activities happen in various places such as fake massage salons, residential brothels, on the street, at truck stops, or at hotels and motels (Keiper and Perry, 2019).

The Carpenter and Gates’ study estimates that every year, between 3,417 and 8,108 victims are exploited by the commercial sex industry in San Diego County (Carpenter and Gates, 2016). The study also estimates that law enforcement may be able to capture 15 to 20 percent of the traffickers (Carpenter and Gates, 2016). Around 79 percent of victims are born in the United States, 11.4 percent are born in Mexico, and the rest are born in other countries (Carpenter and Gates, 2016).

Based on a collection of 623 adult and 661 underage victims, the average age of the victims in San Diego County at the time of being recruited by traffickers was 16.1 years (Carpenter and Gates, 2016). The study shows that no resident of the San Diego County, regardless of being wealthy or poor, is immune to sex trafficking. Victims have been detected, whether they were a sex worker or a resident, in all of San Diego County’s cities. Furthermore, in all of the 20 schools that were observed in this study, which are all dispersed throughout the county, students were exposed to sex trafficking incidents (Carpenter and Gates, 2016).
Dank et al. found that twenty five percent of pimps were former drug dealers, and 18 percent of them continued selling drugs while working as a pimp. Gangs were engaged in pimping in five of these cities. Pimps relocated and moved their victims along different circuits and took the women and girls into different cities using social networks. Law enforcement has reported on different types of circuits including local, statewide, regional, and national circuits. Pimps use social networks and contact pimps from other cities to collect information regarding law enforcement activities and local events before moving to their next location (Dank et al., 2014).

Factors such as “neighborhood influence, family exposure to sex work, lack of job options, economic necessity, family and peer encouragement, childhood trauma, and social acceptance” have been mentioned by both pimps and sex workers as the reasons people become a part of underground commercial sex activities. To stay organized and continue running their business with minimum risk, pimps depend on people under their control (friends, family members, and complicit legal businesses) for recruiting, transportation, security, and other operations. These additional actors help pimps develop their business and protect them from being identified by law enforcement (Dank et al., 2014).

Human trafficking results in high unlawful profits that, along with the low risk of being captured by law enforcement, stimulate trafficking activities (Bocinski, 2017). One reason for the high profitability of sex trafficking activities is that, unlike illegal items like drugs that can be sold and used only once, women working in the commercial sex industry can be sold by traffickers every day and even several times per day and generate money for the traffickers continuously for several years. The small risk along with the large profits have encouraged many crime syndicates to engage in sex trafficking activities (Monzini, 2004). This combination has
also caused the creation of many new professional sex trafficking networks. Scattered groups involved in trafficking have come together to form complicated organized networks that can handle all types of operations, from recruiting and transporting to even pimping (Monzini, 2004).

Studies illustrate that investment in human trafficking can produce a 100 to 1000 percent return (Pennington et al., 2009). The International Labour Organization projected that human trafficking creates annual unlawful profits of $150 billion, two thirds of which ($99 billion) is created by sex trafficking, and the rest being created by labor trafficking (Bocinski, 2017). A sex trafficking victim and a labor trafficking victim can make $21,800 and $4,800 in profit per year, respectively (Bocinski, 2017).

It has been reported that exploited women in Germany can make U.S. $7,500 per month, 93 percent of which (U.S. $7,000) is collected by the pimp (United Nations Office on Drugs and Crime, 2004). Based on an Interpol projection in Europe, women that are exploited in the sex industry generate around U.S. $124,000 for their pimps each year (Monzini, 2004).

Many poor families in rural areas in Thailand receive an offer between $200 and $2000 for their daughter to go and work in promised jobs in cafeterias or plants. However, after transporting these girls to the city, traffickers sell them into brothels and use them for sex labor. A brothel owner that uses 20 girls and forces them to have sex with 14 customers daily can make a monthly revenue of $80,000 (Nathan, 2019).

Based on the 2014 Polaris report, one third of the 693 victims of sex trafficking stated that they used to be kept in hotels and motels to provide commercial sex. Based on this report, on average, the traffickers could earn from $500 to $1500 per night (Godoy et al., 2016).

Dank et al. tried to estimate the size and understand the “structure of the underground commercial sex economy” (UCSE) in eight large U.S. cities (Dank et al., 2014). The estimated
results illustrate that the illegal commercial sex industry could have earned between $39.9 and $290 million in these eight cities in 2007 (Dank et al., 2014).

Carpenter and Gates conducted a study for the U.S. Department of Justice on “The Nature and Extent of Gang Involvement in Sex Trafficking in San Diego County” in 2016. The study estimated that the underground commercial sex business in San Diego County earned $810 million per year (Carpenter and Gates, 2016). That makes the business the third largest profitable illegal industry, after drug dealing with $4.76 billion and illegal firearms trading with an estimated $920 million per year (Carpenter and Gates, 2016). Comparing this revenue to the macro-economic organization income like “Otay Mesa Port of Entry” with $800 million or “the San Diego’s entire Natural Resources and Mining Sector” with $900 million demonstrates how large San Diego’s underground sex industry is (Carpenter and Gates, 2016).

Figure 2.1 shows the annual profit per victim in different sectors. Sex trafficking has the highest annual profit ($21,800) and is almost five times the next highest, which is labor exploitation profit ($4,800).

![Annual profit per victim per sector of exploitation (US $)](image)

*Figure 2.1. Annual profit per victim per sector of exploitation (US $)*  
*Source: Emory Global Health Institute, 2016*

Table 2.2 compares eight major U.S. cities’ illegal markets for sex, drug, guns, and other illegal businesses in 2003 and 2007. In three cities including Atlanta, Miami, and San Diego, the
sex market was larger than the illegal drugs and guns markets. This was true for the total sum of each market, as well. The total sex market economy in the eight cities was larger than the total drugs market and total guns market.

Table 2.2. Estimates of illegal markets for sex, drugs, guns and other goods (millions of U.S. Dollars)

<table>
<thead>
<tr>
<th>City</th>
<th>Year</th>
<th>Sex</th>
<th>Drugs</th>
<th>Guns</th>
<th>Other</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta</td>
<td>2003</td>
<td>238</td>
<td>104</td>
<td>169</td>
<td>14,500</td>
<td>15,011</td>
</tr>
<tr>
<td>Atlanta</td>
<td>2007</td>
<td>290</td>
<td>117</td>
<td>146</td>
<td>16,000</td>
<td>16,553</td>
</tr>
<tr>
<td>Dallas</td>
<td>2003</td>
<td>99.40</td>
<td>134</td>
<td>171</td>
<td>16,900</td>
<td>17,304</td>
</tr>
<tr>
<td>Dallas</td>
<td>2007</td>
<td>98.80</td>
<td>191</td>
<td>171</td>
<td>19,000</td>
<td>19,461</td>
</tr>
<tr>
<td>Denver</td>
<td>2003</td>
<td>47.20</td>
<td>54.70</td>
<td>58.40</td>
<td>7,470</td>
<td>7,630</td>
</tr>
<tr>
<td>Denver</td>
<td>2007</td>
<td>39.90</td>
<td>63.90</td>
<td>47.40</td>
<td>7,820</td>
<td>7,971</td>
</tr>
<tr>
<td>Miami</td>
<td>2003</td>
<td>302</td>
<td>93.40</td>
<td>106</td>
<td>15,300</td>
<td>15,801</td>
</tr>
<tr>
<td>Miami</td>
<td>2007</td>
<td>235</td>
<td>95.70</td>
<td>118</td>
<td>14,700</td>
<td>15,149</td>
</tr>
<tr>
<td>San Diego</td>
<td>2003</td>
<td>124</td>
<td>105</td>
<td>46.60</td>
<td>8,490</td>
<td>8,766</td>
</tr>
<tr>
<td>San Diego</td>
<td>2007</td>
<td>96.60</td>
<td>96.30</td>
<td>47.70</td>
<td>8,740</td>
<td>8,981</td>
</tr>
<tr>
<td>Seattle</td>
<td>2003</td>
<td>50.30</td>
<td>87.30</td>
<td>83.10</td>
<td>9,840</td>
<td>10,061</td>
</tr>
<tr>
<td>Seattle</td>
<td>2007</td>
<td>112</td>
<td>87.40</td>
<td>60.10</td>
<td>11,800</td>
<td>12,060</td>
</tr>
<tr>
<td>DC</td>
<td>2003</td>
<td>155</td>
<td>111</td>
<td>150</td>
<td>17,700</td>
<td>18,116</td>
</tr>
<tr>
<td>DC</td>
<td>2007</td>
<td>103</td>
<td>103</td>
<td>160</td>
<td>20,300</td>
<td>20,666</td>
</tr>
<tr>
<td>Total</td>
<td>2003</td>
<td>1,015.90</td>
<td>689.40</td>
<td>784.10</td>
<td>90,200.00</td>
<td>92,689.40</td>
</tr>
<tr>
<td>Total</td>
<td>2007</td>
<td>975.30</td>
<td>754.30</td>
<td>750.20</td>
<td>98,360.00</td>
<td>100,839.80</td>
</tr>
</tbody>
</table>

Source: Dank et al., 2014

‘The U.S. National Human Trafficking Hotline’ (NHTH) aims to help and support the victims and survivors of human trafficking all over the country by connecting them to emergency shelters, transportation, trauma therapists, and asking for help from law enforcement. They received 246,267 calls, webforms, and emails between 2007 and June 2019, and 56,504 distinct trafficking cases were detected as a result. During this time period, 62,371 high indicator victims (victims with “a high level of indicators of human trafficking”) and 74,594 moderate indicator victims (victims with “several indicators of human trafficking, but lack core details of force, fraud, or coercion”) were identified (Polaris, 2020).
In 2018, the hotline received 41,088 contacts, leading to the detection of 10,949 human trafficking cases. The number of identified victims in the United States in 2018 with high and moderate indicators was 14,701 and 21,864, respectively (Polaris, 2020). In 2018, at least 7 out of 10 specified cases of human trafficking (7,859 cases) in the United States were sex trafficking related (Figure 2.2). Less than 6 percent of these cases were related to only labor trafficking. Based on this information, sex trafficking dominates the human trafficking activities in the United States (Polaris, 2020).

Figure 2.2. Human trafficking cases in the United States in 2018
*Source*: Polaris, 2018

Figure 2.3 illustrates the distribution of potential trafficking cases in the United States in 2018. These cases have been concentrated in the West (mostly California), East, and Southeast of the country. As the figure demonstrates, the states that have been used as the target region in this study (Texas, Louisiana, Mississippi, Florida, Alabama, and Arkansas) are among the states that have a high number of human trafficking cases. An interesting point in this figure is that Highway I-10, between Texas and Florida, has shown to be involved in a high number of potential human trafficking cases.
Figure 2.3. Distribution of Human Trafficking Cases across the United States in 2018
Source: Polaris, 2018

Regarding the identified victims, Figure 2.4 shows the percentage of survivors for the different kinds of human trafficking in the United States in 2018. According to these statistics, more than 63 percent of identified survivors are the victims of sex trafficking. Comparing Figure

![Pie Chart]

Figure 2.4. Number of identified victims across the United States in 2018
Source: Polaris. 2018
2.4 to Figure 2.2 shows that, as we could expect, on average, the number of victims identified in each sex trafficking case is less than the number of identified survivors in each labor trafficking case.

Information regarding the age, race, and ethnicity of the identified victims is shown in Figure 2.5. As the figure illustrates, one out of three identified victims was a minor, showing that a large extent of sex trafficking in the country involves children. More than 83 percent of victims with specified gender were female, and Latinos had the highest share of the different victim ethnicities.

Figure 2.6 gives the number of victims of labor trafficking and sex trafficking for 13 different age categories in the United States in 2018. Most identified victims (survivors) at the time of entry into labor and sex trafficking were between 15 and 17 years old, with 243 survivors of sex trafficking and 31 survivors of labor trafficking. In 2018, 31 percent of the identified victims of sex trafficking were under 15 years old, 60 percent were under 18 years old, and 75 percent were under 21 years old (Figure 2.6).
Figure 2.6. Age at the time of entry into sex or labor trafficking

*Source:* Polaris, 2018

Table 2.3 shows the human trafficking indicators for the six states under investigation in this research. These six states altogether had 2,176 total reported human trafficking cases in

### Table 2.3. Human trafficking indicators for the states under investigation in 2018

<table>
<thead>
<tr>
<th></th>
<th>Alabama</th>
<th>Arkansas</th>
<th>Florida</th>
<th>Louisiana</th>
<th>Mississippi</th>
<th>Texas</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of contacts (2007 - 2018)</td>
<td>1,761</td>
<td>1,238</td>
<td>13,817</td>
<td>2,833</td>
<td>1,144</td>
<td>19,419</td>
<td>40,212</td>
</tr>
<tr>
<td>Number of Contacts (2018)</td>
<td>255</td>
<td>202</td>
<td>1,885</td>
<td>302</td>
<td>194</td>
<td>2,312</td>
<td>5,150</td>
</tr>
<tr>
<td>Reported Human trafficking cases (2007 - 2018)</td>
<td>467</td>
<td>337</td>
<td>4,203</td>
<td>851</td>
<td>399</td>
<td>5,349</td>
<td>11,606</td>
</tr>
<tr>
<td>Reported Human trafficking cases (2018)</td>
<td>89</td>
<td>85</td>
<td>767</td>
<td>149</td>
<td>86</td>
<td>1,000</td>
<td>2,176</td>
</tr>
<tr>
<td>Number of High victims (2007 - 2018)</td>
<td>604</td>
<td>554</td>
<td>6,637</td>
<td>1,122</td>
<td>834</td>
<td>8,946</td>
<td>18,697</td>
</tr>
<tr>
<td>Number of High victims (2018)</td>
<td>154</td>
<td>75</td>
<td>1,098</td>
<td>267</td>
<td>170</td>
<td>3,024</td>
<td>4,788</td>
</tr>
<tr>
<td>Number of Moderate victims (2007 - 2018)</td>
<td>544</td>
<td>560</td>
<td>5,846</td>
<td>1,150</td>
<td>513</td>
<td>8,987</td>
<td>17,600</td>
</tr>
<tr>
<td>Number of Moderate victims (2018)</td>
<td>100</td>
<td>144</td>
<td>1,468</td>
<td>238</td>
<td>93</td>
<td>2,534</td>
<td>4,577</td>
</tr>
</tbody>
</table>

*Source:* Polaris, 2018
2018, which was approximately one fifth of all reported cases throughout the country. In 2018, Texas with 1000 cases and Florida with 768 cases ranked second and third (after California) among all U.S. states. Louisiana, with 149 reported cases, ranked twenty first, being above 29 other states (Polaris, 2020).

In 2018, Florida, Texas, and Louisiana were among the states with the highest per capita human trafficking cases, ranking 8th, 14th, and 15th, respectively (Nathan, 2019). Houston, Baton Rouge, New Orleans, and Dallas were among the U.S. cities with the highest per capita human trafficking cases, ranking 7th, 10th, 13th, and 23rd, respectively (Nathan, 2019).

2.1.3. Victims and Traffickers

The victims of human trafficking can be men, women, girls, boys, U.S. citizens, foreigners that were trafficked from other countries, or legal and illegal migrants that have already been in the United States (Clawson et al., 2009).

Different victims of sex traffickers may experience different situations at the time of recruiting. Some victims may engage in a loving relationship with a person who later forces them into sex trafficking activities. Some are dragged into the commercial sex industry through fake promised jobs like modeling or dancing. Some are required by their parents or other family members to provide sex and end up in commercial sex trafficking (Keiper and Chiaramonte, 2019). Among the victimized women that contacted the National Hotline, 36.9 percent claimed that they were trafficked by their partners (Bocinski, 2017).

Traffickers move victims around regularly to decrease the possibility of being identified by law enforcement and increase their profits. The moving of the victims ensures that they do not have enough time to making any trusting relationships with their customers. Also, moving victims around segregates them from the location and culture that they get used to and decreases
the probability that they can run away and report to the police. Rotation can happen between different countries or between different cities of just on country (Aronowitz et al., 2010).

According to the 2018 Federal Human Trafficking Report, victims of more than half of the criminal sex trafficking cases in 2018 were children (Figure 2.7). In fact, the number of cases involving children (51.6%) were more than 3-fold the number of cases involving adults (16.3%), which shows how children are especially in danger of being exploited by sex traffickers.

![Figure 2.7. Active criminal human trafficking cases by age of victims in 2018](image)

*Figure 2.7. Active criminal human trafficking cases by age of victims in 2018*

*Source: Currier and Feehs, 2019*

As we saw before (Figure 2.5), 1 out of 3 identified victims of sex trafficking whose ages were recorded in the United States in 2018 was a minor. The sex trafficking of children that are born in the country is the most frequent type of human trafficking of citizens in the United States (Godoy et al., 2016). The National Center for Missing and Exploited Children (NCMEC) has approved a conservative estimate of 100,000 domestic-born children that are at risk for sexual exploitation every year (Godoy et al., 2016).

The ‘Six-year Analysis of Sex Traffickers of Minors’ study by Arizona State University found that 1,416 individuals were arrested for trafficking children for sex in the United States
between 2010 and 2015 (Roe-Sepowitz, 2019). As Figure 2.8 shows, the number of sex trafficking cases involving children increased continuously between 2010 and 2015 with a 271 percent increase, from 97 cases in 2010 to 360 cases in 2015.

![Sex Trafficking cases of Minors in the United States 2010 - 2015](image)

**Figure 2.8.** Sex trafficking cases involving minors in the United States between 2010 and 2015  
*Source:* Roe-Sepowitz, 2019

These cases resulted in the arrest of the sex traffickers of minors in all states except for Alaska, Hawai‘i, West Virginia, and Wyoming. Sex traffickers whose victims were specifically only minors had an average age of 28.5 years. This average declined between 2010 and 2015. Around one fourth of the identified traffickers were female and three quarters of them were African American. The absolute majority (98.8 percent) of the traffickers were U.S. citizens. Almost 20 percent of the sex traffickers whose victims were minors were involved in gang organizations. The victims were moved around between many states, anywhere from 2 to 17 states with an average of 2.7 states (Roe-Sepowitz, 2019). Most of the traffickers used hotel rooms to provide for their clients and email, online ads, and cellphones for advertisement. In more than 40 percent of cases (592 cases), sex traffickers used “Backpage.com” for advertising (Roe-Sepowitz, 2019).
In the 1,416 cases, 941 victims were found, and their information was collected. The victims were between 4 and 17 years old at the time of recruiting. The average age of the victims at the time of recruiting and at the time of being identified was 15 and 15.5 years, respectively. Approximately 67 percent of the victims were runaways and only less than half of the victims knew their traffickers (Roe-Sepowitz, 2019).

Based on this report, California (15.8%), Florida (10%), Texas (7.7%), New York (6.3%), and Tennessee (4%) had the highest percentage of arrests where sex traffickers of minors were caught. About 44 percent of all sex traffickers whose victims were minors who were arrested in the United States between 2010 and 2015 were arrested in these five states (Roe-Sepowitz, 2019). The results of this study illustrated that hotel rooms (56.6%), out call locations (21.4%), houses (13.8%), and streets (12.3%) had the highest share of different sex trafficking venues. These numbers give further evidence that hotel rooms have been used as the main location for providing illegal sex activities (Roe-Sepowitz, 2019).

In an FBI Cross Country operation in 2013, minors trafficked for sex were found in more than 70 U.S. cities, 60 percent of whom were living in foster care or group homes during the exploitation (Godoy et al., 2016). Throughout the ensuing FBI operation in 2015 that focused on human trafficking, 149 victims were identified, with a 12-year-old child as the youngest victim (Godoy et al., 2016).

Based on a projection by the Office of Juvenile Justice and Delinquency Prevention, approximately 1.6 million minors run away from home in the United States every year, many of whom are at risk of being exploited by sex traffickers. According to estimates from some studies, 30 to 50 percent of homeless children are victimized by sex traffickers, regardless of their gender
(Godoy et al., 2016). The length of time that children are homeless has a positive impact on the probability of being victimized by commercial sex traffickers.

Statistics from the National Center for Missing and Exploited Children (NCMEC) demonstrate a continuous rise in the sex trafficking of missing and runaway children. It is estimated that twenty percent of the 11,800 underage runaways in 2015 were exploited by sex traffickers, almost three quarters of which were foster care residents or in the care of social services when they ran away (Godoy et al., 2016). Domestic minor sex trafficking is believed to be the most under-cited, under-detected, and the most life-threatening type of commercial sex trafficking (Beautiful Ones Ministries, Inc., 2015).

Figure 2.9 illustrates the movement patterns of sex traffickers exploiting minors. There are three different patterns in this figure that belong to different trafficking groups. Each pattern covers seven to eight different states. In Pattern 1, the trafficker circulates the victim between eight different states in the northeastern part of the country. In Pattern 2, the trafficker moves around in seven southeastern states. Pattern 3 is much more interesting and demonstrates how some of the sex traffickers move their victims all around the country. In this pattern, the trafficker starts from the Northeast (MI), goes to the center of the country (CO), and then moves to the Southeast (FL). From there they go to Texas and then finally move to the more western states like Arizona, Nevada, and California (Roe-Sepowitz, 2019).

Pimps use both online and face-to-face techniques to recruit victims. For instance, pimps usually approach homeless minors and wait around youth shelters to seek out the children living there (Cardenas, 2017). Williamson and Prior list “bus stops, train stations, malls, homeless shelters, schools, and individual’s homes” as the places that are more often used by sex
traffickers to recruit their victims (Williamson and Prior, 2009). Minors recruited by pimps are usually 12 to 14 years old.

![Maps showing the relocation of sex traffickers around the United States.](image)

Figure 2.9. Examples of the relocation of sex traffickers around the United States
Source: Roe-Sepowitz, 2019

In some cases, legitimate enterprises such as “employment, modeling, and marriage agencies” have been deployed “to recruit young women and children” (Hodge and Lietz, 2007). In these cases, the victims are promised a good life in usually more wealthy countries, and the victims typically have no clue about the slavery that they are about to be forced into (Hodge and Lietz, 2007).
Kidnapping or guerilla pimping is another method that has been used by traffickers. Guerilla pimping happens when the victimization process involves kidnapping, imposing the victim into sex trafficking, and possibly selling the victim to someone else (Logan et al., 2009). In this approach, people that are not willing to leave their country may be kidnapped and transferred to another country by an individual who is familiar to them. Usually, traffickers bribe the custom officers to cross the victims to the other side of a border (Hodge and Lietz, 2007).

Based on Roe-Sepowitz’s study, traffickers have used various tactics to control their victims including “threatened the victim with a firearm” (11.1%), “physical assault with a weapon” (26.7%), “threats of harm and psychological abuse” (36.7%), “drugs to control their minor victim” (20.7%), and “sexual violence” (36.3%) (Roe-Sepowitz, 2019). Based on this study, in 177 cases (23.2% of cases), the sex traffickers had victims who were runaways. These victims were recruited either by being promised to receive money and wealth (81 cases) and shelter (78 cases), or by friendships (80 cases) and love relationships (77 cases) (Roe-Sepowitz, 2019).

Godoy et al. classified sex traffickers into six groups. The first group is crime organizations and gangs. The second group, called Romeo, is sometimes connected to gangs. They approach girls and young women as a romantic interest to manipulate them. The third group are CEOs who promise young women a good legitimate job but trap them into commercial sex activities. Gorilla pimps, the fourth group of traffickers, have no prior history with their victims and use tactics such as “kidnapping, violence, drugs, and blackmail” to force them into the commercial sex industry. The fifth group consists of “biological parents, legal guardians, foster parents, relatives, and their companions,” who are the most forceful traffickers that enter the minors into the sex trafficking industry. Finally, the last group are the secondary profiteers
that consist of businesses and institutions such as “motels and hotels, taxi services, restaurants, clothing stores, and strip clubs” that receive some profit from being linked to commercial sex trafficking (Godoy et al., 2016).

An investigation in Mississippi demonstrates that domestic minor sex trafficking often begins with a family member and ends in being abused by other people. If the mother is a sex provider, then she typically involves her child in the sex industry as well, making her the pimp in that specific instance. In situations like this, where the pimp is a family member, it would be very difficult to detect the pimps. In family trafficker cases, the children may go to school, function regularly, and be involved in their community activities, but they are still victims (Beautiful Ones Ministries, 2015).

Thousands of women from the area around the former Soviet Union leave their countries every year from reasons like job offers to being promised a hand in marriage. Many of these women are linked to foreign men through “marriage agencies” (Hughes, 2004). Most of these women end up being victims of violence, sexual mistreatment, and trafficking. In some cases, women are abused or killed after they are married to the man that the marriage agency set them up with.

Traffickers usually take advantage of vulnerable people with emotional needs, particularly children and adolescents who can be pressed, terrified, and manipulated very easily (Hachey and Phillippi, 2017). In all forms of trafficking activities, the biggest factors that entice victims to enter the commercial sex market are “poverty, early childhood trauma or abuse, substance abuse or addiction disorders, and housing insecurity” (Macias-Konstantopoulos et al., 2013). Other factors such as family misbehavior and conflict, experiencing violence at home, mental health issues, and being abused by family members increase people’s vulnerability and
the chances of being exploited by traffickers (Hachey and Phillippi, 2017). Living in a poor neighborhood is the most significant social factor that can lead a person to be sexually exploited in the United States (Logan et al., 2009).

The reasons that many young women who are assured love and a secure future would take the risk of involving themselves in the sex trafficking market are the immense monetary and economic benefits that it could bring them. Sex trafficking activities also create large profits for the criminal enterprises that run these criminal businesses due to how these activities have a very high revenue and low cost. The cost is low because the victims do not get paid at all or receive a small part of the money that they make, and the risk of being identified is low as well. So, the incentive for both the victims and the traffickers are economical (Aronowitz, 2010).

Different studies have listed different risk factors as the potential ones that sex trafficking victims face. Even though many factors get repeated from study to study, there are some factors that are in one study but not in another. As an example, two lists from two different studies have been provided in Boxes 2.2 and 2.3.

The largest risk factor that can lead to a girl being dragged into sexual activities is her age, and the risk increases if a girl has been sexually abused and/or has had an unstable home life (Godoy, et al. 2016). In the United States, the average age to start working as a commercial sex provider for girls is between 12 and 14 years, and for boys, it is between 11 and 13 years old (Hachey and Phillippi, 2017).

Based on the United States Department of Health and Human Services, minors who are “exploited through prostitution are most often runaways or throwaways” (Beautiful Ones Ministries, 2015). Two-thirds of all domestic sex trafficking victims ran away from home at least once, and 70 to 90 percent of them had a history of childhood abuse (Beautiful Ones Ministries,
Based on The National Center for Protection of Child Abuse, around 2.4 million minors in the United States run away from home annually (National District Attorneys Association, 2015). After leaving home, kids turn into targets for sex traffickers. Based on the investigations’ projections, 33 percent of homeless minors are attracted “towards prostitution within 48 hours of leaving home” (Emory Global Health Institute, 2016). Almost 20 percent of homeless teens in the United States are LGBT and the vulnerability of LGBT teens to sex trafficking is higher than non-LGBT teens. Based on the U.S. National Coalition for the Homeless, the exploitation rate of homeless LGBT teens and homeless heterosexual teens are 58.7 percent and 33.4 percent, respectively (Martinez & Kelle, 2013).

Children living in foster care don’t often get much love, affirmation, and protection. This makes them vulnerable to sex traffickers that take advantage of these children by using different tricks to drag them into commercial sex activities (Emory Global Health Institute, 2016).

**Box 2.2. Top 10 risk factors reported by sex trafficking survivors**

*Source: Polaris, 2019*
Usually, the minors that have been exploited by sex traffickers are motivated to call their traffickers “daddies” and view themselves as “wives” to give them a feeling that they have a family (Emory Global Health Institute, 2016). Based on the ‘California Against Slavery Research & Education Institution’, in 2012, about 50 to 80 percent of victimized minors in California were officially part of the California welfare system. Also, based on a nationwide FBI investigation in 2013 across seventy cities in the U.S., children from foster care or group homes make up 60 percent of all child sex trafficking victims (Emory Global Health Institute, 2016).

Carpenter and Gates found that victimization, homelessness, and foster care are all associated. Based on the sample data of adult sex trafficking survivors that they collected, 55 percent were homeless, 28 percent stated that they part of the foster care system in one way or another, and 17 percent said that they had spent a part of their lives homeless or in the foster care system (Carpenter and Gates, 2016).

### 2.1.4. Organized Sex Traffickers in the United States

Criminal organizations are active in 126 counties and in over 40 states and U.S. territories (Bouché, 2017). Based on a study that investigated the sex trafficking of minors in the United States, 10.3 percent of traffickers were gang members, and, in 249 cases, sex traffickers crossed the state lines while transporting underage victims (Roe-Sepowitz, 2019). Dank et al. investigated different types of illegal sex activities and their locations in the United States, like “brothels, erotic massage parlors, Internet prostitution, and street prostitution,” but they could not explore the networks and sex activities provided by organized crime (Dank et al. 2014). So, they reported that “the networks of those operating massage parlors, escort services, and beach clubs are thought to be transnational, involving Chinese and Eastern European organized crime,
respectively. However, these networks have proven more difficult to uncover due to resource constraints. As a result, less is known about their network characteristics” (Dank et al., 2014).

Box 2.3. Social determinants and risk factors for trafficking in persons

Source: Hachey and Phillippi, 2017

Based on research related to sex trafficking done by Bouché for the U.S. Department of Justice, there are five different kinds of organized groups (Bouché, 2017):

1. Mom & Pop
2. Crime Ring
3. Gang
4. Cartel/Mafia/Syndicate
5. Illegal Enterprises

Mom & Pop groups are of a small or medium size, having under 30 members. Crime Ring groups are similar to Mom & Pop groups and also are of a small or medium size. Gang groups are active locally or inside the country, but not outside of the border. Cartel, Mafia, and Syndicate are words that are used interchangeably. These groups are large, probably have hundreds of members, and work internationally. They cannot work just locally or in the United States, are very complicated, and are involved in various criminal operations. Illegal Enterprises are a part of many different complicated criminal operations and usually have a business name (Bouché, 2017).

The results of this study illustrate that between 2000 and 2015, about 2,096 people were federally prosecuted in 862 human trafficking cases, 58 percent of which (1,227) worked as part of an organized criminal group (Bouché, 2017). Based on this study, 34 percent of organized groups were involved in both adult and child sex trafficking, 24 percent were involved in just child sex trafficking, and 17 percent were involved in just adult sex trafficking (Bouché, 2017). While 55 percent of the adult victims of sex trafficking had foreign nationality, 92 percent of the minor victims of sex trafficking had U.S. nationality (Bouché, 2017).

These numbers demonstrate that, whereas just over half of the adult victims of sex trafficking had U.S. nationality, almost all minor victims had U.S. nationality. This result reveals how children are more vulnerable to sex trafficking inside their own country.

In this study, Mom & Pop groups took up 35 percent of the organized crime cases. About 71 percent of Mom & Pop groups were involved in just sex trafficking (adult only, child only, or both) through brothels and massage parlors (33%) and Internet prostitution (25%) (Bouché, 2017). Thirty three percent of the organized crime cases were related to Crime Rings and most of
their cases (95%) were involved in commercial sex. They had a high online activity with 47 percent of their cases being Internet prostitution cases. On average, 7 victims were exploited by a Crime Ring (Bouché, 2017). Only six percent of the organized crime cases were related to Gang groups. All Gang related cases showed that they were engaged in the commercial sex industry. They had both street and Internet prostitution and most of their victims in these cases were minors. On average, 8.8 victims were exploited in each Gang case. No cases related to Cartels, Mafias, or Syndicates were found in this study (Bouché, 2017).

Illegal Enterprises made up 26 percent of the organized crime cases and they were involved in all of the different kinds of human trafficking activities (Bouché, 2017). However, they were most often involved in adult sex trafficking (Bouché, 2017). About 50 percent of the sexual activities took place in brothels or massage parlors, and 19 percent in strip clubs. On average, about 65 victims were exploited in each case (Bouché, 2017).

Figure 2.11 shows the distribution of identified centers of human trafficking activities for organized crime groups by county across the United States. While there are a few such bases in the North and the center of the country, most of them are located in the East, Southeast, and West.
A project by the U.S. Department of Justice aimed to examine how gangs were engaged in the sex trafficking network in San Diego County and measure the size of the engagement (Carpenter and Gates, 2016). By using evidence from 154 criminally engaged people, 140 sex trafficking victims, and 141 staff members of 20 high schools around San Diego County, they detected 110 gangs in the area that were involved in sex trafficking activities.

It was assumed that each gang group has its private territories and that they sometimes go to territorial war, especially on issues like drug markets. However, Dank et al. found that rival gang groups would prefer to cooperate instead of competing against each other when it came to prostitution (Dank et al., 2014).

Based on the Roe-Sepowitz et al. study, out of 1,210 detected cases of sex traffickers across the United States between 2010 and 2015, 231 cases (19.1%) were associated to gang groups, half of which were members of international gangs. Almost 80 percent of these cases
were found in the 7 states of California (35.5%), Tennessee (11.7%), Florida (10%), Virginia (6.9%), New York (5.6%), Texas (4.8%), and Colorado (4.3%) (Roe-Sepowitz, 2019).

Comparing the underage victims of gang-affiliated sex traffickers with those of non-gang-affiliated sex traffickers demonstrates that the underage victims of gang-affiliated sex traffickers were much younger, had a higher possibility of being addicted to drugs at the time of recruitment, had a higher probability of being abused sexually before recruitment, and had a larger number of foster care or homeless victims. Gangs generally operate in coastal states or states that have national borders. While the highest rate of international gangs was found in Tennessee, they operated in nine other states as well (Roe-Sepowitz, 2019).

According to federal prosecution documents, the counties that have the highest human trafficking activities organized by criminal groups are Harris County in Houston (TX), Fulton County in Atlanta (GA), and Queens County in Queens (NY) (Bouché, 2017). Based on federal prosecution evidence, ranking the location of sex trafficking activities illustrates that brothels and massage parlors (325 crime locations) have the highest rank and “street prostitution (201 crime locations), internet prostitution (175 crime locations), escort services (48 crime locations), and strip clubs (30 crime locations)” have the next highest ranks, in that order (Bouché, 2017).

2.1.5. The Online Sex Industry

Human beings have been treated as a commodity throughout the history of mankind, but the advancement of technology and communication has taken this problem to a new level by simplifying the prostitution and sex trafficking processes (Maras, 2017). The fast development of communication devices such as the Internet, social networking sites, and cellphones has made it much easier for human traffickers to recruit, market, advertise, connect, manage, and make use of victims over wide geographical areas (Latonero et al., 2012). They use social networks and
online classified sites like Backpage, Craigslist, and Facebook to advertise the sale of human beings, including adults and children, for sexual activities.

The advancement of the Internet has allowed pimps to advertise their victims by simply posting explicit pictures on websites like Backpage, Eros, CityVibe, MyRedbook, and AdultSearch. These online advertisements have changed the place of selling sex from streets to places like “massage parlors, residential brothels, hotels, strip club[s] and gentlemen’s club[s]” (Cardenas, 2017). Usually, these types of advertisements contain “(1) a pimp’s phone number, (2) a description of the sexual act the victims will engage in, (3) a sexually explicit photograph of the victims, and (4) the cost” of the act (Cardenas, 2017). Online classified websites enable pimps to cover more areas by advertising in more places. For example, a person in New Jersey can buy services that are being advertised in New York (Cardenas, 2017).

Furthermore, not having geographical limitations enables pimps to spread their businesses, provides greater concealment from law enforcement, and raises the demand for their victims. This, in turn, leads to an increase in the pimps’ profits. Also, by describing the victim as things like “fresh, cherry, and barely legal”, they inform the buyer that the advertised victim is a minor (Cardenas, 2017).

The influence of the “Internet on prostitution and the sex industry has been revolutionary”, to the point where “it has reshaped, expanded, and repackaged the availability of all types of sexual services over the past decade” (Janson et al., 2013). The creation of websites for sex-related activities has raised extensively and the Internet has turned out to be a “one-stop shop” for sex buyers (Johns). Johns use these websites like a Yellow Pages directory, using chat rooms to support each other, exchange information, and receive advice regarding the locations of
the providers. Accordingly, forms of exploitation have arisen “at a level not seen before” (Janson et al., 2013).

There have been several studies on the impact of social networks and online advertisements on the commercial sex industry and they all demonstrate that human traffickers frequently use social networking and online classified websites for their activities (Hayden, 2014).

A global investigation in 2007 illustrated that “technology is the engine behind the growth of the sex trade…. [It] has become the single greatest facilitator of the commercial sex trade in all of the countries observed” (Janson et al., 2013). An inquiry by the FBI demonstrated that at least 2,800 ads containing minors as a sex provider were posted on Craigslist in just 2008 alone (Janson et al., 2013).

Finding possible victims on the Internet through social networks like Facebook and MySpace has been the initial step in many human trafficking cases. As said before, traffickers have used different tactics to gain the trust of their victims, such as claiming that they are in love with the victims, promising a good life to the victims, etc. (Dixon, 2013). However, a different kind of trafficking tactic begins when a female uses the Internet to search for a job and finds a very good one that requires her to be relocated from her home. After the relocation of the victim, the trafficker will threaten to harm the victim or her family, and, if she does not follow the trafficker’s orders, they will even prevent the victim from contacting their family (Dixon, 2013).

Pimps use online advertisements to increase the demand for prostitution by fascinating possible Johns whose initial purpose of surfing the Internet was not to buy commercial sex (Cardenas, 2017). For instance, a person can be searching for pornography online and might see an advertisement for sex near his home. Since Johns can hide their identity when doing an online
exchange, online advertisements increase the access to unlawful sex activities and encourage Johns to take part in the child sex trafficking market (Cardenas, 2017).

Johns can examine the victims they are buying the services of by using the sexually clear images posted on the advertisement and will still remain unidentified. Also, they can pay for sexual services anonymously by using untraceable online currencies like Bitcoin. In addition to facilitating the buying of commercial sex, the Internet has unintentionally caused the formation of powerful friendships between Johns. For instance, “The Erotic Review” forum helps Johns find and purchase services from their “perfect” victim and gives them advice on how to negotiate aggressively when they are buying sex acts (Cardenas, 2017).

The Internet and high-tech electronic devices have enabled pimps to use social media, chat rooms, and other social websites to recruit children. As an example, a secret operation ran by detectives in Virginia uncovered a pimp that was trying to persuade underage girls to become sex slaves through instant messaging (Cardenas, 2017).

Craigslist was the first online classified website that was inspected by law enforcement and condemned for allowing the posting of child sex services on its website. After Craigslist was enforced to terminate its Adult Services section in 2010, sex traffickers moved to other online classified websites like Backpage. For example, most of the child sex trafficking cases reviewed by the sex trafficking unit of the New York District Attorney’s Office were related to the advertising of child victims on Backpage (Cardenas, 2017).

Backpage allowed the posting of ads related to buying and selling commercial sex with children for a long time by taking advantage of “the Communications Decency Act of 1996” (CDA) and the First Amendment. Under the CDA, communicating websites are protected from being responsible if a third party posts unlawful content on their site. Moreover, if the website
administrators find out that a child sex trafficking ad had been posted on their site, they have no legal duty to delete or block the ad (Cardenas, 2017).

The international communications forums have enhanced the confidentiality and reduced the segregation of the men who abuse women and children and take advantage of them. The Internet creates an unidentified network of support for criminals to share their knowledge, legitimize their actions, and guide and teach less experienced men. In this semi-private environment, small pimps are able to advertise a few females that they control, and large pimps can sell live sex displays and online prostitution from any location in the world (Hughes, 2003).

Based on a report by the AIM Group (an interactive media and classified advertising consulting organization), Backpage was responsible for 80 percent of all child sex trafficking (Riviera et al., 2016). Until 2012, Backpage belonged to Village Voice Media, but was then bought by an “unnamed Dutch holding company” in December 2014 (Riviera et al., 2016).

A trafficking survivor that was pimped on Craigslist explains the way she was treated by her pimp in an open letter to Craigslist: “I was first forced into prostitution when I was 11 years old by a 28-year-old man. I am not an exception. The man who trafficked me sold so many girls my age, his house was called Daddy Day Care. All day, other girls and I sat with our laptops, posting pictures and answering ads on Craigslist. He made $1,500 a night selling my body, dragging me to Los Angeles, Houston, Little Rock — and one trip to Las Vegas in the trunk of a car. I am 17 now, and my childhood memories aren’t of my family, going to middle school, or dancing at the prom. They are of making my own arrangements on Craigslist to be sold for sex, and answering as many ads as possible for fear of beatings and ice water baths” (Janson et al., 2013).
The USA Sex Guide Forum is one of the more active websites where sexual activities are advertised on the Internet. In its FAQ section, the website describes its goal: “to facilitate the exchange of information between men who are looking for sex with women” (Janson et al., 2013). The creator and funder of this website states that: “this website is all about assisting people in obtaining commercial sex services.” On its first page, the website introduces itself as “the Internet’s largest sex travel website” (Janson et al., 2013). To show off how popular it is, the website provides the following statistics to its viewers (Janson et al., 2013):

- 200,000+ Registered Forum Members
- 60,000± Unique Visitors per day
- 230,000± daily page loads

Websites like the USA Sex Guide facilitate illegal sex activities by directing beginners who want to purchase sex services, long-term sex buyers who have not been active for a long time, and visitors from other cities to the “best” places that they can purchase commercial sex (Janson et al., 2013).

After the Senate investigated Backpage’s founders, Michael Lacey and John Larkin, for facilitating prostitution and sex trafficking and Backpage CEO Carl Ferrer was convicted of money laundering and facilitating prostitution, Backpage was shot down (Glaser, 2018). During the investigation, authorities found internal emails that showed how the site’s managers modified the ads to conceal unlawful events by using software that polished texts that could demonstrate unlawful sex activities with children. So, instead of reporting the incident to law enforcement, they changed words such as “amber alert” and “Lolita” from ads to cover up for ads related to child sex activities. In fact, they were aware that traffickers were using their website for advertising child sex activities and helped them continue doing so (Glaser, 2018).
A few days after the shutting down of Backpage, President Trump signed the bills “Stop Enabling Online Sex Trafficking Act (SESTA)” and “Fight Online Sex Trafficking Act (FOSTA)” into law. These laws aimed to hold websites accountable for deliberately letting sex traffickers post ads on their website. The laws also allow for civil lawsuits against these types of websites and increase the ability of law enforcement agencies to pursue the owners of websites such as Backpage. These new laws prevent websites from using the CDA as a shield to protect themselves and allowing sex traffickers to use them to advertise illegal sexual activities (Glaser, 2018).

Figure 2.13 demonstrates the share of different methods of sex trade activities used by adolescent girls in Georgia between August 2007 and August 2010. As the figure shows, the share of which the Internet was used for sex trafficking had an increasing trend and increased from 42 percent in 2007 to 81 percent in 2010.

![Figure 2.13. Methods of providing sex services by adolescent girls in Georgia](source: Emory Global Health Institute, 2016)
2.1.6. Data Availability

Studying human trafficking is very hard, if not impossible, because its population is not known (Jayson, 2013). Not knowing the population causes two problems. First, there is no sampling setting for the population, and therefore, there is no information regarding the size of the victim population and the circumstances that define the victims (Jayson, 2013). Second, since both the traffickers and the victims are involved in illegal actions, they do not like to cooperate and help with studies that try to gather information regarding how they became traffickers or victims. Finding the precise number of underground people that are involved in illegal operations is very hard regardless of whether these people are doing the act voluntarily, by force, or by pressure (Jayson, 2013).

Collecting field data is very difficult and usually researchers have very little to no access to available data that has already been gathered. The cost of creating and supporting sophisticated databases that can be used to store human trafficking data is too high, causing a shortage in the number of trafficking related studies (Keiper and Chiaramonte, 2019).

The absence of valid information and efficient management results in (Keiper and Chiaramonte, 2019):

1. Subpar information management and organization.
2. Inadequate confidentiality shields. The confidentiality of the survivors of human trafficking can be undermined by inefficient data management operations and systems vulnerable to corruption.
3. Access restriction. Most collected data is available only to the enterprise that collected the data (and sometimes to funders) and cannot be used by other researchers, academics, practitioners, and policymakers.
4. Lack of standardization. Usually data sets have different formats and variables depending on the organization and are not standardized.

Based on the Migration Policy Institute, because of the deficiency in data gathering, there is a lack of data on the magnitude of sex trafficking, the way it operates, and efficient approaches to stopping it (Emory Global Health Institute, 2016).

There are several reasons for why it is very hard to track human trafficking incidents in many places. The first reason is that there is no consistent arrangement for data reporting. Some victims are afraid to report to law enforcement agencies, due to traffickers threatening them with violence and alienation. Also, since human trafficking is an illegal act, victims are afraid that if they go to police, they may be arrested or deported. Some other victims do not know the rights they possess under federal and state laws, and, therefore, they do not have any intention to report an incident to the authorities. In some situations, a case that should be prosecuted as human trafficking is prosecuted under other laws by mistake, and therefore does not get recorded as human trafficking. Another reason is that human traffickers use many strategies to prevent their operations and victims from being identified. They carefully watch their victims, change their locations, and hide them in houses with cameras and locked or striped doors and windows. The misunderstanding of human trafficking and what behaviors count as human trafficking makes it difficult for a outsider to report an incident (Mann, 2014).

2.2. Social Network Analysis

Sociology not the only field of science where network analysis is implemented. Network analysis has also been used to examine the connections between different objects in other fields of science including neuroscience, physics, political science, economics, anthropology, management science, statistics, computer science, psychology, and engineering (Denny, 2014).
Generally, social network analysis is a “data mining technique that reveals the structure and content of a body of information by representing it as a set of interconnected, linked objects or entities” (Mena, 2003).

In fact, what makes social network analysis an interdisciplinary exploratory method that has been used in many different areas is how it alone encompasses and incorporates many important qualities, such as information management, visualization methods, data accessibility, and amplified calculating power. One large issue and restriction in all traditional statistical methods is the independency of the observation used in the analysis. However, social network analysis can be applied to large data sets and extract valuable results regardless of this independency (Kirchner and Gade, 2011).

For the past several years, “the theory of networks has been a gold mine,” producing descriptions for social issues in a large variety of scientific fields (Borgatti et al., 2009). Network studies have become so popular lately that the quantity of published papers on social network related issues almost tripled in recent years. It has enabled scientists to solve “the problem of social order: how autonomous individuals can combine to create enduring, functioning societies,” a problem that has plagued social ideology from the era of Plato (Borgatti et al., 2009).

When it comes to network analysis, we have two different sets of data that can be analyzed separately, or, to some degree, in conjunction with each other. One set of data is related to the attributes of subjects (nodes) that can be used to study and understand the subjects. The other set of data contains information regarding the links or relations between the subjects (nodes). These links can be used to understand the network that the subjects make up. The link data set contains the most important network features, such as frequency, relevance, and the
strength of the link between the subjects. These features enable the researcher to analyze the network. While the data set relating to the nodes may be useful for understanding and examining the network, the information about the links are the most important in any network analysis.

The goal of any network analysis is to uncover the relationships between the subjects in question. Therefore, the data regarding the links has a vital role in network analysis (Hanneman and Riddle, 2005). By using the information regarding the links (edges), the strengths and frequencies of the relationships between the subjects can be discovered. In social network analysis, the data regarding the links can also be used to find out how quickly information is spread among the members of the network. The importance, inferentiality, power, level of connectivity, and the paths of the relationships are extremely vital pieces of information that we can get regarding different subjects (nodes) from using network analysis. For example, we can find out which node has more influence on the network members, more power in the network, more connections, shorter paths of connection to other members, etc. Therefore, by giving us this information, the results of network analysis enable us to observe, and, in some networks, predict the pathway, direction, and dispersion speed of an event through a network (Hanneman and Riddle, 2005).

The most important thing that differentiates network analysis from traditional statistical models is that network information focuses on the links and relationships between the subjects, but traditional statistical models concentrate on the characteristics of the subjects. As an example, in a friendship network, traditional data sets can contain information such as age, race, gender, location, and the marital status of the subjects (Hanneman and Riddle, 2005). On the other hand, the network data set can contain information regarding the number of friends that each subject has, the length of the paths to the friends of friends for each subject, and the
centrality of each subject in the friendship network. As we can see, the traditional data set mostly contains statistical characteristics on the subjects, but the link data set contains information regarding the behaviors of the nodes. The link information describes who the members are and how they act and represents their performance or behavior as a whole (Hanneman and Riddle, 2005).

### 2.2.1. The History and Development of Network Analysis

In the eighteenth century, for the first time, European mathematician Leonhard Euler implemented a graphic depiction of network analysis by changing the city of Königsberg and its bridges into nodes and links to solve an amusing problem at the time. Königsberg (formerly in Germany but now a part of Russia) was located around the river of Pregel and was divided into 4 different parts by the river (Figure 2.13). These four parts were connected to each other by 7 bridges. People used to walk around the city on the weekends and pass several of these bridges. While they walked, they created a game to see if one of them could go to all of the parts of the city and go through all 7 bridges without passing through any of the bridges more than once. Euler’s use of mathematical tools in an attempt to answer this question was the first step in the establishment of network analysis.

During the time period from 1800 to the early 1900s, a significant improvement was made by less distinguished social scientists like Eilert Sundt who examined the establishment of social circles between rural Norwegian farmers (Caulkins, 1981).

The “six degrees of separation” idea states that we can utilize network analysis to reveal significant features of the natural world. This idea was created for the first time in 1929 by Hungarian writer Frigyes Karinthy through a story (Luke and Harris, 2007).

While several studies on the attributes of social relationships were published throughout the 1920’s, an important breakthrough wasn’t made until 1934 by psychiatrist Jacob Moreno
(Luke and Harris, 2007). He created a new approach to present links, using points and lines to demonstrate individuals and their ties, and called this new representation a “sociogram”.

![The seven bridges of Köningsberg](image)

**Figure 2.13.** The seven bridges of Köningsberg  
*Source: Luke and Harris, 2007*

Network analysis started to become recognized as its own discipline due to Moreno’s work, and his sociograms were the first precise network analysis instrument (Wasserman and Faust, 1994). From the 1950s to the 1970s, sociologists, anthropologists, and mathematicians collaborated to develop “conceptual, theoretical, and methodological” progress that facilitated the strengthening of the foundation of modern social network analysis (Barnes, 1954).

One of the breakthrough papers in sociometry was a study by Coleman, Katz, and Menzel that investigated relational communication between physicians and the distribution of new drugs (Luke and Harris, 2007). They discovered that the quantity and quality of the social relations of the physicians had impacted their acceptance (Coleman et al., 1957).

In 1959, two mathematicians by the names of Paul Erdos and Alfred Renyi created a random model network and discovered that there was an inverse relationship between the size of a network and the number of links needed to have complete connection between its actors.
(Barabasi and Bonabeau, 2003). This means that for smaller networks, there needs to be more links between the actors for the network to be linked throughout each of its members. Based on their model, to relate 6 billion individuals together, we need each individual to be randomly connected with at least 24 other people (Luke and Harris, 2007).

Freeman recognized four different social network analysis epochs: (1) before 1930; (2) the 1930s; (3) 1940 to 1969; and (4) the modern era (Freeman, 2004). He demonstrates how scientists from different fields such as sociology, anthropology, psychology, mathematics, and physics have played a big role in establishing the community of social network analysts. In his view, social network analysis is a systematic paradigm for studying different issues and is branded by four attributes:

1. social network analysis is “motivated by a structural intuition” and concentrates on the links between subjects instead of the characteristics of the subjects
2. social network analysis is grounded on organized collections of information about the links between different subjects
3. social network analysis is built on graphics
4. it uses mathematical/computational tools to get clear and useful results from the large amount of data regarding the links that exist between the actors.

Accordingly, today, social network analysis is a standard and collective science and, therefore, a factual paradigm for exploration.

In 1969, a researcher by the name of Harrison White started to establish and implement a formal procedure for social network analysis with the help of some other researchers. By using a study by Lévi-Strauss and his associate, White utilized algebra to characterize affiliation constructions. After moving to Harvard University, White had the opportunity to gather together
a large and active group of students and collaborators to promote the network model. This group created several studies on network related issues including a “sociometric study of searches for abortionists”, “investigation of searches for employment”, “analysis of modern American sociology”, and “algebraic methods for representing and analyzing systems of social positions and roles” (Scott and Carrington, 2014).

Another revolutionary study in the field of network analysis is the Bearden et al. paper that used the idea of centrality to explain the power and impact of banks in the American commercial world. Mokken and Stokman’s research in the Netherlands was another groundbreaking study which became the foundation for the examination of “transnational patterns” and “international comparative” inquiries (Scott and Carrington, 2014).

The study of community structure, built on the works of Warner, was another application of network analysis. The researchers Fischer (1977) and Wellman (1979) created studies that remodeled the research field entirely (Scott and Carrington, 2014). Wellman performed several examinations to uncover the altering structure of community relationships in a Canadian city by inspecting the influence of friendship in social incorporation. Wellman investigated the effect of electronic communication tools on the shape and behaviors of interpersonal networks (Scott and Carrington, 2014).

Many other research fields that social network analysis was used in include political networks, social movements, criminality and terrorism, cultural networks, economics, geography, attitudes and behavior, and animal networks. Along with the increase of the application of network analysis to different fields of science, many advancements in the concepts and theories in network analysis have been made.
Starting from the late 1970s, network analysis has experienced an enormous increase in its implementation and methodological contributions (Scott and Carrington, 2014). The application of network methods by scientists from fields outside the social sciences (like physicists) has been one of the most important forms of progress social network analysis has experienced. “By the 1980s, social network analysis had become an established field within the social sciences, with a professional organization (INSNA, International Network for Social Network Analysis), an annual conference (Sunbelt), specialized software (e.g., UCINET), and its own journal (Social Networks)” (Borgatti et al., 2009).

### 2.2.2. Previous Works

Perliger and Pedahzur investigated the potential of using social network analysis in the investigation of political disturbance and terrorism. They claimed that social network analysis techniques can be very valuable for testing some of the existing foundational concepts in the field (Perliger and Pedahzur, 2010). They believe social network analysis can be used for theories concentrating on identifying terrorists (recognizing entities who are more likely to be involved in terrorism) and add a social measurement to the existing socio-demographic profile by observing the social relations of the suspects and differentiating between various roles inside the network (Perliger and Pedahzur, 2010).

They claim that counterterrorism theories constructed on social network analysis could help security services combat terrorists in several ways like demonstrating which group patterns are more defenseless, how the networks could be damaged, which individuals are vital for the ongoing survival of the groups, how the radicalization procedure could be prevented, and how the security services could detect employment routes (Perliger and Pedahzur, 2010).
Fraud investigation and discovery is another field in which researchers have made use of network analysis. With the growing use of network analysis in many different fields of study, inspectors have started to use it to spot information patterns inside product lines while possible criminal groups grow (Kirchner and Gade, 2011). Identifying these criminal groups before they are fully able to establish themselves protects businesses and corporations from losing money. Kirchner and Gade suggest important propositions and theories associated with social network analysis and recommend the use of social network analysis for fraud prevention (Kirchner and Gade, 2011).

Business organizations, especially those that are a part of financial services, telecommunication providers, and public organizations, have started to adopt social network analysis in their struggle against fraud. Social network analysis can increase the efficiency in uncovering fraud issues such as “money laundering, identity fraud, network fraud, denial of service attacks, and terrorist financing” (Kirchner and Gade, 2011).

This method has been applied in vital cases like tracking “terrorist funding after 9/11 attacks” (Kirchner and Gade, 2011). However, for most business, preventing the loss of money is the biggest motive for getting involved in fraud investigation projects. As the second major area of loss, “more than 15 percent of income loss for medium sized businesses in Germany is due to fraud, corruption, and defalcation” (Kirchner and Gade, 2011). As scammers become more and more professional and use new, more advanced approaches in their works, it becomes even more necessary for organizations to recognize the mechanisms behind fraud and the structure of fraud networks (Kirchner and Gade, 2011).

In studying organized criminal groups such as Russian Mafia and an Italian Mafia groups, Campana and Varese encountered that, kinship and violence both increase the group
collaboration (Campana, 2016). However, they found that the effect of violence is much higher than the influence of kinship. So, they usually use violence when they need to rise the commitment to the groups (Campana, 2016).

Network analysis has recently become an important tool for public health researchers and has led to the creation of new health techniques. It is a method of study that is exclusively appropriate for discovering, explaining, and understanding the “structural and relational” characteristics of health (Luke and Harris, 2007). This method “as an operational tool and a hypothetical pattern” helps scientists answer fundamental biological and environmental public health inquiries (Luke and Harris, 2007).

Network analysis has been applied in public health related research to study the ways that viruses such as HIV/AIDS and other sexually transmitted diseases are spread. It has also been implemented in the studying of other issues in the health network including the distribution of knowledge and novelties, the impact of social support and social capital, the impact of individual and social networks on health performance, and the interinstitutional patterns of health organizations (Luke and Harris, 2007).

Network analysis has been used in the field of public health in three different ways: to examine current public health systems, to solve a health issue (investigating if an infection hypothesis elaborates on how STDs spread), and to advance and employ disease prevention (using network features to find essential actors to make the distribution of health information faster) (Luke and Harris, 2007).

Network analysis has been used in public health studies most often as an important technique that can help answer basic scientific questions regarding the social and environmental elements of health (Luke and Harris, 2007). For instance, the CDC applies network analysis “in
their contact-tracing procedures for tracking” transferrable illnesses like tuberculosis (Centers for Disease Control and Prevention, 2005).

“Disease-focused networks are needed to ensure the validation of multiple biological markers and the understanding of pathophysiology of many diseases” (Stevens et al., 2014).

Several studies in disease-focused networks, especially in the area of cancer research, have been developed. In some of these studies, abundant “cancer cluster gene networks… in different types of tumours, including colorectal, ovarian and breast cancers” are discussed (Stevens et al., 2014).

Network analysis has also caused research developments in other areas such as “neurological diseases and Alzheimer’s diseases and neuropsychiatric disorders diseases of the immune system including autoimmune or hematologic diseases; the pathogenesis of coronary heart diseases, fatty liver diseases and endocrine/metabolic conditions” (Stevens et al., 2014).

Network analysis techniques have also been used for things like collecting information regarding how diseases develop and how patients react to the treatment of the diseases (Figure 2.14).

Network analysis of endocrine diseases and the use of network analysis approaches in a wide spectrum of endocrine conditions in a different set of age-related groups: from infancy, through childhood to early and late adulthood.

Figure 2.14. Network analysis in endocrinology

Source: Stevens et al., 2014

Pillai and Kumar offer a method for creating a network model of criminal profiling based on the available information in the field of criminology. The application of probabilistic networks allows the depiction of multidimensional relationships, which have been shown in
previous studies to be influential, among all applicable parameters, in specifying the action of criminals at the crime scene (Pillai and Kumar, 2010).

They use a probabilistic network (PN) modeling approach to draw behavioral patterns and find what elements impact these behaviors. When there is a new case with unidentified criminals and “profile variables are unknown” the information collected from the crime scene is used to find “the unknown variables based on their connections in the structure and the corresponding numerical (probabilistic) weights” (Pillai and Kumar, 2010). In this regard, an effective network model can be implemented to forecast unidentified parameters constituting a criminal profile based on the parameters detected from the crime scene (Pillai and Kumar, 2010).

2.2.3. Using Network Analysis in Criminology Studies

Social network analysis has received substantial attention in the field of criminology after the work of Sparrow (1991), who shed light on the many advantages of using this method in the criminology studies (Morselli et al., 2007). It has been used to explain the general patterns in criminal networks, detect subsets of the members of the network, and find important individuals with high-ranking positions. Such analysis can help identify different strengths and weaknesses within criminal networks and help law enforcement agencies target and pull apart many criminal organizations. For instance, individuals with a relatively high number of links could be at a higher risk of being targeted by law enforcement because such a person would be more easily detected (Bright et al., 2017). In addition to being used for explanatory analysis, network analysis has been used to analyze efforts made by law enforcement to destabilize and destroy criminal organizations (Duijn et al., 2014).

Green et al. used social network analysis on data collected from 2006 to 2014 to describe and forecast gunshot violence in Chicago (Green et al., 2017). They used a two-mode or affiliated network by using the people arrested as one set and the arrests themselves as the
second set. The co-offending network linked each person to their arrest event(s) that they were involved in. Then, the network illustrated the relationships among all the arrested people through their common arrest events. The network consisted of 1,189,225 arrest event nodes, 462,516 person nodes, and 1,458,957 links (Green et al., 2017).

Figure 2.15 shows three different networks that were created for three different groups. The networks illustrate that the gun shot subjects have been related directly (nodes that are next to each other) or indirectly through other subjects.

![Figure 2.15. Three cascades of gunshot violence networks created from the data](image)

Administrative records were analyzed to find out how better strategies and policies for gun violence reduction can be made by creating network models that demonstrate the increase in gun violence as an epidemic through personal communications. The results showed that the epidemic models that were created for the public health issues could have been used to create similar models for controlling gun violence in U.S. cities (Green et al., 2017).

Morselli et al. aimed to investigate the “trade-off between efficiency and security” in criminal and terrorist networks (Morselli et al., 2007). Balancing the trade-off has always been a big continuous challenge for criminal network members. Depending on the network’s activities
and goals, one could be more important for the network than the other. Usually, criminal networks are motivated by money while terrorist networks are established based on ideology. Therefore, the balance of security and efficiency is different for these two different types of networks (Morselli et al., 2007).

The Morselli article presents the efficiency/security trade-off as the interaction between the obligation for members to be connected and act together, and the requirement of security in a dangerous cooperating situation. Time-to-task, or the time it takes go from one action to the next, is shorter for criminal networks, and, therefore, efficiency is more important to them than the group’s security. For terrorist networks, the time-to-task is longer, so security is more important than efficiency. Since terrorists take action a lot less often that other criminals do, terrorist networks have a longer time-to-task (Morselli et al., 2007).

While criminal networks are established based on core and are therefore relatively centralized networks, terrorist networks usually do not have a core. So, the centrality of the terrorist networks is distributed almost equally throughout its entirety. This difference caused variability in the density and centrality of these two types of networks. Therefore, criminal networks are more centralized and the people that are in charge are well identified. However, terrorist networks are less centralized and are established with a peripheral pattern. Evaluating the efficiency/security trade-off illustrates that, in terrorist networks, protection is more important than going through with an action, making them quite different from other criminal networks (Morselli et al., 2007).

Calderoni investigated the positioning pattern in two criminal networks of a mafia-type organization, called Ndrangheta, established in the Calabria area in southern Italy (Calderoni, 2013). The paper uses data from two investigations that collected information from several
sources such as arrest warrants, final judgements from judicial files, “official reports by law enforcement agencies… and news reports” (Calderoni, 2013).

The study concentrates on special attributes of the networks’ members, such as jobs, rankings, the social situations inside each network, and the relationship between these attributes and the members’ positions (centrality scores and clustering coefficient) along with the results of the criminal records (accusation, arrest, conviction and sentence in months) (Calderoni, 2013).

The results demonstrated that high-ranking members are less tied from the core of the criminal operations, putting the medium ranking members in the center of the network. This protects the high-ranking members that are hard to be replaced and shifts the risk to the medium ranking members that are less important and can easily be replaced. This makes it so that no big changes take place when something (such as being arrested) happens to the central (medium ranked) members. The results show that high ranking members have lower frequencies of accusation, arrest, and conviction and have a smaller average sentence compared to the medium ranking members (Calderoni, 2013).

In a recent study, Bright et al. used network analysis to evaluate the efficiency of five law enforcement operations that were designed to destabilize and destroy criminal networks (Bright et al., 2017). They examined three law enforcement operations that attacked social capital (members that have money) in criminal networks and two interferences that attacked human capital (members that have “precursor chemicals” that could be used in the illegal manufacturing of narcotics) (Bright et al., 2017).

The results of this analysis indicated that the elimination of the members in terms of their betweenness centrality scores (social capital) was the most effective policy, resulting in the destruction of the networks with the minimum number of elimination phases. Eliminating
members that have money (human capital) was found to be less efficient than eliminating members with high betweenness centrality scores. However, both approaches are fairly consistent and effective in destroying criminal networks (Bright et al., 2017).

Unal uses social network analysis to investigate PKK related “narco-terror” and five illegal drug dealing groups in the Turkish territory (operated in Turkey, Central Asia, Europe, and the Balkans). He aimed to detect and compare their methods in choosing security or efficiency in a security/efficiency tradeoff framework (Unal, 2019). This research quantitatively inspects the security/efficiency trade-off using two different procedures. First, Unal described the basic attributes of Turkish narco-terror and illegal drug networks to find their overall security/efficiency trade-off. Then, based on claims that terrorist networks are more security oriented, this study tried to find out if terrorist networks are different from illegal drug networks based on their prioritizing of efficiency or security (Unal, 2019).

The data for this research was collected from official government records. The sample networks had 145 actors, 71 of which belonged to the drug networks and the rest (74) belonged to the terrorist networks. Unal used social network analysis and different network metrics to explain relationship patterns and topographies and find the importance of both security and efficiency for the sample networks. The results showed that there was a very small difference in the average interconnection and centrality scores between narco-terror and illegal drug networks (Unal, 2019).

The analysis results of these two kinds of networks does not show a strong basic dissimilarity between them in the balancing of security and efficiency. Overall, the results demonstrate that efficiency is more important than security for both types of networks (Unal, 2019).
A study by Cinar et al. aimed to assess the efficiency of three different approaches to find out if a network goes under the terrorist, cocaine, or noncriminal network category (Cinar et al., 2019). These three approaches are “network analysis metrics, modeling with a decision tree, and network motif frequency analysis” (Cinar et al., 2019). Identifying a network as a criminal organization can help law enforcement trace and dismantle the group before they can act. The results illustrate that the use of these three instruments can result in critical developments in differentiating all three kinds of networks. They demonstrate that these techniques are appropriate to be utilized as backup verification by law enforcement agencies in their combat against criminal groups who use social networks for their crimes (Cinar et al., 2019).

In this study, sixteen different network metrics were used to investigate 14 criminal and networks 10 noncriminal networks. First, the researchers calculated the social network metrics for the identified noncriminal and criminal networks, such as terrorist and cocaine trading networks. They did this to assess the efficiency of these metrics in differentiating distinct kinds of networks. Using network analysis as the first approach, each metric is assessed separately. Instead of assessing each metric separately, the second technique, decision trees, assesses the different combinations of network metrics to find out which ones are most powerful (Cinar et al., 2019).

They collected data pertaining to terrorist networks and a bit of the data pertaining narcotic and noncriminal networks from a UCINET software package. The collected data was transformed into undirected network patterns. Noncriminal networks are social groups without any identified criminal actions. These networks include social groups such as the company staff or groups of friends in sport clubs or schools. Cocaine networks contain groups of people that
trade cocaine products. Motifs are small subgroups that are typically made up of 3 or 4 actors that can be deployed to identify compound network patterns (Cinar et al., 2019).

The results illustrate that decision tree models and the motif frequencies can be implemented as trustworthy supportive methods for differentiating criminal and noncriminal networks (Cinar et al., 2019).

Morselli and Petit investigated and assessed the pattern of a drug importing network that was working in Montreal, Canada (Morselli and Petit, 2007). The network was secretly monitored for 2 years without a single arrest. In this regard, it was a very special case to examine the mechanism of a criminal network under powerful monitoring and dismantling.

The electronic contact records that were captured and collected throughout the investigation period were used to reconstruct the importing network. The results exposed the way network centralization and key actor situations are dynamic attributes of criminal networks subject to significant restrictions (Morselli and Petit, 2007). The research shows “how a criminal network decentralizes and is re-ordered in response to intense law-enforcement targeting” (Morselli and Petit, 2007).

Mcillwain applies an anthropological method of social network analysis to examine organized crime at the local, national, and international levels (Mcillwain, 1999). The study states that, by grasping the mechanisms behind human relationships and the networks they form, one get insight into organized criminal operations from any time, location, and culture. So, based on this study, understanding the relationships between the members of a criminal network is the key for realizing an organized crime network (Mcillwain, 1999).

Morselli and Roy try to investigate the effect of brokers, or middle-men, on crime-commission procedures to find out how essential brokers are for keeping criminal networks
flexible. A broker is a network member that connects detached people that could either belong to the same network or belong to different networks and organizations (Morselli and Roy, 2008). Morselli and Roy examine the activities of two criminal, stolen vehicle dealing rings by a joint model made up of social network and crime-script analysis. They evaluate the way that “diverse degrees of brokerage” are spread over group activities and how the elimination of important brokers could have an interruptive effect on the criminal network via a decrease in the possibility of crime-script transformations and flexibility alternatives. They state that, based on previous studies, having a flexible structure is more beneficial for organizations (networks) and gives them larger probability of survival compared to networks with restricted structures (Morselli and Roy, 2008).

Morselli and Roy also investigated the coordination of groups with flexible structures through the integration of crime-script and social-network methods. This integration enables the researchers to rearrange criminal schemes (the resale of stolen vehicles) in a context that stand in for both the pattern of the network and the decision making procedures of the criminals. Within this context, a mutual tie is detected in the brokerage positions that are filled by individuals that are vital for evolving flexibility inside the whole crime network. The elimination of important brokers can greatly decrease the flexibility of a group and therefore decrease the chance of coordination between the rest of members (Morselli and Roy, 2008).

Simply put, when it comes to social connection, “brokers do better,” for other people count and depend on them. The investigated stolen-vehicle groups were centralized and strong because they had brokerage attributes that enlarged the extent of flexibility for reaching the cooperative aim. Eliminating the key brokers decreased this flexibility to the degree that none of the crime groups could operate (Morselli and Roy, 2008). The approach used in and the results of
this research are very beneficial for law enforcement agencies or investigating destabilizing policies in many types of criminal networks. This approach can be used for other types of criminal operations as well, such as money-laundering activities and terrorist attacks (Morselli and Roy, 2008).

Morselli and Giguere examined the way that lawful organizations help the construction of criminal networks and highlighted the supporting role of some contributors to criminal groups (Morselli and Giguere, 2006). The digital observation information that they used was collected in a two-year period (from 1994 to 1996) by Canadian, English, Spanish, Italian, Brazilian, Paraguayan, and Colombian law enforcement agencies. This operation, dubbed “Project Caviar”, focused on several hashish and cocaine dealing routes that started from Montreal and spread across the aforementioned countries (Morselli and Giguere, 2006).

After clearing and filtering the data, they were able to come up with a network with 110 actors. The network members were divided into two groups, traffickers and non-traffickers, and a binary directional matrix was created. Eighty-two actors were detected to be traffickers who took part in scheduling and organizing the transportation of drugs. The rest (28 actors) were identified as legitimate, or non-trafficker actors. This second group provided legal products and services to the network and did not directly participate in dealing the drugs (Morselli and Giguere, 2006).

Using the results of the case, they found that, while the majority of legitimate individuals (non-traffickers) had minor contributions to the criminal network construction, a small number of them had important contributions in two different ways (Morselli and Giguere, 2006):
1. they recruited other people, including traffickers, into the network
2. “they were influential directors of relationships with both non-traffickers and traffickers.”.
The existence of these types of contributors that are parts of legal institutions demonstrates how non-criminal people can assist criminal organizations in ways other than providing them with legal services, products, and professionals. However, while there is an obvious connection between legitimate and criminal organizations, the existence of legitimate individuals in criminal frameworks is not clear. Regardless of whether the acts of these individuals are minor or significant, overall, they facilitate criminal operations (Morselli and Giguere, 2006).

Bichler et al. review previous work that have used social network analysis to collect information regarding the patterns of organized drug trafficking groups (Bichler et al., 2017). The researchers try to find out if previous works support the claim that crime organized networks have an insecure structure. Also, they want to find out whether targeting social capital actors or human capital actors is more efficient when trying to disrupt the activities of a criminal group. They found the ways that social network analysis can help examine the organizational pattern of criminal enterprises by analyzing the collective results of 34 investigations that studied 54 illegal drug provider networks (Bichler et al., 2017). They used different sources such as EBSCO Host, JSTOR, Simon Fraser University’s Fast Search, and Google Scholar to find studies that were issued after 1990 that used social network analysis and its metrics to investigate at least one drug trafficking group (Bichler et al., 2017).

The results of analyzing the collected works showed that drug trafficking networks usually “spread from a relatively dense core in short chain-like structures” (Bichler et al., 2017). In addition, they demonstrated that these structures are visible throughout the drug delivery network. The research recommends that, to control crime more effectively, the actors in the drug delivery networks that need to be targeted are those with high centrality and human capital like
directors. Furthermore, based on these results, drug trafficking networks are more likely to have a tendency towards security and to have a centralized pattern, and, therefore, attacking central actors can disrupt the network (Bichler et al., 2017). However, the results showed that the targeted members could be replaced with several other members, causing there to be a downside to this strategy.

The paper states that, in the case where there is enough information about the network links, high ranking members and significant players in the drug trafficking networks can be detected by using centrality analysis. Eliminating high ranking members with good resources could divide the network into lesser parts and increases the possibility of dismantling the entirety of the network (Bichler et al., 2017).

Ressler states that the largest current danger to the United States comes from terrorist groups and not from “formal states” (Ressler, 2006). Unlike formal wars that are won through military power, information is what wins wars against terrorist organizations. The U.S. Department of Homeland Security has had to change their focus as of late due to the recent spike in terrorist activities, necessitating the use of a new tool like social network analysis (Ressler, 2006).

The way that terrorist groups are made up of connected individuals who have financial support, are brought together by a shared ideology, and move all around the world make them perfect subjects for social network analysis. Social network analysis can give us important information regarding special qualities that terrorist groups possess, including network employment, network assessment, and the spread of their extreme ideologies. It can also be used to update the strategies used by the U.S. Homeland Security and establish counter terrorism measures with higher efficiencies (Ressler, 2006).
After the 9/11 terrorist attacks, social network analysis started gaining more popularity in the media and started to become a topic of greater interest for the government and many large universities. Major media outlets like the Washington Post and Dallas Morning News published articles discussing the possible advantages of the network analysis. In addition to identifying terrorists, network analysis can be implemented to find the different mental and emotional impacts of terrorism. The major result of terrorism is fear, which is often spread by network systems like the media, online connections, and individual links. For instance, the quantity of links that a person has to victims of terrorism can affect that person’s awareness of the probability of terrorist attacks (Ressler, 2006).

To find patterns in a large drug trafficking enterprise in New York City, the researcher Natarajan employed recorded conversations and other trail documents (Natarajan, 2000). By implementing social network analysis and other methods on the collected data, the researcher tries to identify the position of each of the enterprise’s members and what they contribute to the organization.

This study found that the criminal organization under investigation was a “corporate” enterprise that had many members with lots of members and many different labor partitions. As a result, low ranking operational members did not have much contact with the higher ranking members in the organization and could not give law enforcement any information about those higher ranking members. The results showed that phone calls were the most frequently used method of connection between the enterprise’s directors, illustrating the importance of wiretaps and the information they can provide to law enforcement agencies and social scientists that work on such criminal networks.
Natarajan examined 2,408 wiretap discussions that were collected during the prosecution of a heroin trading enterprise in New York City in the 1990s (Natarajan, 2006). The study had two different tasks. First, it aimed to find out whether the people in the trial were just independent people on the street trading illegal drugs or the members of a crime organization, which leads to the question of whether it is possible to find links between these individuals and reach to a network or crime organization. The second task of the research was to “provide a detailed picture of the organizations”, assuming that these individuals are members of an organization (Natarajan, 2006).

To complete these tasks, the collected information was used in five different examination stages. One of these stages made use of collected phone calls to create a social network analysis. As a result, a big network with 294 actors was discovered. However, the network was loosely structured, meaning that the network members did not communicate much between themselves. The network had a core with 38 actors, with almost similar positions, prolonged links, and some kind of job proficiency. There was a smaller group containing 22 members that did not have strong ties with the rest of the core members. However, they were found to have very strong ties between themselves and seemed to all be part of some joint business (Natarajan, 2006). The results of this research are consistent with the results of previous investigations into similar criminal enterprises, which all support the conclusion that they, like drug traffickers, are a collection of small groups that are loosely connected and are not created by cooperating with big and well-constructed crime organizations (Natarajan, 2006).

Ibanez and Suthers used network analysis to investigate U.S. domestic human trafficking in a virtual environment in order to detect trafficking paths (Ibanez and Suthers, 2014). The researchers tried to find characteristics of sex trafficking, using online ads that were distributed
through open Internet sources, and map the relocation patterns of the victims. They discovered that trafficked victims were consistently transported to different places all over the U.S. where there was a demand for them, and that the victims were then advertised online as a result (Ibanez and Suthers, 2014).

They gathered three weeks’ worth of classified online advertisements for adult services from Backpage Hawaii during a period of six weeks in January and February 2013. Hawaii is a major destination for trafficking in the U.S. and that is why Hawaii was chosen for this study. The collected information (1,436 ads) was evaluated to find signs of human trafficking. Relocation paths of possible trafficked victims were specified by using the collected information, and a graph was created to show these domestic paths. The advertised phone numbers were used as keys to track the victims and their customer reviews (Ibanez and Suthers, 2014).

After cleaning the data, 208 phone numbers were left to be analyzed, 165 of which gave evidence that the victims were relocated. On average, each phone number was used in advertisements from 6 different cities, with a minimum and maximum of 2 cities and 44 cities, respectively. Only 44 percent of the phone numbers had a Hawaii’s area code and the rest of the phone numbers had area codes from 23 different states including California, Nevada, Oregon, New York, and Washington. The results of the analysis showed that all but 4 of the U.S. states (Delaware, Maine, New Hampshire, and South Dakota), appeared in the ads, which demonstrates that Hawaii is a destination center for human trafficking. Also, Portland, Oregon was one of the 10 top destination cities for traffickers who entered through Hawaii (Ibanez and Suthers, 2014).

This study led to the discovery of seven different sex trafficking circuits around the United States, three of which are illustrated in Figures 2.16 and 2.17. As these figures show, sex traffickers move around a lot, and often go from one side of the country to the other. For
example, Figure 2.16 shows how the traffickers move from California to Florida, California to New York, and Hawaii to New York.

![Map showing traffic routes](image1)

Figure 2.16. The Western circuit and bi-coastal trends with (left) and without Hawaii (right)
*Source: Ibanez and Suthers, 2014*

Cockbain et al. aimed to explore the advantages of using social network analysis to help the examination of internal child sex trafficking in the UK (Cockbain et al., 2011). This research examined collected data from two main operations related to both victim and offender networks and tried to find patterns and powerful people in the networks.

![Map showing different circuits](image2)

Figure 2.17. Two different Eastern Circuits
*Source: Ibanez and Suthers, 2014*

This research uses data from 25 offenders and 36 victims obtained from two police investigations. Two networks were created using the victim data (one for each operation) and
two were created using the offender data (four networks in total). Cockbain et al. demonstrated that, to understand the offenders, analyzing the network of the offenders is not enough; it is also necessary to analyze the network of victims. The results showed that a more developed social network analysis can be created to produce new understandings by using information and software in more efficient and logical ways without increasing the cost (Cockbain et al., 2011).

They claimed that social network analysis is an important technique that assists in the creation of appropriate strategies in several ways (Cockbain et al., 2011):

1. it can help make efficient policies and find critical actors to interrupt trafficking networks
2. it can inspire a new, smarter way to balance individual assumptions built on previous experiences
3. it can detect significant ties or actors that can be used for multi-agency cooperation
4. it can create “proactive interventions” in order to attack traffickers using various different methods.

They used information from records such as court visits, “video interviews of victims and criminals, text messages between offenders and victims, and formal charge lists” from two law enforcement investigations (Cockbain et al., 2011). To examine the different patterns of child sex trafficking in the UK, a network was created and the centrality measures for all of its actors were calculated. They found that only a few people had very strong links to other actors and played central roles in the network. They stated that, while victim networks had frequently been created and used, offender network had barely been used to study child sex trafficking even though they have always been active (Cockbain et al., 2011).

Mancuso uses social network analysis in a case study to investigate the role of madams in Nigerian sex trafficking networks (Mancuso, 2014). For this study, information on the members
of Nigerian criminal groups and their link data were gathered from different arrest warrants. Network centrality measures were calculated by using telephone conversations as the link between entities. The results showed that madams play a critical role in the sex trafficking networks, which is consistent with the results of other studies. Nigerian women who were sex trafficking slaves who became sex traffickers themselves after paying off there are called “madams”. Madams are more often than not the major actors in the sex trafficking networks of Nigeria. They are the ones who usually manage all of the phases of turning victims into sex slaves from the beginning point to the destination (Mancuso, 2014).

Social network analysis was implemented to examine the centrality of madams in Nigerian sex trafficking systems. A network was created and the degree and betweenness centrality measures were calculated. The network analysis results illustrated that madams played a very significant role in the sex trafficking networks of Nigeria. However, the betweenness centrality measures showed that, in terms of brokerage, madams did not have similar centralities. Among eight recorded madams, three had high betweenness centrality values and one had intermediate values (Mancuso, 2014).

Based on these results, the economic and relational resources of the madams were the main factors that determined how much control the madams had over the rest of the network. So, this means that most madams can be split into two different groups. One group would be madams with good economic and relational resources that can manage the whole trafficking process from the initial point to the destination, and the second group would be madams who are only really used for recruiting jobs (Mancuso, 2014).

The results recommend that the madams with high betweenness centrality values more often than not that have the ability to traffic their victims internationally. So, madams do not
have the same dominant rank based on their brokerage positions. A madam should be able to also function both inside and outside of Italian borders and be a part of linked organizations that traffic people globally to be able to receive a brokerage position in the network (Mancuso, 2014).

Rostami and Mondani created three social networks based on intelligence, surveillance and co-offending datasets to investigate a Swedish street gang (Rostami and Mondani, 2015). By comparing these three networks using distance, centrality, and clustering measures, we can learn how we may get different results for the same situation when using data from different sources. The results show that the importance of the ranks of the actors changes by changing the data set used to create the network, so they concluded that the data source could have a critical impact on the results of investigations.

In this regard, those that use the results of different studies (investigators, policy makers, experts, etc.) must be aware of how influential the source of the information used in the study is on the obtained results, and, therefore, be careful when making policy or extracting inferences from these results. Nevertheless, the researchers emphasize the reliability of social networks as an instrument for investigating and studying criminal organizations (Rostami and Mondani, 2015).

2.3. Authorship Attribution

Finding out the probability that a document or text is written by a specific author by examining their previous documents is called authorship attribution or authorship identification (El Manar and Kassou, 2014). Authorship identification techniques compare the similarity of an anonymous text with a set of texts or documents with known authors and search for the most similar ones. The author of the anonymous document is potentially the same author who wrote the most similar text from the set of documents with known authors (Andrejkova and Abdulwahed, 2016). So, the aim of authorship analysis is to explore the attributes of a document
or text to find its writer. Authorship analysis is derived from stylometry, which is a field in linguistic research that deals with the “statistical analysis of literary style” (Zheng et al., 2006).

Author attribution relies on the assumption that each author has a unique writing style, similar to a fingerprint. This makes it possible to use several quantifiable features in written texts that are often consistent over a collection of an author’s texts (Ebrahimpour et al., 2013). The diction and grammar style that an author uses can be analyzed to identify the authorship of anonymous documents. Many different stylometry techniques are used to derive linguistic styles from documents of known authors to find the authorship of documents with unknown authors (Nirkhi et al., 2016). The Merriam Webster dictionary defines stylometry as “the study of the chronology and development of an author's work based especially on the recurrence of particular turns of expression or trends of thought” (https://www.merriam-webster.com/dictionary/stylometry).

While stylistics and authorship studies have a lot in common, they also vary in many aspects. Stylistic analysis is more of an exploratory tool that is used to uncover the structures of writing style. However, authorship attribution has a forensic characteristic, where evidence of authorship is found based on certain literary traits in the document (Schreibman et al., 2004).

Data mining applies statistics, machine learning, and artificial intelligence on large data sets (especially unstructured data) to extract useful information. It has been applied to a broad range of issues from database searches to DNA analysis to text classification (Ebrahimpour et al., 2013). Authorship identification covers a vast range of issues from different fields, including fraud detection, terrorist-related online texts, forensic analysis, criminal groups (such as human trafficking), activities related to online texts, blackmailing, intrinsic plagiarism and external
plagiarism. The extreme increase in Internet accessibility around the world has made these issues much more problematic for authorities (Andrejkova and Almarimi, 2016).

There is a general belief in stylometry studies that authors usually write unconsciously, and this is obvious from the vocabulary, grammar, and punctuation that they use. These indicators differentiate authors from each other and therefore can be reliably used to identify the authors of certain texts (Maitra et al., 2015). Unconsciously writing causes things like one’s grammar and sentence structure to become somewhat automated, increasing the prospect that the use of automatic author identification that makes use of such attributes is turns out to be successful. The contents of a text and the grammatical style used to write it make each text unique, allowing authorship classification to be possible (Maitra et al., 2015).

Authorship attribution studies are categorized into the 4 different fields of authorship identification or attribution, authorship verification, authorship profiling, and authorship clustering (Qian et al., 2017). In authorship identification studies, researchers aim to find the most likely author for an unidentified document using its similarity to documents with known authors. Authorship verification studies try to find out if an unidentified document was created by a particular author given a set of documents that they wrote. Author profiling is the finding of an author’s individual characteristics such as gender, age, native language, or personality type by analyzing texts or documents written by them (Qian et al., 2017). Author clustering is done to classify a set of documents that belong to different authors in different clusters so that each cluster contains only one of the authors’ documents (Nirkhi et al., 2016).

Usually, author clustering is used when labeled samples are not available. The terms “author identification”, “authorship attribution” and author profiling” have a substantial overlay and usually get used interchangeably (Adhikari and Subramaniyan, 2017).
Text classification has been applied to a variety of studies including but not limited to data mining, databases, machine learning, information retrieval, image processing, medical diagnosis, and organization. The task of classification is to categorize a collection of texts or documents into different groups or classes based on the predictions of the classifier for each document or text (Allahyari et al., 2017).

2.3.1. History of Authorship Attribution

The use of quantitative methods in studies on a text’s style and authorship has been standard for a long time, even before advance computing devices had been invented. The use of stylometry to identify document legitimacy goes back to as far as the 4th century (Adhikari and Subramaniyan, 2017). There is a general belief that non-traditional authorship attribution or stylometry was initially established in the middle of the 19th century (1851), when a mathematician named Augustus de Morgan used word lengths as a measure to identify the author of “The Letter to the Hebrews, in the New Testament” (Ebrahimpour et al., 2013). He recommended that using longer words could help differentiate some of the Bible’s authors from each other (Ebrahimpour et al., 2013). Mendenhall’s work on the plays of Shakespeare in 1887 was another old noteworthy authorship attribution task (Oza et al., 2016). He used this method to solve the Bacon-Shakespeare dispute in 1901 (Oza et al., 2016). By studying the writing styles of Shakespeare, Bacon, and Marlowe, Mendenhall figured out that the writing styles of Shakespeare and Marlowe could hardly be differentiated from each other, but both were quite different from Bacon (Can, 2014). The main difference between them was that Shakespeare used to use lots of four-character words while Bacon’s texts had high frequencies of three-character words. Zipf in 1932 and Yule in 1938 continued authorship attribution works by presenting statistical analyses for different documents (Oza et al., 2016).
An important innovation was made in 1963 when Mosteller and Wallace examined the 85 Federalist Papers, 12 of which did not have a specific author. They wanted to identify each author’s style by the function words that they used. Function words are words with insignificant meanings that usually express an author’s attitude or mood (Can, 2014). Since function words are usually used instinctively and are independent of the text’s topic and what the author would like to carry in the text, they are quite useful when trying to identify an author’s style. For example, an author might prefer a specific manner of expression or a specific collection of function words, and the same collection of function words could be used by the author in almost all of their texts, regardless of the topic (Can, 2014). Alexander Hamilton’s writing style is exactly like the writing style of James Madison, to the point where they have almost “identical sentence length distributions” (Juola, 2006). However, Mosteller and Wallace demonstrate used different sets of function words to work around this issue. For example, the frequency of the function word “upon” in Hamilton’s texts is more than 14 times the frequency of this term in Madison’s texts (3.24 and 0.23 times per 1000 words, respectively) (Holmes, 1998).

Applying the Bayesian model to these features demonstrated that Madison probably wrote all 12 anonymous papers. These findings only confirmed the results found by older studies, but this independent study was still a significant accomplishment. Even today, the issue with the Federalist Papers is observed as a very tough problem to solve, and so, it has been used as an informal benchmark for testing the performance of many authorship attribution techniques that have been established since then (Can, 2014).

Since the end of the 19th century, scientists established “non-traditional” techniques that aimed to discriminate quantifiable features in a document or corpus in order to detect the author of an anonymous text (Can, 2014). There is a general belief that the use of computers in
authorship research was started by Alvar Ellegard in 1962 with the Junius Letters. However, Ellegard used a computer just to perform some calculations on the words (that were counted manually) and not to count the words. It was Mosteller and Wallace that made computers a larger part of the authorship attribution process for the first time in their work on identifying the authorship of the twelve disputed Federalist Papers (Schreibman et al., 2004). New author identification methods are not limited to the analyzation of stylometric features and also take into account other feature of documents, innovative data/text mining methods, and machine learning techniques (Adhikari and Subramaniyan, 2017).

Authorship identification is a very important tool because of its extensive use in different scientific and practical fields (Qian et al., 2017). During the past century, computer and linguistic experts have been working together with humanitarian researchers to create computerized techniques that aid in the authorship attribution process. All writers have unique writing customs that impact the format and content of their texts, and these researchers employ machine learning techniques to measure and analyze these features (Rocha et al., 2017).

2.3.2. How Authorship Attribution Works (Steps in Authorship Attribution)

The two main groups of stylometric analysis methods are called supervised and unsupervised methods (Altamimi et al., 2019). Supervised methods can be used when there is prior knowledge regarding the authors of the texts or documents, and we can label them before using them in the classification analysis. On the other hand, if we do not have any such prior knowledge, we need to apply the unsupervised methods to classify the documents or texts.

As an example, in a forensics investigation, if we aim to find the author of a specific text or document and we have a list of suspects, we can use supervised techniques by acquiring a sample text from each suspect and comparing the samples with the text in question (Altamimi et al., 2019).
There are several supervised methods that can be used in authorship studies. Among them are decision trees, support vector machines (SVM), neural networks, and linear discriminate analysis. Principal component analysis (PCA) and cluster analysis are among the unsupervised methods that usually get used in authorship analysis (Altamimi et al., 2019). Authorship attribution is mostly treated as a text classification task and, therefore, these methods depend on sets of texts from known authors for training purposes.

Authorship attribution consists of five main phases: data collection, text preprocessing, feature extraction, model creation, and author identification. Figure 2.18 demonstrates a very simple authorship identification process flowchart. In the first step, a set of documents or texts is collected, and, in the preprocessing step, is divided into training and test data sets. The training data set is used to train the classification model.

![Figure 2.18. A simple authorship identification processing chart](Source: Stamatatos, 2009)
The third step involves extracting stylometric features. There are four different types of stylometric “features including lexical, syntactic, structural, and content-specific features” (El Manar and Kassou, 2014).

Text authorship typically make use of stylometric features, such as “Letter frequencies, N-gram frequencies, Function word usage, Vocabulary richness, Lexical richness, Distribution of syllables per word, Word frequencies, Hapax legomena, Hapax dislegomena, Word length distribution, Word collocations, Sentence length, Preferred word positions, Prepositional phrase structure, Distribution parts of speech, and Phrasal composition grammar” (Maitra et al., 2015). However, the impact of each type of stylometric feature on the authorship attribution results varies from study to study. Therefore, there is no general agreement on the use of which stylometric features will more often result in high performance outputs for authorship identification problems (Maitra et al., 2015).

Then, the extracted features are changed to numeric vectors to be used by a classifier method. In the fourth step, a classifier is used to create the classification model, and the extracted features from the training data are used to train the model. There are various text classification algorithms, and the ones that have been used more often are Linear Discriminant Analysis, Decision Trees, Naïve Bayes, Logistic Regression, Supper Vector Machines, and Neural Networks.

After the model has been created and trained, it uses the extracted features from the test data set to estimate the accuracy of the results. A created model with high performance results can then be used on anonymous documents to identify their authors.

2.3.3. Authorship Attribution of Short Texts

Traditionally, authorship attribution is used to identify the potential author of one or more long documents among a handful of candidates. Koppel et al. state that nearly all previous
authorship attribution studies focused on assigning a relatively long unidentified text to an author among a small and closed collection of candidates, which is the simplest type of authorship attribution (Koppel et al., 2011). They state that this type of authorship attribution, however, is rare in the real world.

Real world authorship attribution problems usually deal with many author candidates, a document or text that contains a small number of words, and the probability that none of the known candidates are the writer of the text in question (MacLeod and Grant, 2011). Extracting stylometric features is easier and more reliable for longer documents than short ones. For example, identifying the author of a novel will be easier and will result in more reliable identification than finding the author of a text message, because more features and information regarding the writing structure of an author can be collected from a novel than a text message (Rocha et al., 2017).

As mentioned before, with the fast spread of the Internet, the use of it for posting inappropriate messages and illegal acts, from fraud activities and human trafficking to terrorist activities, has increased. Using the Internet for this sort of activity has become a key concern for all modern societies. The biggest challenge that makes it difficult to combat these kinds of activities is the anonymous nature of these inappropriate messages that are spread on the Internet. In response to this concern, finding the people behind such activities has become an important task in recent decades. Among these tasks, identifying the authors of inappropriate, illegal, or terrorist related messages has been one of the most important in recent studies (Zheng et al., 2006).

In forensic investigations, identifying the people behind different social media pages has become extremely difficult, if not impossible, due to how the mask of anonymousness has been
bolstered by recent technological developments, such as “smartphones with pre-paid SIM cards, public Wi-Fi hotspots, and distributed networks” (Rocha et al., 2017). In some forensic investigations, a short message with just a few words, such as a tweet with less than 140 characters, is the only evidence an investigator can use to identify a suspect. In such cases, the question at hand would be how the investigator can identify the author precisely with such a short text (Rocha et al., 2017).

Texts with less than 75 words are considered to be short texts (Altamimi et al., 2019). Traditionally, stylometry analyses have been applied to long texts. The recent focus on the authorship attribution of short texts is the result of an increase in cybercrimes, cyberbullying, and phishing emails, which all often appear as short messages (Saha et al., 2018). In this regard, the number of studies with a large number of authors and short texts has risen in recent years (Luyckx and Daelemans, 2008).

To solve the issue of identifying an author with only short texts, some researchers recommend converting short messages into long texts by merging them together (Rocha et al., 2017). This approach can be useful for increasing the accuracy of the results, but it is not practical because, as mentioned before, there may be very little to just one message(s) available in many forensic investigations.

The use of some stylometric features, like structural features, can be very inefficient when trying to identify the author of short texts like instant messages, SMS messages, and social network messages, which is not the case for long texts. The reason for this is that most of these messaging platforms put restrictions and limitations on the number of words that can be used in a message, which can reduce the control of the authors when writing their texts and therefore change the author’s writing style/habits (Altamimi et al., 2019).
Many authorship attribution studies that made use of statistical or machine learning methods overestimated the significance of features drawn from training data sets due to how they concentrate on a very small number of author candidates (Luyckx and Daelemans, 2008). Therefore, they perform better when there are fewer authors. Also, many researches employ a big training data set that usually cannot be obtained in real world situations such as forensic investigations. This is an additional factor that could result in an overestimate of the accuracy rates in some studies (Luyckx and Daelemans, 2008). When using authorship attribution on short texts, the researcher has access to very few short documents with many, many possible authorship candidates, causing a significant reduction in the accuracy of the results.

There have been several studies examining the authorship attribution of tweets using different classification methods. So far, models created based on SVMs have had a better performance for classifying tweets in comparison to Naïve Bayes, “Source-Code Authorship Profiling, and other simple similarity measures” (Rocha et al., 2017).

2.3.4. Previous Works

In this section, the results of several previous works, especially those regarding short texts, are examined. In recent years, the focus from using attribution studies on fictional, biblical, and political texts has changed to the identification of the authors of short texts, like blogs and SMS texts (MacLeod and Grant, 2011). Using online messages for unsuitable or unlawful ambitions has become a severe problem in recent years (Zheng et al., 2006). “Online texts are shorter, noisier, and they have a greater number of candidate authors” (MacLeod and Grant, 2011).

Koppel et al. suggested a technique to examine the dissimilarity between unidentified texts created by anonymous and known textual samples (Koppel et al., 2004). Their work achieved an accuracy rate of 95.70 percent for texts with at least 500 words. However, when
comparing this accuracy rate with the online messages that usually have less than 500 words, this method was inefficient (Nirkhi et al., 2016).

In their author identification study, Iqbal et al. applied k-means on two separate data sets with 3 and 10 authors and obtained a classification accuracy rate of 90 and 80 percent for the 3 and 10 author data sets, respectively (Iqbal et al., 2010). In another study, Iqbal et al. examined email authorship verification and extracted 292 usable features from the emails. They achieved Equal Error Rates from 17.1 percent to 22.4 percent (Iqbal et al., 2008). In this study, they used a different method called Author Miner that makes use of different lexical, syntactical, structural, and content-specific features. By applying this method on a subset of the Enron dataset, with 6 to 10 authors, and 10 to 20 texts per author, they achieved an authorship identification accuracy rate of 80.5 percent and 77 percent for 6 authors and 10 authors, respectively. As the Iqbal et al. studies show, an increase in the number of authors has a negative impact on the accuracy of the classification results.

Chen and Hao used the Enron e-mail dataset with 40 authors and found 150 stylistic features for authorship verification (Chen and Hao, 2011). They achieved classification accuracy rates of 84 and 89 percent for 10 normal length emails and 15 short emails, respectively. Canales et al. applied a verification procedure on the “sample online test documents” of 40 students to ID the students who took the online tests. They applied the K-Nearest Neighbor (KNN) classifier to keystroke dynamics and 82 stylistic features. With text sizes between 1,710 and 70,300 characters, they achieved an Equal Error Rate of 30 percent (Nirkhi et al., 2016).

Abbasi and Chen analyzed eBay comments and forum posts and achieved an accuracy rate of 94 percent for a data set with 100 authors (Abbasi and Chen, 2008). Houvardas and Stamatatos employed a collection of training data sets, using 2500 texts from 50 authors. They
used character 3-grams, 4-grams and 5-grams as the experiment’s features and obtained an accuracy rate of 73.08 percent (Houvardas and Stamatatos, 2006). With a data set containing only 10 authors, Chaski achieved a 95.70 percent accuracy rate in his authorship identification study (Chaski, 2005).

Hadjidj et al. in their authorship attribution study employed two different classifiers, the C4.5 and SVM, on a subset of three authors from the Enron Dataset. By using the C4.5 method, they achieved accuracy rates of 77, 73, and 83 percent for sender identification, sender-recipient identification, and sender-cluster identification, respectively. The accuracy rates for the SVM method were 71, 69, and 83 percent for sender identification, sender-recipient identification, and sender-cluster identification, respectively (Hadjidj et al., 2009).

Saha et al. collected some messages from Twitter and also tried to examine the accuracy of the authorship attribution of short texts. They selected 20 authors randomly with 400 tweets per author. They were able to get an accuracy rate of 96 percent and concluded that a data set with 200 short texts per author and 4 to 5 candidate authors could result in a good performance (Saha et al., 2017).

Khmelev and Tweedie in their authorship attribution experiment applied the Markov chains method on a collection of Russian texts (Khmelev and Tweedie, 2002). By using character n-grams as style features, they achieved an accuracy of 73 percent for a multi-class classification task. Peng et al. applied character n-gram language methods to a set of 10 authors with 20 texts each from newswire articles in Greek and achieved an accuracy rate of 82 percent (Zhao et al., 2006).

Layton et al. collected 6,000 tweets written by 50 people, meaning 120 tweets per person. By using a 3-gram method, they accurately classified these tweets 70 percent of the time (Layton
et al., 2010). They concluded that, to have good accuracy rates, 120 tweets per person would be a significant threshold.

In another authorship attribution study, Nirkhi and her colleagues applied two classification methods, SVM and KNN (K-Nearest Neighbor algorithm), on the Reuter-50-50 dataset. The average accuracy rate was 80 percent and 92 percent for KNN and SVM respectively (Nirkhi et al., 2014).

To examine the authorship identification of short texts, Green et al. gathered tweets written by 12 individuals with a range of 120 to 900 tweets per person (Green et al., 2019). They used Style Markers and Bag-of-Words (BOW) as the features to analyze the collected data with and used SVMs to classify the messages. The results of their classification illustrate that using Style Markers results in higher accuracy rates than using Bag-of-Words features (60 percent to 76.75 percent for BOWs versus 75.1 percent to 92.3 percent for Style Markers). However, adding messages for two more authors reduced the accuracy rate for Style Markers sharply to 40.5 percent from the 92.3 percent obtained for 12 people (Green et al., 2019). This study demonstrates how an increase in the number of authors when classifying short texts can have a great negative influence on the classification accuracy rate.

Ragel et al. concentrated on the authorship identification of short texts and used unigrams as the features to find the authorship of a collection of SMSs. They put a 140 character restriction on each SMS and used NSU corpus, which has more than fifty thousand English SMS messages due to its large data size (Ragel et al., 2013). To find a suitable model for similarity between the messages, they used two different techniques to calculate the distance: cosine distance and Euclidean distance. They collected SMSs from 20 authors with more than 500 SMSs per author. They examined the effect that the number of authors and the size of the training data set had on
the accuracy rates of the results. The researchers discovered that increasing the number of authors causes a linear decline in the accuracy rates. The results illustrate that, by using the cosine similarity distance metric with unigrams, the threshold to get the highest accuracy rates is 10 SMSs per author (Ragel et al., 2013).

Allison et al. concentrated on identifying the authors of emails (Allison et al., 2008). They collected short emails (75 words each) from nine individuals with 174 to 706 emails per person. They used the Enron Email corpus and 2-grams, 3-grams, and term frequency measures. They implemented SVMs to classify the emails and came up with a 86.74 percent accuracy rate (Allison et al., 2008). Corney et al. used 4,369 emails containing 50-200 words each from 325 authors (Corney et al., 2002). They obtained an accuracy rate of 70 percent using the SVM method. The Allison et al. and Corney et al. studies both used emails as the text corpus and SVMs for the classification, but obtained different accuracy rates. This is due to the variation in the number of authors each study had and the different word counts per email the studies allowed, which shows how significant the impact of the number of authors and the size of the texts is on the classification accuracy rates (Altamimi et al., 2019).

Chen et al. and Chen and Zheng established an authorship identification model to investigate the identity-tracing problem in English and Chinese online messages (El Bouanani and Kassou, 2014). The four kinds of stylometric features they used were lexical, syntactic, structural and content-specific features, and the three classification methods that they used were decision trees, SVMs, and backpropagation neural networks. The accuracy rates of the results ranged from 70 percent to 95 percent, and the SVM method performed much better in comparison to the decision tree and neural networks methods (El Bouanani and Kassou, 2014).
Abbasi and Chen studied the authorship identification of online messages posted on extremist group web forums in Arabic and in English. The classification methods that they used were decision trees and SVMs. The results of this study had a high performance with 83 percent and 97 percent accuracy for Arabic and English messages respectively (Abbasi and Chen, 2005).

Qian et al. examined three different deep learning methods on authorship identification and one method on authorship verification. The two sets of data that were used were a subset of the Reuters archive of newswire stories (C50) and the Gutenberg data set that was collected from Project Gutenberg’s website. They achieved accuracy rates of 69.1 percent and 89.2 percent on the C50 and Gutenberg data sets, respectively (Qian et al., 2017).

Argamon and Levitan studied the advantage of using function words in authorship attribution. They applied SVM classifiers on twenty novels and achieved success rates above 90 percent (Bozkurt et al., 2007). They claimed that an effective technique in authorship attribution is using function words.

In an authorship recognition study, Stamatatos et al. achieved success rates of 65 percent and 72 percent using Multiple Regression and Discriminant Analysis methods, respectively (Stamatatos et al., 2001). By employing a mixture of lexical measures and style indicators, they were able to classify the writers of Greek newspaper articles with 87 percent accuracy (Stamatatos et al., 2001). They discovered that there is a strong relationship between the lengths of the documents and the accuracy rates of the classification, so that for documents shorter than 1,000 words, lexical measures, style markers, or a combination of the two cannot be used to identify the author with a high accuracy rate.

Diederich et al. used SVM classifiers with a different set of parameters and could identify the authors with success rates of 60-80 percent, depending on the set of parameters that were used (Diederich et al., 2003).
Kjell studied the authorship attribution of text samples by applying neural networks and Bayesian classifiers to the data set. The results performed well and had success rates of 80-90 percent (Kjell, 1994).

Bozkurt et al. collected 25,559 articles from Turkish newspaper Milliyet written by 18 different authors who wrote at least 500 articles each (Bozkurt et al., 2007). They used different feature sets including function words, stylometry, and Bag-of-Words. They applied several classifiers like Bayesian classifiers with Gaussian density, SVMs, histograms, K-Nearest Neighbor, Parzen windows, and k-means clustering on these feature sets. The highest accuracy rate that they attained 95 percent from the use of the SVM classifier on the Bag-of-Words feature set (Bozkurt et al., 2007).

In an experiment by Luyckx and Daelemans, 145 authors were used to study the impact of having many authors but limited training data on feature selection and learning efficiency (Luyckx and Daelemans, 2000). To examine the impact of the number of authors on the performance of the results, they started their authorship model with 2, 5, and 10 authors, then increased the number of authors to 20, 50, and 100 in the next experiment, and finally, included all of the 145 authors in the model. For 2 authors, they got an average accuracy of 96.90 percent. The accuracy rate went on to decrease to 88, 82, and 76 percent as the number of authors increased to 5, 10, and 20 authors. When the number of authors was increased to 50 and higher, the accuracy rate dropped significantly and fell below 52 percent. When all 145 authors were included, the accuracy rates plummeted all the way down to 34 percent (Luyckx and Daelemans, 2000). Tables 2.4 and 2.5 show the summaries of the previous studies on the authorship attribution of long and short texts, respectively.
In summary, many researchers have applied various classification methods, using many different features on long and short length documents. Most of these studies were able to achieve results with a high or relatively high performance rate. Many factors influenced the accuracy of the results, including the number of authors, the number of documents, the length of each document, which features were implemented, which classification techniques were used, and even the language the text was written in.

Table 2.4. The summary of the literature review of the stylometric features on long texts

<table>
<thead>
<tr>
<th>Author</th>
<th>No. of Suspects</th>
<th>Feature Types</th>
<th>Classification type</th>
<th>Accuracy</th>
<th>Goals of study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zheng et al. 2006</td>
<td>20</td>
<td>Lexical, structural, Syntactic, and content specific</td>
<td>SVM decision tree, and NN</td>
<td>97.69% for SVM, 96.66% for NN and 93.36% for C4.5</td>
<td>identification</td>
</tr>
<tr>
<td>Tan, et al. 2010</td>
<td>2</td>
<td>13 Syntactic and 4 lexical</td>
<td>Naïve Bayes</td>
<td>81.58%</td>
<td>Identification</td>
</tr>
<tr>
<td>Steyvers, et al. 2004</td>
<td>85</td>
<td>Author- topics and topic-word models</td>
<td>SVM</td>
<td>72%</td>
<td>Topic discovery</td>
</tr>
<tr>
<td>Stamatos 2007</td>
<td>50</td>
<td>Common n-gram</td>
<td>SVM</td>
<td>70%</td>
<td>Identification</td>
</tr>
<tr>
<td>Pavele, et al. 2009</td>
<td>20</td>
<td>Conjunctions and adverbs</td>
<td>Prediction by partial matching (PPM), and SVM</td>
<td>83-86% for PPM, 82.9-84% for SVM</td>
<td>Identification</td>
</tr>
<tr>
<td>Monaco, et al. 2013</td>
<td>30</td>
<td>Lexical and syntactic</td>
<td>K-NN</td>
<td>91.5%, EER 8.5</td>
<td>Authentication</td>
</tr>
<tr>
<td>Koppel, et al. 2004</td>
<td>10</td>
<td>Common words or partial word (n-gram)</td>
<td>SVM</td>
<td>95.7%</td>
<td>Authentication</td>
</tr>
<tr>
<td>Iqbal, et al. 2010a</td>
<td>158</td>
<td>Lexical, syntactic, and structural</td>
<td>Bayesian network</td>
<td>80.6%, EER 19.4</td>
<td>Authentication</td>
</tr>
<tr>
<td>Comrie, et al. 2002</td>
<td>4</td>
<td>structures, stylistic function words and gender attributes</td>
<td>SVM</td>
<td>70.2%</td>
<td>Gender discovery</td>
</tr>
<tr>
<td>Baeyen, et al. 2002</td>
<td>8</td>
<td>50 Function words, 8 punctuation</td>
<td>Entropy-weighted linear</td>
<td>88.1%</td>
<td>Identification</td>
</tr>
<tr>
<td>Orebuaugh 2006</td>
<td>4</td>
<td>Sentence structure, emoticon, and abbreviation, etc.</td>
<td>Naïve Bayes</td>
<td>99.29%</td>
<td>Identification</td>
</tr>
<tr>
<td>Howedi, et al. 2014</td>
<td>10</td>
<td>Lexical, structural, Syntactic, and content specific character N-gram</td>
<td>Naïve Bayes and SVM</td>
<td>96%</td>
<td>identification</td>
</tr>
<tr>
<td>Ragel et al. 2013</td>
<td>70</td>
<td>unigrams</td>
<td>cosine similarity and the Euclidean distance</td>
<td>25%</td>
<td>Identification</td>
</tr>
</tbody>
</table>

Source: Altamimi, 2019
Table 2.5. The summary of the literature review of stylometric features on short texts

<table>
<thead>
<tr>
<th>Author</th>
<th>No. of Suspects</th>
<th>Feature Type</th>
<th>Classification</th>
<th>Accuracy</th>
<th>Goals of study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loyton, et al. 2010</td>
<td>50</td>
<td>Character n-grams</td>
<td>SCAP Algorithms</td>
<td>70%</td>
<td>Identification</td>
</tr>
<tr>
<td>Green, et al. 2013</td>
<td>12</td>
<td>Bag-Of- Words and style markers</td>
<td>SVM</td>
<td>12 users were tested gain 40.5%,</td>
<td>Identification</td>
</tr>
<tr>
<td>Allison, et al. 2008</td>
<td>9</td>
<td>Word frequency, 2-grams, 3-grams and stem words</td>
<td>Multimodal Hierarchical SVM</td>
<td>78.46% 87.05% 86.74%</td>
<td>Identification</td>
</tr>
<tr>
<td>Zheng, et al. 2006</td>
<td>20</td>
<td>Lexical Syntactic, structural</td>
<td>SVM and C4.5</td>
<td>97.69% and 93.36%</td>
<td>Identification</td>
</tr>
</tbody>
</table>

Source: Altamimi, 2019
CHAPTER III
METHODOLOGY

3.1. Network Analysis

3.1.1. Introduction

Sociometry, the initial name given to network analysis, is an innovated approach in investigating social communities (Proskurnikov and Tempo, 2017). It gives researchers the ability to quantify the social connections and links that exist between the members of social groups (networks). Moreno came up with a significant graphical instrument called the sociogram, which was a graph that depicts the fundamental construction or pattern of a group and the position each actor has within the group (Moreno, 1934). He frequently used the word “network” in his works to depict a collection of actors that are enclosed together through some sort of long-term connections (Moreno, 1951). Thereafter, the term “social network” was created to designate a construction established by social actors (individuals or groups) that have specific social links with one another. By broad use of mathematical approaches and analytical models, sociometry initiated the integrative science of Social Network Analysis to investigate the basic concepts of social networks and social activities (Proskurnikov and Tempo, 2017).

Network analysis is more a mathematical approach than a statistical one. A significant difference between mathematical and statistical approaches is that mathematical methods treat the data as deterministic while statistical approaches treat the data as probabilistic. Furthermore, mathematical approaches use the whole population and not a sample of the population and therefore see the data as real or final, while statistical approaches use a sample of the population and see the data as a possibility of the real world.

While inferential analysis that is based on sample data is a main part of traditional statistical analysis, this is not the case for network analysis. In fact, in network analysis, usually
the researchers examine the network in a specific population and do not aim to generalize the results of the analysis to a larger population of a similar network. So, the inferential analysis does not have any use. Even if there is a case that the researcher would like to generalize the results to a larger, similar population, they will not be able to do it because the population (or sample) that has been used in the network analysis has not been drawn as a random sample.

3.1.2. Basic Definitions

First, we need to define some terms that are most typically used in network analysis that establish the foundations of any network.

1. **Node, vertex, or actor**: any entity (individual, object, or any member of network) of a population under study that could be related or not related to other entities within the same population (Denny, 2014).

![Figure 3.1. Four actors or nodes](source: Denny, 2014)

2. **Tie, edge, or relation**: defines a certain and definite relation between two actors. Connections such as “trade partnership”, “using the same communication service”, and “living in the same neighborhood” are some examples of edges (Denny, 2014).

There are two types of relationships or edges: undirected and directed (Figure 3.2). In an undirected relationship, the direction is meaningless, so that if actor A is related to actor B, then actor B is related to actor A in the same way. For example, friendship is an undirected relationship because it does not make any difference if we say Jack is a friend of Ryan or to say
Ryan is a friend of Jack. However, in a directed relationship, the direction is very important. For example, if we define exporting products among countries as a relationship, then the United States may export a product to Canada, but not vice versa.

![Directed and undirected relationships](image)

**Figure 3.2. Directed and undirected relationships**

*Source: Denny, 2014*

3. **Network or graph**: represents a set of actors and their ties.

4. **Weighted Ties**: shows the strength of connection between different pairs of a network. For example, in a weighted tie network for trade between countries, the thickness of link between countries changes based on value of trade between them (Denny, 2014). Two countries with a higher trade value have a relatively thicker edge than two countries with a lower amount of trade (Figure 3.3).

![A directed network with weighted ties](image)

**Figure 3.3. A directed network with weighted ties**

*Source: Denny, 2014*

5. **Geodesic Distance**: the shortest path or the path with the lowest number of links between two actors, or, the least number of links (ties) that must be passed through to get between any two nodes. For example, for the network in Figure 3.4, the shortest path between A and D is the A-B-C-D path which has three ties. Therefore, the Geodesic Distance between actors A and D is 3 which is equal to the Geodesic Distance between actors A and F.
Figure (3.5) illustrates three network graphs with different shapes. As we can see, the shape of graph has a significant impact on the centrality and power in the network.

3.1.3. Using Graphs to Represent Social Relations

To characterize data relating to the structure of connections between subjects (nodes), social network analysts borrow two tools from mathematics: graphs and matrices. By using graphs and matrices, most parameters in network analysis can be calculated. Network analysis usually makes use of one specific type of graph. This graph is made up of a combination of nodes and lines that are used to illustrate the subjects and their links.
Social network analysis is based on Graph Theory, which is a component of mathematics. It consists of a set of theories and approaches that assume that the actions of entities (individuals, groups, organizations) are intensely influenced by their relationships to others and the networks in which they are attached (Fox and Everton, 2015).

Network analysis can be used for formal descriptions as well as modeling, evaluating, and testing a hypothesis. Regarding formal description, network analysis offers a terminology and a set of official definitions for stating theoretical concepts and properties that can be used for model development, specification, and hypothesis testing. Also, network analysis can be used for testing relational theoretical concepts by using statistical tools on collected network data (Wasserman and Faust, 1994).

Unlike other social and statistical theories that focus on the different observations’ attributes, social network theories involve concepts, definitions, and methods that describe the status of different relationships. In this regard, the way that network analysis is used for descriptive and statistical analysis is very different from the way that other formal and traditional statistical and social sciences are used.

The main difference between social network analysis and other methods of data analysis is that in network analysis, everything including theoretical concepts, collected data, and hypothesis tests is about the relationships between the objects and not their attributes. While network analysis is used to find relational patterns to create structures among the observations, other statistical methods disregard the interactive information (Wasserman and Faust, 1994).

In standard and traditional statistical methods, the independence of the observations is a fundamental key to do the statistical analysis. On the other hand, in network analysis observations are not isolated units and the objects do have influence on the behavior of one
another. Typically, the aim of network analysis is to find the type and strength of this influence and interdependence (Wasserman and Faust, 1994). As an example, to study the outcome of a group meeting regarding the decisions that they make, focusing on the attributes of individual members of the group (the way standard statistical methods work) without looking at the extent of influence that these members have on each other may give us inaccurate results. In such a situation, network analysis, by analyzing the relationships among members, their interactions, and the extent of influence that each specific member has on other members, can give us much more accurate results than standard social and statistical methods (Wasserman and Faust, 1994).

In fact, sometimes a small number of members may have such a big influence on the other members of group that the group’s outcome decision is determined by those few influential members. In this regard, the primary goal of network analysis is to understand the behavior of objects and study the pattern and structure of the relations between the objects. The examination of the individual characteristics of objects is the secondary goal.

A significant difference between the social network analysis technique and the traditional “network model of organization” is that social network analysis does not need to be combined with any prior assumption regarding the pattern of the network. Therefore, it will be easier to use social network analysis to solve problems that would normally be solved by the use of organizational theory (Von Lampe, 2009). The advantage of using network analysis is that instead of assuming the presence of a pattern or structure a priori, it stems from the gathering of data in a relational approach (Campana and Federico 2012).

Carrington and Papachristos have mentioned that criminal network studies are more exploratory and descriptive than theory-testing (Carrington, 2011; Papachristos, 2014). However,
the problem of reliable data being inaccessible is one of the main reasons for there not being much research on criminal network analysis (Campana and Federico, 2012).

Social network analysis would be useful in finding out which subjects (nodes) interact in a network, the quality and quantity of connection between the subjects, the impact of each subject, what incentives they have, and the patterns in the network (International Rescue Committee, 2016). The information resulting from network analysis then could be used for (International Rescue Committee, 2016):

1. improved knowledgeable project strategy
2. customer/companion contribution in project strategy and/or assessment
3. companion/shareholder drawing
4. knowledgeable program evolutions
5. programming in a struggle complex situation

3.1.4. Data in Network Analysis

In network analysis, there are two different sets of data that can be analyzed separately, or, to some degree, in conjunction with each other (Hanneman and Riddle, 2005). One set of data is related to the attributes of subjects (nodes) that can be used for the study and understanding of subjects. The other data set includes information regarding the links or relations between subjects (nodes) which can be used to understand the networks the subjects make up (Hanneman and Riddle, 2005). The link data set contains the most important network features, such as frequency, relevance, and the strength of the link or relation between the subjects. These features enable the researcher to analyze the network. The goal of any network analysis is to uncover the relationship between the subjects. In the social network analysis, the link information also can be used to find out how fast the information is spread among the network members (nodes).
Importance, inferentiality, power, level of connectivity, and the path of the relationship are the most critical pieces of information that we can get for different subjects (nodes) as a result of network analysis. For example, we can find out which subject has more influence on the network members, which node has more power in the network, which subject has more connection and a shorter path of connection to others, and so on and so forth. Therefore, by giving us this information, the results of network analysis enable us to observe and, in some networks, to predict, the pathway, direction, and speed dispersion of an event through a network.

Since networks work based on connectivity, when an event is happening, it passes different steps over time to spread throughout the whole network. Analyzing the network gives a researcher the ability to predict the future possible steps by analyzing the current and previous steps. In this regard, network analysis can be used for prediction even though this method is categorized as an unsupervised statistical method (Hanneman and Riddle, 2005)

Usually, traditional data is put into a rectangular table, with its rows being the subjects or observations and its columns being the measurements of the subject’s attributes. The essentials of data construction help us learn how subjects are alike or different from each other by comparing characteristics that have been recorded in the rows. We can also learn how attributes are alike or different from each other in their distributions over the subjects by comparing the columns.

On the other hand, network data is put into a square table (called an adjacency matrix) with the same set of subjects (node names) in rows and columns, which is the most important difference between traditional data and network data (Celko, 2015). The number of rows/columns of an adjacency matrix is equal to the number of nodes in the associated network.
More often than not, the adjacency matrix is a binary matrix which is used for unweighted networks. In this case, each cell of the table illustrates the presence or absence of a relationship under investigation between any pair of subjects. Such a matrix is the initial point in network analysis. Table 3.1 illustrates the data in an adjacency matrix that shows a network of friendship for six people.

Table 3.1. Network data for friendship among 6 people

<table>
<thead>
<tr>
<th></th>
<th>Mary</th>
<th>Sam</th>
<th>Jack</th>
<th>Abram</th>
<th>Ryan</th>
<th>Jacob</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mary</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sam</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Jack</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Abram</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Ryan</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Jacob</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

In this table, a “1” depicts the presence of a friendship between two people in the group and a “0” means that there is not a friendship between those two people. Notice that the diagonal cells are empty because they would identify a friendship of person with themselves, which is meaningless. As opposed to traditional data, here we can find the similarity or dissimilarity among the subjects by comparing either rows or columns. For example, comparing rows tell us that Mary and Abram are similar due to how they share the same friends (Jack and Ryan). Since the table is symmetric around the table’s diagonal, comparing the columns brings us to the same conclusion as comparing the rows. Notice that this table is symmetric because “friendship” is an undirected relationship. However, for a directed relation, such as sending and/or receiving an email, the table would not be symmetric because the in-coming and out-going ties are not necessarily equal. For example, Actor A may send emails to Actor B but not vice versa.

Binary measures most often constitute the relational parts of data in network analysis. Therefore, a large amount of the advancements in Graph Theory and many of the procedures
created for the measuring of characteristics of subjects (nodes) were developed for binary data. However, when we are facing a weighted network, the adjacency matrix will not be a binary matrix and, instead of “0”s and “1”s, each cell contains the weighted value between two nodes.

3.1.5. Populations, Samples, and Boundaries

Traditional (non-network) studies want the subjects or observations to be independent so, they use probability or other sampling methods to choose a set of individuals or subjects from the population. In this approach, each observation or node is treated as a distinct “replication” that can be changed with any other actor without influencing the results (Hanneman and Riddle, 2005). On the other hand, since network models concentrate on the connections between subjects, subjects cannot be sampled independently. When we choose a subject, we have to contain all other subjects that are connected to the chosen subject within our data set. Therefore, instead of using samples, network methods lean towards using the whole population which has been defined based on some boundaries that have been imposed by the researcher (Hanneman and Riddle, 2005).

For example, a network study may include all of the persons at a network provider, all of the members of a specific church, all of the workers of an institution, or all of the players of a sport team as the subjects of observation in the research (Hanneman and Riddle, 2005).

However, the population under study could be a subset of a larger population that is defined by the research’s boundaries. For example, if we want to study the friendship network for a classroom in a specific school, then our population will be all of the students in that classroom, which is a subset of the school’s students, and that in turn is a subset of the students in the entire region, and so on and so forth. If we would like to study the friendship network for the whole school, then our population would be all of the students in that school. Since network
analysis uses the whole population, having definitive boundaries for the population under investigation is a vital issue.

As said above, since network analysis uses the whole population and not samples, there should be some boundaries to define the population precisely to make sure that the right actors are included in the data set. These boundaries can be set up by two different sources. The first source of generating the boundaries are the subjects themselves. For example, if we would like to study the relationship among professors in a college, members of a specific club, or people living in a subdivision, then all of the members of these institutes should be included in the data set. In such situations, the population is well defined before we even decide to study the network (Hanneman and Riddle, 2005). The second source of boundaries is the researcher. The researcher may use any “demographical”, “bionomical”, or “regional” border to identify the population boundaries. For example, we could be studying the network or coauthors in a big university, so we might set the boundaries to be professors who are coauthors.

3.1.6. Basic Notations from Graph Theory

Graph theory is based on several core properties, three of which are the most basic definitions that are related to our analysis (Proskurnikov and Tempo, 2017).

**Definition 1.** Graph: A graph is a collection of pairs of elements \((v_i \text{ and } e_i)\) that come from two different finite sets. The first element of each pair represents a node or vertex \((v_i)\) and the second element of the pair represents an edge or arc \((e_i)\). In a mathematical format, we can define a graph as (Proskurnikov and Tempo, 2017):

\[
\text{Graph } G = (V, E) \text{ where:}
\]

\[
V = (v_1, \ldots, v_n) \text{ and } E \subseteq V \times V \text{ are finite sets}
\]

\[
v_i = \text{nodes or vertexes of } G
\]
\[ e_i = \text{edges or arcs} \]

Also, a graph adjacency matrix \( A = (a_{ij}) \) is used to illustrate the links or relationships between the nodes \((v_i)\). Based on Graph Theory, if there is a connection between \(v_i\) and \(v_j\) then we have a link so that \(a_{ij} > 0\).

**Definition 2.** Adjacency Matrix: For graph \( G = (V, E) \), the adjacency matrix or connection matrix is a nonnegative matrix \((A = (a_{ij}), \ i \text{ and } j \in v)\) with rows and columns labeled by graph vertices. If \(v_i\) and \(v_j\) are adjacent, then \(a_{ij} > 0\), otherwise \(a_{ij} = 0\) (Proskurnikov and Tempo, 2017). The elements in the diagonal of this matrix are zero. The matrix would be symmetric if the graph is undirected.

**Definition 3.** Weighted Graph: sometimes each edge has a numerical value which is called a weight. A weighted graph contains three sets as \( G = (V, E, A) \), which the first two sets \((V, E)\) forms the graph and \(A\) is a set of weights (Proskurnikov and Tempo, 2017). Any non-weighted graph can be changed to a weighted graph by adding a binary adjacency matrix \(A\) to that.

\[ A = (a_{ij}) \ i, j \in v, \ a_{ij} = 1 \text{ if } (j, i) \in E, \text{ and } a_{ij} = 0 \text{ otherwise}. \]

**3.1.7. Power**

There is a general agreement among sociologists that power is an essential attribute of social communities (Hanneman and Riddle, 2005). However, only a little compromise exists regarding the characteristic of power and the way that its sources and outcomes should be explained and examined.

In social network analysis, power is the result of connection and the ability to influence another network’s actors. An actor that has a few or no connections cannot influence other actors and therefore has no power. In this regard, power is associated with density. In a network with
low density, not much power can be found. There is a possibility of having more power where the network has higher density (Hanneman and Riddle, 2005).

Identifying the “most important” powerful actors in a social network is one of the main uses of Graph Theory in social network analysis. Quantifying network properties is an objective that many researchers have been trying to achieve since the 1930s. To demonstrate the difference between important and not important nodes in a network, several different measures have been created. These measures are known as network centrality measures (IBM Corporation, 2012-2013). Most social network analysis research involves the measure of centrality to find the key actors in a network. There are different scales of centrality that have been created for different tasks, and the adequacy of each scale depends on the issue under investigation and the availability of the data (Hanneman and Riddle, 2005).

**Network Centrality:** Centrality illustrates the importance of actors based on their position in a network (Hanneman and Riddle, 2005). However, depending on the framework and purpose of the network, the definition of centrality is different from one network to another. Some network centrality measures are degree, closeness, betweenness, and eigenvector.

**Degree:** Degree is a simple centrality measure that counts the number of connections that each node has in a network (Hanneman and Riddle, 2005). This measure is different for undirected and directed networks. For an undirected network, degree centrality for each actor is calculated based on the number of undirected connections that the actor has. For a directed network, there are in-degree and out-degree centrality measures. The out-degree centrality for a node is the number of outgoing arrows that come out from a node and go to neighboring nodes. A node’s in-degree centrality is equal to the number of incoming arrows that come from neighboring nodes.
Figure 3.6 displays four different examples of networks. In all of these examples, centrality is higher for X in compare to Y. In the first (left) graph, the in-degree centrality for Actor X and Actor Y is five and zero, respectively. In this graph, depending on the type of link, Actor X is more important than Actor Y. As an example, suppose that each arrow illustrates one report to Actor X. In this case, Actor X receives five reports, each coming from a different person. In the second graph, while the out-degree centrality measure for Actor X is five, Actor Y has a zero out-degree centrality. In this graph, if we define the links as the association between drug dealers, then Actor X is in charge of five other drug dealers, which shows he is more important than Actor Y. In the third graph, if we remove Actor X, then the network is split into two halves. Since Actor X connects these two isolated parts of the network, therefore Actor X has a very important role in the network. Finally, in the last (right) graph, in total, Actor X has shorter pad to all other nodes than Actor Y and therefore, Actor X is more important and influential.

**Figure 3.6. Four different examples of centrality measures**  
*Source: Adamic, 2013*

**Betweenness:** Betweenness is another tool for measuring centrality in a network. Betweenness centrality measures the number of times an actor connects two other actors along their shortest path in the network (Adamic, 2013). Linton Freeman created this scale to measure how an individual (actor) can control communication between the people in a social network. For actor
Xi, betweenness centrality is the number of pairs of actors (Xj and Xk) that are connected through actor Xi in their shortest paths (Adamic, 2013). So, we have (Adamic, 2013):

\[ C_B(i) = \sum_{j<k} \frac{g(i)}{g_{jk}} \]

Where \( C_B(i) = \) betweenness centrality for actor i

\( g_{jk} = \) the number of geodesics connecting j and k

\( g_{jk}(i) = \) the number of geodesics that actor i is on

Most often we normalize this formula as follows:

\[ C_B'(i) = \frac{C_B(i)}{\left[(n-1)(n-2)/2\right]} \quad , \quad n = N-1 \quad , \quad N = \text{number of nodes} \]

**Closeness Centrality**: Closeness centrality shows how close an actor is to the rest of the actors in a network (Adamic, 2013). The closeness centrality of each node measures the average inverse distance of that node to the rest of the nodes in a network (Adamic, 2013). Therefore, actors that are a shorter distance from all of the other actors (or have a shorter path to access other actors) would have a higher closeness centrality and are in a more important position in the network.

Usually, closeness centrality is normalized by the (N-1), where N is the number of actors and \( d(i,j) \) is the shortest path between nodes i and j (Adamic, 2013).

Closeness Centrality

\[ C_c(i) = \left[ \sum_{j=1}^{N} d(i,j) \right]^{-1} \quad \text{and} \quad i \neq j \]

Normalized Closeness Centrality

\[ C_c'(i) = \left[ \frac{\sum_{j=1}^{N} d(i,j)}{N-1} \right]^{-1} \quad \text{and} \quad i \neq j \]

As stated before, the connection in a network can be directional or non-directional. In a directional network, there is a source and there is a receiver. The source is the entity that initiates
the action and the receiver is the entity that receives the action. In contrast, in non-directional networks, we cannot recognize one entity as the initiator and the other one as the receiver.

Networks can also be categorized in two groups based on whether the information regarding the strength of the connection between the entities in the network pattern (network with weighted ties) is included. A network with a dichotomous relationship shows the presence or absence of a relation between the actors. However, a valued relationship network not only shows the absence or presence of the relations, but also shows how strong the relationship between every pair of entities is.

In summary, we can classify networks based on the relationship between their entities in four different categories as shown in Table 3.2.

Table 3.2. Network categories base on connection types

<table>
<thead>
<tr>
<th>Direction</th>
<th>Scale</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Directional</td>
<td>Dichotomous</td>
<td>Jack send email to Kevin</td>
</tr>
<tr>
<td>Directional</td>
<td>Valued</td>
<td>Jack send 10 emails to Kevin</td>
</tr>
<tr>
<td>Non-directional</td>
<td>Dichotomous</td>
<td>country A and country B have trade relationship</td>
</tr>
<tr>
<td>Non-directional</td>
<td>Valued</td>
<td>Trade between country A and country B was $750 millions</td>
</tr>
</tbody>
</table>

Source: IBM Corporation, 2012-2013.

3.1.8. One-Mode and Two-Mode Networks

Depending on the issue under investigation and the collected data set, the resulting network could be a one-mode or a two-mode network. A two-mode network, also known as an affiliation network or bipartite graph, is the simplest formation of multimodal networks that contains two modes or two sets of actors. In a two-mode network, nodes can be divided into two distinctive sets so that each set of nodes does not have any ties between themselves (Ghani et al., 2013).
For example, if we would like to graph a network of coauthors of academic papers with their affiliated academies, we will have two sets of data, one set contains the name of the affiliated academies and the other sets consists of the names of the coauthors. So, the graph links each author to their workplace.

However, we can always change a two-mode network into a one-mode network through “projection” (Opsahl, 2013). The projection procedure is when one of the sets under consideration (which is more important for the researcher) is selected and two actors in the set would be connected if they have been connected to the same node of the other set (Opsahl, 2013).

3.1.9. Applying Network Analysis

In this study, we used both one-mode and two-mode networks. With the one-mode networks, each phone number was used as a node and advertisement IDs and the similarity of the advertisement texts were used as the links that connected different phone numbers.

With two-mode networks, we had two sets of data: phone numbers and the cities that the ads with the phone numbers were posted.

3.2. Authorship Attribution

3.2.1. Introduction

Authorship identification is one of the significant issues in the field of Natural Language Processing (NLP) (Qian et al., 2017). In these types of problems, the researcher attempts to identify the author of an anonymous document by the similarity of its features to the features of the documents with known authors (Nazar and Pol, 2006; Bozkurt et al., 2007).

Both supervised and unsupervised machine learning methods can be used for authorship analysis (Nirkhi et al., 2016). With unsupervised learning techniques, prior information is not required. These techniques use the derived features of the samples to categorize them into
different groups that have common attributes (Nirkhi et al., 2016). Unsupervised learning methods are used to identify unseen patterns in unlabeled data sets. Using these methods is much easier than supervised techniques. These methods do not require training steps, and, as a result, we are not required to label them before using the method. So, it can be used for analyzing any textual data set without putting in much effort. Unsupervised methods are more suitable for data examination (Juola, 2006).

Two unsupervised learning techniques that have frequently been used in text mining are clustering and topic modeling. Clustering is a method where a set of texts or documents is categorized into different groups based on similarity while topic modeling uses a probabilistic method to categorize a set of documents based on different themes (Allahyari et al., 2017).

With supervised methods, the researchers must have a priori information regarding the category labels, which usually contains a sample of texts of certain authors (Juola, 2006). Supervised learning techniques require a pre-labeled data set to be used for training to classify an unlabeled data set. So, applying supervised methods is more difficult and time consuming since a data set has to first be labeled manually to be able to be used as the training data set. Some supervised models that have been used by many researchers are the Support Vector Machine (SVM), Logistic Regression, decision trees, multinomial Naïve Bayes, and nearest neighbor classifiers (Sebastiani, 2002). Supervised learning methods are more often used when it comes to text classification.

One advantage of supervised learning methods versus unsupervised learning methods is that they enable us to calculate the accuracy measures for the analysis (Allahyari et al., 2017). Another advantage of a supervised learning algorithm is that it can be trained to solve a variety of classification problems. These methods have two main phases: learning and testing. In the
learning stage, the algorithm is trained by the user via examples. In the second stage, the method classifies the anonymous documents (Nazar and Pol, 2006).

Applying text mining to a large data set is a complicated procedure that requires taking several steps before getting the desired results. As data gets more and more unstructured, there will be more and more complicated steps to go through.

Most text mining studies have used long documents and only a small number of researches have used short texts. Using short documents in text mining is hard for several reasons. Short texts or documents, such as text messages, tweets, and emails usually have poor sentence structure, use informal language, and are messy when compared to long texts. In cases like Twitter, a limitation on the number of words that can be used in the message increases the difficulty of analyzing the text (Altamimi et al., 2019).

The most frequently used approach to prepare the texts and documents for the text mining process is the use of bag-of-words technique. This approach works based on the frequency of each word or phrase in each document without paying attention to the order that they show up in the text. These frequency values are used in the next stage as vectors for machine learning analysis and statistical examination (Allahyari et al., 2017).

Overall, there is no universal belief among researchers regarding the framework, method, number of words, and stylometric features to use for text analysis when it comes to short texts that have poor structure and informal language (Altamimi et al., 2019). Usually, short text studies have used the SVM method for classification because they found that this method was superior to other classification methods in this instance (Altamimi et al., 2019).

Depending on the data set, the issue being studied, and the aim of the study, there are many approaches to attribution authorship studies, and each approach can be involved in
different steps with various sub-steps. However, in this section, we will go through the procedure and work algorithm that is suitable for and used in our study.

Authorship identification and text classification framework that has been used in this study has several phases as follows (Mayo, 2017):

1. “Data Collection or Assembly
2. Data Preprocessing
3. Data Exploration & Visualization
4. Model Building
5. Model Evaluation.”

Figure 3.7 illustrates a general framework for the authorship attribution of online texts. This framework shows different phases for the authorship attribution procedure, but these steps are not completely separated sequences, making them not actual different steps.

3.2.2. Collecting Data

The first step in text authorship identification is collecting data or preparing the raw corpus. In our study, advertisements posted on the Backpage website by sex providers were scraped. The data involved six different states including Louisiana, Alabama, Arkansas, Florida, Mississippi, and Texas, and was collected from May 2017 to February 2018.

Sample size

One of the key questions in any stylometry and authorship identification study is the minimum sample size required to achieve a high accuracy rate (Eder, 2015). So far, there has not been any complete and inclusive answer to this question. A study by Eder in 2015 suggests that the minimum sample size for a document to be identified is 5000 words (Eder, 2015). However, based on another study by Eder in 2017, the minimum number of words needed for achieving
reliable results is less than 2000 words, which is much less than the number of words that he recommended in his 2015 study (Eder, 2017).

![Figure 3.7. A general framework for authorship attribution of online texts](source: Zheng et al., 2006)

### 3.2.3. Data Preprocessing

One of the most important phases in any text mining project is preparing the text or preprocessing, before applying the classification method. As an example, doing a text classification job requires taking several steps, first of which being preprocessing the text. This stage could have a significant impact on the accuracy of classification results (Allahyari et al., 2017). Data preprocessing contains several phases such as tokenization, stemming,
lemmatization, filtering, and noise removal to prepare the text for the next steps (Uysal and Gunal, 2014).

**Tokenization:** Tokenization is the first step in the text preprocessing. If we break a text or a part of it into smaller pieces, each piece is named as a token. In this regard, tokenization could be breaking a document or a paragraph into sentences, or breaking a sentence into words and phrases, or breaking words and phrases into characters (Webster and Kit, 1992).

**Lemmatization:** The task of Lemmatization is to group together the varied forms of a word so that they can be evaluated as a single word in the analyses (Allahyari et al., 2017). For example, we may see different forms of the word “eat”, such as “to eat, eats, ate, eaten, and eating” in a text. Through lemmatization, all of these different forms of “eat” will be replaced by the single word “eat”. For another example, lemmatization would change “worse” and “worst” to “bad”.

**Stemming:** the purpose of stemming is to find the stem or roots of words in the corpus, which usually involves eliminating affixes such as suffixes, prefixes, infixes, and circumfixes (Allahyari et al., 2017). As an example, “running” is changed to “run”. Therefore, steaming methods depend on the language of the text or documents used for text mining and are different from one language to another one. Stemming algorithms were introduced by Lovins in 1968 for the first time (Allahyari et al., 2017).

**Filtering:** the next step of text preprocessing contains many procedures including changing or removing words or characters. There are several types of words and phrases that have no use in text mining analysis and should be deleted from the text as a part of the preprocessing step. These types of words and phrases include stop words and words and phrases that appear in the text very seldom and therefore do have not influence on the text mining process. Stop words are words that are repeated in the text many times but cannot be used for discriminating different
texts and do not have valuable information in regard to text mining, such as articles (the, a, in, an), prepositions, and conjunctions (Saif et al., 2014). Also, some characters that have no use in the text mining process, like punctuation marks, could be deleted from the text in this step. Changing all words or characters to lowercase, removing numbers or changing them to text format, and stripping white space are among other things that happen in this step (Mayo, 2017). As we can see, “preprocessing relies heavily on pre-built dictionaries, databases, and rules” which already are available and can be used in programming languages capable of text mining such as Python (Mayo, 2017). These processes have a significant influence on the accuracy of the final results.

**Noise Removal:** Tokenization, lemmatization, stemming, and filtering are the usual procedures that are used in any authorship tribulation work. However, noise removal is a much more general operation that can be different from one study to another. Noise removal tasks can happen anywhere during or after the previous steps, and sometimes may be needed in more than one step during the preprocessing. Removing text file headers, footers, HTML, XML, markups, and metadata are some examples of noise removal tasks (Mayo, 2017).

### 3.2.4. Model Building

After finishing the preprocessing phase, we have a set of tokens ready to be used for building our classification model. However, there is a major challenge in applying machine learning to natural language. Machine learning algorithms work with numbers, while natural language is text. Therefore, the text must be converted into numbers. This process is called text vectorization. When it comes to text analyzing, text vectorization is the most essential phase in the machine learning process. Since vectorization methods impact the performance of the results significantly, it is very important to select a vectorization method that will produce suitable results (Stecanella, 2019).
3.2.4.1. Vector Space Model

Suppose we have a finite set of documents as $D = \{d_1, d_2, \ldots, d_m\}$, where $m$ is the number of documents or texts in the set, and $d_j$ illustrates each document or text in the set ($j = 1$ to $m$). Also, assume that $V = \{w_1, w_2, \ldots, w_n\}$ where $V$ is the vocabulary or the collection of all words used in the set of documents ($D$), $n$ is the total number of words used in the documents, and $w_i$ is each word in the vocabulary ($i = 1$ to $n$) (Allahyari et al., 2017).

In text mining, the first thing to do is use the Term Space Model (or Vector Space Model) to change the text into numeric vectors and represent them using these created vectors. The Term Space Model assigns a number to each word of each text in the collected documents. This number indicates the importance or weight of the word in the document (Allahyari et al., 2017).

The Boolean model and Term Frequency - Inverse Document Frequency (TF-IDF) model are two of the most prominent term weight models that have been used in text mining analysis. With a Boolean model, a non-negative number ($\omega_{ij} \geq 0$), which is a weight, is assigned to each term ($w_i$) for each document ($d_j$). If a term is present in a document, its $\omega_{ij}$ will be larger than zero, and for the terms that are absent from a document, their corresponding $\omega_{ij}$ will be equal to zero (Allahyari et al., 2017).

**Term frequency-inverse document frequency (TF-IDF):** The innovation of TF-IDF algorithms has been groundbreaking for machine learning techniques, particularly in NLP related works like text classification (Stecanella, 2019). The TF-IDF model is an information retrieval method that is used for weighting terms (Bozkurt et al., 2007). In this approach, to find the significance of each term, a weighted measure of all terms used in the texts are calculated (Rocha et al., 2017). The TF-IDF method highlights the importance of crucial terms that have frequently been used by a certain author and decreases the importance of certain unimportant terms like function words (Rocha et al., 2017).
TF-IDF techniques have several advantages. Firstly, they are easy to calculate and can be simply used for calculating the similarity between two documents. Second, because of the normalization of the word frequencies by IDF, highly frequent words do not impact the results of classification. Finally, they can be used “to extract the most descriptive terms in a document” (Kowsari et al., 2019).

After converting words into numbers, the TF-IDF scores can be used in machine learning techniques, like Naïve Bayes and Support Vector Machines, to accomplish the text analysis task. The texts that have similar relevant terms/words will have comparable vectors, and that is what we are searching for in a machine learning method. This approach can increase the performance of the analysis results in comparison to the simple approaches such as word counts (Stecanella, 2019).

TF-IDF was designed for to search for documents online and can find the documents that are most related to the requested document. For instance, if we search for “inverse document frequency” through a search engine, the results would be found and ranked based on the relevance of the documents that are found to the “inverse document frequency” term. The TF-IDF approach will assign the highest score to the result most closely related to the “inverse document frequency” term, causing that document to receive the highest rank. All search engines that we currently use on a day to day basis use TF-IDF scores in their algorithm (Stecanella, 2019).

In text analysis with machine learning, TF-IDF techniques help with the classification of data and the drawing of keywords, which in turn makes the processing of the data very quick (Stecanella, 2019). The TF-IDF model consists of two separate parts, Term frequency (TF) and inverse document frequency (IDF). The Term Frequency of each term (tf$_{ij}$) is the number of
times that the term occurs in a text \((n_{ij})\) divided by the total number of terms in that text
\((\sum_{i=1}^{\infty}(w_{ij}))\). Every text or document has its own term frequency. So, the term frequency for term \(i\) in document \(j\) is calculated as (Allahyari et al., 2017):

\[
tf_{ij} = \frac{n_{ij}}{\sum_{i=1}^{n}(w_{ij})}
\]

The second part, inverse data frequency (IDF), can be calculated for each term \((w_i)\) by taking the logarithm of the number of total documents divided by the number of documents that hold the term \(w_i\). Inverse data frequency is used to find the weight of rare terms over all texts in the collection. So, we have (Allahyari et al., 2017):

\[
idf(w_i) = \log\left(\frac{N}{n_i}\right)
\]

In this formula, \(N\) is the number of total documents in the data set and \(n_i\) is the number of documents in the data set that contain the term \(w_i\) (Allahyari et al., 2017).

The Term Frequency - Inverse Document Frequency (TF-IDF) for each term in the corpus is calculated by multiplying the TF by the IDF as (Allahyari et al., 2017):

\[
tf_{\cdot, idf} = w_{ij} = tf_{ij} \times idf(w_i) = \left[\frac{n_{ij}}{\sum_{i=1}^{\infty}(w_{ij})}\right] \times \log\left(\frac{N}{n_i}\right), \quad i = 1 \text{ to } n
\]

In fact, TF-IDF normalizes the term frequency (TF) by the inverse document frequency (IDF) to decrease the weight of words that appear in the document set more often and increase the effectiveness and influence of the terms that appear rarely in the whole collection (Allahyari et al., 2017).

Each document can be characterized by a vector of term weights \(\omega(d_i) = (\omega(d_i, w_1), \omega(d_i, w_2), \ldots, \omega(d_i, w_v))\). There are different methods to calculate the similarity between documents including cosine similarity, which can be calculated as follows (Allahyari et al., 2017):
\[ S(d_1, d_2) = \cos(\theta) = \frac{d_1 \cdot d_2}{\sqrt{\sum_{i=1}^{v} w_{1i}^2} \cdot \sqrt{\sum_{i=1}^{v} w_{2i}^2}} \]

At this point, the data set is ready to be used in a classification model. There are many classification methods, but we will only use a few that have shown more consistent high performances based on the information acquired from reviewing previous studies.

### 3.2.4.2. Classification Methods

Machine learning techniques are advanced and sometimes complicated algorithms that can be used to identify the potential author of an anonymous text. In these methods, each author is viewed as a probable class employing the collection of previously described features that have been defined beforehand. Then a classifier is required to discriminate potential authors.

As we discussed before, applying authorship attribution to social media requires discovering a collection of stylometric features that cover the variety of the language used in online messages (Rocha et al., 2017). However, such a collection would contain an infrequent large number of terms that creates high dimensional vectors. Since the online messages are too short, the authorship attribution of these texts necessitates a large training data set to improve the classification accuracy and a fast algorithm to be able to analyze the high number of features that have been collected (Rocha et al., 2017). Authorship verification is a 1:1 categorization job with two categories. One category contains the identified author’s texts as the positive category, and the second category, which contains the rest of the texts from all other authors, as the negative category. Nevertheless, the invention of supervised techniques that enhanced the accuracy of authorship attribution results has made these approaches the most prominent in the field (Rocha et al., 2017).
There are several factors that impact the accuracy of classification in authorship attribution studies. Some of these factors are the language and the length of the text, the number of authors and documents, and the nature of the features of the text (Maitra et al., 2015). There have been numerous developments in authorship attribution techniques, but most of these developments have been related to studies with small groups of authors. However, in the situations that there are many author candidates and/or the text is short, such as emails and online texts, detecting the author of an anonymous text is not an easy task (Brocardo et al., 2013).

**Simple Statistics**

Simple descriptive statistics are the simplest method of supervised analysis which have been used from the 1800s. For instance, by collecting texts that are written by two different authors, the word lengths for each text can be computed and $t$-tests can be used to test the inequality of the means for the two authors (Juola, 2006). In the next step, logistic regression can be used to estimate the authorship of new unidentified texts. In a case where there are more than two authors, ANOVA can be used. The same approach can be applied to other sets of features such as the average number of syllables in each word and number of words in each sentence. However, these simple models cannot achieve reliable results (Juola, 2006). So, we use machine learning classifiers.

**Machine Learning Classifiers**

The innovation of machine learning classifiers and clustering techniques was a breakthrough point in authorship attribution research. These models require a pre-labeled training data set that is converted to numerical vectors and is used in the learning step of the model to find borders among different authors by minimizing a classification loss function (El
Bouanani and Kassou, 2014). The results of the learning step are then used to predict the author of unidentified documents.

There are several supervised machine learning methods that can be used for text classification tasks. In this study, we use four of these methods that have frequently been used by other researchers and achieved good results. These methods are Support Vector Machine (SVM), Naive Bayesian classifier, Logistic Regression, and Neural Networks. We will compare the results of these techniques to find out which approach gives better results with our data (Tsimboukakis and Tambouratzis, 2010). A machine learning structure for classification has four elements (Jurafsky and Martin, 2019):

1. A feature that characterizes the input
2. A classification function that calculates the predicted category (y hat) for each observation (x) through p(y|x)
3. “An objective function for learning” often including “minimizing error on training” data set
4. A method for optimizing the objective function.

**Support Vector Machine Methods**

The Support Vector Machine (SVM) is an innovative machine learning technique that was presented by Vapnik in 1995. As a supervised machine learning method, SVM can be applied to classification problems. This method is established based on the Structural Risk Minimization foundation, which is taken from computational learning theory (Zheng et al., 2006).

SVM techniques are the most advantageous methods for authorship attribution tasks. The key factor that makes these techniques unique and different from other methods is that SVM techniques are capable of processing thousands of different inputs and therefore can handle
situations where there are too many dimensions. In authorship attribution studies there are too many features, most of which provide vital information that should be used in the model. This increases the number of features that should be analyzed and, in turn, increases the number of dimensions. SVM techniques can handle these large data sizes and achieve high performance results in a more efficient manner than some other techniques (Diederich et al., 2003). This should elucidate why SVMs are very useful in authorship attribution studies. Studies that used SVM techniques in authorship attribution tasks have created reliable, high-performance results (Diederich et al., 2003).

One significant advantage of SVM techniques is that all terms in the document can be chosen as the features, and, therefore, we do not need to go through the feature selection process. This makes it possible to use all words in a text directly as features (Diederich et al., 2003). So, the ability to manage data sets with millions of observations and producing high performance results, are two of the characteristics of this method that have made it very popular among the researchers.

The SVM model aims to preprocess the data so that the features are represented in a high dimensional space that are usually higher than the initial feature space, where the features’ categories become linearly distinguishable. By using a suitable non-linear mapping from the initial feature space to the prolonged feature space, a hyperplane can be specified that precisely splits data from two categories (Tsimboukakis and Tambouratzis, 2010). The use of SVMs in text mining studies has led to the creation of high performance results, especially when it has been operated on TF-IDF features. SVMs have been used in a diverse variety of problems including text and object recognition and classification and face identification (Juola, 2006).
However, these methods have a very complicated mathematical foundation. SVM is a technique that draws discriminating “hyperplanes in a vector space model, but it is risk-sensitive”, which makes it different from other techniques (Juola, 2006). Risk-sensitivity means that the assumed vector is not just a dividing hyperplane, but it is a dividing hyperplane with the largest margin of error that is possible. However, not any set of data could be divided using a hyperplane separator. In such cases, an SVM with a nonlinear kernel function is used to specify a separating space for classification (Juola, 2006).

The results of scholars like Abbasi illustrate that SVM techniques can achieve a higher performance than other classification techniques like neural networks, decision trees, and Latent Dirichlet Allocation (LDA) (Juola, 2006). However, this does not mean that SVM should simply be used in any study without implementing other techniques and comparing the results with the results of SVM. One technique may work very well in one case but can produce very poor results in a different case (Juola, 2006).

Having large dimensions is a text mining data specification which can lead to the overfitting of results. To prevent overfitting, the number of features needs to be reduced. One of the benefits of the use of SVMs, especially when applied to text mining, is that they do not require the number of features to be reduced to avoid the problem of over-fitting (Corney, et al., 2002).

The goal of using SVMs is to come up with a model that has the minimum true error. With such a model, the possibility of producing an error on a new and randomly selected test observation will decrease. What SVM does is that it provides a model that controls the model complication (VC-Dimension) to minimize the bound on the true error. This prevents the results
of SVM models from being over-fitted, a key issue that other semi-parametric models have (Diederich et al., 2003).

SVMs have become prevalent in attribution authorship studies. Put simply, a linear SVM is a hyperplane that splits a collection of observations in two positive and negative sets with maximum interclass distances or margins. Figure 3.8 illustrates a hyperplane with the related margin (Diederich et al., 2003).

SVM uses the best hyperplane that it can find (Figure 3.8) to classify the n-dimensional space set of features (resulting from raw data) (Ebrahimpour et al., 2013). Figure 3.8 demonstrates an example of how an SVM uses a hyperplane to separate two different categories of a data set.

![Figure 3.8. Linear SVM hyperplane with maximum margin](source: Diederich et al., 2003)

the margin of the classifier. The margin can be maximized through an optimization process:

\[
\text{minimize } (1/2) \|w\|^2 \text{ subject to } y_i (w \cdot x_i + b) \geq 1, \quad \forall i
\]
For separating the data, the SVM uses a linear function such as \( f(x) \) to divide the \( n \)-dimensional vectors into two groups, the positive and negative categories, as follows (Ebrahimpour et al., 2013):

\[
f(x) = w \cdot x + b = \sum_{i=1}^{n} w_i x_i + b
\]

In this formula, \( x \) is the \( n \)-dimensional input vector, \( w \) is the weight vector (“normal vector to the hyperplane”) and \( b \) illustrates the bias, which is the difference between the hyperplane and the actual value. If the value of \( f(x) > 0 \), then \( x \) will go to the positive category, and if \( f(x) < 0 \), then \( x \) will be assigned to the negative category (Ebrahimpour et al., 2013). This distance from the hyperplane to the closest positive and negative data point determines where \( x \) is the \( i \)-th training observation and \( y_i \in \{ -1, 1 \} \) is the right result of the SVM for the \( i \)-th observation in training data (Diederich et al., 2003). We have to notice that the hyperplane is only specified by the training cases \( x_i \) on the margin, or the support vectors.

The SVM technique was originally a two-category or binary classifier, so that in a case where one has more than two categories (which usually happens), the problem will change to a “multi binary classification” problem. In this case, SVM finds the best hyperplane to divide each pair of categories with (Ebrahimpour et al., 2013).

The linear function cannot be used in all situations, and at times when the problem is more complex, we need to use a kernel function (a method of using a linear classifier to solve a non-linear problem) to separate the data efficiently (Ebrahimpour et al., 2013). In these situations, the SVM can be used as a nonlinear technique by transferring the input space to a very high dimensional feature space to make the training data separable (Figure 3.9).
Logistic Regression

As a very important statistical method, logistic regression has a significant role in the social sciences. This method, which is to some extent associated to neural networks, is the most basic supervised machine learning method for categorization in natural language application.

In fact, we can look at a neural network as a collection “of logistic regression classifiers stacked on top of each other” (Jurafsky and Martin, 2019). Logistic regression can be deployed in a two classes separation of observation, as well as in multi-class categorizations.

Logistic regression is similar to naive Bayes and employs supervised machine learning to classify based on probability. Like any other machine learning classifiers, logistic regression needs a training corpus of n pairs of input $x(i)$ and output $y(i)$. Superscripts $(i)$ is used to show each observation in the training data set which in text mining analysis represent a text or document (Jurafsky and Martin, 2019).

Logistic regression has two steps (Jurafsky and Martin, 2019):

**Training:** in this step researchers trains the structure (particularly the weights $w$ and $b$) by employing “stochastic gradient descent and the cross-entropy loss.”
**Test:** in this step \( p(y|x) \) is calculated for observations from test data set which should return \( y = 1 \) or \( y = 0 \) for each observation depend on which one has a higher probability.

Logistic regression is better than a Naïve Bayes technique for several reasons. Naïve Bayes requires a strong independency of features, but this is not the case for logistic regression. Assuming that two features \( f_1 \) and \( f_2 \) have a very high correlation, if we apply the Naïve Bayes method to these two features, it will produce over-fitted results (Jurafsky and Martin, 2019). On the other hand, logistic regression is very robust to features that have correlation. So, if we apply logistic regression to these features, since they are perfectly correlated, logistic regression would use a weighting procedure, like making a new feature, part of which will be a weight of \( f_1 \) and the other part a weight of \( f_2 \). Using \( f_1 \) and \( f_2 \) with this method, logistic regression can prevent the result from being overestimated (Jurafsky and Martin, 2019). Therefore, in situations like text analysis where we may have many associated features, logistic regression can do “more accurate probability” assignment than Naïve Bayes. Therefore, overall, logistic regression has a higher performance “on larger documents or datasets and is a common default” for these types of tasks (Jurafsky and Martin, 2019).

The key difference between logistic regression and Naïve Bayes comes from the different approaches that these two techniques use for categorizing observations. Logistic regression uses a discriminative method to separate observations while Naïve Bayes uses a generative separator (Jurafsky and Martin, 2019).

There are two distinctive approaches for creating a machine learning model for classification (Jurafsky and Martin, 2019). Suppose we would like to separate dog images from cat images. In a generative method like Naïve Bayes, the goal is to know what dogs and cats resemble. Given an unlabeled picture, the system should determine if the unknown picture better
fits with the specification of dogs or specifications of cats and should assign the picture to the
category that fits better. On the other hand, a discriminative model is only trying to learn how to
differentiate a dog from a cat (learns the differences between these two) without trying to learn
much about either one of them. For instance, in this approach, in the training data, the dogs could
simply be specified as images with an animal wearing a collar while the cats are specified as
images without collars (Jurafsky and Martin, 2019). So, while a discriminative model (like
logistic regression) uses $P(c|d)$ directly to classify the observations, a generative model (like
Naïve Bayes) classifies observations indirectly by computing $P(d|c) \times P(c)$, where $P(d|c)$ is the
likelihood and $P(c)$ is a priori. In fact, the Naïve Bayes method uses a likelihood term that
demonstrates how to generate the features of a document if we have the knowledge that it
belongs to Category c (Jurafsky and Martin, 2019).

**Multinomial Logistic Regression**

In many situations we need more than two categories and multinomial logistic regression
becomes necessary, another name for which being the SoftMax regression or the maxent
classifier (Jurafsky and Martin, 2019). In multinomial logistic regression, the object variable $y$
has more than two categories (C categories) and the goal is to find the possibility that $y$ belongs
to potential class $c \in C$. So, the goal is to find $P(y = c|x)$. “The multinomial logistic classifier
uses a generalization of the sigmoid, called the SoftMax function, to compute the probability $P$
($y = c|x$). The SoftMax function takes a vector $z = [z_1, z_2, ..., z_k]$ of $k$ arbitrary values and maps
them to a probability distribution, with each value in the range $(0,1)$, and all the values summing
to 1” (Jurafsky and Martin, 2019).
Naïve Bayes Classifier

This technique is one of the probabilistic models that was established based on Bayes theorem (El Bouanani and Kassou, 2014). Naïve Bayes classifiers makes comparable categorizations based on a simple calculation implication of Bayes’ theorem to find the possibility of a categorization structure to detect the potential class for the observed data. Since these methods assume that the words/terms used in a text are independent of each other, which is not accurate, they are called “Naïve” Bayes. However, they can achieve accurate results in addition to being fast in the processing and training phases (Juola, 2006).

This model relies on the mutual independency of the features’ frequencies. Under this assumption, having the set of features \{f_1 \ldots f_n\} derived from a text and an author a, we would like to calculate (El Bouanani and Kassou, 2014):

$$p(a|f_1,\ldots,f_n) = \frac{P(v) \cdot P(f_1,\ldots,f_n|a)}{P(f_1,\ldots,f_n)}$$

In this formula, P (f_1 \ldots f_n) is supposed to be uniform and n is constant. Therefore, the text can be classified by calculating:

$$P(f_1,\ldots,f_n|a) = \Pi_i P(f_i|a)$$

Based on Bayes Theorem, we can extract a Naïve Bayesian classifier as (El Bouanani and Kassou, 2014):

$$a = \arg\max_{a\in A} P(a) \Pi_i P(f_i|a)$$

In this formula, P(a) can be assessed by computing the frequency of author “a” in the training data. Even though the use of the Naïve Bayes method may result in less accurate probabilities than logistic regression, it typically produces precise classifications. Also, Naïve Bayes produces high performance results when the data set is very small or the texts are very short (Jurafsky and Martin, 2019). Sometimes the results even outperform logistic regression in such cases.
Furthermore, applying Naïve Bayes is very simple, and, since it does not have an optimization phase, it performs the training procedure very quickly. Therefore, in specific situations, it is more logical to use the Naïve Bayes technique (Jurafsky and Martin, 2019).

**Neural Network Classifier**

Neural networks have been created based on the human brain. They are used in a large number of cooperative simple arithmetic workstations. They are typically designed with three or more “layers” in experimental studies. To minimize the error between the favorite and actual results at the output layer, the program is trained through a process called “backpropagation of error” (Juola, 2006).

The mathematical foundation of neural networks looks like the Latent Dirichlet Allocation (LDA), in which, to combine the most appropriate basic dimensions of the input, a dimensionality reduction is made by the middle layer, and the output layer detects classifying hyperplanes. An important problem that neural networks possess is that, while they usually achieve high accuracy results in classification, there is no clarity regarding the basis being used by the program for classification (Juola, 2006).

### 3.2.5. Model Evaluation

The last step in authorship attribution studies is evaluating the model by calculating the accuracy of the model’s output. After classification, to find the performance of the analysis, the accuracy rate can be calculated as (El Bouanani and Kassou, 2014):

\[
\text{Accuracy rate} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% = \frac{\text{Number correctly identified texts}}{\text{Total number of texts}} \times 100\%
\]

Accuracy rates can vary between zero and 100 percent, and the higher the rate is, the more accurate the results would be.
CHAPTER IV
RESULTS AND DISCUSSION

4.1. Introduction

This chapter has three distinct parts. In the first part, we explore the raw data that we collected. In the second part, we use the results of network analysis to answer questions one through five. In the third part, we discuss the results of the authorship attribution analysis to answer the last two questions of this study.

The main objective of this research is to study Louisiana’s human trafficking issue. Due to how much movement is involved in human trafficking and how spread out certain entities can be, we need to include Louisiana’s neighboring states in the study as well to better understand the problem. So, we include Alabama, Arkansas, Florida, Mississippi, and Texas in the study. Since Texas and Florida are very large, we only include the parts of these two states that are close to Louisiana (16 Texas cities and 4 Florida cities). In total, we use all of the collected data for 4 states and just a part of the collected data for 2 states. The area that is bounded by a red line on the map in Figure 4.1 indicates the area that is included in this study. As the map shows, Louisiana is almost in the center of this area.

4.2. Part One: Exploring the Collected Data

4.2.1. Collected Data

The data was collected and parsed from the website Backpage for a time period of ten months, from May 2017 to February 2018. The collected data has eight variables: ad ID number, phone number, name of the city that the ad was posted, name of the state that the ad was posted, the posting date, age of service provider, the ad’s title, and the ad’s posting body. An ad’s posting body is where the provider is described and where some requirements regarding the customer are. The price charged for the service is sometimes also listed in the posting body. The
The original collected data contained 307,463 observations. As said above, this research mainly focuses on Louisiana, and since Texas and Florida are very large, we did not use all of the data collected for these two states. So, the data from these two states that we need are only from cities that are close to Louisiana. Therefore, we removed the rest of the observations for these two states.

For many of the ads, two different versions of the same ad were scraped while the data was being collected. One version of the ad could have been targeted to the entire state and the other version to just a specific city. These two versions would be exact duplicates of each other with just the slight difference of the state name replacing the city name where the city name would’ve been. Therefore, to clean our collected data, we had to remove all of these state versions of the ads. After this cleaning, there was a total of 123,436 observations left for the
region under investigation (Table 4.1). Around 17 percent of these ads (21,076 ads) were posted in Louisiana.

Table 4.1. Number of ads collected for each state

<table>
<thead>
<tr>
<th>State</th>
<th>Number of collected observations</th>
<th>Observations for Chosen Cities</th>
<th>Number of cleaned Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alabama</td>
<td>37,101</td>
<td>37,101</td>
<td>17,082</td>
</tr>
<tr>
<td>Arkansas</td>
<td>15,472</td>
<td>15,472</td>
<td>7,451</td>
</tr>
<tr>
<td>Florida</td>
<td>94,915</td>
<td>6,439</td>
<td>6,439</td>
</tr>
<tr>
<td>Louisiana</td>
<td>40,667</td>
<td>40,667</td>
<td>21,076</td>
</tr>
<tr>
<td>Mississippi</td>
<td>19,614</td>
<td>19,614</td>
<td>9,723</td>
</tr>
<tr>
<td>Texas</td>
<td>99,694</td>
<td>61,665</td>
<td>61,665</td>
</tr>
<tr>
<td>Total</td>
<td>307,463</td>
<td>180,958</td>
<td>123,436</td>
</tr>
</tbody>
</table>

Number of Cities

The collected information contained 47 cities in the specified area including: 8 cities in Louisiana, 9 cities in Alabama, 6 cities in Mississippi, 4 cities in Arkansas, 16 cities in Texas, and 4 cities in Florida. The cities’ names along with the number of ads that were posted in each city are shown in Table 4.2. Based on the number of ads, New Orleans, with 7,038 ads, ranks fifth after Dallas, Houston, Austin and San Antonio. Baton Rouge, with 4,628, ads ranks sixth among these 47 cities.  

4.2.2. Number of Observations (Advertisements)

The cleaned data contained 123,436 advertisements, with 59,847 advertisement IDs and 27,376 phone numbers. Some ad IDs were used in up to 9 cities, meaning that the individual (or group) that used the ID had been active in 9 different cities. However, more than 98 percent of ad IDs were used for posting ads in just one city. Only 878 ad IDs were used in more than one city.

Table 4.3 displays the distribution of phone numbers by the number of cities the phone number was used in. As the table shows, around 83 percent of phone numbers appeared in the advertisements from only one city. Only one phone number was used in more than 20 cities, and
about 5 percent of all phone numbers (1,423) were used in 3 to 5 cities. Similar to the previous table, this table illustrates the activeness of some advertisers in different cities (and states).

Table 4.2. Distribution of ads by states and cities

<table>
<thead>
<tr>
<th>State</th>
<th>City</th>
<th># of Ads</th>
<th>State</th>
<th>City</th>
<th># of Ads</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alabama</td>
<td>Birmingham</td>
<td>4,274</td>
<td>Arkansas</td>
<td>Little Rock</td>
<td>3,812</td>
</tr>
<tr>
<td></td>
<td>Huntsville</td>
<td>3,153</td>
<td></td>
<td>Fayetteville</td>
<td>1,954</td>
</tr>
<tr>
<td>17,082</td>
<td>Montgomery</td>
<td>2,491</td>
<td></td>
<td>Fort Smith</td>
<td>908</td>
</tr>
<tr>
<td></td>
<td>Mobile</td>
<td>2,474</td>
<td></td>
<td>Jonesboro</td>
<td>777</td>
</tr>
<tr>
<td></td>
<td>Auburn</td>
<td>1,124</td>
<td>Florida</td>
<td>Tallahassee</td>
<td>1,861</td>
</tr>
<tr>
<td></td>
<td>Gadsden</td>
<td>1,086</td>
<td></td>
<td>Pensacola</td>
<td>1,823</td>
</tr>
<tr>
<td></td>
<td>Tuscaloosa</td>
<td>1,021</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dothan</td>
<td>873</td>
<td></td>
<td>Panama City</td>
<td>1,385</td>
</tr>
<tr>
<td></td>
<td>Muscle Shoals</td>
<td>586</td>
<td></td>
<td>Okaloosa</td>
<td>1,370</td>
</tr>
<tr>
<td>Mississippi</td>
<td>Biloxi</td>
<td>2,631</td>
<td>Texas</td>
<td>Dallas</td>
<td>11,603</td>
</tr>
<tr>
<td>9,723</td>
<td>Jackson</td>
<td>2,600</td>
<td></td>
<td>Houston</td>
<td>11,238</td>
</tr>
<tr>
<td></td>
<td>Hattiesburg</td>
<td>1,787</td>
<td></td>
<td>Austin</td>
<td>9,997</td>
</tr>
<tr>
<td></td>
<td>North MS</td>
<td>1,705</td>
<td></td>
<td>San Antonio</td>
<td>9,076</td>
</tr>
<tr>
<td></td>
<td>Meridian</td>
<td>801</td>
<td></td>
<td>Fort Worth</td>
<td>6,306</td>
</tr>
<tr>
<td></td>
<td>South West MS</td>
<td>199</td>
<td></td>
<td>Killeen</td>
<td>2,910</td>
</tr>
<tr>
<td></td>
<td>Beaumont</td>
<td>2,453</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Denton</td>
<td>1,948</td>
<td></td>
<td>Tyler</td>
<td>1,243</td>
</tr>
<tr>
<td></td>
<td>Tyler</td>
<td>1,243</td>
<td></td>
<td>Longview</td>
<td>1,137</td>
</tr>
<tr>
<td></td>
<td>Lake Charles</td>
<td>2,264</td>
<td></td>
<td>College Station</td>
<td>991</td>
</tr>
<tr>
<td></td>
<td>Shreveport</td>
<td>1,682</td>
<td></td>
<td>San Marcos</td>
<td>726</td>
</tr>
<tr>
<td></td>
<td>Monroe</td>
<td>992</td>
<td></td>
<td>Texarkana</td>
<td>682</td>
</tr>
<tr>
<td></td>
<td>Alexandria</td>
<td>796</td>
<td></td>
<td>Brownsville</td>
<td>592</td>
</tr>
<tr>
<td></td>
<td>Houma</td>
<td>568</td>
<td></td>
<td>Waco</td>
<td>575</td>
</tr>
<tr>
<td></td>
<td>Huntsville</td>
<td>188</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Since our focus is on Louisiana, it will be helpful to see how many of these phone numbers were used in Louisiana cities. As Table 4.4 illustrates, more than 81 percent of these phone numbers were not used in the advertisements that targeted Louisiana cities. Around 13
percent of these phone numbers were used only in Louisiana cities and 5.2 percent of these phone numbers were used in both Louisiana cities and other cities of neighboring states.

Table 4.3. Distribution of phone numbers by city

<table>
<thead>
<tr>
<th>No. of Cities covered by a phone number</th>
<th>No. of Phone numbers</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>More than 20 (43 cities)</td>
<td>1</td>
<td>0.0%</td>
</tr>
<tr>
<td>11 to 20</td>
<td>10</td>
<td>0.0%</td>
</tr>
<tr>
<td>6 to 10</td>
<td>107</td>
<td>0.4%</td>
</tr>
<tr>
<td>3 to 5</td>
<td>1,423</td>
<td>5.2%</td>
</tr>
<tr>
<td>Two</td>
<td>3,226</td>
<td>11.8%</td>
</tr>
<tr>
<td>One</td>
<td>22,609</td>
<td>82.6%</td>
</tr>
<tr>
<td>Total</td>
<td>27,376</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Examining the phone numbers shows that 2,710 (9.9 percent) of the 27,376 phone numbers that were used in posted ads have a Louisiana area code. New Orleans has the largest share of phone numbers that have Louisiana area codes, with 35 percent (Table 4.5).

Table 4.4. Distribution of phone numbers by region

<table>
<thead>
<tr>
<th>Activity Region</th>
<th>Number of Phone Numbers</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Active in LA cities only</td>
<td>3,598</td>
<td>13.1%</td>
</tr>
<tr>
<td>Active in LA cities and other cities</td>
<td>1,421</td>
<td>5.2%</td>
</tr>
<tr>
<td>No LA cities</td>
<td>22,357</td>
<td>81.7%</td>
</tr>
<tr>
<td>Total</td>
<td>27,376</td>
<td>100%</td>
</tr>
</tbody>
</table>

Examining the area codes of phone numbers used in the posted ads shows that two thirds of the ads (80,078 ads) used local phones, meaning that the city the ad was posted in and the area code of the provided phone number matched. In a third of the ads, the advertiser did not use a local phone number. The phone numbers that were used in the collected ads contained more than 390 area codes from different cities all over the 50 states. However, we are not sure whether this diversity of area codes is the result of buying phone numbers online or shows that these entities that posted ads in Louisiana and its neighboring states may have been traveling all over the whole country and bought these phone numbers while working in other states.
Table 4.5. Distribution of phone numbers that have Louisiana area codes

<table>
<thead>
<tr>
<th>Area code</th>
<th>City or Area</th>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>225</td>
<td>Baton Rouge</td>
<td>539</td>
<td>19.9</td>
</tr>
<tr>
<td>318</td>
<td>northern Louisiana</td>
<td>467</td>
<td>17.2</td>
</tr>
<tr>
<td>337</td>
<td>southwestern Louisiana</td>
<td>562</td>
<td>20.7</td>
</tr>
<tr>
<td>504</td>
<td>New Orleans</td>
<td>950</td>
<td>35.1</td>
</tr>
<tr>
<td>985</td>
<td>Sections of southeast LA which are not within the area code 504</td>
<td>192</td>
<td>7.1</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>2,710</td>
<td>100.0</td>
</tr>
</tbody>
</table>

**4.2.3. The Lifetimes of Phone Numbers and Ad IDs**

Two important variables that may help legal forces track and find people that post online advertisements are the time periods that a phone number and an ad ID are used by the advertisers. Since using a phone number or an ad ID for a longer period of time increases the risk of detection by law enforcement, the advertisers try to change their ad IDs and contact numbers frequently to decrease the risk.

For the collected information, the longest and the shortest time period that a phone number was used was 233 days and 1 day, respectively. On average, each phone number was used for 25.3 days. Regarding the lifetime of ad IDs, the longest time period that an ad ID was used was 207 days with an average time period of 2.06 days. As we can see, ad IDs are more prone to frequent changes than phone numbers.

Figures 4.2 and 4.3 represent the weekly and monthly distributions of the lifetime periods of the phone numbers used in the collected ads. Based on this information, 47 percent of the phone numbers were used for just one day and more than 74 percent of phone numbers were used for less than one month. Only 1 percent of phone numbers (273 phone numbers) were used for more than 6 months.
Figure 4.2. Weekly distribution of lifetime period of the phone numbers

Figure 4.3. Monthly distribution of lifetime period of the phone numbers
Table 4.6 illustrates the number of times that a specific phone number was used in the different advertisements. More than 60% of the phone numbers were used only once or twice in the ads. About 10 percent of the phone numbers were used in more than 10 advertisements.

Table 4.6. Number of times each phone number was used in ads

<table>
<thead>
<tr>
<th>Number of times a phone number was used</th>
<th>Number of phones numbers</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11,767</td>
<td>42.98</td>
</tr>
<tr>
<td>2</td>
<td>4,758</td>
<td>17.38</td>
</tr>
<tr>
<td>3 to 5</td>
<td>5,263</td>
<td>19.22</td>
</tr>
<tr>
<td>6 to 10</td>
<td>2,891</td>
<td>10.56</td>
</tr>
<tr>
<td>11 to 20</td>
<td>1,763</td>
<td>6.44</td>
</tr>
<tr>
<td>21 to 50</td>
<td>796</td>
<td>2.91</td>
</tr>
<tr>
<td>51 to 100</td>
<td>118</td>
<td>0.43</td>
</tr>
<tr>
<td>101 to 200</td>
<td>18</td>
<td>0.07</td>
</tr>
<tr>
<td>201 to 899</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>more than 900 times</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>27,376</td>
<td>100</td>
</tr>
</tbody>
</table>

More than 37 percent of the ads were posted on a Thursday, making it the day that the most ads were posted. Tuesday ranks second with 15.4 percent. The lowest number of ads (less than 6 percent) were posted on Saturdays.

### 4.3. Part Two: Network Analysis

In the previous part I tried to explore the collected data. In this part I will discuss the results of network analysis to answer the research questions. These questions are:

1. Is there evidence of sex trafficking organizations and networks?
2. Is there evidence that sex trafficking organizations operate in multiple cities and states?
3. Is there evidence showing key members of sex trafficking networks?
4. Is the difference between the life expectancy of phone numbers used by individual providers and organized providers statistically significant?
5. Is the difference between the average ages of individual adult service providers and organized adult service providers statistically significant?

6. What is the minimum number of ads per entity (threshold) needed to classify the ads into organizations?

7. Are classification methods equally accurate for identifying the organization associated with an ad for escort services?

The ultimate goal of collecting data was to find potential criminal organizations or networks that could be behind the sex trafficking advertisements. I used a network analysis model to attempt to reach this goal and see if I could find any such networks. To create any network, we need to define the actors and the relationship that links these actors. In this study, the actors are the individuals or potential groups that posted online ads for selling adult services. However, since we did not have any personal information regarding the advertisers, we used phone numbers as a proxy for the advertisers. So, in our network, actors are the phone numbers. To link these phone numbers together, we used two different links: ad IDs and ad textual content similarity. Finding the textual content similarity requires using authorship attribution techniques. Therefore, a secondary goal of this study was to find out how we could use authorship attribution techniques to group (or relate) together the ads that were posted by the same advertiser through the textual contents of the ads.

Every day, tens to hundreds of sex trafficking advertisements are posted online through different websites and social networks. The most challenging questions for legal enforcement are who posted the ads and whether these ads were posted by individual adult service providers or organized sex traffickers.
If the ads that come from the same people (or criminal organizations) always used the same ad ID and/or phone number, the people behind the ads could be identified easily. However, these ads, even if they are posted by the same entities, have different ad IDs and/or phone numbers which makes it hard to track the advertiser.

By using network analysis and text mining techniques, we looked for connections between ads with different ad IDs and/or phone numbers to find the unique entity that posted these ads. Finding such a connection will help us identify potential human and sex trafficking networks that work behind the scenes and the geographical locations that they work in.

4.3.1. Who is who?

As I mentioned before, the actors that are the base of our analysis are the phone numbers. However, what is important for us is not the phone number itself, but the entity (as an individual or a group) that uses the phone number. We would like to find out if there is any network or connection among any set of these phone numbers (the people that use these phone numbers) and if so, try to reveal the network. It seems that, to do this, we just need to apply a network model to our data set.

Figure 4.4 is the network that is created by using all observations (123,436 ads) without labeling the data. As we can see, even without the addition of labels, the graph is very unclear and does not give us any valuable information. Since too many phone numbers and ad IDs are included in the graph, it does not show clearly which phone numbers are connected to each other. If we add the phone numbers and ad IDs as labels to the graph it would be even more chaotic and useless.
Figure 4.4. Creating a network without labels, using the whole data set

Now, as an example, we use a very small subset of our data that consists of only 30 ads, as shown in Table 4.7.

Table 4.7. A subset of collected data include 30 ads (used as an example)

<table>
<thead>
<tr>
<th>Ad ID</th>
<th>Phone No</th>
<th>Ad ID</th>
<th>Phone No</th>
<th>Ad ID</th>
<th>Phone No</th>
</tr>
</thead>
<tbody>
<tr>
<td>ID9511</td>
<td>2056390613</td>
<td>ID1275</td>
<td>2056435381</td>
<td>ID1983</td>
<td>2056564945</td>
</tr>
<tr>
<td>ID2463</td>
<td>2056390613</td>
<td>ID5438</td>
<td>2056435381</td>
<td>ID1983</td>
<td>2056600176</td>
</tr>
<tr>
<td>ID7516</td>
<td>2056390613</td>
<td>ID1359</td>
<td>2056435381</td>
<td>ID1983</td>
<td>2056600191</td>
</tr>
<tr>
<td>ID2345</td>
<td>2056390613</td>
<td>ID1291</td>
<td>2056435381</td>
<td>ID1983</td>
<td>2056600486</td>
</tr>
<tr>
<td>ID4329</td>
<td>2056390613</td>
<td>ID9261</td>
<td>2056435381</td>
<td>ID5038</td>
<td>2056601225</td>
</tr>
<tr>
<td>ID7645</td>
<td>2056390613</td>
<td>ID4039</td>
<td>2056435381</td>
<td>ID5038</td>
<td>2013059880</td>
</tr>
<tr>
<td>ID8743</td>
<td>2056390613</td>
<td>ID3925</td>
<td>2056435381</td>
<td>ID5038</td>
<td>2013424361</td>
</tr>
<tr>
<td>ID3186</td>
<td>2056390613</td>
<td>ID1983</td>
<td>2056435381</td>
<td>ID5038</td>
<td>2056149619</td>
</tr>
<tr>
<td>ID5214</td>
<td>2056390613</td>
<td><strong>ID1983</strong></td>
<td>2056510314</td>
<td>ID5038</td>
<td>2056149634</td>
</tr>
<tr>
<td><strong>ID4329</strong></td>
<td>2056435381</td>
<td><strong>ID1983</strong></td>
<td>2056564731</td>
<td>ID5038</td>
<td>2056149801</td>
</tr>
</tbody>
</table>
Applying a network model to the data set illustrated in Table 4.7 gives us a very clear network, as show in Figure 4.5. This figure demonstrates how phone numbers are connected through ad IDs.

Figure 4.5. Network created by using a subset of our data (30 ads)

I use this simple example to explain how the network analysis technique works here in our data analysis. This network was created by connecting the ad IDs and phone numbers. As the graph illustrates, the network puts these 30 observations (ads) in 4 different groups. Three of these groups are related to each other through either a phone number or an ad ID.
Group 1 shows that nine advertisements with different ad IDs used a unique phone number (205-639-0613). Therefore, all of these nine ads are posted by the same entity. In the second group, nine advertisements with different ad IDs use a unique phone number (205-643-5381). However, these two groups have a common ad ID (ID 4329) that connects them and demonstrates that both groups of ads are posted by the same entity.

On the other hand, in Group 3, we see one specific ad ID number (ID 1983) that used seven different phone numbers in its posted ads, and one of these phone numbers is the same as the phone number that was used by the second group (205-643-5381). Therefore, all of these 17 ad IDs and 8 phone numbers in Groups 1, 2, and 3 come from the same entity.

However, we cannot find any connection between Group 4 and the other groups through ad IDs and/or phone numbers. Therefore, the analysis cannot find any relationship between the fourth group of ads and the other three groups.

In conclusion, by using these 30 observations and connecting the different groups of ad IDs and phone numbers, the network analysis revealed that 6 ads came from one source (the fourth group with ad ID 5038) and the other 25 ads were posted by the same entity (Groups 1, 2, and 3). As we can see in our data, the network analysis connects the different observations by their common ad IDs. So, to be able to identify any connection or network, we need to have a graph similar to Figure 4.5 that gives us a clear picture of how the phone numbers, and therefore the people that use the phone numbers, are connected.

If instead of using 30 ads or all 123,436 ads, we use two subsets of ads with 700 ads for each subset, we can have a graph as illustrated in Figure 4.6. So, if we use up to 700 ads, we can recognize some networking relations among the observations as long as we do not add any labels to the network. In this figure we can see more than 40 relatively large and small groups. Some of
them only have 2 to 3 connections and some others have much more. This network does not contain all ads, so we do not get very large groups.

Figure 4.6. Networks created by using two different subsets of our data (700 ads each)

However, even for 700 ads, when we add the labels to the graph, it gets very crowded and makes the relationships and connections unrecognizable. Therefore, we need to do the network procedure behind the scenes, find the potential groups, and then make a clear graph out of the identified potential groups.

4.3.2. Approaches to Finding Entities

As I mentioned before, we use two different links to find the connected phone numbers and identify the entities that posted the ads. These two links are:

- Identifying entities by matching phone numbers through ad IDs
- Identifying entities by matching phone numbers using authorship identification

4.3.3. Identifying Entities by Matching Phone Numbers Through Ad ID’s

One way to connect different phone numbers that belong to a specific entity (an individual or a potential trafficker) that has posted ads is to use ad IDs. If two different phone
numbers show up in two different advertisements that have the same ad ID, then these two phone numbers belong to the same entity. The following example demonstrates how we can match phone numbers by using ad IDs. We can break down the process in four different steps. In the first step, we connect two phone numbers (6014022382 and 6016585611) that have a common ad ID (9511648), meaning that both phone numbers belong to the same entity. In the second step, we find another ad ID (9173488) that used the phone number 6016585611. Therefore, this new ad ID also belong to the same entity that used the ad ID 9511648. In the third step, we find an ad with ad ID 91734 but with a new phone number (9175809864) and therefore this phone number can be connected to the previous ones. If we summarize steps 1 to 3, we reach step 4, which shows 3 phone numbers that are connected and belong to the same entity.

Figure 4.7. An example of matching phone numbers by using ad IDs

The flow chart in Figure 4.8 illustrates how we use ad IDs to find and group the phone numbers that belong to the same entity. In fact, this flow chart is a detailed explanation of Figure 4.7.

4.3.4. Results of Matching Advertisements by Using Ad IDs

Table 4.8 illustrates the results of matching phone numbers by ad IDs. We found 1,822 entities with more than one phone number, one entity with 11 phone numbers, and 1,364 entities with two phone numbers.
Now, the question is that if an entity that has previously posted several ads posts a new ad that has a new ad ID and phone number, then how can we connect the new phone number to the previous one? In such a case, we cannot identify the entity by matching the new ad ID and phone number with the previous ads. To solve this problem, we must use a different method to help us verify the ownership of the new ad: text mining.
Table 4.8. Results of matching phone numbers by using ad IDs

<table>
<thead>
<tr>
<th>No. of Matched Phone Numbers the Entity Has</th>
<th>No. of Entities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entities with 11 phone numbers</td>
<td>1</td>
</tr>
<tr>
<td>Entities with 8 phone numbers</td>
<td>2</td>
</tr>
<tr>
<td>Entities with 6 phone numbers</td>
<td>11</td>
</tr>
<tr>
<td>Entities with 5 phone numbers</td>
<td>29</td>
</tr>
<tr>
<td>Entities with 4 phone numbers</td>
<td>111</td>
</tr>
<tr>
<td>Entities with 3 phone numbers</td>
<td>303</td>
</tr>
<tr>
<td>Entities with 2 phone numbers</td>
<td>1,364</td>
</tr>
<tr>
<td>Total</td>
<td>1,822</td>
</tr>
</tbody>
</table>

Table 4.9 illustrates 5 real observations that have been extracted from our data set. As we can see, each observation has a unique ad ID and phone number. Therefore, there is no way to connect these observations (ads) through their ad IDs and phone numbers.

Table 4.9. Five illustrated observations with unique ad ID and phone number with text

<table>
<thead>
<tr>
<th>Ad_ID</th>
<th>Title</th>
<th>Posting Body</th>
<th>phones</th>
</tr>
</thead>
<tbody>
<tr>
<td>54098098</td>
<td><img src="https://via.placeholder.com/150" alt="Image 1" /></td>
<td>?? Dr..&lt;br/&gt;??Addictive?? &lt;br/&gt;??Unforgettable?? ??Dr..&lt;br/&gt;??Addictive?? &lt;br/&gt;??Unforgettable?? &lt;br/&gt;??All??</td>
<td>8177440249</td>
</tr>
<tr>
<td>61149983</td>
<td><img src="https://via.placeholder.com/150" alt="Image 2" /></td>
<td>??Dr..&lt;br/&gt;??Addictive?? &lt;br/&gt;??Unforgettable?? ??Dr..&lt;br/&gt;??Addictive?? &lt;br/&gt;??Unforgettable?? &lt;br/&gt;??All??</td>
<td>8104934312</td>
</tr>
<tr>
<td>28264813</td>
<td><img src="https://via.placeholder.com/150" alt="Image 3" /></td>
<td>Available!! Best In Town!!??&lt;br/&gt;??Dr..&lt;br/&gt;??Addictive?? &lt;br/&gt;??Unforgettable?? &lt;br/&gt;??All??</td>
<td>3372055102</td>
</tr>
<tr>
<td>28199388</td>
<td><img src="https://via.placeholder.com/150" alt="Image 4" /></td>
<td>Available!! Best In Town!!??&lt;br/&gt;??Dr..&lt;br/&gt;??Addictive?? &lt;br/&gt;??Unforgettable?? &lt;br/&gt;??All??</td>
<td>3372464062</td>
</tr>
<tr>
<td>24799438</td>
<td><img src="https://via.placeholder.com/150" alt="Image 5" /></td>
<td>Available!! Best In Town!!??&lt;br/&gt;??Dr..&lt;br/&gt;??Addictive?? &lt;br/&gt;??Unforgettable?? &lt;br/&gt;??All??</td>
<td>8329548439</td>
</tr>
</tbody>
</table>

However, if we look at the textual parts of these ads, we can see that the first two observations have similar texts and the other three ads have similar texts as well. So, there is a very high possibility that the first two ads have the same source and the other three ads were posted by the same entity. In this example, using authorship attribution or text classification techniques enable us to identify two entities by grouping the first two phone numbers together in one group and the other 3 phone numbers in the second group. These phone numbers could not be connected to each other without the use of text mining techniques.

So, we used text mining as our second tool to match phone numbers that could not be matched through ad IDs. We used the textual contents of ads to identify and group the ads that
may come from the same source (entity). However, as explained before, because of the small amount of words that are used in each ad, the ads are classified as short texts. The authorship identification of short texts is not an easy task and, therefore, identifying an advertiser through text mining is not easy.

4.3.5. Results of Matching Phone Numbers Using Both Approaches

After combining the results of matching phone numbers from both approaches (ad IDs and text mining), we detected 23,805 entities from 123,436 ads. Table 4.10 highlights some facts extracted from our data set after matching the phone numbers.

Table 4.10. Some facts from data set after matching the phone numbers

<table>
<thead>
<tr>
<th></th>
<th>Total number of ads</th>
<th>Total number of entities</th>
<th>Entities that have ads in only one city</th>
<th>Entities that have only one ad</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Ads</td>
<td>123,436</td>
<td>23,805</td>
<td>19,523 (82.0%)</td>
<td>10,387 (43.6%)</td>
</tr>
<tr>
<td>(6 States)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Louisiana</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of entities that did not post any ads in Louisiana</td>
<td>19,316 (81.1%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entities that posted ads only in LA</td>
<td>3,483 (14.6%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entities that posted ads in both LA and other states</td>
<td>1,006 (4.2%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Louisiana cities with ads</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total number of posted ads in Louisiana</td>
<td>21,076 (17.1%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entities that have at least one ad per week</td>
<td>109</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entities that have at least one ad per day</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entities that posted an ad in only 1 state</td>
<td>22,276</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entities that posted an ad in 2 states</td>
<td>1,261</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entities that posted an ad in 3 states</td>
<td>199</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entities that posted an ad in 4 states</td>
<td>46</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entities that posted an ad in 5 states</td>
<td>17</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entities that posted an ad in the all 6 states</td>
<td>6</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

More than 81 percent of the detected entities did not post any ads in Louisiana. Around 47 percent of the entities posted only one ad during the ten-month time period that we collected the data. There could be three reasons for such a large number of one-time advertisers. Firstly, some of these ads may have been posted by entities that posted many ads, but we were not able
to connect them. Secondly, some entities from other regions may have visited the region for a short period of time and posted an ad. Finally, some entities may have posted an ad and did not find any success, so they did not continue advertising.

We found 1,623 (7%) entities with more than one phone number (Table 4.11). Also, we found two entities with a very high number of phone numbers, one of them with 212 and the second one with 144 phone numbers. Around 1,621 entities had between 2 and 49 phone numbers, and 22,181 (93%) entities had only one phone number. However, there is a possibility that some of these entities that were detected with only one phone number actually had more than one phone number but we could not connect the phone numbers.

Table 4.11. Distribution of entities based on number of their phone numbers

<table>
<thead>
<tr>
<th>No. of phone numbers</th>
<th>No. of entities</th>
<th>Cumulative No. of entities</th>
</tr>
</thead>
<tbody>
<tr>
<td>More than 200 Phone No.</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>50 to 200 Phone No.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>20 to 49 Phone No.</td>
<td>13</td>
<td>15</td>
</tr>
<tr>
<td>10 to 19 Phone No.</td>
<td>26</td>
<td>41</td>
</tr>
<tr>
<td>5 to 9 Phone No.</td>
<td>134</td>
<td>175</td>
</tr>
<tr>
<td>4 Phone No.</td>
<td>95</td>
<td>270</td>
</tr>
<tr>
<td>3 Phone No.</td>
<td>334</td>
<td>604</td>
</tr>
<tr>
<td>2 Phone No.</td>
<td>1,020</td>
<td>1,624</td>
</tr>
<tr>
<td>Only one phone number</td>
<td>22,181</td>
<td>23,805</td>
</tr>
<tr>
<td>Total</td>
<td>23,805</td>
<td>23,805</td>
</tr>
</tbody>
</table>

Based on the number of posted ads, 20,956 (88%) entities posted less than ten ads, which means less than one ad per month on average (Table 4.12). One entity posted more than 2,000 ads and 51 entities posted between 100 and 2,000 ads. On average, each entity posted 5.2 ads over 10 months, or one ad every two months. It means that many entities have not been active in posting online ads. Nevertheless, there is a possibility that some or many of these ads may have belonged to the same entity and we were simply not able to connect them.
Table 4.13 displays the distribution of entities based on the number of cities that each entity covers. While 82 percent (19,523) of the entities were active in just one city, 35 entities were active in more than 10 cities and 159 entities were active in more than 5 cities.

Table 4.12. Distribution of entities by number of their ads

<table>
<thead>
<tr>
<th>Number of ads</th>
<th>Number of entities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entities with less than 10 ads</td>
<td>20,956</td>
</tr>
<tr>
<td>Entities with 10 to less than 20 ads</td>
<td>1,732</td>
</tr>
<tr>
<td>Entities with 20 to less than 30 ads</td>
<td>568</td>
</tr>
<tr>
<td>Entities with 30 to less than 40 ads</td>
<td>239</td>
</tr>
<tr>
<td>Entities with 40 to less than 50 ads</td>
<td>101</td>
</tr>
<tr>
<td>Entities with 50 to less than 100 ads</td>
<td>156</td>
</tr>
<tr>
<td>Entities with 100 to less than 200 ads</td>
<td>35</td>
</tr>
<tr>
<td>Entities with 200 to less than 300 ads</td>
<td>11</td>
</tr>
<tr>
<td>Entities with 300 to less than 500 ads</td>
<td>2</td>
</tr>
<tr>
<td>Entities with 500 to less than 1000 ads</td>
<td>2</td>
</tr>
<tr>
<td>Entities with 1000 to less than 2000 ads</td>
<td>1</td>
</tr>
<tr>
<td>Entities with more than 2000 ads</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>23,805</td>
</tr>
</tbody>
</table>

4.3.6. Potential Traffickers in Louisiana

Since our goal is to uncover possible networks, we used entities that have more than one advertisement and posted ads in more than one city. More than four thousand entities (around one fifth of the entities) posted ads in more than one city. Also, since we would like to focus on Louisiana, we removed entities from our data set that did not post any advertisements in Louisiana. After applying these changes, we got a data set with 1,310 entities that were active in more than one city and posted an ad in at least one city in Louisiana. This is the data set we used to build up our network.

These 1,310 entities that were left in our data set posted 24,449 ads (out of 123,436 ads) in 47 cities. Of these entities, 384 entities were active only in Louisiana (in 8 cities) and 1,006
entities were active in both Louisiana and other states. In Louisiana, two entities posted at least one ad per day (on average) and 109 entities posted one ad per week.

Table 4.13. Distribution of entities by number of cities covered by each entity

<table>
<thead>
<tr>
<th>Number of cities covered by entity</th>
<th>Frequency (number of entity)</th>
<th>Cumulative frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>43</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>39</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>21</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>20</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>19</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>18</td>
<td>2</td>
<td>7</td>
</tr>
<tr>
<td>15</td>
<td>2</td>
<td>9</td>
</tr>
<tr>
<td>14</td>
<td>2</td>
<td>11</td>
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<tr>
<td>12</td>
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<td>13</td>
</tr>
<tr>
<td>17</td>
<td>3</td>
<td>16</td>
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<tr>
<td>13</td>
<td>4</td>
<td>20</td>
</tr>
<tr>
<td>10</td>
<td>6</td>
<td>26</td>
</tr>
<tr>
<td>11</td>
<td>9</td>
<td>35</td>
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<tr>
<td>9</td>
<td>14</td>
<td>49</td>
</tr>
<tr>
<td>8</td>
<td>22</td>
<td>71</td>
</tr>
<tr>
<td>7</td>
<td>22</td>
<td>93</td>
</tr>
<tr>
<td>6</td>
<td>66</td>
<td>159</td>
</tr>
<tr>
<td>5</td>
<td>136</td>
<td>295</td>
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<tr>
<td>4</td>
<td>315</td>
<td>610</td>
</tr>
<tr>
<td>3</td>
<td>873</td>
<td>1,483</td>
</tr>
<tr>
<td>2</td>
<td>27,99</td>
<td>4,282</td>
</tr>
<tr>
<td>1</td>
<td>19,523</td>
<td>23,805</td>
</tr>
<tr>
<td>Total</td>
<td>23,805</td>
<td>23,805</td>
</tr>
</tbody>
</table>

4.3.7. Cities by Common Entities

As we saw in the previous chapter, reviewing previous studies and official reports regarding traffickers reveals that they usually move the victims into different cities for two different reasons. The first reason is to decrease the risk of being identified by law enforcement. The second reason is to expand their market and increase their profits. So, to identify the entities, first we need to track them and find out the cities that they are active in. Even though we have all
of the information regarding the cities that each entity has been working in, there is way too much for us to be able to go through all of the entities one by one. So, we summarize the result in Table 4.14 to show the number of common entities between cities in Louisiana and cities in other states. As an example, only two entities have posted ads in both Alexandria and Auburn.

As the table shows, New Orleans and Baton Rouge, with 197 common entities, have the highest number of common entities. The pairs of Lake Charles – Houston (125 common entities), Lake Charles – Lafayette (117 common entities), New Orleans – Houston (108 common entities), Lake Charles – Beaumont (107 common entities), and Baton Rouge – Lafayette (106 common entities) are in the next ranks. One interesting point in this table is that we cannot find any cell with a “zero” value. This means that all possible pairs out of the 47 cities that we have in the region have at least one common entity. In other words, moving around from city to city is a behavior that occurs in all of these cities.

Figure 4.9 depicts common entities between cities in Louisiana and cities in the other 5 states. The cities with larger numbers of entities have a larger circle. Notice that, to make this graph, we did not include the entities that did not post any ads in Louisiana. That is why we see that New Orleans and Baton Rouge have much larger circles than Houston and Dallas. If we were to use the entire data set to make this graph, then cities like Houston and Dallas would have much larger circles than Baton Rouge and New Orleans.

The betweenness centrality measure for the network illustrated in Figure 4.9 is calculated. The results show that New Orleans, Shreveport, Lake Charles, and Baton Rouge with 3.51, 2.42, 1.96, and 1.16 have the highest betweenness centrality, respectively. This means that most entities pass through these four cities to go to the other 43 cities that exist in the network.
<table>
<thead>
<tr>
<th>City</th>
<th>Alexandria</th>
<th>Baton Rouge</th>
<th>Houma</th>
<th>Lafayette</th>
<th>Lake Charles</th>
<th>Monroe</th>
<th>New Orleans</th>
<th>Shreveport</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alexandria</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baton Rouge</td>
<td>18</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Houma</td>
<td>16</td>
<td>28</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lafayette</td>
<td>27</td>
<td>106</td>
<td>28</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lake Charles</td>
<td>32</td>
<td>88</td>
<td>25</td>
<td>122</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monroe</td>
<td>21</td>
<td>17</td>
<td>17</td>
<td>20</td>
<td>23</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New Orleans</td>
<td>22</td>
<td>197</td>
<td>48</td>
<td>95</td>
<td>84</td>
<td>24</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shreveport</td>
<td>19</td>
<td>45</td>
<td>15</td>
<td>33</td>
<td>46</td>
<td>40</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Auburn</td>
<td>2</td>
<td>5</td>
<td>3</td>
<td>6</td>
<td>5</td>
<td>5</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>Austin</td>
<td>7</td>
<td>54</td>
<td>7</td>
<td>32</td>
<td>59</td>
<td>10</td>
<td>61</td>
<td>42</td>
</tr>
<tr>
<td>Beaumont</td>
<td>5</td>
<td>40</td>
<td>7</td>
<td>38</td>
<td>107</td>
<td>8</td>
<td>38</td>
<td>22</td>
</tr>
<tr>
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<td>45</td>
<td>9</td>
<td>13</td>
<td>27</td>
<td>9</td>
<td>76</td>
<td>10</td>
</tr>
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<td>Birmingham</td>
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<td>14</td>
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<td>6</td>
<td>47</td>
<td>11</td>
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<tr>
<td>Brownsville</td>
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<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>College Station</td>
<td>1</td>
<td>16</td>
<td>4</td>
<td>16</td>
<td>30</td>
<td>5</td>
<td>15</td>
<td>12</td>
</tr>
<tr>
<td>Dallas</td>
<td>2</td>
<td>37</td>
<td>4</td>
<td>23</td>
<td>22</td>
<td>6</td>
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<td>3</td>
</tr>
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<td>2</td>
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</tr>
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<td>2</td>
<td>2</td>
<td>5</td>
<td>6</td>
<td>14</td>
<td>11</td>
</tr>
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<td>18</td>
<td>3</td>
<td>14</td>
<td>22</td>
<td>5</td>
<td>26</td>
<td>34</td>
</tr>
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<td>Gadsden</td>
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<td>5</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>Hattiesburg</td>
<td>5</td>
<td>21</td>
<td>6</td>
<td>10</td>
<td>13</td>
<td>9</td>
<td>32</td>
<td>7</td>
</tr>
<tr>
<td>Houston</td>
<td>6</td>
<td>97</td>
<td>6</td>
<td>58</td>
<td>125</td>
<td>11</td>
<td>117</td>
<td>36</td>
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<td>Huntsville</td>
<td>1</td>
<td>12</td>
<td>4</td>
<td>5</td>
<td>12</td>
<td>5</td>
<td>14</td>
<td>10</td>
</tr>
<tr>
<td>Huntsville TX</td>
<td>2</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>7</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Jackson</td>
<td>4</td>
<td>54</td>
<td>5</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>55</td>
<td>23</td>
</tr>
<tr>
<td>Jonesboro</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Killeen</td>
<td>1</td>
<td>19</td>
<td>3</td>
<td>12</td>
<td>25</td>
<td>6</td>
<td>18</td>
<td>19</td>
</tr>
<tr>
<td>Little Rock</td>
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<td>20</td>
<td>2</td>
<td>11</td>
<td>20</td>
<td>8</td>
<td>23</td>
<td>29</td>
</tr>
<tr>
<td>Longview</td>
<td>1</td>
<td>6</td>
<td>3</td>
<td>8</td>
<td>15</td>
<td>5</td>
<td>7</td>
<td>29</td>
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<tr>
<td>Meridian</td>
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<td>12</td>
<td>3</td>
<td>5</td>
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<td>9</td>
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</tr>
<tr>
<td>Mobile</td>
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<td>26</td>
<td>3</td>
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<td>7</td>
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<td>23</td>
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</tr>
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<td>1</td>
<td>1</td>
<td>1</td>
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</tr>
<tr>
<td>North Mississippi</td>
<td>7</td>
<td>8</td>
<td>5</td>
<td>6</td>
<td>9</td>
<td>10</td>
<td>19</td>
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</table>

(table cont’d.)
<table>
<thead>
<tr>
<th></th>
<th>Alexandria</th>
<th>Baton Rouge</th>
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<th>Lafayette</th>
<th>Lake Charles</th>
<th>Monroe</th>
<th>New Orleans</th>
<th>Shreveport</th>
</tr>
</thead>
<tbody>
<tr>
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<td>1</td>
<td>5</td>
<td>3</td>
<td>4</td>
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</tr>
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<td>Panama City</td>
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<td>8</td>
<td>3</td>
<td>6</td>
<td>4</td>
<td>4</td>
<td>16</td>
<td>4</td>
</tr>
<tr>
<td>Pensacola</td>
<td>3</td>
<td>22</td>
<td>5</td>
<td>8</td>
<td>13</td>
<td>4</td>
<td>31</td>
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</tr>
<tr>
<td>San Antonio</td>
<td>1</td>
<td>35</td>
<td>4</td>
<td>25</td>
<td>52</td>
<td>5</td>
<td>35</td>
<td>33</td>
</tr>
<tr>
<td>San Marcos</td>
<td>2</td>
<td>10</td>
<td>3</td>
<td>10</td>
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<tr>
<td>Southwest</td>
<td>5</td>
<td>6</td>
<td>4</td>
<td>4</td>
<td>9</td>
<td>7</td>
<td>9</td>
<td>7</td>
</tr>
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<td>Mississippi</td>
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<td>18</td>
<td>3</td>
<td>6</td>
<td>11</td>
<td>8</td>
<td>20</td>
<td>11</td>
</tr>
<tr>
<td>Tallahassee</td>
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<td>10</td>
<td>3</td>
<td>6</td>
<td>7</td>
<td>6</td>
<td>10</td>
<td>16</td>
</tr>
<tr>
<td>Texarkana</td>
<td>2</td>
<td>17</td>
<td>5</td>
<td>6</td>
<td>12</td>
<td>8</td>
<td>14</td>
<td>7</td>
</tr>
<tr>
<td>Tuscaloosa</td>
<td>2</td>
<td>11</td>
<td>3</td>
<td>11</td>
<td>16</td>
<td>6</td>
<td>10</td>
<td>32</td>
</tr>
<tr>
<td>Tyler</td>
<td>2</td>
<td>8</td>
<td>4</td>
<td>6</td>
<td>8</td>
<td>5</td>
<td>9</td>
<td>8</td>
</tr>
<tr>
<td>Waco</td>
<td>2</td>
<td>8</td>
<td>4</td>
<td>6</td>
<td>8</td>
<td>5</td>
<td>9</td>
<td>8</td>
</tr>
</tbody>
</table>

Figure 4.9. Common entities between cities in Louisiana and other cities
Figure 4.10 displays the common entities between only the cities of Louisiana. In comparison to the previous figure, this graph shows a very clear picture of the common entities between these cities. For example, New Orleans, Baton Rouge, Lake Charles, and Lafayette have a large number of common entities. In other words, many entities posted ads in these cities and constantly moved between them. Again, the larger the circle, the higher the number of entities.

Figure 4.10. Common entities between cities in Louisiana
4.4. Exploring Some of the Potential Organized Networks

The main reason for this analysis was to identify potential human trafficking networks in Louisiana. We have found at least 61 entities that can be addressed as such potential networks. However, since it is not possible to go through all of these identified potential networks or groups, I discuss six of them in more detail. I pick potential networks or groups that posted a large number of ads in several cities, had many different phone numbers, and were active in at least a city in Louisiana. Table 4.15 shows basic information for these six entities.

Table 4.15. Basic information for six potential networks

<table>
<thead>
<tr>
<th>Entity</th>
<th>Number of states</th>
<th>Number of cities</th>
<th>Number of posted ads in</th>
<th>No. of phone numbers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>LA</td>
<td>Other states</td>
<td>Total</td>
</tr>
<tr>
<td>2015588661</td>
<td>4</td>
<td>4</td>
<td>13</td>
<td>17</td>
</tr>
<tr>
<td>2012996889</td>
<td>6</td>
<td>7</td>
<td>32</td>
<td>39</td>
</tr>
<tr>
<td>2055234457</td>
<td>5</td>
<td>4</td>
<td>17</td>
<td>21</td>
</tr>
<tr>
<td>2103906108</td>
<td>6</td>
<td>4</td>
<td>15</td>
<td>19</td>
</tr>
<tr>
<td>2259608214</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>2056878484</td>
<td>4</td>
<td>4</td>
<td>13</td>
<td>17</td>
</tr>
</tbody>
</table>

4.4.1. Network 1 (Entity # 2015588661)

This network used 141 phone numbers in 2,386 ads in Alabama (7 ads), Mississippi (6 ads), Louisiana (242 ads), and Texas (2131 ads). The area codes of the phone numbers used by this entity shows that these phone numbers came from 36 cities spread between 19 different states (Table 4.16). As the table shows, as many as 36 phone numbers used by this entity had a New York area code and 16 of them had a California area code. This variety of area codes could be the result of buying online phones, or could show the possibility that the people of this group had traveled around the whole country and had been in many states like New York, California, Massachusetts, and Oregon, or a combination of both online phone numbers and massive
travelling. Advertisements posted in other states should be examined to see if this entity had been active in other states or not.

Based on our data set that only covers 6 states, this group posted ads in four states but mainly targeted Texas and Louisiana (they may or may not have a larger number of ads in other states that we did not cover in this study). In Louisiana, this group posted ads in Baton Rouge (108), New Orleans (69), Lafayette (58), and Lake Charles (7). More than 75% of their ads were posted in Austin, Dallas, Houston, and San Antonio.

Table 4.16. Area code of phone numbers used by entity # 2015588661

<table>
<thead>
<tr>
<th>State</th>
<th>Number of phone No.</th>
<th>State</th>
<th>Number of phone No.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Texas</td>
<td>58</td>
<td>Connecticut</td>
<td>1</td>
</tr>
<tr>
<td>New York</td>
<td>36</td>
<td>Georgia</td>
<td>1</td>
</tr>
<tr>
<td>California</td>
<td>16</td>
<td>Indiana</td>
<td>1</td>
</tr>
<tr>
<td>Illinois</td>
<td>6</td>
<td>Iowa</td>
<td>1</td>
</tr>
<tr>
<td>Louisiana</td>
<td>4</td>
<td>Massachusetts</td>
<td>1</td>
</tr>
<tr>
<td>New Jersey</td>
<td>3</td>
<td>North Carolina</td>
<td>1</td>
</tr>
<tr>
<td>Utah</td>
<td>3</td>
<td>Rhode Island</td>
<td>1</td>
</tr>
<tr>
<td>Mississippi</td>
<td>2</td>
<td>Virginia</td>
<td>1</td>
</tr>
<tr>
<td>Nevada</td>
<td>2</td>
<td>Unknown</td>
<td>1</td>
</tr>
<tr>
<td>Oregon</td>
<td>2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 4.11 demonstrates the distribution of phone numbers used by this group in different cities. Most of the phone numbers were used in Dallas, Houston, and Austin. They used 14 different phone numbers in Baton Rouge and 6 different phone numbers in New Orleans.

So far, we have looked at some of the attributes of this entity or group but not the actual network that demonstrates the relationship among the different phone numbers. So, the next graph (Figure 4.12) illustrates the connection between different phone numbers. Due to the large amount of phone numbers, the graph will not come out very clear if we use the phone numbers to label the actors in the network. To solve this problem, the labels that show the phone numbers for each node are removed from the graph.
The graph demonstrates the pattern of connections between different actors. As we can see, some phone numbers are central, some are on edges, and others are in the middle. To find central phone numbers, two centrality measures (betweenness centrality and closeness centrality) were computed. Since there are too many phone numbers, only phone numbers with the highest centrality measures have been illustrated in Table 4.17.

Figure 4.11. Distribution of phone numbers used by Entity # 2015588661 in different cities

The betweenness centrality for each actor in a network is the number of times that the actor connects two other actors to each other through their shortest paths. It was introduced by
Linton Freeman as a scale for measuring the control of an individual (actor) on the communication among people in a social network.

Figure 4.12. Observed network for entity # 2015588661 without label

Table 4.17. The phone numbers with the highest betweenness and closeness centrality measures in the network

<table>
<thead>
<tr>
<th>Phone number</th>
<th>Betweenness</th>
<th>Phone number</th>
<th>Closeness</th>
</tr>
</thead>
<tbody>
<tr>
<td>6824088359</td>
<td>5223.00</td>
<td>6463406146</td>
<td>0.00199</td>
</tr>
<tr>
<td>9293299490</td>
<td>2594.48</td>
<td>2244136765</td>
<td>0.00196</td>
</tr>
<tr>
<td>6282204140</td>
<td>2343.63</td>
<td>9293299490</td>
<td>0.00189</td>
</tr>
<tr>
<td></td>
<td></td>
<td>6282204140</td>
<td>0.00180</td>
</tr>
</tbody>
</table>
Closeness centrality shows how close an actor is to the other members of the network. The closeness centrality of each actor measures the average inverse distance of that actor to the rest of actors in the network (Adamic, 2013). Therefore, actors that are a shorter distance from all of the other actors (or have a shorter path to access other actors) would have a higher closeness centrality.

In a sex trafficking group, the pimps or traffickers have the authority over the victims and have a central position in the network. If the identified group is really an organized sex trafficking group, then there is a high probability that the phone numbers with high centrality measures belong to the traffickers. So, when looking at all of the phone numbers after detecting a network, those with the highest centrality measures are the most important to investigate.

To look at this network in a different way, we can recreate the network by focusing on a central actor, or a phone number with the highest centrality measure. We would like to see the network from the point of view of the central phone number and see how the system is organized from that central point and how the other phone numbers are far from this central actor.

I used two of these phone numbers with the highest centrality measures as a root to recreate the network. I used phone numbers 6824088359 and 6282204140 as a root to recreate the network in Figures 4.13 and 4.14. In order to have a clear graph, we had to remove the labels. In these two graphs, the network starts from the root phone number, grows as a tree, and finally reaches the edge phone numbers. These two graphs are very different from each other and from Figure 4.12. In Figure 4.13, the root phone number is directly related to 15 other phone numbers and then is connected to the other phone numbers through these 15 actors. In Figure 4.14, the root phone number is directly connected to only 5 phone numbers and then is connected to other phone numbers through these 5 numbers. Comparing these two rooted networks demonstrates
that the second network has one level of connection less than the first one. The first rooted network has six levels of connection while the second network has seven levels.

Another interesting point is that one of these central phone numbers has the area code of San Francisco (628), which is very far away from the region under investigation. This phone number was used in ads posted in Houston for a period of four months, from October 2017 to January 2018.

Figure 4.13. Recreating the network by using central phone number 6824088359 as the root

4.4.2. Network 2 (Entity # 2012996889)

This entity was active in 39 of the 47 cities spread between the six states. They posted 1,827 ads (8 ads per day on average), 229 of which were posted in Louisiana. They used 210 different phone numbers. These phone numbers contained the area codes of at least 60 cities around the country from 25 different states, even though they were extracted from ads that were posted in the 6 states that were under investigation (Table 4.18). This entity posted ads in 7 cities
in Louisiana, with focusing on Baton Rouge (133 ads) and Lafayette (63 ads). They posted many ads in San Antonio, Austin, Dallas, Houston, Birmingham, Fort Worth (TX), and Tallahassee.

Figure 4.14. Recreating the network by using central phone number 6282204140 as the root

<table>
<thead>
<tr>
<th>State</th>
<th>Number of Phone No.</th>
<th>State</th>
<th>Number of Phone No.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Texas</td>
<td>111</td>
<td>Pennsylvania</td>
<td>2</td>
</tr>
<tr>
<td>Alabama</td>
<td>19</td>
<td>Indiana</td>
<td>1</td>
</tr>
<tr>
<td>California</td>
<td>15</td>
<td>Massachusetts</td>
<td>1</td>
</tr>
<tr>
<td>Louisiana</td>
<td>11</td>
<td>Maryland</td>
<td>1</td>
</tr>
<tr>
<td>Florida</td>
<td>8</td>
<td>Michigan</td>
<td>1</td>
</tr>
<tr>
<td>New York</td>
<td>8</td>
<td>Montana</td>
<td>1</td>
</tr>
<tr>
<td>Georgia</td>
<td>6</td>
<td>Mississippi</td>
<td>1</td>
</tr>
<tr>
<td>Connecticut</td>
<td>4</td>
<td>New Jersey</td>
<td>1</td>
</tr>
<tr>
<td>Oklahoma</td>
<td>4</td>
<td>Ohio</td>
<td>1</td>
</tr>
<tr>
<td>Illinois</td>
<td>3</td>
<td>Rhode Island</td>
<td>1</td>
</tr>
<tr>
<td>Tennessee</td>
<td>3</td>
<td>Virginia</td>
<td>1</td>
</tr>
<tr>
<td>Minnesota</td>
<td>2</td>
<td>West Virginia</td>
<td>1</td>
</tr>
<tr>
<td>Nevada</td>
<td>2</td>
<td>Unknown</td>
<td>1</td>
</tr>
</tbody>
</table>
Figure 4.15 displays the distribution of the phone numbers based on the cities that they were used in. Similar to the previous network, most of the phone numbers were used in the larger cities in Texas. Some phone numbers were used by this group for just one day while other numbers were used for more than 6 months. Several phone numbers were made in the middle of August 2017 and terminated at the beginning of January 2018. As the network shows, this group was active more in Baton Rouge and Lafayette than New Orleans.
Figure 4.16 illustrates the pattern of connection between different phone numbers used by this entity. For the purpose of clarity, the labels (phone numbers) have been removed from the graph.

Figure 4.16. Observed network for entity # 2012996889 without label

Based on the network pattern, it seems that this network is not very centralized. Since this entity has too many phone numbers, we could not show the centrality measures computed for all
of the phone numbers. So, only phone numbers with the highest centrality measures are displayed in Table 4.19. Even though the graph does not show much centrality throughout the network, the calculated measures demonstrate relatively high centrality measures for some phone numbers. Some of these high centrality phone numbers have area codes from West Virginia (304), Denver (303), and Los Angeles (310), which are fairly far from the states the data was collected from. This increases the possibility that this entity is an organized group. A Los Angeles phone number was used in ads posted in Dallas and Austin between August 16 and October 26.

Table 4.19. Betweenness and closeness centrality measures for entity # 2012996889

<table>
<thead>
<tr>
<th>Phone number</th>
<th>Betweenness</th>
<th>Phone number</th>
<th>Closeness</th>
</tr>
</thead>
<tbody>
<tr>
<td>3185281349</td>
<td>7817</td>
<td>3043099809</td>
<td>0.00060</td>
</tr>
<tr>
<td>3043099809</td>
<td>7734</td>
<td>3185281349</td>
<td>0.00059</td>
</tr>
<tr>
<td>2542338378</td>
<td>6670</td>
<td>3109272418</td>
<td>0.00058</td>
</tr>
<tr>
<td>2546309761</td>
<td>6599</td>
<td>2055979571</td>
<td>0.00057</td>
</tr>
<tr>
<td>2055979571</td>
<td>6210</td>
<td>2546309761</td>
<td>0.00056</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3036473911</td>
<td>0.00051</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2542338378</td>
<td>0.00045</td>
</tr>
</tbody>
</table>

We use phone number 3185281349, which has relatively high betweenness and closeness centrality measures, as a root to recreate the network from this phone number point of view. The recreated network displays 18 levels of connection between the phone numbers (Figure 4.17).

4.4.3. Network 3 (Entity # 2055234457)

This group posted 287 ads in 4 cities in Louisiana and 17 cities in Alabama, Florida, Mississippi, and Texas. They posted ads in Baton Rouge (5 ads), Lake Charles (4 ads), Shreveport (4 ads), and Lafayette (1 ad). Austin, Dallas, Fort Worth, Killeen, and San Antonio were other main targets for this group.

This group had a large variety of phone area codes from many states. They used 42 phone numbers with area codes from 22 cities spread between the 10 different states of Alabama,
Texas, Louisiana, Colorado, Florida, Missouri, California, Iowa, Nevada, and Kansas. Figure 4.18 shows the phone numbers with the cities that they were used in. Similar to the previous groups, most of the phone numbers were used in the larger cities in Texas.

Figure 4.17. Recreating the network by using central phone number 3185281349 as the root

The connection pattern network for this entity is displayed in Figure 4.19. This network consists of 4 subgroups of phone numbers that have been connected through a few other phone numbers. Table 4.19 contains the centrality measures computed for this entity. We used the phone number with the highest centrality measure to recreate the network (Figure 4.20). This recreated network has 8 levels of connection.
Figure 4.18. The phone numbers that were used by this entity with the locations that they were used in.

4.4.4. Network 4 (Entity # 2103906108)

This group posted 213 ads in 19 cities within the 6 states. Of these ads, 48 were posted in 4 Louisianan cities. Most of these ads were posted in Baton Rouge (22 ads), New Orleans (21 ads), Auburn (41 ads), Austin (23 ads), and San Antonio (29 ads).

This group used 31 different phone numbers. These phone numbers had area codes for 18 different cities from Texas, Louisiana, Alabama, Delaware, Arkansas, Tennessee, Nevada (Las
Vegas), Florida, and Guam. Figure 4.21 shows how these 31 phone numbers were used in the 19 different cities.

Figure 4.19. Observed network for entity #2055234457

<table>
<thead>
<tr>
<th>Phone number</th>
<th>Betweenness</th>
<th>Closeness</th>
</tr>
</thead>
<tbody>
<tr>
<td>2142546089</td>
<td>533</td>
<td>0.0067</td>
</tr>
<tr>
<td>2548636206</td>
<td>359</td>
<td>0.006</td>
</tr>
</tbody>
</table>
Figure 4.22 illustrates the connection pattern between the phone numbers used by this entity. This network looks decentralized, but calculating the centrality measures shows that two phone numbers are much more central in comparison to the rest. The two phone numbers with the highest centrality measures are 3183732903 and 3023574668. The area code for the second phone number (302) belongs to Denver, Colorado and was used in ads posted in New Orleans. These two phone numbers are next to each other and are located in the center of the network.
Figure 4.21. The phone numbers that were used by this entity with the cities that they were used in

The betweenness centrality for these two phone numbers are 246.6 and 245.5, respectively. The next highest closeness centrality belongs to the phone number 2815440043, with the value 161. The same phone numbers (3183732903 and 3023574668) have the highest closeness centrality measures with 0.0096 and 0.0093, respectively.
Figure 4.22. Observed network for entity # 2103906108

4.4.5. Network 5 (Entity # 2259608214)

This group posted 184 ads in 6 cities, 68 of which were posted in 4 cities in Louisiana. These ads were posted in Panama City (102 ads), Dallas (14 ads), Baton Rouge (13 ads), Lafayette (52 ads), Lake Charles (1 ad), and New Orleans (2 ads).

This group used 23 phone numbers in their ads. These phone numbers had the area codes of 10 cities from the 8 states of Louisiana, South Dakota, Arizona, Nevada, Georgia, Florida, Kansas, and Ohio. Panama City was the center of activity of this entity, as shown by how 19 of this entity’s phone numbers were used in this city.
Figure 4.23. The phone numbers that have been used by this entity with the cities that they have been used.

Figure 4.24 demonstrates the pattern of connections between the phone numbers for this entity. Two phone numbers that are next to each other and are located in the center of the depicted network have the highest closeness and betweenness centrality measures. These two phone numbers are 8506302985 and 7063529874 with betweenness centrality of 151 and 150, respectively. The closeness centrality measure for both phone numbers is the same and is equal to 0.021. Similar to the previous entities, one of the two phone numbers that have the highest centrality measures has an area code from out of the region; area code 706, which belongs to the city of Augusta, Georgia.
4.4.6. Network 6 (Entity # 2056878484)

This group posted 123 ads in the 4 states of Louisiana, Florida, Alabama, and Texas. Most of these ads were posted in Texas and 14 of them were posted in Louisiana. Most of their ads were posted in Houston (43), Birmingham (17), and Dallas (12). In Louisiana, they posted ads in Baton Rouge (2 ads), Lake Charles (8 ads), Monroe (2 ads), and Shreveport (2 ads). This group used 18 different phone numbers. These phone numbers had 12 different area codes from 9 states: Alabama, Texas, Idaho, Louisiana, Florida, California, Arizona, Georgia, and Tennessee. Figure 4.25 shows the cities that the phone numbers were used in.

Figure 4.26 displays the connection pattern between the phone numbers used by this entity. Two phone numbers, 5045100218 and 3464201898, play a central role in this network.
The closeness centrality measure is the same for both phone numbers and is equal to 0.0227. The betweenness centrality measures for these phone numbers are 70 and 56, respectively. One of these two phone numbers had the New Orleans area code and the other one had the Houston area code.

Before closing this part, I would like to bring up one special entity that was found in the data set. This entity (entity # 5122986477) posted ads in 43 cities spread between the states of Alabama, Florida, Louisiana, Mississippi, and Texas. The entity posted 947 ads, 189 of which were posted in 8 cities in Louisiana, which were New Orleans, Baton Rouge, Houma, Lafayette, Lake Charles, Monroe, Alexandria, and Shreveport.

The ads posted by this entity invited people to visit their websites (www.fling.com and https://promos.filing.com). They rarely posted individual ads. They used two phone numbers, but one of the phone numbers was used only in a few ads. This entity is an organized sex trafficking network that connects the sex seeker to the sex providers. On one of their websites they introduce themselves as: “What is Fling.com? Fling is an online space for people who would like to have fun! Use our Fling promo code to get access to the horniest people in your area. Meet other members in your area looking for some great times. Profiles can be made discreet, safe, and fun!” (https://promos.filing.com).

4.5. The Answers to Questions 1 through 3

By now, the first three questions have been answered. We found entities that posted numerous amounts of ads in many different cities and also used many different phone numbers, large portion of which had area codes from cities outside the region under consideration. Some of the phone numbers used in the ads posted in the region being studied have area codes from cities outside the region under consideration including New York, California, Montana, Arizona,
and even Guam. Putting all of this information together led us to believe that some of these identified entities could be organized crime groups that are involved in human trafficking.

Figure 4.25. The phone numbers that have been used by this entity with the cities that they have been used

We also identified the time period that each phone number was used in and the cities and states that each entity posted ads for. Posting ads in different cities and states shows how these entities move around between different cities and states. Similarly, the diversity of the phone area codes, especially since many of them belong to cities and states out of the region under
investigation, illustrates a large probability that these people move all around the country, whether it be from the north (Montana) to the south (Louisiana) or from the east (New York and Florida) to the west (California and Texas).

Figure 4.26. Observed network for entity # 2056878484

Last but not the least, we calculated the centrality measures for a few entities as an example. We showed that some of the phone numbers are more central than others and we took some of these centralized phone numbers and used them as roots to illustrate how they were connected with other phone numbers.

4.6. The Answers to Question 4

In this section we try to answer Question 4, which was:

Is the difference between the life expectancy of phone numbers used by individual providers and organized providers statistically significant?
Using the available information, the life of each phone number is defined as the time period between the first and the last time that a phone number appeared in the posted ads. Given the characteristics of the available information, answering this question is a little tricky. For example, almost half of the identified entities (43.6%) posted only one ad during the time period that the data was collected. In other words, of the 27,376 total phone numbers, 10,387 phone numbers were used only one time and in one ad only, and we were not able to connect these phone numbers to other phone numbers. Since we did not collect data for a long enough time period and were not able to connect these phone numbers to other numbers, we do not have enough information to find out whether they (the phone numbers that were used only one time) belong to a specific individual or an organized criminal group.

To overcome these issues, we had to use a subset of the data to warrant a rational comparison between individual entities and potential organized group entities. So, we used a subset of the entities that posted ads for at least 150 days (5 months or more). Using this subset enabled us to separate an individual entity from a potential organized group with a higher probability.

We found a total of 570 entities along with 1,955 phone numbers that posted ads for 150 days or more. From these entities, 61 were potential organized criminal groups that altogether had 991 phone numbers and posted 11,646 ads. The other 509 entities were individual entities that altogether had 964 phone numbers and posted 13,929 ads. So, based on this subset of data, on average, we have around 2 phone numbers per individual entity and 16 phone numbers per potential organized entity. These two groups together make up 20 percent of all collected ads. As we can see, the quantities of phone numbers are very close for both groups (991 verses 964).
To find the average lifetime of phone numbers for these two groups (individual and potential organized entities), the lifetime of each phone number was calculated as the difference between the first day and the last day that the phone number was used in the ads. The average phone number lifetime for individual entities was 100.63 days, which is almost two times the average phone number lifetime for potential organized entities (51.68 days). Now we can test the following hypothesis:

H₀: Individual and potential organized entities have the same phone number lifetimes
H₁: Individual entities have a higher phone number lifetime than potential organized entities

This is a one-tail test and usually a t-test is used to test such hypothesis. The formula that is used for this t-test is (Levine et al., 2017):

$$T = \frac{\bar{Y}_1 - \bar{Y}_2}{\sqrt{s_1^2/N_1 + s_2^2/N_2}}$$

In this formula, N₁ and N₂ illustrate the sample sizes, Sample means are shown by \(\bar{Y}_1\) and \(\bar{Y}_2\), and \(S_1^2\) and \(S_2^2\) are the sample variances.

We reject the null hypothesis that the two means are equal if: \(|T| > t_{1-\alpha, \nu}\)

where \(t_{1-\alpha, \nu}\) is the critical value of the t distribution with \(\nu\) degrees of freedom and \(\alpha\) is the level of significance. The parameter \(\nu\) is calculated as (Levine et al., 2017):

$$\nu = \frac{(s_1^2/N_1 + s_2^2/N_2)^2}{(s_1^2/N_1)^2/(N_1-1) + (s_2^2/N_2)^2/(N_2-1)}$$

The information needed for doing this test is summarized in Table 4.21. Using these values, the calculated t-value is 16.21 and the degrees of freedom is 1,777, which is a very large
Table 4.20. Calculated statistics for organized and individual entities phone number lifetime

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>STDEV</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Potential Organized Entities</td>
<td>50.68</td>
<td>57.39</td>
<td>991</td>
</tr>
<tr>
<td>Individual Entities</td>
<td>100.63</td>
<td>77.16</td>
<td>964</td>
</tr>
</tbody>
</table>

number. Since the calculated degrees of freedom is too large, the critical values for t distribution and z distribution are the same. Therefore, we can use either t critical values or z critical values for this test. The critical t value for a one tail test with $\alpha = 0.0005$ and degrees of freedom of 1000 is equal to 3.30. Therefore, we have:

\[
\text{Calculated t-value} = 16.21 > 3.30 = t_{0.0005, 1000} \Rightarrow \text{we reject the null hypothesis}
\]

The result of the t-test indicates that, at a significance level of 0.0005, the phone number lifetime is higher for the phone number used by individual entities in comparison to the phone numbers that were used by the potential organized entities, which fulfills our expectation.

4.7. The Answers to Question 5

Is the difference between the average ages of individual adult service providers and organized adult service providers statistically significant?

With the same reasoning that we used for answering question 4, we used the same subset of data from question 4 to find the answer for this question. We have to notice that in many ads, the age that was used in the posting body may not be the real age of the provider. So, the reason for having this question is to obtain some idea regarding the age of individual and potential group providers even though they may not be very precise numbers. However, if we assume that both groups of entities do not report real ages on their ads, then it will only have a small impact on the difference between the average ages. As an artificial example, if both groups decrease the real age of providers by 5 years, the difference between the real and unreal average age of both groups would be the same.
For some of the phone numbers, more than one age was used in the posted ads. This could have several reasons:

1. It could be because of different people with different ages used the same phone number.
2. The person that posted the ads (pimp) was different from the actual provider (victim) and this person did not know the exact age of the provider. Therefore, they used different ages on different ads.
3. The provider did not use her real age and, therefore, used different ages in different ads.

As a result, the sample size that is used for this question is larger than the one that was used for Question 4. Table 4.22 contains the mean, standard deviation, and sample size for the potential organized entities and individual entities. Based on this information, the average age of the providers who are a part of individual entities is 3.5 years higher than those who are a part of potential organized entities.

Table 4.21. Calculated statistics for organized and individual entities age

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>STDEV</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Potential organized entities</td>
<td>23.90</td>
<td>3.89</td>
<td>1774</td>
</tr>
<tr>
<td>Individual entities</td>
<td>27.46</td>
<td>6.15</td>
<td>1662</td>
</tr>
</tbody>
</table>

Null and alternative for one tail hypothesis for this question are:

\( H_0: \) Providers from individual and potential organized entities have the same average age.

\( H_1: \) Individual entity providers have a higher average age than potential organized entity providers.

The calculated t-value and degrees of freedom for testing this hypothesis is 20.13 and 2774, respectively. So, we have:

\[
\text{Calculated } t\text{-value} = 20.13 > 3.30 = t_{0.0005, 1000} \Rightarrow \text{we reject the null hypothesis}
\]
Based on the result of the hypothesis test, we reject the null hypothesis that the average of age for these two groups are the same, which meets our expectation.

4.8. The Answers to Questions 6 and 7

We used network analysis to find the potential organized groups that posted online ads for providing adult services. To do this, we needed a link to connect the phone numbers to be able to identify the potential traffickers through their phone numbers. Ad IDs were used as the primary link to connect different ads and phone numbers to identify their unique source. However, ad IDs and phone numbers both frequently change over time. We are able to connect two different ads from the same entity only as long as they have either the same ad ID or the same phone number. But the question is that if an entity posts a new ad with a new ad ID and phone number then how can we connect this ad to the previous ads that have been posted by this entity? As we said before, there is one more piece of information in the collected ads that could be used to connect the different ads. This piece of information is the text content of the ads. Using text mining can help us group or classify different ads based on their text similarity, and therefore connect the ads that were posted by the same entity but did not share the same ad ID and/or phone number. In fact, we tried to put different ads with different ad IDs and phone numbers in the same group based on their textual similarity.

4.9. Authorship Identification

To apply an authorship identification model on our data set, we needed to preprocess the data. The goal of authorship identification in this study was to use the similarity of the textual contents of the ads to find out if they were posted by the same entity. Therefore, we aimed to classify the different ads based on the similarities in their textual contents. As we discussed in Chapter 3, there are two types of text classifying methods, which are unsupervised and supervised methods. Using unsupervised methods is very easy and efficient, but the problem is
that we cannot test the accuracy of the results. Therefore, we had to use supervised methods. However, using supervised methods requires that the data be manually labeled before applying the classification method. So, it almost took us 4 months to go through more than 123 thousand ads and label them manually by comparing their textual contents. In fact, we did the authorship classification of ads manually and we did not need to take a further step to use automated approaches for the identification of the advertisers. However, spending our time labeling the data set gave us the opportunity to use the data set for testing the possibility of using automated authorship identification techniques to classify human trafficking ads for the first time. This part can add to the literature of the authorship attribution of short texts which is a relatively new field of study.

The most important issue in any authorship attribution study is the accuracy of the results. Two factors that significantly impact the accuracy of the results of authorship attribution studies, especially when studying short texts, are the size of the texts and the classifying technique. Since this was the first time that adult service provider ads were used for authorship classification tasks, we needed to find out two things.

First, there were different techniques for authorship classification and we needed to know which one would work best for our specific data set. The second issue was related to the short nature of our textual data that causes this task to be categorized as the authorship attribution of short texts. Since each ad had a small number of words, the number of ads posted by each entity could be important in regard to the accuracy of the identification of the entity. Different entities had different numbers of ads. The number of ads posted by an entity could be between one ad and several hundreds of ads. So, the question was, what is the minimum number of ads that
needs to be posted by each entity to enable us to classify the ads with an acceptable rate of accuracy?

In this section we try to answer these two questions:

- 6. What is the minimum number of ads per entity (threshold) needed to classify the ads into organizations?
- 7. Are classification methods equally accurate for identifying the organization associated with an ad for escort services?

We used supervised classification methods to answer these questions. As we discussed in detail in the previous chapter, using supervised authorship classification techniques requires preparing the data set in several steps. The first step was to manually label the data so that we could group the phone numbers. The second step was preprocessing the data, which included tokenization, lemmatization, stemming, filtering, and noise removing. We used the Scikit-learn package in Python to do the preprocessing tasks that also included removing tags, HTML decoding, changing all words to the lowercase, and removing bad symbols and stop words. Also, we deployed an information retrieval algorithm that is used for weighting terms and is called Term Frequency-Inverse Document Frequency (TF-IDF). With this algorithm, each term in the text is replaced with a weighted measure that shows the importance of the term and can be used as the input for the next step, which is the machine learning.

There are several supervised machine learning methods that can be used for text classification tasks. In this study, we used four methods that have frequently been used by other researchers and produced good results, especially in short text classification analyses. These methods are multinomial Support Vector Machines (SVM), Naïve Bayes, Logistic Regression, and Neural Networks.
To test the impact of the number of advertisements per author (entity) on the accuracy of the results of classification, we divide the ads into 10 different groups, as shown in Table 4.23. We put each entity in one of these groups based on their number of ads. For example, an entity that posted 15 ads was assigned to the last category of Table 4.23. We applied these four different classification methods to each of the 10 categories of entities and calculated the accuracy rates. Since we have 4 different classifiers and 10 categories of ads, we have 40 combinations of methods and categories and therefore 40 accuracy rates (Table 4.23). We use Table 4.23 to answer Questions 6 and 7.

Table 4.22. Accuracy rates of the classification of ads for different classifiers and number of ds

<table>
<thead>
<tr>
<th>Category</th>
<th>Number of Classes</th>
<th>Number of Ads</th>
<th>Multinomial Naïve Bayes</th>
<th>Logistic Regression</th>
<th>SVM</th>
<th>Neural Networks</th>
</tr>
</thead>
<tbody>
<tr>
<td>More than 100</td>
<td>52</td>
<td>13,520</td>
<td>66.59</td>
<td>95.59</td>
<td>93.66</td>
<td>92.14</td>
</tr>
<tr>
<td>More than 90 to 100</td>
<td>11</td>
<td>1,052</td>
<td>95.51</td>
<td>96.25</td>
<td>97.38</td>
<td>93.63</td>
</tr>
<tr>
<td>More than 80 to 90</td>
<td>17</td>
<td>1,443</td>
<td>94.33</td>
<td>98.02</td>
<td>96.88</td>
<td>88.10</td>
</tr>
<tr>
<td>More than 70 to 80</td>
<td>21</td>
<td>1,576</td>
<td>97.92</td>
<td>98.52</td>
<td>98.52</td>
<td>98.22</td>
</tr>
<tr>
<td>More than 60 to 70</td>
<td>42</td>
<td>2,732</td>
<td>94.18</td>
<td>97.53</td>
<td>97.23</td>
<td>94.18</td>
</tr>
<tr>
<td>More than 50 to 60</td>
<td>55</td>
<td>3,048</td>
<td>93.22</td>
<td>98.04</td>
<td>97.91</td>
<td>97.13</td>
</tr>
<tr>
<td>More than 40 to 50</td>
<td>95</td>
<td>4,261</td>
<td>87.71</td>
<td>96.72</td>
<td>95.22</td>
<td>95.97</td>
</tr>
<tr>
<td>More than 30 to 40</td>
<td>226</td>
<td>7,916</td>
<td>92.12</td>
<td>97.30</td>
<td>95.99</td>
<td>96.33</td>
</tr>
<tr>
<td>More than 20 to 30</td>
<td>500</td>
<td>12,265</td>
<td>84.63</td>
<td>95.12</td>
<td>93.60</td>
<td>93.70</td>
</tr>
<tr>
<td>More than 10 to 20</td>
<td>1537</td>
<td>22,518</td>
<td>76.05</td>
<td>94.21</td>
<td>90.91</td>
<td>91.97</td>
</tr>
</tbody>
</table>

To answer Question 6, we compare the accuracy rates in Table 4.23 across the rows. Even though there are some fluctuations when we move from one row to another, there is no steady decrease or increase in the accuracy rate values when we move down each of the table’s rows, from the first row of the table (more than 100 ads per entity) to the last row (more than 10 to 20 ads per entity). This means that these classification algorithms have the same accuracy rate for any number of ads per entity as long as each entity posts more than 10 ads. So, there is no
threshold for an increase or decrease in accuracy rates in response to a change in the number of ads posted by each entity.

To answer Question 7, we compared the accuracy rates across the last four columns of Table 4.23. For each category of ads (each row), we compared the computed accuracy rates that were achieved by using the four different methods of classification. From the 40 calculated accuracy rates, 36 rates are over 90 percent. This means that all of these methods worked very well on our data set. However, logistic regression achieved better results than the other methods. It produced higher accuracy rates in 8 out of the 10 categories, was tied with SVM in one category, and was less than SVM in only one category (more than 90 to 100 ads). So, we can say that, for our data, logistic regression achieves better performance rates than the other three methods, though the difference is not very large. If we want to rank these four methods based on their performances, logistic regression ranks first, and then SVM, neural networks, and Naïve Bayes rank second, third, and fourth, respectively.

So, in summary, even though there is not a large difference between the accuracy rates achieved by these four different classification methods, it is still worthwhile to mention that the use of logistic regression produced the highest accuracy rates and multinomial Naïve Bayes produced the lowest.

4.10. Conclusion

We started this chapter exploring the raw data and then turned our focus to the results of the network analysis to find potential organized entities. After cleaning the 307,463 collected observations, we ended up with 123,436 observations. We had 123,436 ads posted in 47 cities over the six states of Alabama, Arkansas, Florida, Louisiana, Mississippi, and Texas. The ads altogether used 27,376 phone numbers with more than 390 area codes from different cities all
over the United States. Some phone numbers were used only once while others were used for up to 8 months. On average, each phone number was used for 25.3 days.

By applying the network method, using the phone numbers as the actors and the common ad IDs and the similarity of the textual contents of the ads as the links, we were able to uncover 23,805 entities. Among them, 1,310 entities were active in at least Louisiana. These are the entities that we focused on in regard to identifying potential trafficking groups.

The results of the network analysis identified many entities that can be classified as organized human trafficking groups. These entities posted many ads in different cities and used many different phone numbers with area codes from cities all over the United States including those that are in the states of Montana, Texas, New York, and California.

To group the ads that were probably posted by the same entity together, we applied the authorship identification technique to the adult service provider ads. The results indicate that as long as we have more than 10 ads per provider, we can classify the ads with very high accuracy rates by using machine learning methods. We used four different classification methods, which were multinomial Naïve Bayes, Logistic Regression, SVM, and Neural Networks to classify the ads based on their textual similarity. We found that Logistic Regression resulted in the highest accuracy rates.
CHAPTER V
SUMMARY AND CONCLUSION

A global investigation in 2007 illustrated that “technology is the engine behind the growth of the sex trade…. [It] has become the single greatest facilitator of the commercial sex trade in all of the countries observed” (Janson et al., 2013).

During the past decades, online advertisements for sex trafficking have rapidly increased in numbers. Results of trafficking survivor surveys show that share of survivors that were advertised online increased from 38 percent before 2004 to 75 percent after this year (Bouche, 2018). Another report shows that 70 percent of child sex trafficking survivors have been traded online sometime during their exploitation (Couch, 2014). Around 73 percent of cases of suspected sex trafficking in the United States were related to Backpage (Peled, 2018).

The advancement of the Internet and the development of smart phones have created a unique situation for sex traffickers that allows them to be connected to each other at anytime and anywhere, no matter where they are or how great the distance between them is. This new technology has made it easier for sex traffickers to contact and recruit their victims and advertise and sell them online. During the past two decades, the online advertisement of sex trafficking has increased while other forms of advertising have decreased. This increase in online advertisements has increased the demand for sexual services by providing more accessible information to buyers in addition to turning some potential customers into practical buyers. The Internet has made it possible for traffickers to control their victims remotely via things like cameras, which, in turn, enable them to manage and control a higher number of victims at the same time and also find more customers for their victims through online advertising.

Another problem that is caused by online sex trafficking is that the victims cannot be traced easily and identifying the traffickers is more difficult for law enforcement, since they use
online services and sometimes digital currency, such as bitcoin, in their monetary transactions. The Internet has assisted traffickers in their criminal activities by helping them easily find, contact, and recruit victims by offering fake and fraudulent promises and/or friendships through social networks like Facebook, Instagram, Twitter and chatrooms. Facilities such as the aforementioned social media platforms have enabled traffickers to have access to more potential victims and decrease the time and effort required for recruiting them.

Sex traffickers took advantage of the Internet to increase their illegal businesses and turn trafficking into one of the fastest growing criminal markets around the world, with an annual turnover of $99 billion (Canessa, 2018). Sadly, more than fifty percent of the victims of sex trafficking are children, many of which were exploited through the Internet (Canessa, 2018).

In addition to social networks and chatrooms, online classified websites are used as cheap, fast, and easy ways to advertise, buy, and sell victims frequently with little risk of being identified by law enforcement. Online devices give traffickers the ability to advertise their victims on many different platforms and in many different locations at the same time. This leads to an expansion of their market and an increase in customers. Online devices also help traffickers market their victims to customers (describe and present), test the new markets, locate the potential buyers, and move the victims to a buyer’s location without being identified by police. However, this new technology is not only helpful for traffickers; it’s more of a double-edged sword. It can help researchers and law enforcement agencies employ new techniques to identify sex traffickers the same way that it can help the sex traffickers develop their businesses. Online advertisements can be deployed to provide practical information at appropriate times to law enforcement agencies and other authorized organizations to take down traffickers and help the victims (Latonero, 2011). The first step for preventing and fighting human trafficking is to
identify potential traffickers. Gathering online information for implementing numerical and textual data mining analysis can give us a clear view of human trafficking and make the pool of potential sex trafficking cases more accurate.

This study has two ultimate goals. The primary goal of this study is to identify the potential organized sex traffickers in Louisiana. The secondary goal is to apply authorship attribution techniques to use the similarity of different ads as the link between actors (phone numbers), in addition to using ad IDs as the primary link. Even though these two goals are two different unrelated issues, they are interrelated for this study. We use network analysis to identify the potential organized adult service providers, and, to set up the network, we need a link to relate the different actors (phone numbers) in the network. In this regard, the similarity of the textual contents of the posted ads, which can be calculated by using authorship attribution techniques, are used as the secondary link in this study.

Due to the dynamic and transitory characteristics of human trafficking, we need to include Louisiana’s neighboring states of Arkansas, Mississippi, Alabama, Texas, and Florida into the study to better understand the problem and extract useful information. However, since Texas and Florida are very large states, we only included the cities that are close to Louisiana, which includes 16 cities in Texas and 4 cities in Florida. So, our data contains the full data sets for four states and part of the data sets for two other states.

The data was collected and parsed from Backpage for a time period of ten months, from May 2017 to February 2018. The collected data has eight variables: ad ID number, phone number, name of the city that the ad has been posted, name of the state that the ad has been posted, posting date, age of service provider, the ad’s title, and the ad’s posting body. An ad’s posting body is the field where the advertiser gives a description of the service that will be
provided and puts some requirements regarding the customer, and sometimes, the price that is being charged. The collected data contained 307,463 observations that needed to be cleaned. Cleaning the data set involved removing the ads that were from the parts of Texas and Florida that were not included in the study and the duplicate ads. After cleaning the data set, we were left with 123,436 ads (observations). For Louisiana alone, we had data on 21,076 ads (17.1 percent of all ads).

The collected information came from 47 cities in the specified area, which ended up being 8 cities in Louisiana, 9 cities in Alabama, 6 cities in Mississippi, 4 cities in Arkansas, 16 cities in Texas and 4 cities in Florida. New Orleans (with 7,038 ads), Baton Rouge (with 4,628 ads) and Lafayette (with 3,108 ads) rank fifth, seventh, and eleventh among these 47 cities, respectively.

Around 59,847 advertisement IDs were used for posting these 123,436 ads and the ads contained 27,376 phone numbers. Usually each ad ID was used in just one city and only 1.5 percent of ad IDs appeared in more than one city. Exploring the distribution of the phone numbers across the cities illustrates that more than 82 percent of the phone numbers were used in only one city and 5.2 percent of them were used in ads that were posted in more than two cities. One hundred and eighteen phone numbers appeared in ads that were posted in 6 to 43 cities. Around 10 percent of the phone numbers (2,710 phone numbers) had a Louisiana area code.

The examination of phone numbers shows that 9.9 percent (2,710) of the phone numbers that were used in posted ads had a Louisiana area code. Among the Louisiana area codes, New Orleans had the largest share (35%). In one third of the ads, the area code did not match the city, meaning that the ad used a non-local phone number.
The phone numbers had more than 390 different area codes from different cities all over the U.S. This means that there is a possibility that some of these entities who posted ads in Louisiana and its neighboring states were traveling to other states as well.

The longest and the shortest time periods that a phone number in the collected ads was used were 233 days and 1 day, respectively. However, these numbers are not deterministic, because there is a possibility that some of these phone numbers were used before and/or after the time period that the ads were collected for this study, and therefore could have a longer lifetime.

A phone number’s lifetime is one of the most important factors that help law enforcement agencies track and find advertisers. Using a phone number for a longer time period increases an advertiser’s risk of being identified by law enforcement. So, the advertisers try to change their contact numbers frequently to decrease the risk of being identified.

More than 47 percent of the phone numbers were used just for one day. More than 74 percent of the phone numbers were used for less than one month. Only 1 percent of the phone numbers (273 phone numbers) were used for more than 6 months.

Organized sex traffickers usually use different phone numbers to make it difficult for law enforcement agencies to identify them. More than 60 percent of the phone numbers were used only 1 or 2 times in posted ads. About 10 percent of the phone numbers were used in more than 10 advertisements.

More than 37 percent of the ads were posted on Thursday, and the lowest number of ads (less than 6 percent) were posted on Saturday.

This study sought to answer the following questions:

1. Is there evidence of sex trafficking organizations and networks?

2. Is there evidence that sex trafficking organizations operate in multiple cities and states?
3. Is there evidence showing key members of sex trafficking networks?

4. Is the difference between the life expectancy of phone numbers used by individual
   providers and organized providers statistically significant?

5. Is the difference between the average ages of individual adult service providers and
   organized adult service providers statistically significant?

6. What is the minimum number of ads per entity (threshold) needed to classify the ads into
   organizations?

7. Are classification methods equally accurate for identifying the organization associated
   with an ad for escort services?

By using the network analysis model with phone numbers as actors or nodes and ad IDs
and text similarity as links, we extracted 23,805 entities from 123,436 ads. We found 1,623
entities (7%) with more than one phone number. We found two entities with a very high number
of phone numbers, one of them with 212 and the second one with 144 phone numbers. Around
93 percent (22,181) of entities only used one phone number and 1,621 entities used between 2
and 49 phone numbers.

Based on the number of posted ads, 20,956 (88%) entities posted less than ten ads, which
is one ad per month on average (Table 3.18). One entity posted more than 2,000 ads and 51
entities had between 100 and 2,000 ads. On average, each entity posted 5.2 ads.

Since our goal is to identify potential networks, we use the entities that posted ads in
more than one city. More than four thousand entities (around one fifth of the entities) posted ads
in more than one city. Also, since we would like to focus on Louisiana, from these 4000 entities,
we removed those that did not post any advertisements in Louisiana. After applying these
changes, we had a data set with 1,310 entities that were active in more than one city and also,
posted at least one ad in Louisiana. This was the data set that we used to build up our network. This collection of entities posted 24,449 ads (out of 123,436 ads) in 47 cities. About 304 of these entities were active only in Louisiana (8 cities) and the rest of them (1,006 entities) were active in other states as well.

To track the different entities, it was important to know which cities they were active in. In this regard, we created a table to show the common entities between different cities in the region. Based on this information, New Orleans and Baton Rouge, with 197 common adult service providers, had the highest number of common entities. This means that 197 adult service providers (individual or group entities) provided service in both the cities of New Orleans and Baton Rouge. The pairs of Lake Charles – Houston (125), Lake Charles – Lafayette (122), New Orleans – Houston (117), Lake Charles – Beaumont (107), Baton Rouge – Lafayette (106), Huston – Baton Rouge (97), New Orleans – Lafayette (95), and Baton Rouge – Lake Charles (88) were the next highest ranks. These numbers illustrate how traffickers move their victims between many different cities.

To better understand the movement pattern of adult service providers in the region, we created a network with cities as the nodes and “common adult service providers” as the link (please see Figure 4.11 for more detail). The centrality measurement for the network shows that New Orleans and Shreveport had the highest betweenness centrality with 3.51 and 2.42, respectively. The betweenness centrality measure demonstrates how each city has been used as a bridge for connecting other cities in the network. New Orleans and Lake Charles had a high betweenness centrality shows that, in comparison to other cities, many adult service providers in these two cities were active in other cities as well, meaning that these two cities were like bridges in the network.
Among Louisiana’s cities, New Orleans, Baton Rouge, Lake Charles, and Lafayette had the largest number of common entities. In the other words, many entities move between these cities and post ads in them.

The primary objective of this study is to identify the potential human trafficking networks in Louisiana. We have found many entities that can be addressed as such potential networks. However, since it is not possible to go through all of the identified potential networks or groups, I discussed six of these entities in more detail in Chapter 4 as examples. These six entities had many ads and phone numbers and posted ads in several cities. These entities that were chosen as potential organized sex trafficking groups posted between 123 to 2,386 ads, provided services in 6 to 39 cities, and used between 18 to 210 phone numbers (please see Table 4.22 For more details). These 6 entities together posted one fifth of all of the ads that were posted by the 1,310 total entities that were active in more than one city and posted at least one ad in Louisiana.

Examining these six potential groups shows that they were active in 4 to 6 states and in many cities. One interesting point was the area codes for the phone numbers that were used by these entities. For example, the phone numbers of one entity had area codes from 60 different cities spread out between 25 different states all over the country. Another entity had area codes from 36 cities spread between 19 different states. Even though these ads were posted in the six states under consideration, the area code numbers often included New York, California, and Montana. However, having phone numbers with area codes from other states does not necessarily mean that these adult service providers worked in those states. Since these phone numbers could just be Google phone numbers or numbers used over the Internet, more investigation is needed to find out if these providers have been active in those places.
By analyzing the results of the network analysis, the first three questions were answered. We found entities that were potentially organized human trafficking groups that posted many ads in many different cities and used many different phone numbers. Also, we identified the time period that each phone number was used in, and the cities and states that each entity posted ads for, which shows how these entities moved around between different cities and states. Similarly, the variety of phone number area codes, specifically how many of them belonged to cities and states out of the region under investigation, shows the possibility that these entities move all around the country from the north (Montana) to the south (Louisiana) and from the east (New York and Florida) to the west (California and Texas).

Answering the fourth research question involved looking for any statistically significant difference between the life of phone numbers of individual providers and organized providers. Using the available information, the life of each phone number is defined as the time period between the first and the last time that a phone number appeared in the posted ads. Given the data and the available information, answering this question was a little tricky. For example, almost half of the identified entities (43.6%) posted only one ad during the period under investigation. In other words, of the 27,376 total phone numbers, 10,387 phone numbers were used only one time without being identified as related to other phone numbers. However, there is a possibility that these phone numbers have been used for a longer time in other states outside the region under investigation. Also, there is a possibility that these phone numbers were used before or after the time period that we collected the data, and, therefore had a longer lifetime. Since we do not have information regarding whether these phone numbers were active in states other than the ones we studied and did not collect data for a very long time period, we cannot determine if they belong to a single individual or a potential organized group.
To overcome these issues, I had to use a subset of the data that warrants a rational comparison between individual entities and potential organized group entities. I used a subset of the entities that posted ads for at least 150 days (5 months or more). Using this subset enabled us to separate an individual entity from a potential organized group with a higher probability.

We found 570 entities that used 1955 phone numbers and posted ads for 150 days or more. From them, 61 entities were potential organized entities that used 991 phone numbers and posted 11,646 ads. The other 509 entities were individual entities that used 964 phone numbers and posted 13,929 ads. These two groups together made up 20 percent of all collected ads. As we can see, the number of phone numbers that each group used are very close (991 versus 964). To find the average lifetime of the phone numbers for these two groups (individual and potential organized entities), the lifetimes of all of the phone numbers used by them were calculated. The average phone number lifetime for individual entities was 100.63 days, which is almost two times the average phone number lifetime for potential organized entities (51.68 days). Having a one-tail test resulted in a rejection of the null hypothesis that individual entities and potential organized entities had the same phone number lifetimes at a significance level of 0.0005 (or 0.05 percent).

To answer question 5, we used the same subset of data that we used to answer question 4. Question 5 is about whether the difference between the average ages of individual providers and organized providers is statistically significant.

For some of the phone numbers, more than one age was used in the posted ads. This could have several reasons. Two reasons could be different people were using the same phone number or the age could be intentionally lowered to increase appeal. Another reason could be that the person that posted the ads was different from the actual provider, and this person did not
know the exact age of the provider and, therefore, used different ages on different ads. As a result, the sample size that was used for this question is larger than the one that was used for question 4.

The average age for individual and “potential organized group” service providers were 23.9 and 27.4 years, respectively. Using a one-tailed test results in a rejection the null hypothesis of the average age of these two types of providers are equal at a significance level of 0.0005 (or 0.05 percent). So, we conclude that potential organized groups keep their phone numbers for shorter time periods to lower the risk of being identified by law enforcement. Furthermore, potential organized groups, on average have younger providers since they have the ability to replace the older providers with younger ones while this task is impossible for individual workers.

The primary goal of this research was to find potential organized groups that post online ads for selling adult services. First the ad IDs and phone numbers were used to connect different ads and to identify the unique entity that posted the ads, which could be an individual or an organized group. However, the ad IDs and phone numbers change over time. We were able to connect two different ads from the same entity as long as they had either the same ad ID or the same phone number, but if an entity posts a new ad with a new ad ID and a new phone number, how can we connect this ad to the previous ads that have been posted by this entity? As we mentioned before, there is one more variable in the collected ads that can be used for connecting different ads that were posted by the same entity. This variable is the text content of the ads. The use of text mining can help us group or classify different ads based on their text similarity, and therefore connect the ads that were posted by the same entity but have different ad IDs and
phone numbers. In fact, we tried to put different ads in the same group based on their authorship attributions.

To use the authorship attribution technique to connect and group ads that have been posted by the same entity brings up more important questions, such as

1. Can authorship attribution techniques be used to classify such short messages?
2. If yes, then what techniques can achieve a higher performance for our data set?

Answering these two questions requires a new chapter to be added to this research, for it makes the exploration of literature regarding statistical techniques specific to authorship attribution studies, which is a very broad and vast topic, necessary.

Authorship attribution works go back as far as 1,887 to the works of Mendenhall. It has its roots in stylometry, which is a field of science that is used to specify the statistical characteristics of the style of textual documents. Even though authorship attribution studies have been a topic of relevance for many years, authorship attribution works only involved few long documents with small numbers of author candidates. A recent and relatively new field of authorship attribution that is more realistic and practical (and is related to this work) deals with a large number of short documents that can have many potential authors. Having short texts in addition to many author candidates turns the authorship attribution process into a more complex issue that needs more sophisticated techniques, the likes of which are usually involved in machine learning methods.

Authorship Identification and Text Classification Framework has 5 stages: data collection, data preprocessing, data exploration and visualization, model building, and model evaluation (Mayo, 2017).
Data preprocessing, which is one of the most important steps in any text mining project, consists of several phases, being tokenization, stemming, lemmatization, filtering, and noise removal. This step is very important and has a significant influence on the performance of the final results. After implementing tokenization and lemmatization to our data set and filtering out the noise from the data set, we get a clean tokenized data set that is ready to be used in the classification model. However, there is still one problem that needs to be solved. The data set contains textual information that is not appropriate to be used in the model. So, we need to convert the texts to numbers so that they can be used by the model. A vector space model is an algebraic model for turning text documents into numbers and index terms.

The Vector Space Model assigns a number to each word of each text or document in the collected documents and this number specifies the importance or weight of the represented word in the document. There are several different ways to do this, but the Term Frequency-Inverse Document Frequency (TF-IDF) is one of the most powerful that can be used for conversions. The innovation of TF-IDF was a very important moment for machine learning, particularly NLP related works like text classification. In this approach, to find the significance of each term, a weighted measure of all terms used in the texts are calculated. The TF-IDF method highlights the importance of crucial terms that have frequently been used by a certain author and decreases the importance of terms such as function words (Rocha et al., 2017).

TF-IDF techniques have several advantages. The weighing is easy to calculate and can be used simply for calculating the similarity between two documents. Also, because of the normalization of the word frequencies by IDF, high frequent words do not impact the results of classification. Finally, it can be used to extract the most descriptive terms in a document (Kowsari et al., 2019).
After converting words into numbers, the TF-IDF scores can be used in machine learning techniques to accomplish the text analysis task. The innovation of machine learning classifiers and clustering techniques was a breakthrough point in authorship attribution research. The two main groups that machine learning algorithms can be divided into are supervised and unsupervised models. The supervised models (that have been used in this study) require a pre-labeled training data set that is converted to numerical vectors and is used in the learning step of the model to find borders among different authors by minimizing a classification loss function (El Bouanani and Kassou, 2014). The results of the learning step are then used to predict the author of the unidentified texts from the testing set.

There are several supervised machine learning methods that can be used for text classification tasks. In this study, we use four of these methods that have frequently been used by other researchers and achieved good results. These methods are Support Vector Machines (SVMs), the Naïve Bayesian classifier, Logistic Regression, and Neural Networks. We applied these techniques to our data set and compared the results to find out which approach gives the best results with our data.

A machine learning model for classification has four elements (Jurafsky and Martin, 2019):

1. A feature that characterizes the input
2. A classification function that calculates the predicted category (y hat) for each observation (x) through p(y|x).
3. “An objective function for learning” often including “minimizing error on training” data set
4. A method for optimizing the objective function.
Support Vector Machine (SVM) is an innovative supervised machine learning technique that was presented by Vapnik in 1995 and can be applied to text classification problems. It is established based on structural risk minimization which is borrowed from computational learning theory (Zheng et al., 2006).

SVM techniques are the most advantageous methods for authorship attribution tasks. The key factor that makes these techniques unique and different from other methods is that SVM models can handle situations where there are too many dimensions. SVMs are capable of processing thousands of different inputs. In authorship attribution studies, documents are typically long and there are too many features, most of which provide vital information that should be used in the model. This increases the number of features, and, in turn, increases the number of dimensions. SVM techniques can handle large data sizes and achieve high performance results more efficiently than other techniques like neural networks (Diederich et al., 2003). This illustrates why SVMs are very useful in authorship attribution studies. Authorship attribution studies that have used SVM techniques have achieved reliable, high-performance results (Diederich et al., 2003).

One significant advantage of SVM techniques is that all terms in the document can be chosen as the features, and, therefore, we do not need to go through the feature selection process. Also, it does not necessitate feature preprocessing and weighting. This make it possible to use all words in a text directly as features (Diederich et al., 2003). So, the ability to manage data sets with millions of observations along with creating results with high performance are two of the characteristics of this method that have made it very popular among researchers.

SVM techniques aim to preprocess the data so that the features are represented in a high dimensional space that usually are higher than the initial feature space, where the features’
categories become linearly distinguishable. By using a suitable non-linear mapping from the initial feature space to the prolonged feature space, a hyperplane can be specified that precisely splits data into two categories (Tsimboukakis and Tambouratzis, 2010). The use of SVMs in text mining studies very often results in high performance results, especially when it has been operated on TF–IDF features. SVM techniques try to bypass two problems that usually appear in other classification methods, which are the ability to handle the computational work when the data set has too many dimensions and resolve the problem of overfitting. For these reasons, SVMs have been used in a wide variety of problems including text classification and object recognition.

Having large dimensions is a characteristic of text mining data that can lead to an overfitting of the results. To prevent overfitting, the number of features need to be reduced. One of the benefits of using SVMs, especially when applied to text mining, is that they do not require the number of features to be reduced to avoid the problem of overfitting (Corney et al., 2002).

Logistic regression is another model that was used for text classification in this study. It is one of the most important statistical methods used in social and natural sciences. In natural language applications, logistic regression is the most basic supervised machine learning method for text categorization and has a very close association with neural networks. In fact, a neural network can be seen as a collection of logistic regression classifiers loaded on top of each other. Logistic regression can be used on two class separations as well as on multi-class categorizations (Jurafsky and Martin, 2019).

Logistic regression is similar to Naïve Bayes and employs supervised machine learning to classify based on probability. Like any other machine learning classifier, logistic regression needs a training corpus to train the model. However, logistic regression is better than Naïve
Bayes for several reasons. Naïve Bayes requires features that have a strong independency while this is not the case for logistic regression. Assume that two features f1 and f2 are perfectly correlated. If we apply the Naïve Bayes method to these two features, it will produce overfitted results. On the other hand, logistic regression is very robust to correlated features. So, if we apply logistic regression to these features, since they are perfectly correlated, logistic regression would use a weighing procedure, like making a new feature where a part of which would be a weight of f1 and the other part a weight of f2. Using f1 and f2 with this method, logistic regression can prevent the result from being overestimated. Therefore, in situations like text analysis that we may have many associated features, logistic regression can do more accurate probability allocation than Naïve Bayes. So, overall, logistic regression results in a higher performance on larger documents or data sets and is a common default for these types of tasks (Jurafsky and Martin, 2019).

The difference between logistic regression and Naïve Bayes comes from different approaches that these two techniques use for categorizing the observations. While logistic regression uses a discriminative method to separate the observations, Naïve Bayes uses a generative separator (Jurafsky and Martin, 2019). While a discriminative model (like logistic regression) uses $P(c|d)$ directly to classify the observations, a generative model (like Naïve Bayes) classifies observations indirectly by computing $P(d|c) \times P(c)$, where $P(d|c)$ is the likelihood and $P(c)$ is a prior (Jurafsky and Martin, 2019).

The Naïve Bayes classifier technique is a probabilistic model that was established based on Bayes Theorem (El Bouanani and Kassou, 2014). Naïve Bayes classifiers make comparable categorizations based on Bayes’ theorem to find the possibility of a categorization pattern to detect the potential class for the observed data. Since these methods assume that the words/terms
used in a text are independent of each other, which often is not accurate, they are called “Naïve” Bayes. However, they can achieve accurate results, in addition to being fast in the processing and training phases (Juola, 2006).

Neural network is another model that was used for text classification in this study. Neural networks were created based on the human brain and they are involved in a large number of cooperative simple arithmetic workstations. In experimental studies, they are typically designed with three or more “layers”. To minimize the error between the favorite and actual results at the output layer, the program is trained through a process called “a backpropagation of error” (Juola, 2006).

The last step in authorship attribution studies is evaluating the model by calculating the accuracy of the model’s output. Accuracy rates vary between zero and 100 percent; the higher the rate is, the more accurate the results would be. We used the calculated accuracy rates to answer the last two research questions as:

- Question 6. What is the minimum number of ads per entity (threshold) needed to classify the ads into organizations?

- Question 7. Are classification methods equally accurate for identifying the organization associated with an ad for escort services?

To answer these two questions, we used four different supervised algorithms for classifying the ads. These methods are multinomial Neural Networks, Logistic Regression, Naïve Bayes, and Support Vector Machines (SVM). Also, to find the minim number of ads (threshold) that we need in order to be able to classify authors accurately, we divided the ads into 10 different groups by how many ads there are per author, such as more than 100 ads per author, more than 90 to 100 ads per author, more than 80 to 90 ads per author, and so on and so forth to
more than 10 to 20 ads per author (Table 4.33). We applied these four different classification algorithms on all 10 groups of ads and calculated the accuracy rate for each algorithm-group pair. So, in total, we calculated 40 accuracy rates.

To answer question 6, we compared the accuracy rates for each classification technique across different groups of ads. Even though there are some increases and decreases between these rows, there is no steady decrease or increase in the accuracy rate values when we move from the first group of ads (more than 100 ads per entity) to the last group of ads (more than 10 to 20 ads per entity). This means that these classification algorithms have the same accuracy rate for any number of ads per entity as long as each entity (or author) posts more than 10 ads. Therefore, there is no threshold for an increase or decrease in accuracy rates in response to a change in the number of ads posted by each entity.

To answer question 7, we compared the accuracy rates in each group of ads across four different classification techniques. For all 10 ad groups, the accuracy rates calculated for multinomial Naïve Bayes were less than the rates calculated for logistic regression, neural network and SVM. However, the differences were fairly miniscule. So, among these four classification algorithms, the Multinomial Naïve Bayes method had the lowest accuracy rates.

Comparing the accuracy rates of the classification by logistic regression and SVM indicated that the results of classification by logistic regression were more accurate than those of SVM. Comparing the accuracy rates of classification of all ten groups of ads illustrated that only for one group (between 90 and 100 ads), the results of the classification by SVM were more accurate than the results of logistic regression and for one group (between 70 and 80 ads), they were the same. For the other 8 groups, the classification by logistic regression was more accurate than the classification by SVM.
So, in summary, there was not a large difference between the accuracy rates of these four different classification algorithms, but the use of logistic regression had the highest accuracy rates and Naïve Bayes had the lowest accuracy rates.

Limitations and Recommendations

The most important limitation in this method is that we cannot track the owner of the phone numbers. So, as an example, when we identify a potential organized group of adult service providers with 140 phone numbers, we do not know how many people are using these phone numbers.

We have two recommendations. The first recommendation is to use the data for all 50 states to better understand the movement of adult service providers across the country. The second recommendation is that the methods used in this study can be used by law enforcement to identify and break down the potential organized human trafficking groups. Based on information achieved from the literature review and the U.S. government announcement, most human trafficking usually happens by small criminal groups and there is no specific evidence for the involvement of large criminal organizations such as the Mafia in these types of activities. So, analyzing online posted ads could be a very effective approach for identifying and taking down these small human trafficking groups.
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