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Assessing the Reuse Potential of Objects.

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ASSESSING THE REUSE POTENTIAL OF OBJECTS

A Dissertation

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in

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by

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Abstract

In this research, we investigate whether reusable classes can be characterized by object-oriented (OO) software metrics. Three class-level reuse measures for the OO paradigm are defined: inheritance-based reuse, inter-application reuse by extension, and inter-application reuse as a server. Using data from a software company, we collected metrics on Smalltalk classes. Among the 20 metrics collected are cyclomatic complexity, Lorenz complexity, lines of code, class coupling, reuse ratio, specialization ratio and number of direct subclasses. We used stepwise regression to derive prediction models incorporating the 20 metrics as the independent variables and the reuse measures, applied separately, as the dependent variable. Inheritance-based reuse and inter-application reuse by extension can be predicted using a subset of the 20 metrics. Two prediction models for inheritance-based reuse and inter-application reuse by extension were validated using a new set of 310 Smalltalk and VisualAge applications and subapplications. Validation results show that it is possible to predict whether a class from one application can be reused by extension in another application. We also conducted a t-test to test whether the mean metric values between reusable and non-reusable classes are the same. Results suggest that there exists significant differences in the mean metric values between the reusable and non-reusable classes.

Chapter 1. Introduction

1.1 Software Measurement

Measurement has a central role in engineering disciplines [Fen91]. Traditional engineering disciplines are marked by the availability of precise, well understood, standardized metrics which are based in the physical sciences [Den81]. Gerald Weinber said that maturity in every engineering and scientific discipline is marked by the ability to measure [Gil77]. Software engineering is the collection of techniques concerned with applying an engineering approach to the construction of software products. It has been seen as a partial solution to poor quality systems, delivered late, and over-budgeted [Fen91; Ghe91].

In software engineering, measurement has been ignored to a large extent, detaching it from the normal scientific view of measurement [Fen91]. This lack of measurement is one of the criticisms found in software literature which merits further investigation. The progress of metric research has been slow due to complexity of software development and problems with methodology [She93]. [Jon91] called this progress an art form or craft rather than an engineering discipline.

Software and computer science may have more in common with economics, psychology, and political science than with the physical sciences because of the problems with measurement. The approach to software metrics must be made in a careful, scientific way marked by the traditional scientific paradigm of hypothesis, evaluation, criticism, and review [Den81].

Some of the factors that have discouraged or delayed research in and applications of effective software metrics are:

1. Misconceptions of the goal of software metrics.
2. Practitioners' lack of educational background in numerical thinking for the control of software productivity.
3. Some design diagrams are insensitive to mathematical reasoning/modeling-traditional flowcharts, data flow diagrams, finite-state diagrams, action diagrams, general graph oriented diagrams, decision trees.
4. Complacent attitude of software maintainers with respect to software measurement.
5. Complacent attitude of software maintainers with lines of code (LOC) and general graph thinking which is the basis of some complexity measures.
6. Programmer productivity measures intimidates programmers about possible firing.
7. Private software packages including cost estimation models and computer-aided software engineering (CASE) tools without known supporting scientific foundations have the potential to entrench and establish 'certification'. [Eji91].
8. Measurements are intrusive [Jon91].

Software engineers have feared and resisted measurement as they dread destroying the "beauty" of software. Gerald Weinber claimed that under the artist's command, measurement becomes the servant of beauty [Gil77].

Formally, *measurement* is the process by which numbers or symbols are assigned to attributes of entities in the real world in such a way as to describe them according to clearly defined rules. Two broad purposes of software measurement are for tracking a software project and for predicting important characteristics of projects

[Fen91], [Sch93]. Also, its aims are technical and managerial in nature. These managerial and technical aims include characterization, evaluation, control, improvement of software quality, increased productivity, comparison, and estimations [Roc94]. In software engineering, indirect measurement is usually employed and used in a predictive capacity. However, there is a need to link the indirect to the direct measure [She93].

Metric and measure have been used synonymously in software engineering literature. A *metric* is a member of the class of mathematical functions called measure functions. A *measure* is definable on some definite structure, abstract or concrete, and discrete or continuous. A metric measure is then meaningful with respect to some well-defined sets or spaces [Eji91]. Simply stated, a software metric defines a standard way of measuring some attribute of the software development process [Gra87]. In mathematics, metric and measure are defined as follows:

A *measure* m is a mapping $m:A \rightarrow B$ which yields for every empirical object $a \in A$ a formal object (measurement value) $m(a) \in B$.

A *metric* is a criterion to determine the difference or distance between two entities [Zus91].

[Zus91] gives a comprehensive survey about software measurement and metrics from the literature. The IEEE Standard Dictionary of Measures to Produce Reliable Software defines *measure* as: a quantitative assessment of the degree to which a software product or process possesses a given attribute[Zus91]. It is worthwhile to note that [Zus91] claims that the results of measurement are difficult to interpret if too many properties of a program are combined in one number. Information is lost if only a single-

valued measure is used. A vector of measures can provide complete information on each individual property of a program. This research will use metrics to convey a measurement of a software engineering product.

In software engineering, empirically desirable qualities of a good measure, as enumerated in [Eji91], are:

1. Empirically and intuitively persuasive. It must satisfy notions of what object or parameter is being measured.
2. Simple and computable. It should be convenient to teach and use, and require only simple and well-formed formulas.
3. Consistent and objective. It should always yield unambiguous, reliable, and consistent results independent of environmental changes of mathematical transformations. An observer should be able to confirm the same measure using the same formula or guidelines.
4. Measure rationalism. It must belong to the class of measure functions.
5. Consistency of units and dimensions.
6. Programming language independence or invariance.
7. Feedback effect. It should psychologically reflect the philosophy of its practices within the context of its goals.

Three classes of entities whose attributes are measured are [Fen91; Zus91]:

1. Processes which are software related activities with a time factor.
2. Products which are any artifacts, deliverables, or documents which arise from the software life cycle.
3. Resources which are the items which are inputs to process.

Metrics for the traditional non-OO paradigm have been discussed, criticized and praised in computer literature. Lines of code, Halstead's Software Science, McCabe's Cyclomatic Complexity, Albrecht's Function Point are among the popular and widely-used metrics to date. [She93; Ke394; Ke494; Ke594; Ke694; Ke794;Jon91].

[Chi94, Chi91] listed two criticisms about software metrics. First, metrics that are applied to traditional, non-object oriented software design are criticized for having no solid theoretical and mathematical basis [Eji93; Fen90; Mel90; Sch93]. Second, as applied to object oriented (OO) design and development, software metrics developed with traditional methods do not support key OO concepts such as classes, inheritance, encapsulation and message passing. [Hen92] pointed out that traditional methods emphasize function-oriented view that separate data and procedures. Traditional languages and programming practices have critical data structures defined globally, and passed from procedure to procedure [Smi90]. The OO philosophy, on the other hand, brings data and functionality together. [Mey88] stated that an object-oriented design(OOD) decomposition of a software system is based on the classes of objects the system manipulates and not on the functions the system performs.

OO methods in software development serve several uses[McG92]:

1. Promote reusability due to support for data abstraction. Reuse can be accomplished by selection, decomposition, configuration, or evolution.
2. Facilitate maintenance due to information-hiding.
3. Exploit commonality across applications and across system components.
4. Reduce complexity since OO techniques relieves the designer from having a complete solution before beginning the design process.

1.2 Software Reuse

Reusable software was initially described as off-the-shelf software components used as building blocks of larger systems [Weg87]. This concept was pioneered by D. McIlroy [McI76]. Software reuse has been around since the 1960s but is rarely practiced effectively [Coa91]. Software reuse is believed to be a key in higher productivity and quality in software development [Big87]. Studies were conducted to support this claim[Fra96]. Agresti and Evanco [Agr92] showed that project characteristics of 16 Ada subsystems that have a high level of reuse correlate with a low defect density. Browne et al. [Bro90] showed that a high correlation exists between the measures of reuse rate, development time, and decreases in number of errors. The system used was called the reusability-oriented parallel programming environment (ROPE), a software component reuse system that helps designers find, understand, modify and combine code components. Card et al. [Car86] studied software design practices in a FORTRAN computing environment. They showed that for modules reused without modification, 98 percent were fault-free and 82 percent were in the lowest cost per executable statement category. Chen and Lee [Che93] developed an environment to manufacture C++ components. Their results showed improvements in software productivity of 30 to 90 percent measured in lines of code developed per hour. Gaffney and Durek [Gaf89] proposed cost/productivity models that specified the effect of reuse on software quality (number of errors) and software development schedules. They showed that the number of uses of the reusable software components directly correlates to the development product productivity.

The importance of reuse stems from the desire to avoid duplication and capture commonality in undertaking similar tasks [Weg87]. According to [Car95], reusing code that already exists speeds development and reduces the cost of writing and maintaining an application. [Agr88] listed the following benefits of reuse:

1. Productivity through the use of existing components. Productivity can be achieved since reuse reduces the amount of documentation and testing required [Tra88, Tra95].
2. Reliability through the use of proven components.
3. Consistency through using the same components in many places.
4. Manageability through the use of well-understood components.
5. Standardization through the use of standard components.
6. Software cost reduction [McC92].

Early versions of FORTRAN had a math library that constituted reusable code [Car95]. [Fre87] pointed out that the traditional mathematical subroutine libraries served as one of the starting points for an early concept of reusability. Reuse of numerical computation routines is successful due to the following reasons[Big87]:

1. The domain is very narrow and contains only a small number of datatypes.
2. The domain is well-understood since its mathematical framework has evolved over hundreds of years. People understand the domain, and readily understand what function a component performs with little description of that function.
3. The underlying technology is static, hence the library of parts is stable.

However, it is equally true that there exist domains where the underlying technology is rapidly changing. An example of such a domain is the workstation domain wherein systems software has a short life, and is therefore not reusable [Big87].

[Fre87] defined the object of reusability as any information which a developer may need in the process of creating software. Code fragments, logical structures, functional architectures, external knowledge, environment-level information are representative types of reusable information [Fre87]. Compilers, operating systems, linear programming packages, statistics libraries, prototypes, data models, life cycle processes, are also reusable resources [Weg87;Hor87;McC92]. [Pri87] classified levels of reuse as:

1. Reuse of ideas and knowledge.
2. Reuse of particular artifacts and components.

Frakes and Terry [Fra96] categorized reuse models and metrics into:

1. Reuse cost benefit models which include economic cost-benefit models, quality and productivity analyses.
2. Maturity assessment models which categorize how advanced reuse programs are in implementing systematic reuse.
3. Amount of reuse metrics which monitors reuse improvement effort by tracking percentages of reuse for life cycle objects.
4. Failure model analysis which provides an approach to measuring and improving a reuse process based on a model of the ways a reuse process can fail.
5. Reusability metrics which indicate the likelihood that a component is reusable. The pertinent question asked is, are there measurable attributes that indicate the potential reusability of a component?
6. Reuse library metrics which are used to manage and track usage of a reuse repository.

[McG92] coined the term 'editor inheritance' to describe a form of reuse in the procedural paradigm which is simply copying and modifying an existing code. This process, also called 'scavenging' or 'salvaging' code, has its own problems. [Car95]:

1. Finding the needed code can be difficult.
2. There is little assurance that code appearing in another program is correct.
3. Separating a piece of code from its containing program is difficult due to dependencies that piece of code has to its containing program.
4. Scavenged code often needs nontrivial changes to work in a new program.

Other impediments to successful software reuse are [McC92]:

1. Determining what is reusable.
2. Lack of standardization in programs.
3. Programming language dependence.
4. Deciding what goes in the library.
5. Understanding side effects from change.
6. Describing and classifying software components.
7. No management support for reusability.
8. Biggest benefits of reusability are long term.
9. Not practical to retrofit reusability into existing software components.

Essential properties of reusable code are [Car95, Den88, Nie92]:

1. Easy to find and understand.
2. Reasonable assurance that it is correct.
3. Requires no separation from any containing code.
4. Requires no changes, or minor modifications to be used in a new program.

5. Interface is both syntactically and semantically clear.
6. Interface is written at appropriate (abstract) level.
7. Component does not interfere with its environment.
8. Component is designed as object-oriented.
9. Separates the information needed to use software, its specification, from the details of its implementation, the body.
10. Component exhibits high cohesion/low coupling.
11. Component and interface are readable by persons other than the author.
12. Component is written with the right balance between generality and specificity.
13. Component is accompanied by documentation to make it traceable.
14. Component is standardized in the areas of invoking, controlling, terminating its function, error-handling, communication, and structure.
15. Component should constitute the right abstraction and modularity for the application.

When the overall effort to reuse code is less than the effort to create new code, then code reuse will be attractive to users [Pri87].

Can reuse be measured? [Hal88] emphasized the need to ascertain what sort of reuse is meant. For example is it:

- The number of times the code is incorporated into other codes?
- The number of times the code is executed?
- The number of times the incorporating code is executed?
- A figure of merit reflecting value or utility or saving?

[Coa91] envisions that OO reuse will become more important than code and data reuse as OOA, OOD and OOP gain acceptance in the field. [McG92] gave the following

levels of reuse for OOP: abstract-level, instance-level, customization reuse, and source code reuse. In abstract level reuse, high-level abstractions are reused for additional classification dimensions or to understand the problem domain modeled by the structures. Instance-level reuse creates instances of existing classes. Instance-level reuse is the quickest and most economical form of reuse. Customization reuse means that a reuser can inherit information from an existing class, override certain methods, and add new behaviors. Source code reuse is creating a subclass of an existing class, without any knowledge of the implementation of the parent classes. [Lor94] classified reuse into: white box and black box. White box reuse entails examination of the internals of the code component. Black box reuse is reusing functionality through a defined interface, without examining the internals of the code component.

[Mey88] claimed that the most promising technique in attaining reusability is OOD, defined as "the construction of software systems as structured collections of abstract data type implementations." OO classes, called abstract data type implementations in the OOD definition of [Mey88], have important structured relationships among each other. Two noteworthy relations are client and inheritance relations. A class is a client of another class when it makes use of the other class's services, as defined in the interface. Inheritance is the process of obtaining or reusing properties through a relation such as parent-child, or general-specific [Lew95]. The inheritance feature of OOP allows redefinition of children classes based on parent classes. Inheritance provides a way of building reusable classes from existing ones. Any changes in the operations in the parent classes are automatically inherited by children classes. Without the inheritance feature, every class must be developed as an

independent entity. The net effect of inheritance is a reduction of code to be developed by virtue of existing operations from the parent classes [Nie92]. Moreover, the relations client and inheritance help achieve reusability. An object encapsulates an entity that has a set of operations and attributes. Encapsulation means that implementation details of the data structure and algorithms used in the operations are hidden from the user and the only visible part is the interface. According to [Nie92], encapsulated objects provide a high degree of reusability since they can be used in different systems without changing the interfaces. [Lor94] claimed that one of the key benefits of OO is the additional support for reuse. Tasks in OO systems can be accomplished by requesting services, i.e. reusing, from other objects.

This section defined and described the benefits of software reuse. Some benefits are increased productivity, higher software quality, and reduction in software cost. Essential properties of reusable code were given. Also, categories of reuse models and metrics were listed. Moreover, impediments to successful software reuse were given. Furthermore, this section discussed why OOD and OOP are promising techniques in attaining reusability.

1.3 Research Objectives

The goals of this research are:

1. To define class level OO metrics that quantify reuse.
2. To investigate the statistical relationship of reuse metrics with existing OO and non-OO metrics.
3. To derive a prediction model for measuring reusability.
4. To statistically validate the prediction model using empirical data.

1.4 Motivation of Research

Metric research of the OO paradigm is still in its infancy. This work provides three quantitative measures of reuse and a set of statistically validated OO metrics, which will aid in reusability. A standard set of quality metrics may be available in the future [Sch93]. This set of metrics must be anchored in theory and practice.

Metric research is needed because code and design metrics can be used in a way that is analogous to statistical quality control [Kit90]. OO code can be accepted or rejected based on a range of metric values. Rejected OO code can be changed until the metric values fall within the specified acceptable range.

Furthermore, experience reports and metric data from projects are needed. Project data will help empirically validate product metrics. A position paper in [OOP92] reports: "We need more experience and data from projects. We want to have a workshop next year and invite interested participants to focus on the product metrics we have recommended and help us validate them."

In a group position statement in [OOP93], the following issues were cited as needing further research:

- The relationship between easily measured quantities and desired results.
- Development of metrics and instrumentation that programmers find informative, not threatening.
- Collection and evaluation of empirical data of all sorts, especially for metrics validation, development of norms, and assessment of the impact of reuse on productivity and quality.

Moreover, measuring software quality may be related to the economic success of an institution. "It is obvious that the need for accurate measurements of software productivity and quality is directly related to the overall economic importance of software to industry, business, and government. That means that measurement is now a mainstream software activity, and it is one that is on the critical path to corporate and national success [Jon91]."

Lastly, most of the OO metrics have not undergone empirical validation [Bas96]. This research will help further the reuse research agenda by defining three new reuse metrics and then empirically validating those metrics on data collected from a real-world software organization.

This research differs from other work in the following ways. First, we defined three new OO reuse measures. Second, we automatically collected empirical metrics data from implemented Smalltalk classes using a tool written in Smalltalk. Third, we performed three statistical analyses to achieve the goals of this research. One of the goals is to assess whether an OO class has reuse potential based on the metric values of the class. Fourth, we empirically validated the resulting regression equations.

In this chapter, we give an overview of the dissertation research. Chapter 2 contains a survey of object-oriented metrics and related research. In Chapter 3 we describe the metrics used in this study. It also presents the data and discusses the statistical analysis of the data. Finally, we describe the results in Chapter 4.

Chapter 2. Review of Literature

2.1 Survey of Object-Oriented Metrics

Chidamber and Kemerer [Chi94] presented six metrics for OOD that are especially designed to measure aspects peculiar to the OO approach. These metrics are weighted methods per class, depth of inheritance tree, number of children, coupling between objects, response for a class and lack of cohesion of methods. This suite of metrics, based upon measurement theory, incorporates viewpoints of OO software developers. It is evaluated against Weyuker's criteria for validity. The Weyuker properties are:

1) Noncoarseness: Given a class P and a metric m another class Q can always be found such that: $m(p) \neq m(Q)$.
2) Nonuniqueness: There can exist distinct classes P and Q such that $m(P) = m(Q)$.
3) Design Details are Important: Given two class designs, P and Q, providing the same functionality, this does not imply that $m(P) = m(Q)$.
4) Monotonicity: For all classes P and Q, the following must hold: $m(P) <= m(P+Q)$ and $m(Q) <= m(P+Q)$ where $P+Q$ is the combination of P and Q, that is, $P+Q$ is the class whose properties are the union of the properties of the component classes.
5) Nonequivalence of Interaction: $\exists P$, $\exists Q$, $\exists R$, such that $m(P) = m(Q)$ does not imply that $m(P+R) = m(Q+R)$.
6) Interaction Increases Complexity: $\exists P$ and $\exists Q$ such that: $m(P) + m(Q) < m(P+Q)$.

Empirical data for the [Chi94] metrics were collected from two commercial projects that used C++ and Smalltalk programming languages, respectively. Automated tools were used to collect the metrics. From two C++ libraries with 634 classes that are

used in the design of graphical user interfaces, metrics data were collected. From the second organization, which is a semiconductor manufacturer, metrics data were collected for 1459 classes that are used for developing machine control and manufacturing systems. Since there are no design artifacts available at both organizations, the metrics were collected from code.

In section 2.1.1, class-level metrics are described.

2.1.1 Class Level Metrics

In this section, the following class-level metrics are described: weighted methods per class, depth of inheritance tree, number of children, coupling between objects, response for a class, lack of cohesion of methods [Chi94], coupling through message passing, coupling through abstract data types, number of local methods, size metrics [Li93], fan-in and fan-out [Teg95].

Weighted Methods Per Class (WMC).

The *WMC* of a class with n methods is the sum of the static complexities of all methods, that is,

$$WMC = \sum_{i=1}^{n} C_i$$

where C_i = static complexity of method i. WMC = n if $C_i = 1$ for all $i = 1,2, ..., n$.

Static complexity was not specifically defined to allow for generic application of *WMC*. Some traditional static complexity metrics such as McCabe's cyclomatic complexity, may be appropriate. McCabe's cyclomatic complexity is based on the

control flow or decision structure of a software module [McC94, Jon91], defined as

$$V(G) = e - n + 2$$

where G is a connected, directed acyclic graph,

e = number of edges of G.

n = number of nodes of G.

A node represents a block of code with one entry point and one or more exit points. The nodes are connected by edges.

Any static complexity metric that has the property of an interval scale can be used. *WMC* relates to the definition of complexity of an object and indicates time and effort needed to develop and maintain an object. A large *WMC* may indicate the impact on children who inherit all methods defined in the class. Also, a large *WMC* may be indicative of application specificity of a class, which limits reuse possibility. *WMC* satisfies Weyuker's properties 1,2,3,4,5 but not property 6.

The empirical data from both organizations showed that most classes have a small number of methods (0 to 10). It was also noted that examining outliers can give significant insights on specific classes. A class with 87 methods was observed to have reuse potential.

Depth of Inheritance Tree (DIT).

DIT = depth of the inheritance of the class or height of the class in the inheritance hierarchy or maximum length from the node to the root of the tree for multiple inheritance cases.

DIT relates to scope of properties, i.e. extent of the influence of a property. It measures how many ancestor classes can potentially affect the class. A class with a large

DIT metric is complex due to a large number of methods it is likely to inherit. Also, a large *DIT* indicates potential reuse of inherited methods.

DIT satisfies Weyuker's properties 1,2,3,5 but not property 6. Property 4 is satisfied if *P* and *Q* are siblings but is not satisfied if *P* and *Q* are neither children nor siblings of each other.

The empirical data from both organizations showed a low median value for *DIT*. This shows that classes tend to be close to the root in the inheritance hierarchy. This characteristic can warn designers about failure to take advantage of reuse through inheritance.

Number of Children (NOC).

NOC = number of immediate sub-classes subordinate to a class in the class hierarchy.

NOC, which relates to scope of properties, measures how many sub-classes will inherit the methods of the parent class. A class with a large *NOC* may require more testing and may be harder to maintain. A large *NOC* may indicate reuse potential through inheritance and may also indicate improper abstraction of the parent class.

NOC satisfies Weyuker's properties 1,2,3,4,5 but not property 6.

Findings indicate that reuse through inheritance may not be fully adopted by the two organizations since empirical data shows low *NOC* for both of them.

Coupling Between Objects (CBO).

CBO = number of non-inheritance couples with other classes.

CBO relates to the notion of an object being coupled with another when methods of one use methods or instance variables of another. An object with high *CBO* may need

more rigorous testing and may be harder to reuse. It is easier to reuse an independent class. A class with low *CBO* may be indicative that this class promotes modularity and encapsulation. *CBO* satisfies Weyuker's properties 1,2,3,4,5 but not property 6.

Empirical data showed that *CBO* values were smaller in the C++ environment than in the Smalltalk environment. Also, the data suggests that coupling between classes is an increasing function of the number of classes in the application.

Response For a Class (RFC).

RFC = cardinality of the response set (*RS*) of a class

where *RS* = number of all methods in the class + number of methods called by methods in the class.

RFC is a measure of the attributes of an object and communication between objects. A high *RFC* may indicate that an object is complex and hence may require more testing time and may be harder to maintain. *RFC* satisfies properties 1,2,3,4,5 but not property 6.

The empirical data from both organizations showed small *RFC* values. The median values of RFC for the Smalltalk environment are higher than the C++ environment.

Lack of Cohesion in Methods (LCOM).

Given a class C with methods $M_1, M_2, \ldots, M_n$ and $\{I_i\}$ = set of instance variables used by method M_i. Let $P = \{(I_i,I_j)|I_i \cap I_j = \varnothing\}$ and $Q = \{(I_i,I_j)|I_i \cap I_j \neq \varnothing\}$.

$LCOM = |P| - |Q|$, if $|P| > |Q|$

$= 0$ otherwise.

LCOM is the number of disjoint sets formed by the intersection of the *n* sets. It provides a measure for disparate nature of methods in the class and may help identify flaws of the design process. Few disjoint sets means great similarity of methods. The larger the number of similar methods, the more cohesive the class. *LCOM* satisfies properties 1,2,3,5 but not properties 4 and 6.

Empirical data shows that at least 50% of classes for both companies have cohesive methods.

Failure of all Chidamber and Kemerer metrics to satisfy property 6, i.e. interaction increases complexity) implies that dividing a class into more classes could increase a complexity metric.

The implementation independence of these metrics was demonstrated through the empirical data from both C++ and Smalltalk environments.

In addition to Chidamber and Kemerer metrics, Li and Henry, [Li93], proposed an additional OO metric, namely coupling through inheritance, which uses DIT and NOC.

Coupling through Message Passing (MPC).

MPC = number of send statements defined in a class.

MPC measures the complexity of message passing among classes.

Coupling thru abstract data types (DAC).

DAC = number of ADTs defined in the class.

A class is an implementation of an ADT [Hen92]. A larger DAC means the more complex the coupling of the class with other classes.

Number of Local Methods (NOM).

NOM = number of local methods.

NOM is a measure of the interface of a class. A larger NOM means that the class's interface is more complex.

Size Metrics (SIZE1 and SIZE2).

SIZE1 = number of semicolons in a class.

SIZE2 = number of attributes + number of local methods.

SIZE1 is the traditional lines of code (*LOC*) metric while *SIZE2* measures the number of properties defined in a class.

Tegarden [Teg95] slightly modified the definition of *MPC* and called it fan-in and fan-out.

Fan-In

Fan-In = number of unique messages sent from all other objects to the object

Fan-Out

Fan-Out = number of unique messages that the object sends to all other objects

Chung [Chu92] defined coupling of a method to be the sum of input and output coupling. Class complexity was defined as the sum of complexity of its component methods.

In Section 2.1.2, system level metrics are described.

2.1.2 System Level Metrics

Kolowe, [Kol93] classified *NOC* as a system-level metric. In addition to NOC, he proposed three system level metrics namely, number of class hierarchies, number of class cluster, and association complexity.

Number of Class Hierarchies (NCH).

NCH simply counts the number of fundamental clusters of concepts that the system deals with.

Number of Class Clusters (NCC).

NCC = number of disjoint sets formed by the intersection of the sets of classes associated with each class.

Association Complexity (AC).

$AC = A - C + 2P$ where

A = number of associations in the class diagram.

C = number of classes in the class diagram.

P = number of disconnected parts in the class diagram.

Kolewe found that class coupling and response for a class are seemingly useful in predicting high defect rates. He also claims that *AC* is analogous to McCabe's metric. He argued that system level metrics are less useful due to insufficient OO systems with which to compare the metric values. It will be hard to say whether a system is too complex.

Section 2.1.3 discusses three dependency metrics: afferent coupling, efferent coupling, and instability.

2.1.3 Dependency Metrics Within Groups of Classes

Martin [Mar95] proposed three dependency metrics applicable to a class category. A class category is a group of highly cohesive classes.

Afferent Coupling (Ca).

Ca = number of classes outside this category that depend upon classes within the category.

Efferent Coupling (Ce).

Ce = number of classes outside this category that are depended upon by classes within this category.

Instability (I).

$I = Ce / (Ca + Ce)$

I = 0 indicates a maximally stable category while I = 1 indicates a maximally unstable category.

The following design guidelines given by McGregor and Sykes [McG92], relate to quality of a class design:

1) Information hiding: The only members of the public interface of a class should be the methods of the class.
2) Limitations on messages: A class should not expose its implementation details, even through public accessor operations.
3) Narrow interfaces: An operator should be a member of the public class interface if and only if it is to be available to users of instances of the class.
4) Strong cohesion: Each operator that belongs to a class either accesses or modifies some of the data of a class.
5) Weak coupling: A class should be dependent on as few other classes as possible.

6) Explicit information passing: The interaction between two classes should involve only explicit information passing.

7) Subclassing as subtyping: Each subclass should be developed as a specialization of the superclass with the public interface of the superclass becoming a subset of the public interface of the subclass. Inheritance should be used for defining subtype relationships. Inheritance should not be used when client-server relationship between two classes is more appropriate.

Shepperd and Ince [She93] observed that the evaluation criteria of OOP design guidelines tend to be qualitative and subjective.

Barnes and Swim [Bar93] believe that existing reusable software components of high quality can be used to rapidly produce quality software. They proposed a quality object-oriented language (QOOL) that enables the inheritance of software metrics. The object-oriented programming (OOP) class concept is extended to include methods to evaluate, variables to retain, how well classes are designed and implemented and how well they perform. QOOL includes goal-based, syntax-based and execution-based metrics. Its major advantage is touted to be as a reduction in the burden of measurement through inheritance and automation. They developed a QOOL integrated programming support environment (IPSE) in Actor 3.0, named ActQOOL. This prototype gathers syntax-based metrics from a class, namely the number of messages to self as opposed to other objects; number of methods; number of instance variables; average, maximum and minimum V(G) per method; average, minimum, maximum variables per method; Halstead vocabulary, program level, intelligent content; number of lines of code; and

number of local variables. They believe that QOOL can be helpful with reuse decisions. Syntax-based metrics can be used as a first-pass evaluation of candidate classes. QOOL can also be used throughout the software product lifecycle. It can identify trouble areas and software failures immediately.

Barnes and Swim claim that more work is needed at the conceptual, empirical and implementation levels to evaluate QOOL. It is the conceptual work of further specifying quality metrics that helps to motivate this research.

LaLonde and Pugh, [LaL94], showed that many static OO metrics can be generated easily from the Smalltalk image including:

1) System queries: total classes without super classes; total classes; total methods; average (avg) instance variables per class; avg instance variables per concrete class; avg width of classes with subclasses; avg class height; avg lines per method; avg comment lines per method; avg code lines per method; avg methods per class; avg inherited methods per class; avg inherited methods excluding object methods; avg refined methods per class; avg new methods per class; avg reused methods per class.

2) Library queries: avg lines per method; avg code lines per method;avg comment lines per method.

3) Class queries: avg lines per method; avg code lines per method;avg comment lines per method.

The research need for statistically and scientifically validated OO metrics can no longer be ignored. For OOP to reach maturity like traditional engineering disciplines, it

must have a set of standardized, precise and statistically validated metrics. Metrics for Object Oriented Software Engineering (MOOSE) as proposed in [Chi94] are said to be the most used suite of measurements for OO software (OOPSLA, 1993). MOOSE metrics were evaluated using Weyuker's six properties. Empirical data were also collected but were not validated. Also, MOOSE has never been empirically validated using reusability as the quality factor. In this research, we empirically validate a subset of MOOSE and other OO metrics using reusability as the quality factor. As MOOSE metrics begin to show strong empirical validity, there is a need to statistically validate them and to investigate their use to predict reusability.

2.2 Related Studies

2.2.1 Fonash

Fonash [Fon93] collected static metrics from 284 Ada software modules using an Ada Static Source Code Analyzer Program. Among the metrics collected were: McCabe complexity, Halstead volume, number of source lines, number of Ada statements, type of module, number of comment lines, ratio of number of comment lines and number of source lines, maximum nesting, number of formal parameters, number of call statements, generic type declaration, generic function parameters, and number of data types. Three categories of code were evaluated: code reused without modification, code reused after extensive modification (i.e. greater than 25% of the code was modified), and code for new application. The goal of the log-linear statistical analysis performed was to determine if there exists significant differences in the collected measures among the three reuse categories. Number of lines of comments, average program nesting, number of formal parameters, generic function specification, number of call statements, number of

with statements, ratio of number of with and number of procedures and functions, and number of data types, differed significantly between the code reused without modification and reused after extensive modification categories. Fifteen measures (eg. McCabe complexity, Halstead volume, number of Ada statements, number of data types and formal parameters per module sub-components) had significant differences between the code reused without modification and the code new for application categories.

Fonash collected metrics on Ada modules. Ada is an object-based language. Moreover, reuse was defined in terms of modified code. In contrast, this research collects class metrics from Smalltalk. Reuse is defined in terms of OO concepts, such as inheritance and extensibility.

2.2.2 Karunanithi and Bieman

Karunanithi and Bieman [Kar93] listed reuse measures for object-oriented systems from three perspectives: client, server, and system. When a module *M* uses a program unit *P*, *M* is a client and *P* is a server. The client perspective is the perspective of a new system or a new component. It focuses on how a new class reuses existing components. On the other hand, the server perspective is the perspective from the library component's point of view. The analysis focuses on how the entity is reused by other program entities. The system perspective is a view of reuse in the overall system, including servers and clients. Examples of reuse from a server perspective are: number of direct clients, number of indirect clients, size of server interface, number of direct client invocations of server, and number of paths to indirect clients. No statistical validation of the proposed measures was given.

2.2.3 Li and Henry

Li and Henry, [Li93] concluded that there is a strong relationship between metrics and maintenance effort in OO systems. Maintenance effort was defined as the number of lines changed per class in its maintenance history. They used two commercial software products, UIMS (User Interface System) and QUES (QUality Evaluation System). Both were designed and developed using Classic-ADA. They used multivariate statistical analysis as a tool to arrive at their conclusions. Moreover, maintenance effort can be predicted from combinations of *DIT*, *NOC*, *MPC*, *RFC*, *LCOM*, *DAC*, *WMC*, *NOM*. These results were successfully cross-validated.

Li and Henry [Li93] used an OO dialect of Ada, least-squares regression and number of changes in components as dependent variable to study maintainability. We use VisualAge for Smalltalk, least-squares regression, and reusability as dependent variable.

2.2.4 Basili et al.

[Bas96] empirically assessed whether the OO design metrics presented in [Chi93] can be used to predict the probability of detecting fault-prone classes. Data were collected from eight management and information systems projects developed in a university setting using an OO analysis and design method, C++ programming language, GNU software development environment, and OSF/Motif, Sparc Sun stations. For each of the 180 classes across the eight systems, OO design metrics were collected using GEN++, a customizable language independent code analyzer. The response variable is binary, i.e. was a fault detected in a class during testing phases? A logistic regression

was used to analyze the relationship between metrics and the fault-proneness of classes. Their findings were:

1. The larger the *WMC*, the larger the probability of fault detection. For graphical user interfaces classes, new, and extensively modified classes, the results were more significant.
2. The larger the *DIT*, the larger the probability of fault detection. Results were more significant when new and extensively modified classes were considered.
3. The larger the *RFC*, the larger the probability of fault detection.
4. The larger the *NOC*, the lower the probability of fault detection. They explained this result by the combined facts that most classes do not have more than one child, and that verbatim reused classes are somewhat associated with a large *NOC*. In [BasB96], the authors observed that reuse has a significant negative factor on fault density, i.e. the higher the number of times a class has been reused, the lower is the class' fault density, explaining why large *NOC* classes are less fault prone.
5. *LCOM* was found to be insignificant in all classes.
6. *CBO* is significant, more particularly so for graphical user interface classes.

[Bas96] performed multivariate logistic regression with classification threshold = 0.5. Classes predicted as faulty contain a large number of faults. Results show that OO metrics are useful predictors of fault-proneness.

Lastly, Basili et al. stated that the code metrics maximum level nesting in a class, number of function declarations, and number of function calls appear to be somewhat poorer predictors of class fault-proneness. Code metrics can only be collected after the

code is written, while design metrics can be collected early in the software development life cycle.

The preceding study differs with the research described in this dissertation in the following ways: programming language used to collect metrics (C++ vs. Smalltalk), dependent variable used (fault-proneness vs. reusability) and statistical analysis employed (logistic regression vs. linear regression). Table 2.1 summarizes the studies.

Table 2.1. Comparison of reuse and metrics studies.

	Programming Language	Dependent Variable	Statistical Analysis
Fonash[93]	Ada	Reusability	Log-linear
Karunanithi and Bieman[Kar93]	Any OO language	None	None
Li and Henry[Li93]	Classic-ADA	Maintainability	Least squares linear regression
Basili et al.[Bas96]	C++	Fault-proneness	Logistic regression
Reyes and Carver	Smalltalk	Reusability	Least squares linear regression.

In Chapter 3, we present the metrics used in this research and the tool used to collect the metrics. We also define the reuse measures, data, and the statistical analysis used in the research.

Chapter 3. Materials and Methods

The purpose of this work was to assess the value of a set of metrics to measure reuse potential. We identified a set of twenty metrics, listed in Figure 3.1, to characterize Smalltalk classes. We identified statistical techniques to measure the goodness of the metrics to predict reuse. Section 3.1 defines the set of metrics, and Section 3.2 describes the tool used to extract these metrics. Section 3.3 defines the reuse measures. Finally in Section 3.4, we present the data and discuss the statatistical analysis of that data. Appendix A lists the glossary of terms used in this research.

3.1 Metrics Extracted

In order to investigate reuse potential, we computed 20 metrics. These 20 metrics were chosen because they are representative of metrics found in object-oriented and metric literature [Bar93], [Chi94], [Hen96], [Li93], [Lor94], [McC94], [Teg95], they are potential indicators whether a class is reusable or not, or they were computable using the metaclass *Class* of VisualAge for Smalltalk. In each of the following metric definitions, *C* represents a class.

- **Number of direct subclasses (NDSub)**

  NDSub(C) = number of immediate children of *C* in the Smalltalk image[Chi94] (3.1)

  Smalltalk image is defined as:

  " Smalltalk file that provides a development environment on an individual workstation. An image contains object instances, classes, and methods. It must be loaded into the Smalltalk virtual machine in order to run [VAG95]".

  A large *NDSub* may indicate reuse potential through inheritance.

Metric	Abbreviation
Number of direct subclasses	*NDSub*
Number of all subclasses	*NSub*
Number of methods	*NOM*
Number of instance methods	*NIM*
Number of class variables	*NCV*
Number of instance variables	*NIV*
Number of class method categories	*NCMC*
Number of instance method categories	*NIMC*
Number of all superclasses	*Nsup*
Cyclomatic complexity	*CycC*
Number of public methods	*NpubM*
Number of private methods	*NpriM*
Class coupling	*CC*
Reuse ratio	*U*
Specialization ratio	*S*
Lines of code	*LOC*
Number of statements	*NOS*
Lorenz complexity	*LC*
Number of message sends	*NMS*
Number of parameters	*NP*

Figure 3.1. Object-oriented metrics.

- **Number of all subclasses (NSub)**

  NSub(C) = number of *C*'s children in the Smalltalk image up to the leaves (3.2)

  A large *NSub* may indicate reuse potential through inheritance.

- **Number of methods (NOM)**

  NOM(C) = number of instance methods of *C* + number of class methods of *C* (3.3)

In Smalltalk, an instance method provides behavior for a particular instance of a class and a class method provides behavior for a class. Ways to create instances of a class are usually defined in class methods [VAR95]. Li and Henry [Li93] categorized *NOM* as an interface metric.

- **Number of instance methods (NIM)**

  NIM(C) = number of public and private instance methods of *C*. (3.4)

NIM is related to the amount of collaboration being used. Large *NIM* may indicate that *C* is complex and hard to maintain. Small *NIM* may be indicative that *C* is reusable since *C* provides a set of cohesive services instead of a mixed set of capabilities [Lor94]

- **Number of class variables (NCV)**

  NCV(C) = number of class variables of *C*. (3.5)

Class variables are data that are shared by the instance and class methods of the defining class, together with its subclasses. They can be viewed as localized globals that provide common objects to instances of a class. A low *NCV* may indicate that much of the work is done by instances, which is [Lor94]'s recommendation.

- **Number of instance variables (NIV)**

  NIV(C) = number of instance variables of *C* (3.6)

  Instance variables are private data that can be accessed only by instance methods of the defining class and its subclasses. They provide a mechanism for sharing information among methods [Smi90]. *NIV* may be used as a size measure for a class. A large *NIV* may indicate that *C* is coupled with other objects in the system and thus, reduce reuse [Lor94].

- **Number of class method categories (NCMC)**

  NCMC(C) = number of categories among the class methods of *C*. (3.7)

  In VisualAge for Smalltalk, a category is a logical association of a group of methods within a class, with a name assigned by the class developer. For example, the *NCMC* value of class *MetricsRepository* in Figure 3.2 is 4.

- **Number of instance method categories (NIMC)**

  NIMC(C) = number of categories among the instance methods of *C*. (3.8)

  For example, the *NIMC* value of class *Metric* in Figure 3.3 is 5

- **Number of all superclasses (NSup)**

  NSup(C) = number of superclasses of *C* up to the *Object* root class (3.9)

  The greater number of superclasses a class has, the greater number of methods it is likely to inherit. The greater the number of inherited methods, the more complex it is to predict its behavior [Chi94].

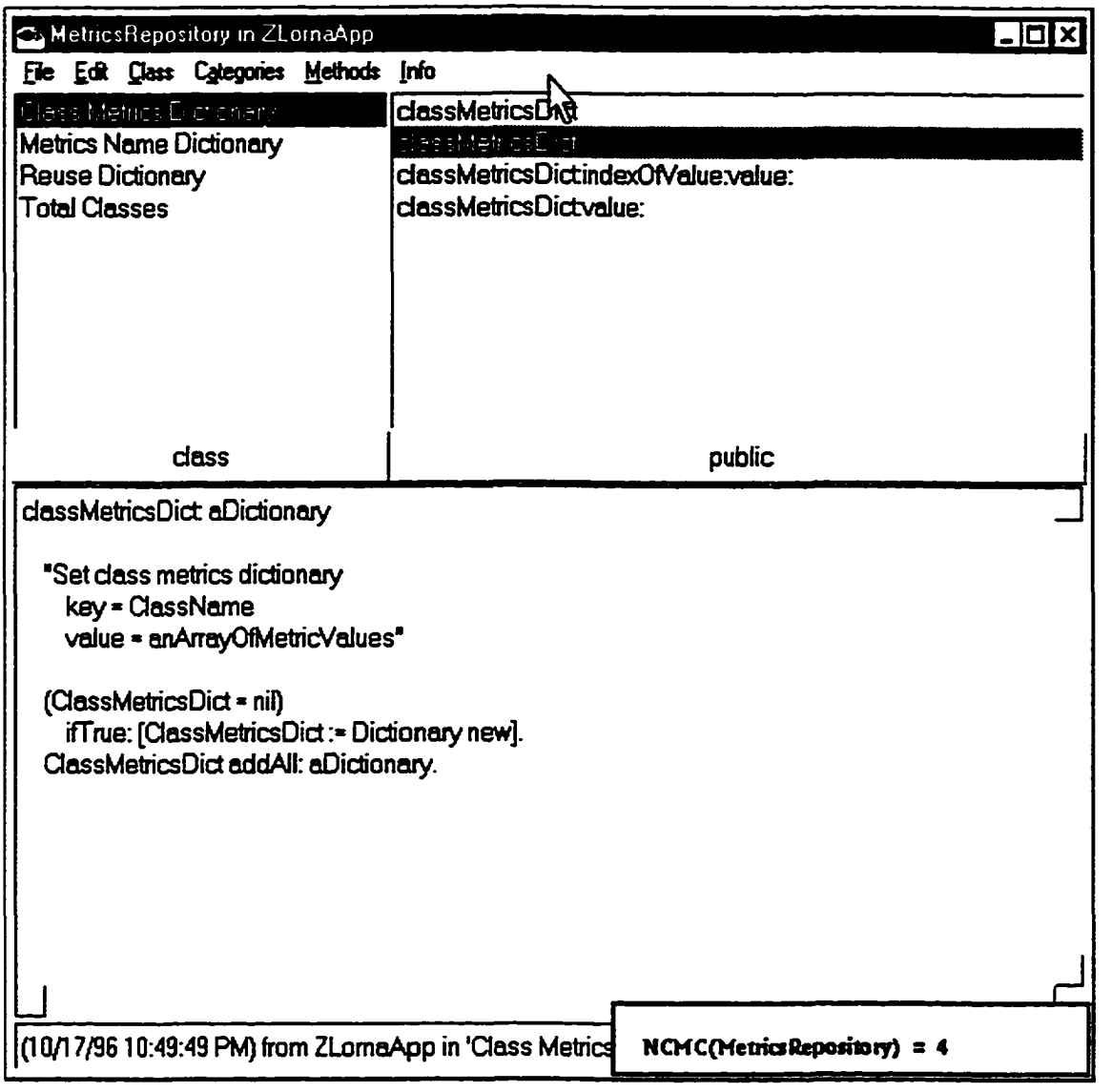

Figure 3.2. Example of NCMC metric value.

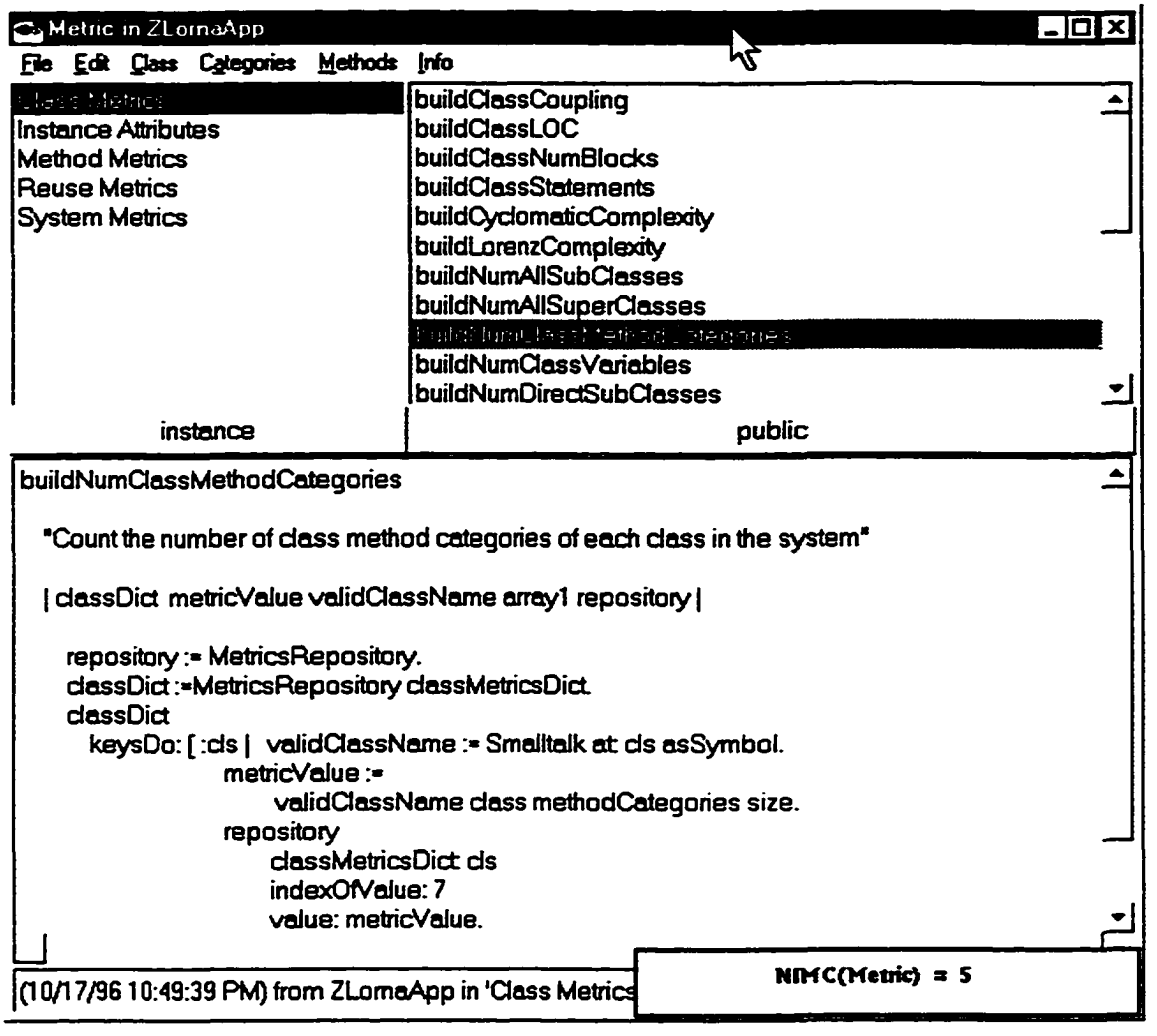

Figure 3.3. Example of NIMC metric value.

- **Cyclomatic complexity (CycC)**

Let C be a class with n methods $m_1, m_2, m_3,\ldots,m_n$. Let e_i = number of exit points in m_i.

$$CycC(C) = \sum_{i=1}^{n}[(e_i - 1) + 2] \tag{3.10}$$

CycC, which is related to control flow complexity, was initially used for the traditional programming paradigm. The difficulty in understanding a program is related to the number of loops, jumps, and selections a program contains [She93].

CycC is similar to the weighted methods per class (*WMC*) metric defined in [Chi91] and [Chi94]. Redundant code in software systems should be eliminated to facilitate reuse. McCabe states [McC94]:

> "It's definitely to our advantage to locate and eliminate redundant code, so that we can increase the amount of reuse and reduce total complexity of our software."

An observation exists that independent implementations of the same functionality tend to have the similar control flow structure [McC94].

- **Number of public methods (NPubM)**

NPubM(C) = number of public methods of class C. (3.11)

In VisualAge and IBM Smalltalk, declaring a method as public is a designation that application developers can use to indicate that a method is part of the programming interface of the application they are developing.

Public methods are services available to other classes. This metric may indicate the amount of services being used by other classes, and hence is a good measure of the responsibility of a class [Lor94].

- **Number of private methods (NPriM)**

NPriM(C) = number of private methods of a class. (3.12)

In VisualAge and IBM Smalltalk, declaring a method as private is a designation that application developers can use to indicate that a method is only for internal use within the application they are developing.

- **Class coupling(CC)**

Coupling between classes measures the interrelationships or dependencies that bind classes together. Message connection between classes is one of the forms of coupling[Lor94]. A class is coupled to another class if it calls methods of that class.

CC(C) = number of classes called by methods of class *C* (3.13)

Since Smalltalk is an untyped language, class coupling can only be inferred from message names. The calculation takes all messages sent by methods of a class. The following assumptions are made:

- Message names that have local (super/sub/self) implementation are assumed to be sent to the receiver class and are therefore ignored for coupling calculation.

- Messages that have more than one implementing class:

  - If the classes have a parent-child relationship, the coupling is assumed to be with the parent.

  - If the classes do not have a parent-child relationship, the coupling is assumed to be with both classes.

-If there is any direct reference to a class, include it as a coupled class. [OTI96].

This definition counts inheritance and non-inheritance couples. In constructing independent modules, class coupling should be minimized [Hen96]. The class/superclass

relationship on the other hand inherently increases coupling [Boo94]. [Lor94] claimed that reuse encourages lower level of coupling and inheritance encourages higher levels of coupling.

- **Reuse ratio (U)**

$U(C)$ = number of C's superclasses / total number of classes in C's hierarchy. (3.14)

A value close to 1 is characteristic of linear hierarchy and a value close to 0 indicates a shallow depth and a large number of leaf classes [Hen96]. *U* can be classified as a measure of potential reuse.

- **Specialization ratio (S)**

$S(C)$ = number of subclasses / number of superclasses. (3.15)

S measures the extent to which a superclass has captured the abstraction since a large value of *S* indicates a high degree of subclassing [Hen96]..

- **Lines of Code(LOC)**

$LOC(C)$ = number of physical lines of code ignoring comments. (3.16)

LOC is not a new metric. Its basis is program length which has been used as a predictor of program characteristics such as reliability and ease of maintenance [She93]. Metric studies in the traditional programming paradigm have used *LOC* as a baseline for evaluation [Alb83;She93]. As a baseline, it is expected that an effective code metric will perform better than *LOC* [She93]. *LOC* was included in this study in part because project data is available on this metric [Lor94]. This metric does not take into account coding style, and hence is a relatively suspect measure [Lor94].

- **Number of Statements (NOS)**

$NOS(C)$ = number of statements in a class. (3.17)

A statement is defined by:

- Unary, binary or keyword messages

- Assignments.

- Cascade expressions.

- Messages sent (including the return expressions).

NOS is a relatively unbiased method size measure. A large *NOS* may be indicative of function-oriented coding style. On the other hand, a small *NOS* may indicate that the class is requesting services, i.e. reusing, from other classes[Lor94].

- **Lorenz Complexity (LC)**

Lorenz complexity is a method measure that finds the complexity of a method based on weighted attributes of the method [Lor94].

Application Program Interface(API) calls	5.0
Assignments	0.5
Binary expressions	2.0
Keyword messages	3.0
Nested expressions	0.3

[Lor94] proposed this complexity measurement arguing that traditional complexity measures like McCabe's cyclomatic complexity are less useful in OO code. Traditional complexity measures focus on factors like number of decision points in the code of a function, which are from IF-THEN-ELSE constructs. Well-designed OO code on the other hand, has fewer IF statements and no case statements. A complexity measurement is based on the number and types of messages was thus proposed.

The *LC* method measure was extended to the class level by summing *LC* method measure values for each method in the class. Let *C* be a class with *n* methods m_1, m_2, $m_3,\ldots,m_n$. Let lc_i = Lorenz complexity of m_i.

$$LC(C) = \sum_{i=1}^{n} lc_i \tag{3.18}$$

LC is again similar to the weighted methods per class (*WMC*)metric in [Chi91] and [Chi94].

- **Number of message sends (NMS)**

Let *C* be a class with *n* methods m_1, m_2, $m_3,\ldots,m_n$. Let s_i = number of message sends in m_i.

$$NMS(C) = \sum_{i=1}^{n} s_i \tag{3.19}$$

This type of coupling through message passing metric was proposed in [Li93]. In Smalltalk, a message send is a channel of communication from one object to another that asks the receiving object to execute a method. Much of the communication among objects will occur by sending messages, if classes are properly designed [Smi90]. *NMS* is a relatively unbiased method size measure [Lor94].

- **Number of parameters (NP)**

Let *C* be a class with *n* methods m_1, m_2, $m_3,\ldots,m_n$. Let a_i = number of parameters in m_i.

$$NP(C) = \sum_{i=1}^{n} a_i \tag{3.20}$$

NP can be used as a connectivity measure. Relatively few objects should be passed as arguments or parameters to methods [Hen96]. A high *NP* puts a heavy burden on the client [Lor94].

3.2 Class Metrics Collector

We developed the Class Metrics Collector to collect the metric data. The design of the class metrics collector (CMC) is based on a Source Code Metrics Analyzer described in [Bel96]. Using use cases and Class Responsibilities Collaborators (CRC) cards, as described in [Boo94], four classes were used in the design of the metrics analyzer. Table 3.1 shows the CRC cards for classes *Metric*, *MetricsFile*, *GUI* and *Tool* [BelR96].

We constructed an automated CMC using VisualAge for Smalltalk Professional ™, an object-oriented application development language from IBM. CMC has six implemented classes: *Metric*, *MetricsRepository*, *MetricsDriver*, *MetricsFile*, *ReuseRepository* and *UserViews* as shown in Figure 3.4. *Metric* calculates 18 OO metrics, 2 traditional metrics and 3 reuse metrics. *MetricsRepository* and *ReuseRepository* hold the metric values for each of the classes considered. The data structure used is a dictionary where the key is the class name and the value is an array of metric values. *MetricsFile* writes the values stored in *MetricsRepository* and *ReuseRepository* in an ASCII comma-delimited file. *UserViews* includes interfaces that allow one to view the class metric values and set the file name of the ASCII comma-delimited file. Metrics are calculated using the metaclass *Class* of VisualAge, and a code metric tool (CMT) from Object Technology International Inc. (OTI). The

Table 3.1. CRC cards used to design a metric analyzer.

Metric	
Responsibilities	***Collaborators***
knows its value	
knows its threshold	MetricsFile
knows its description	
knows its journal_ref	
gets value	Class
knows its kind (system, class, method)	
sets thresholds	MetricsFile
MetricsFile	
Responsibilities	***Collaborators***
knows filename of Smalltalk code	GUI
knows filename of metric thresholds	GUI
retrieves Smalltalk code	FileIO
retrieves results	GUI
retrieves metric thresholds	FileIO
saves metric thresholds	Metric, FileIO
saves metric values	Metric, FileIO
Tool	
Responsibilities	***Collaborators***
knows views chosen (exemptions, details, all)	GUI
knows if counting external methods	GUI
knows quality indicator type (smiley, traffic light)	GUI
analyzes	MetricsFile, Metric
modifies thresholds	Metric
knows all possible metrics, initialize	MetricsFile
GUI	
Responsibilities	***Collaborators***
starts tool	Tool
selects file	User, FileIO, MetricsFile
Tells tool to analyze	Tool
displays results	Metric, Tool, MetricsFile
sets view	User, Tool
gets values	User
saves	MetricsFile
prints	FileIO
exits	

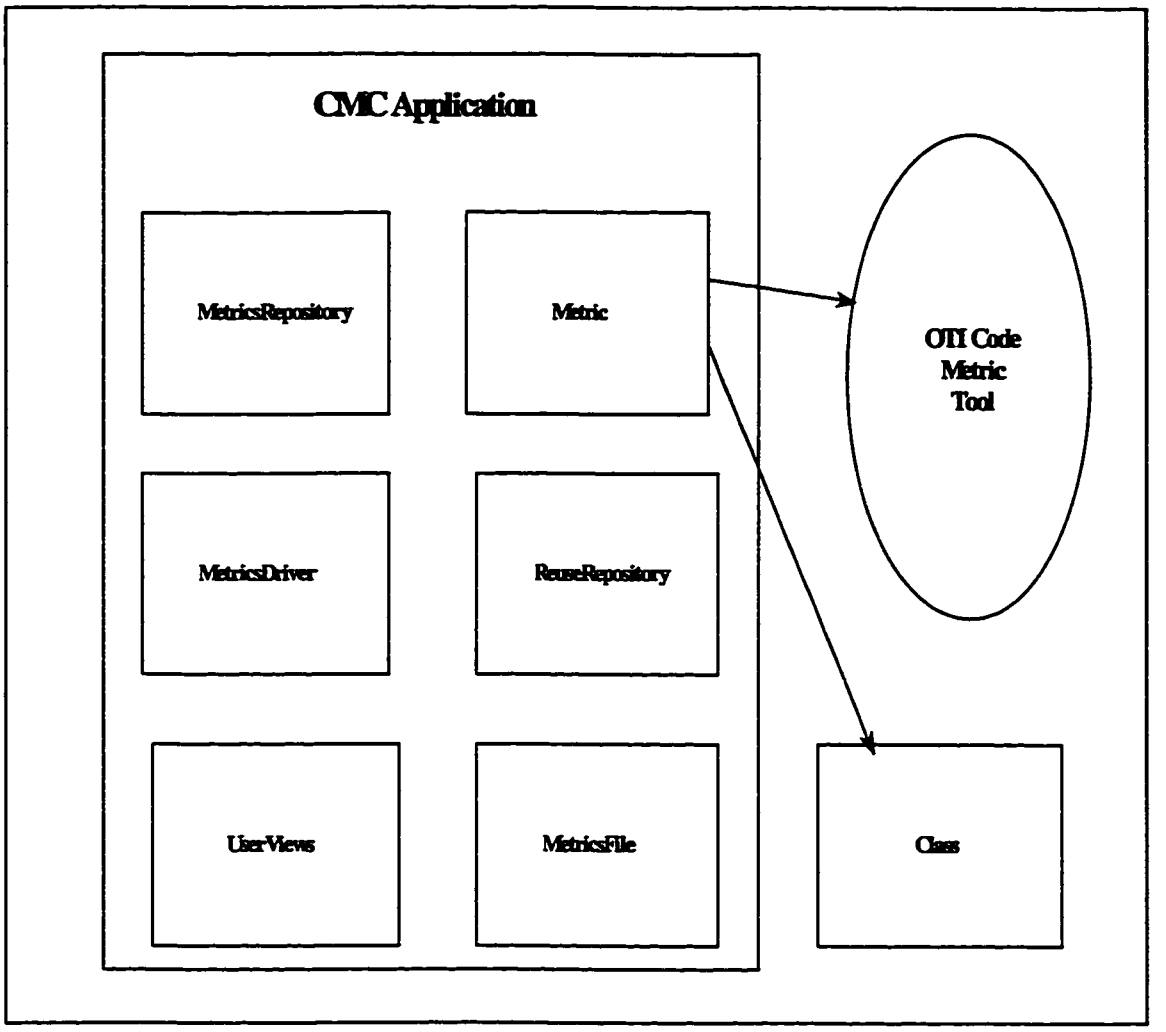

Figure 3.4. CMC classes.

CMT from OTI is linked to CMC to compute cyclomatic complexity, class coupling, lines of code, number of statements and Lorenz complexity. Fifteen metrics and three reuse metrics are computed using methods from the metaclass *Class*. A metaclass is "the class of a class; or a class whose instances are themselves classes" [Boo94].

Figure 3.5 shows a user interface view of the automated CMC. The list box labeled *Classes* holds the 2029 implemented classes. The text box at the top labeled *Application* is the application where the highlighted class is defined. For example, the *Collection* class is defined in the *CLDT* (Common Language Data Type) application. The container with two columns labeled *Metric Name* and *Value* holds the metric names and values of the highlighted class from the *Classes* list box. For example, the class *Collection* has the following metric values: *NumAllSuperclasses* = 1; *NumPublicMethods* = 34; *ReuseRatio* = 0.02. Moreover, the text box labeled *Total # of Classes* is the size of the classes list box. A dictionary inspector will be shown if the button labeled *Show Class Dictionary* is pushed. A dictionary inspector shows the key-value pairs of a given dictionary. In this case, the dictionary inspector will show the class name - metric value pairs. The file pull-down menu enables the user to save the metrics to an ASCII comma-delimited text so that it can be imported to MS Excel and Statistical Analysis System version 6.07 for regression and data analysis.

Figure 3.6 shows a portion of the saved metrics file where the first column is the class name, the next 20 columns are the metric values, and the last 3 columns are the values for the three proposed reuse measures.

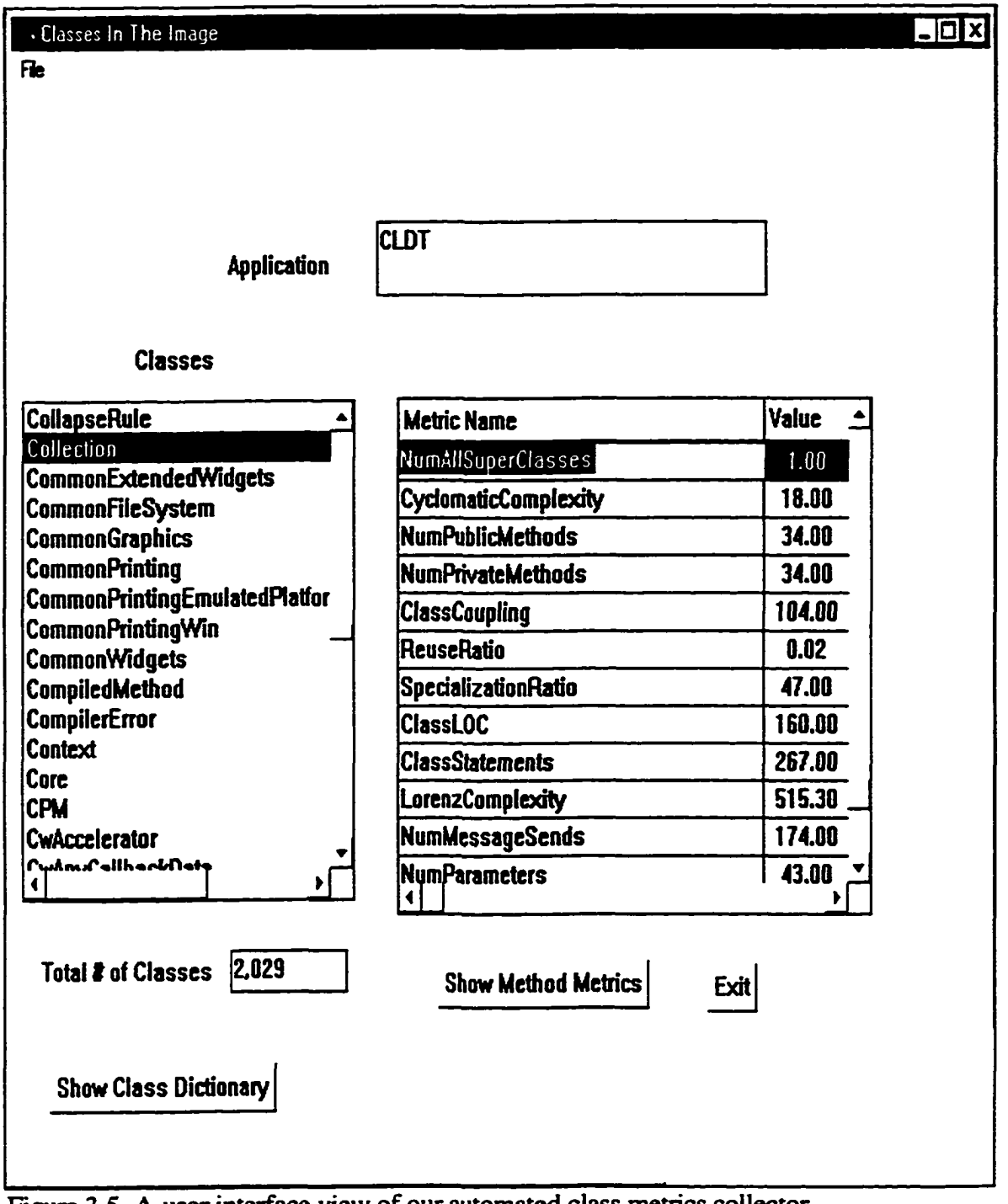

Figure 3.5. A user interface view of our automated class metrics collector.

```
ClassName, NDSub, NSub, NOM, NIM,NCV, NIV, NCMC, NIMC, NSup, CycC, NPubM, NPriM, CC, U, S, LOC,NOS, LC, NMS, NP
Array,2,2,11,9,0,0,2,5,4,17,10,1,57,0.08,0.5,30,51,123,38,14,30,3,1475
ArrayedCollection,4,10,34,30,0,0,1,4,3,11,22,12,23,0.06,3.333,129,249,473.7,136,37,325,1,0
Association,1,1,20,18,0,2,2,5,2,7,15,5,79,0.125,0.5,52,100,164.4,45,16,21,3,116
Bag,0,0,15,11,0,1,4,2,2,3,11,4,0,0.04,0,23,38,67.7,23,9,0,0,2
Behavior,1,7,284,282,0,9,2,14,1,47,103,181,227,0.111,7,957,1568,2812.3,836,200,685427,13,13
Block,3,4,29,28,0,0,1,6,1,25,20,9,36,0.167,4,117,211,429.2,127,60,124,3,1
```

Figure 3.6 An ASCII comma delimited saved metrics file that can be imported to MS Excel or SAS 6.07.

3.3 Reuse Measures

In this section, we define three class-level reuse metrics are defined: inheritance-based reuse (*RInherit*), inter-application reuse by extension (*RExt*) and inter-application reuse as a server (*RServ*). These measures are based on reuse approaches discussed in object-oriented literature [McG92], [Nie92], [Kar93].

3.3.1 Inheritance-based reuse (*RInherit*)

Proponents of OOP claim that inheritance is a great tool for software reuse. Subclasses naturally inherit behavior in the form of methods[Lor94]. In [Smi90]:

> "Using inheritance, a programmer can define a system of classes, or user-defined data types, wherein it is convenient to define subsequent classes in terms of their similarities to (and differences from) existing classes. In this manner, existing source code can be *reused* by deriving new classes that accommodate changes in the application."

Let C be a class, B be a container for overridden methods of C, and $|B|$ be the number of elements in B. If method m_i of C is overridden in three subclasses of C, m_i will appear three times in B. Then,

$$RInherit(C) = NOM(C) * NSub(C) - |B|. \tag{3.21}$$

This reuse measure is referred to as potential reuse. For example, in Figure 3.7,

$$\begin{aligned} RInherit(ClassW) &= NOM(ClassW) * NSub(ClassW) - |B| \\ &= 4 * 3 - 0 \\ &= 12 \end{aligned}$$

The rationale behind equation (3.21) is that C's methods are also methods of each of the subclasses of C by virtue of inheritance. In the preceding example, the methods <, >, <=, >= of class ClassW are 'reused' 12 times. To illustrate the case

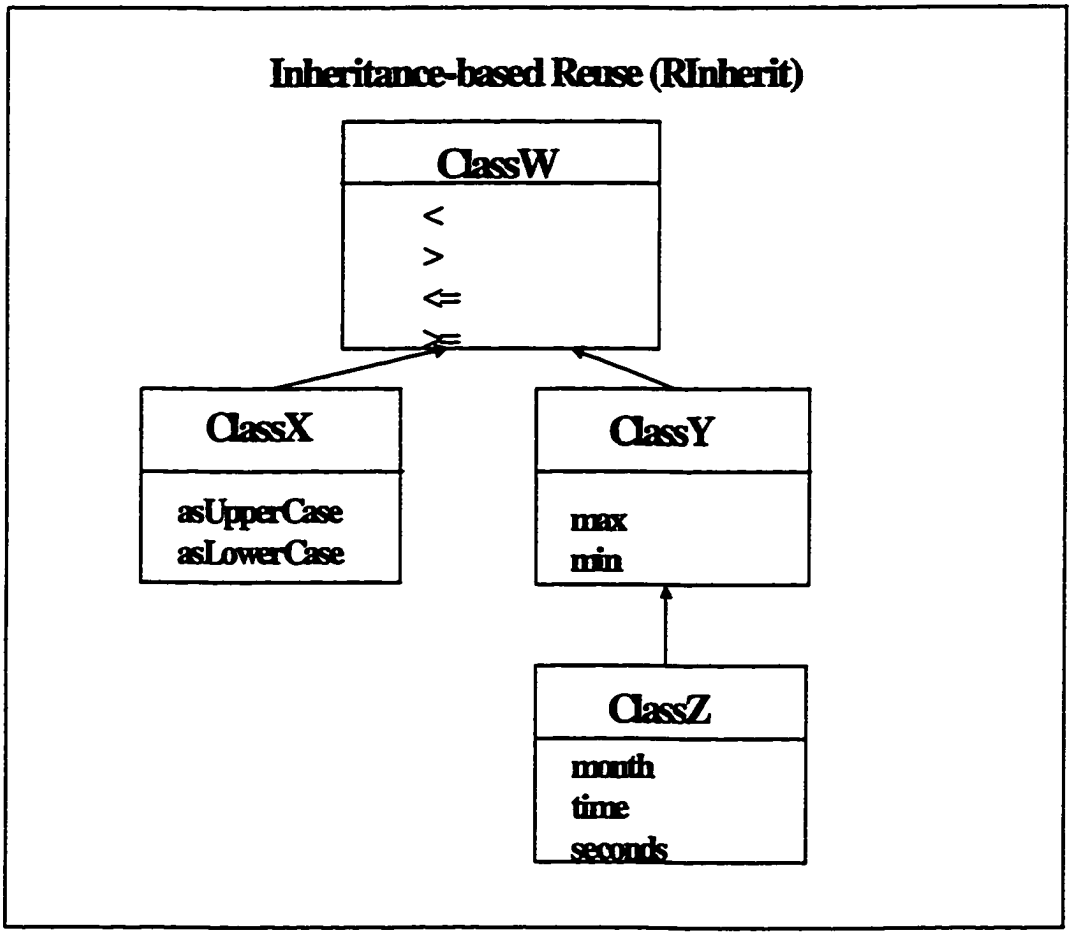

Figure 3.7. Example of inheritance-based reuse where no methods are overridden.

where there is an overridden method, consider Figure 3.8. Method < of *ClassW* was overridden in *ClassX* and *ClassZ*, hence,

$$RInherit(ClassW) = NOM(ClassW) * NSub(ClassW) - |B|$$

$$= 4 * 3 - 2$$

$$= 10$$

Thus, the inheritance-based reuse metric is a measure of inheritance activity.

3.3.2 Inter-application reuse by extension (*RExt*)

We define application as it is defined in VisualAge for Smalltalk which is:

> "A collection of defined and extended classes that provides a reusable piece of functionality. An application contains and organizes functionally related classes."[VA95].

This definition is not to be confused to mean a complete software system, such as banking or an accounting system.

Let *C* be a class, *A* be the application where *C* is defined, and *Aprime* be the set of all applications in the image minus *A*. Then,

$$RExt(C) = \text{number of times a class } C \text{ was extended by classes from applications in } Aprime. \quad (3.22)$$

A class extension is defined as :

> 'An extension to the functionality of a class defined by another application. The extension consists of one or more methods that define the added functionality or behavior. These methods cannot modify the existing behavior of the defined class; they can only add behavior specific to the application that contains the extended class.'[VA95].

This reuse measure is called actual reuse. For example in Figure 3.9, the class *Magnitude* of application *App2* was extended by class *MyDate* of application *OAppM* and class *MyTrigo* of application *OAppV*. Therefore, $RExt(Magnitude) = 2$.

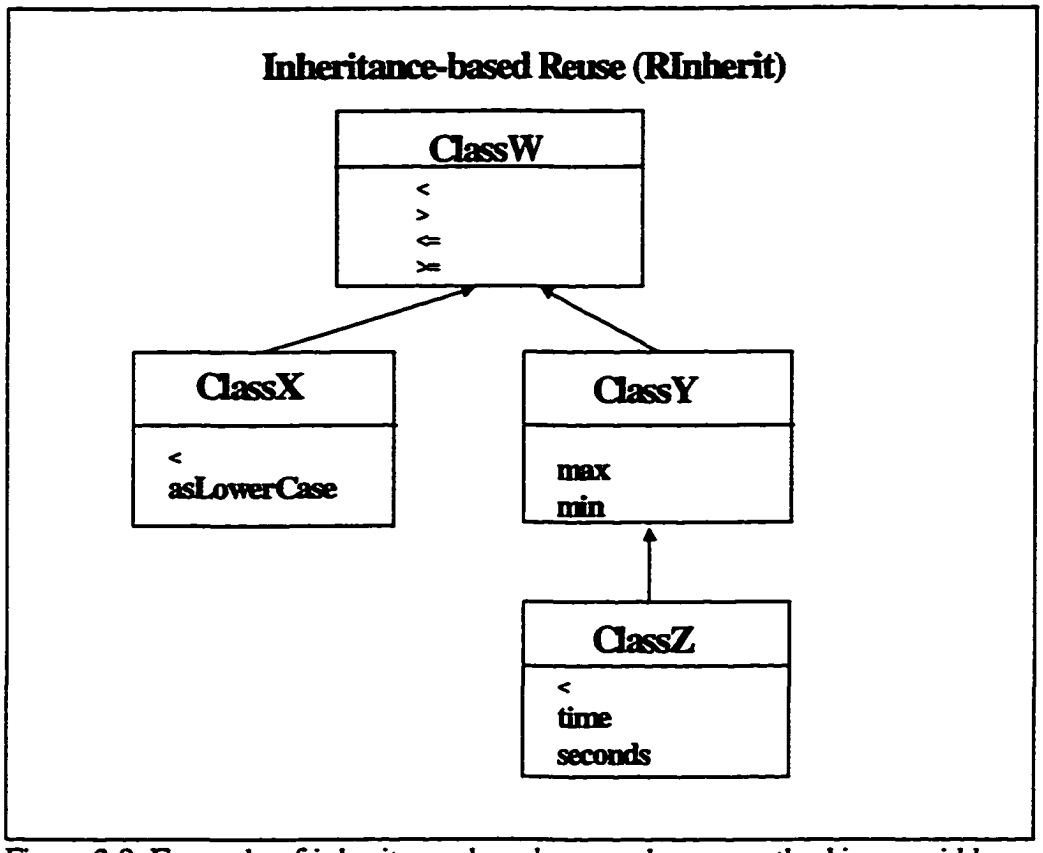

Figure 3.8. Example of inheritance-based reuse where a method is overridden.

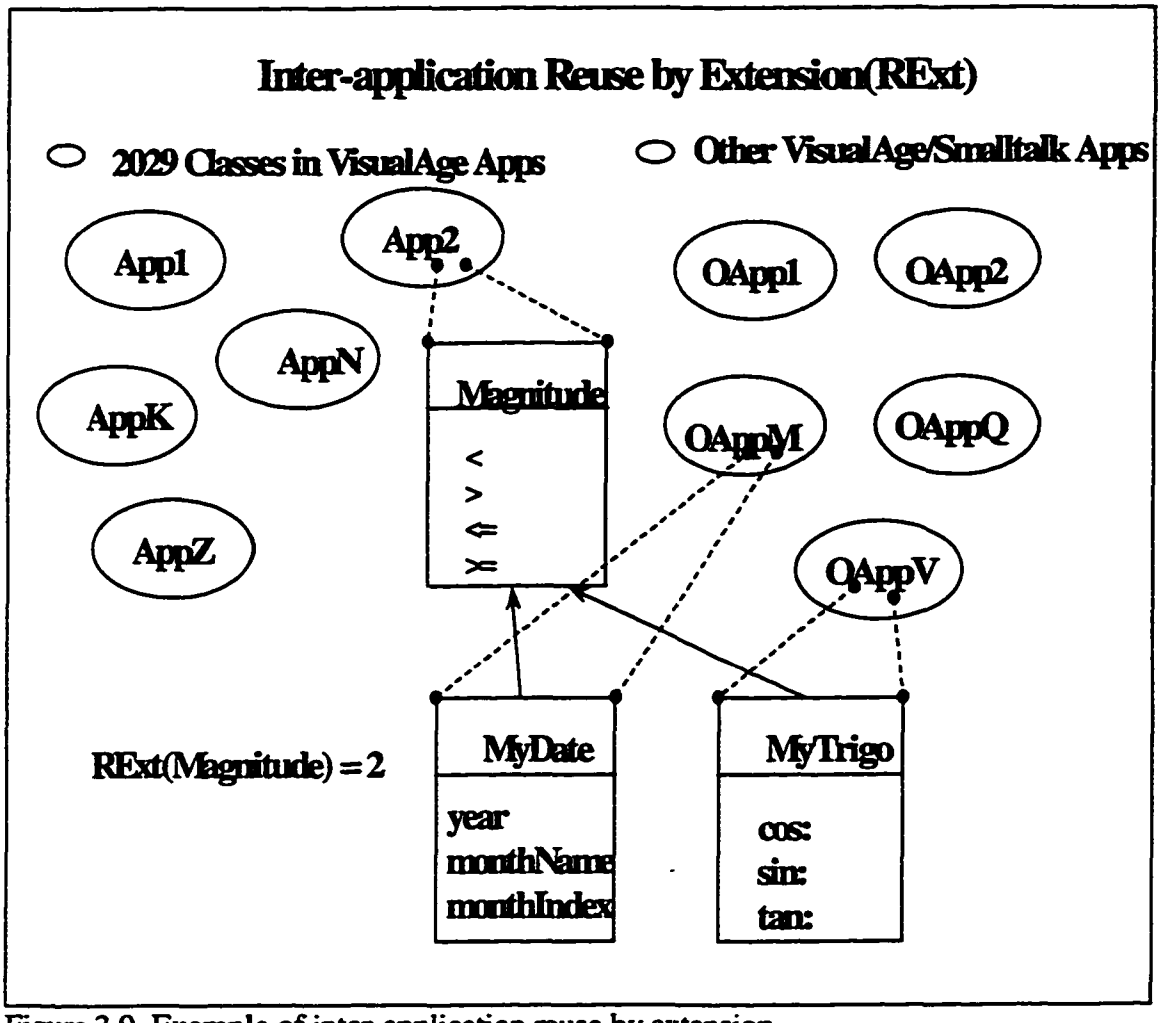

Figure 3.9. Example of inter-application reuse by extension.

3.3.3 Inter-application reuse as a server (*RServ*)

Let *C* be a class, *A* be the application where *C* is defined, and *Aprime* be the set of all applications in the image minus *A*.

RServ(C) = number of times *C* was directly referenced by classes from applications in *Aprime*. (3.23)

Equation (3.23) is classified as instance level reuse [McG92]. It also can be viewed as a reuse measure from a server perspective, as defined in [Kar93]. *RServ* differs from the server perspective definition in [Kar93] in the sense that it is only counting services *C* actually gives to classes in other applications in the Smalltalk image. This research excludes those that are inheritance-based references. One can argue that *RServ* is what [Chi93] called non-inheritance coupling, but *RServ* is a kind of reuse nonetheless. For example in Figure 3.10, let the class *Array* be defined in application App2. Suppose classes *A*, *B*, *C* and *D* defined in applications *AppN*, *OApp1*, *OAppM* and *OappV*, respectively, are the only classes in the image to have "*Array* new" as a Smalltalk expression in one of their methods. Then, *RServ(Array)* = 4. This reuse measure is called actual reuse.

3.4 Data and Statistical Analyses

3.4.1 Data

The data used in this research were 2029 implemented VisualAge for Smalltalk classes. Metrics for the 2029 classes were automatically collected using CMC. Reuse data, *RInherit*, *RExt*, and *RServ*, were automatically collected on 310 VisualAge for Smalltalk Professional applications. These applications were written by application developers in a commercial software company. Figures 3.11, 3.12 and 3.13 show the

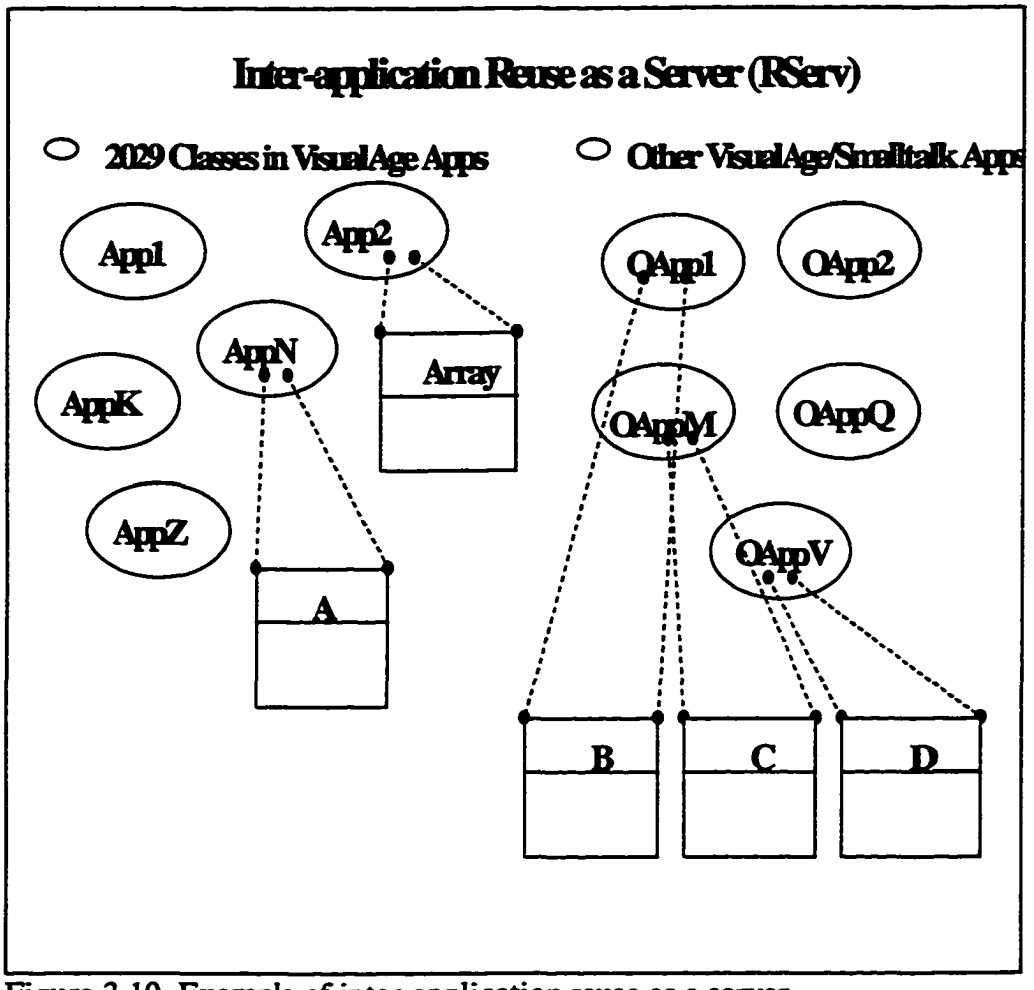

Figure 3.10. Example of inter-application reuse as a server.

```
buildInheritanceReuse
      "Count the number of methods that can be inherited in each class in the system"
      | reuseDict  metricValue validClassName array1 repository |
            repository := MetricsRepository.
            reuseDict :=MetricsRepository reuseDict.
            reuseDict
                  keysDo: [ :cls |  validClassName := Smalltalk at: cls asSymbol.
                                    metricValue := self inheritanceBasedReuseFor: validClassName.

                                                repository
                                                      reuseDict: cls
                                                      indexOfValue: 1
                                                      value: metricValue.].
inheritanceBasedReuseFor: aClass
      |aClassName inheritanceReuse  clsInstMethods clsMethods numOverridenMethods
            subMethods subInstMethods  |
      aClassName := aClass abrAsClass.
      clsMethods := aClassName class selectors.
      clsInstMethods := aClassName selectors.
      inheritanceReuse := aClassName allSubclasses size *
             (clsMethods size + (clsInstMethods size)).
      numOverridenMethods := 0.
      aClassName allSubclasses do:
            [:subCls |
                  subMethods := subCls class selectors.
                  subInstMethods := subCls selectors.
                  numOverridenMethods := (clsMethods size -
                        ((clsMethods epDifference: subMethods) size)) * (subCls allSubclasses size)
                              + numOverridenMethods.
                  numOverridenMethods := (clsInstMethods size - ((clsInstMethods epDifference:
subInstMethods) size))
                        * (subCls allSubclasses size)
                        + numOverridenMethods.  ].
       inheritanceReuse := inheritanceReuse - numOverridenMethods.
       ^inheritanceReuse
```

Figure 3.11. Smalltalk scripts used to compute RInherit.

```
buildInterApplicationReuse

      "Count base classes that were reused by extension in the system"
      | reuseDict  metricValue validClassName array1 repository extendedClassesBag |

            extendedClassesBag := self extendedClasses.
            repository := MetricsRepository.
            reuseDict :=MetricsRepository reuseDict.
            reuseDict
                  keysDo: [ :cls |  validClassName := Smalltalk at: cls asSymbol.
                                    metricValue := extendedClassesBag occurrencesOf: validClassName.
                                          repository
                                                                        reuseDict: cls
                                                                        indexOfValue: 2
                                                                        value: metricValue.].
extendedClasses

      "Return a bag of classes that are extended by applications in the image"

      | allAppsList  extendedClasses |

      extendedClasses := Bag new.
      allAppsList := System epLoadedApplications asSortedCollection: [:a :b| a name < b name].
      allAppsList do: [:e| | xtended |
            xtended := e extended.
            (xtended size = 0)
                  ifFalse: [ xtended do:
                                          [:cls | ((cls controller printString) = e printString)
                                                      ifFalse: [extendedClasses add: cls.
                                                                  ].
                                          ].
                              ].
                        ].
      ^extendedClasses
```

Figure 3.12. Smalltalk scripts used to compute RExt.

```
buildInterAppServerReuse

      "Count the number of all methods from another app referencing each class in the system"

      | reuseDict  metricValue validClassName array1 repository |

            repository := MetricsRepository.
            reuseDict :=MetricsRepository reuseDict.
            reuseDict
                  keysDo: [ :cls |   validClassName := Smalltalk at: cls asSymbol.
                                                metricValue := self
numberOfInterAppMethodsReferencing: validClassName.
                                                repository
                                                            reuseDict: cls
                                                            indexOfValue: 3
                                                            value: metricValue.     ].
numberOfInterAppMethodsReferencing: anObject

      "anObject can be a class, a method
      Return the classes from another application that references anObject "

      | answer methods |

      answer := OrderedCollection new.
      Class subclasses do: [:cl |
            cl isMetaclass ifTrue: [answer add: cl primaryInstance]].
            methods := nil.
      answer do: [:cl |
                  methods isNil
                        ifTrue: [methods := cl allMethodsReferencingLiteral: anObject]
                        ifFalse: [methods addAll: (cl allMethodsReferencingLiteral: anObject)]].
      ^(methods select: [: e | (e methodClass controller = anObject controller) not]) size
```

Figure 3.13. Smalltalk scripts used to compute RServ.

Smalltalk scripts used to compute *RInherit*, *RExt* and *RServ*. For each of the three reuse measures, these 2029 classes were grouped into two categories, those with dependent variable values greater than one, and those with dependent variable values equal to zero or one. The data set used to regress *RInherit* with the 20 metrics was derived as follows: Let A = {2029 implemented classes}.

1) Partition A into two groups *RInheritPlus* and *RInheritZeroOne* where

   RInheritPlus = {classes whose *RInherit* values are greater than 1} and

   RInheritZeroOne = {classes whose *RInherit* values are 0 or 1}.

The data set used to regress *RExt* with the 20 metrics was derived as follows:

1) Let A = {2029 implemented classes}.
2) Partition A into two groups *RExtPlus* and *RExtZeroOne* where

   RExtPlus = {classes whose *RExt* values are greater than 1} and

   RExtZeroOne = {classes whose *RExt* values are 0 or 1}.

The data set used to regress *RServ* with the 20 metrics was derived as follows:

1) Let A = {2029 implemented classes}.
2) Partition A into two groups *RServPlus* and *RServZeroOne* where

   RServPlus = {classes whose *RServ* values are greater than 1} and

   RServZeroOne = {classes whose *RServ* values are 0 or 1}.

For example, in Figure 3.6, the class *Array* is in *RInheritPlus*, *RExtPlus*, *RServPlus* since *RInherit*(*Array*) = 30, *RExt*(*Array*) = 3 and *RServ*(*Array*) = 1475. *Bag* on the other hand is in *RInheritZeroOne*, *RExtZeroOne*, *RServPlus*.

3.4.2 Statistical Analyses

Four statistical analyses were performed to investigate the following questions:

- Are the population means of the reusable and non-reusable groups the same?
- Are there object-oriented metrics that can predict *RInherit*, *RExt* and *RServ*?
- Are the prediction equations for *RInherit*, *RExt* and *RServ* empirically valid?
- Are any of the 20 metrics in the reusable groups correlated?
- Are *RInherit*, *RExt* and *RServ* correlated?

3.4.2.1 Comparison Between Two Groups: Classes that were reused vs. classes that were not reused

The goal of the first statistical analysis was to test the following hypotheses:

1) H_0: The population means of *RInheritPlus* and *RInheritZeroOne* are the same.

   H_1: The population means of *RInheritPlus* and *RInheritZeroOne* are not the same.

2) H_0: The population means of *RExtPlus* and *RExtZeroOne* are the same.

   H_1: The population means of *RExtPlus* and *RExtZeroOne* are not the same.

3) H_0: The population means of *RServPlus* and *RServZeroOne* are the same.

   H_1: The population means of *RServPlus* and *RServZeroOne* are not the same.

The PROC TTEST from SAS was performed to test the hypotheses that the population means of the *RInherit* and *RInheritZeroOne*, *RExt* and *RextZeroOne*, *RServ* and *RServZeroOne* are the same. A test is significant if the two-tailed probability of H_0 being true is five percent or less, i.e. $\alpha = 0.05$. If the p-value associated with $metric_i$ is

less than 0.05, then the mean $metric_i$ values for those classes that were reused and those classes that were not reused are significantly different.

A nonparametric test NPAR1WAY procedure from SAS was also performed since it does not assume anything about that the underlying distribution of the data set. The test statistic used was the Wilcoxon 2-sample test which performs an analysis of the ranks of the data. It is a nonparametric procedure for testing that the distribution of a variable has the same location parameter across different groups [SAS90].

3.4.2.2 Stepwise Regression

The goal of the second statistical analysis was to test the following hypotheses:

1) H_0: The dependent variable *RInherit* is not linearly related to a subset of the 20 metrics.

   H_1: The dependent variable *RInherit* is linearly related to a subset of the 20 metrics.

2) H_0: The dependent variable *RExt* is not linearly related to a subset of the 20 metrics.

   H_1: The dependent variable *RExt* is linearly related to a subset of the 20 metrics.

3) H_0: The dependent variable *RServ* is not linearly related to a subset of the 20 metrics.

   H_1: The dependent variable *RServ* is linearly related to a subset of the 20 metrics.

Stepwise regression was used to test these hypotheses. Using the groups *RInheritPlus*, *RExtPlus*, *RServPlus*, three prediction equations were derived for each of

the proposed reuse measures using the 20 metrics as the independent variables and the reuse measures applied separately, as the dependent variable. SAS was used to perform stepwise regression analyses on the groups of classes that have positive dependent variable values, i.e. groups *RInheritPlus*, *RExtPlus*, *RServPlus*. Only those classes in these groups were considered since this research is concerned with characterizing 'reusable' classes. Sequential variable selection procedures exist that arrive efficiently at a reasonable subset of regressor or independent variables from a large number of possible variables [Mye90]. Stepwise regression adds a variable to the regression model one by one, depending on whether the F statistic for a variable is significant at a given level [SAS90]. After a variable is added to the regression model, stepwise regression deletes any variable already in the model that has an F statistic not significant at a given level. At each stage, a regressor can be entered in the model while another can be eliminated. The rationale is that multicollinearity can render a regressor variable of little value [Mye90]. Multicollinearity involves associations among multiple independent variables. Significance is defined as when the p-value or two-tailed probability of H_0 being true is five percent or less. In [Wei85], p-value is defined as

> "the conditional probability of observing a value of the computed statistic as extreme or more extreme than the observed value, given that H_0 is true."

In this specific case, the p-value is the probability that the regression coefficient is different from zero by chance [Bas96]. If the p-value is less than five percent, there is sufficient evidence to reject H_0.

3.4.2.3. Empirical Validation

The third statistical analysis is for the purpose of empirically validating the prediction equations derived from the stepwise regression analysis. Validation of a prediction system is the process of establishing the accuracy of the prediction system by empirical means, that is, by comparing model performance with known data points in the given environment [Fen91]. In [Bas96],

> "Empirical validation aims at demonstrating the usefulness of a measure in practice and is, therefore, a crucial activity to establish the overall validity of a measure. A measure may be correct from a measurement theory perspective (i.e., be consistent with the agreed upon empirical relational system) but be of no practical relevance to the problem at hand. On the other hand, a measure may not be entirely satisfactory from a theoretical perspective but can be a good enough approximation and work fine in practice."

From the prediction equations derived in Section 2, predicted *RInherit*, predicted *RExt*, and predicted *RServ* were calculated. A new set of 310 applications and subapplications were used to validate the prediction equations derived from the previous section. These applications were not contained in the set of 2029 classes. For each of the 2029 implemented classes, new values for *RInherit*, *RExt* and *RServ* were calculated by CMC with the new set of 310 applications loaded in the VisualAge for Smalltalk image. These new values are the known data points in the validation definition by [Fen91]. If the predicted values are highly correlated with actual values from the new set of data, then the prediction equation gives satisfactory results.

3.4.2.4 Correlation Coefficients

The goal of the fourth statistical analysis is to answer the questions: Are any of the 20 metrics in the reusable groups correlated? Are *RInherit*, *RExt* and *RServ*

correlated? The Pearson product moment correlation coefficient, *r*, is a dimensionless index that ranges from -1.0 to 1.0 inclusive and reflects the extent of a linear relationship between two data sets [MSO97]. For example, if the *r* value associated with *Metric1* and *Metric2* is close to zero, then the metric values of *Metric1* and *Metric2* are not linearly related. On the other hand, if *r* is close to 1, then large values of *Metric1* are associated with large values of *Metric2*. Finally, if *r* is close to –1, then large values of *Metric1* are linearly associated with small values of *Metric2*. The sign of the correlation coefficient indicates whether two variables are directly or inversely related. A negative value means that as *Metric1* becomes larger, *Metric2* tends to be smaller. A positive correlation means that both *Metric1* and *Metric2* go in the same direction [SAS91].

3.5 Summary

This chapter described the materials and method used to investigate the reuse potential of objects. A class metric collector was described which automatically extracts the 20 metrics and the three reuse measures. The data sets used for the study were also presented. Finally the statistical procedures t-test, stepwise regression, and correlation coefficients were described. These procedures will answer these questions:

Are the population means of the reusable and non-reusable groups the same?

Are there object-oriented metrics that can predict *RInherit*, *RExt* and *RServ*?

Are the prediction equations from 2. empirically valid?

Are any of the 20 metrics in the reusable groups correlated?

Are *RInherit*, *RExt* and *RServ* correlated?

Chapter 4 gives the results and discussion.

Chapter 4. Results and Discussion

Sections 4.1 through 4.4 describe the results for each of the four statistical analyses described in Chapter 3.4.2. Section 4.1 discusses results obtained from performing T-test and a nonparametric test to compare mean metric values between the reusable and non-reusable groups. Section 4.2 describes the results of stepwise regression for *RInherit*, *RExt* and *RServ*. Section 4.3 presents results of validating the models derived in Section 4.2. Finally, Section 4.4 discusses the results of testing for correlation among the metrics. In addition Figure 3.1 is included here as Figure 4.1 for the convenience of the reader.

4.1 Comparison Between Two Groups

We answer the question: Are the population means of the reusable and non-reusable groups the same? Section 4.1.1 gives the results of analyzing the data using T-test.

4.1.1 T-test

Sections 4.1.1.1, 4.1.1.2 and 4.1.1.3 describe the results of analyzing the data using t-test. Section 4.1.1.1 gives the results of comparing the groups *RInheritPlus* and *RInheritZeroOne*. Section 4.1.1.2 describes the results of comparing the groups *RExtPlus* and *RExtZeroOne*. Section 4.1.1.3 presents the results of comparing the groups *RServPlus* and *RServZeroOne*.

4.1.1.1 Inheritance-based reuse

Table 4.1 presents the t-test results for the groups *RInheritPlus* and *RInheritZeroOne*. A one-sided test gives the direction of the difference in the mean metric values of classes in *RInheritPlus* and *RInheritZeroOne*. The mean metric values

Metric	Abbreviation
Number of direct subclasses	*NDSub*
Number of all subclasses	*NSub*
Number of methods	*NOM*
Number of instance methods	*NIM*
Number of class variables	*NCV*
Number of instance variables	*NIV*
Number of class method categories	*NCMC*
Number of instance method categories	*NIMC*
Number of all superclasses	*Nsup*
Cyclomatic complexity	*CycC*
Number of public methods	*NpubM*
Number of private methods	*NpriM*
Class coupling	*CC*
Reuse ratio	*U*
Specialization ratio	*S*
Lines of code	*LOC*
Number of statements	*NOS*
Lorenz complexity	*LC*
Number of message sends	*NMS*
Number of parameters	*NP*

Figure 4.1. Object-oriented metrics.

Table 4.1. RInherit: T-test between classes that are reused (+) vs. classes that are not reused (0 and 1).

	Mean	Std Dev	Prob>|T|
NDSub			
0*	0.0107	0.1608	0.0001
+*	4.8822	24.0030	
NSub			
0	0.0108	0.1608	0.0035
+	17.2378	124.6551	
NOM			
0	17.3129	26.4832	0.0001
+	38.3511	55.3401	
NIM			
0	14.0152	24.0546	0.0001
+	32.1622	48.1651	
NCV			
0	0.2609	1.1679	0.6389
+	0.2911	1.2132	
NIV			
0	2.0975	4.5422	0.0001
+	3.6289	5.2388	
NCMC			
0	0.8144	0.8074	0.0001
+	1.1000	1.4442	
NIMC			
0	1.2470	1.3616	0.0001
+	2.2733	2.9515	
NSup			
0	3.5554	1.8553	0.0029
+	3.2378	2.0252	
CycC			
0	6.5649	12.7689	0.0001
+	12.0378	20.7669	
NPubM			
0	8.1989	15.0800	0.0001
+	16.0844	30.8402	
NPriM			
0	9.1140	17.8005	0.0001
+	22.2667	34.2472	
CC			
0	42.2052	65.1300	0.0001
+	62.2133	69.4463	
U			
0	0.1478	0.2024	0.0001
+	0.1159	0.1259	
S			
0	0.0667	2.5170	0.0001
+	7.0384	32.8230	
LOC			
0	79.9924	207.8276	0.0001
+	149.9844	249.6177	
NOS			
0	136.3641	321.0069	0.0001
+	253.4311	417.3737	
LC			
0	273.4148	667.2020	0.0001
+	480.0327	794.1482	
NMS			
0	60.2888	134.2371	0.0001
+	132.2333	218.6975	
NP			
0	10.3743	27.3701	0.0001
+	25.8422	44.9185	

*0 = RInheritZeroOne, number of samples =1579

*+ = RInheritPlus, number of samples = 450

may be used as a guide to judge whether a class will be reused through inheritance at least two or more times.

At $\alpha = 0.05$, the mean *NDSub* value of classes in *RInheritPlus* is greater than the mean *NDSub* value of classes in *RInheritZeroOne*. The mean of *NDSub* in *RInheritPlus* is 4.88, and 0.01 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have approximately five direct subclasses, while classes that are not reusable have a value close to zero. Classes that have an *NSub* value close to zero means that these classes are at the bottom of the hierarchy. They have no children who can inherit their behavior, and thus, are not reusable by inheritance.

At $\alpha = 0.05$, the mean *NSub* value of classes in *RInheritPlus* is greater than the mean *NSub* value of classes in *RInheritZeroOne*. The mean of *NSub* in *RInheritPlus* is 17.24, and 0.01 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have about 17 subclasses, while classes that are not reusable have close to zero subclass. This result is expected since leaf classes have no children who can inherit their behavior.

At $\alpha = 0.05$, the mean *NOM* value of classes in *RInheritPlus* is greater than the mean *NOM* value of classes in *RInheritZeroOne*. The mean of *NOM* in *RInheritPlus* is 38.35 and 17.31 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have about 38 methods, while classes that are not reusable have about 17. This result is expected since classes that have a high number of methods have more inheritance-based reuse potential since these methods will be the behavior that their subclasses will freely inherit. Note that classes in *RInheritPlus* have almost twice the number of methods compared with classes in *RInheritZeroOne*.

At $\alpha = 0.05$, the mean *NIM* value of classes in *RInheritPlus* is greater than the mean *NIM* value of classes in *RInheritZeroOne*. The mean of *NIM* in *RInheritPlus* is 32.16 and 14.01 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have about 32 instance methods, while classes that are not reusable have about 14.

At $\alpha = 0.05$, the mean *NIV* value of classes in *RInheritPlus* is greater than the mean *NIV* value of classes in *RInheritZeroOne*. The mean of *NIV* in *RInheritPlus* is 3.62 and 2.10 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have about four instance variables, while classes that are not reusable have about two.

At $\alpha = 0.05$, the mean *NCMC* value of classes in *RInheritPlus* is greater than the mean *NCMC* value of classes in *RInheritZeroOne*. The mean of *NCMC* in *RInheritPlus* is 1.1 and 0.81 in *RInheritZeroOne*. The mean difference is small, so categorizing whether a class is reusable will be difficult.

At $\alpha = 0.05$, the mean *NIMC* value of classes in *RInheritPlus* is greater than the mean *NIMC* value of classes in *RInheritZeroOne*. The mean of *NIMC* in *RInheritPlus* is 2.27 and 1.25 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have about two instance method categories, while classes that are not reusable have about one.

At $\alpha = 0.05$, the mean *NSup* value of classes in *RInheritPlus* is less than the mean *NSup* value of classes in *RInheritZeroOne*. The mean of *NSup* in *RInheritPlus* is 3.24 and 3.56 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based

reuse value have about three superclasses, while classes that are not reusable have about four.

At $\alpha = 0.05$, the mean *CycC* value of classes in *RInheritPlus* is greater than the mean *CycC* value of classes in *RInheritZeroOne*. The mean of *CycC* in *RInheritPlus* is 12.04 and 6.56 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have cyclomatic complexity about 12, while classes that are not reusable have about seven.

At $\alpha = 0.05$, the mean *NPubM* value of classes in *RInheritPlus* is greater than the mean *NPubM* value of classes in *RInheritZeroOne*. The mean of *NPubM* in *RInheritPlus* is 16.08 and 8.2 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have about 16 public methods, while classes that are not reusable have about eight.

At $\alpha = 0.05$, the mean *NPriM* value of classes in *RInheritPlus* is greater than the mean *NPriM* value of classes in *RInheritZeroOne*. The mean of *NPriM* in *RInheritPlus* is 22.27 and 9.11 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have about 22 private methods, while classes that are not reusable have about nine.

At $\alpha = 0.05$, the mean *CC* value of classes in *RInheritPlus* is greater than the mean *CC* value of classes in *RInheritZeroOne*. The mean of *CC* in *RInheritPlus* is 62.21 and 42.21 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have a class coupling value of about 62, while classes that are not reusable have a value of about 42. This result shows that the higher the *CC* value of a

class, the more likely this class will be reused by inheritance at least two times. As noted earlier, inheritance increases coupling.

At $\alpha = 0.05$, the mean *U* value of classes in *RInheritPlus* is less than the mean *U* value of classes in *RInheritZeroOne*. The mean of *U* in *RInheritPlus* is 0.15 and 0.12 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have reuse ratio about 0.11, while classes that are not reusable have about 0.15.

At $\alpha = 0.05$, the mean *S* value of classes in *RInheritPlus* is greater than the mean *S* value of classes in *RInheritZeroOne*. The mean of *S* in *RInheritPlus* is 7.04 and 0.07 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have specialization value of about seven, while the specialization value of classes that are not reusable is close to zero.

At $\alpha = 0.05$, the mean *LOC* value of classes in *RInheritPlus* is greater than the mean *LOC* value of classes in *RInheritZeroOne*. The mean of *LOC* in *RInheritPlus* is 149.98 and 79.99 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have about 150 lines of code, while classes that are not reusable have about 80.

At $\alpha = 0.05$, the mean *NOS* value of classes in *RInheritPlus* is greater than the mean *NOS* value of classes in *RInheritZeroOne*. The mean of *NOS* in *RInheritPlus* is 253.43 and 136.36 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have about 253 statements, while classes that are not reusable have about 136.

At $\alpha = 0.05$, the mean *LC* value of classes in *RInheritPlus* is greater than the mean *LC* value of classes in *RInheritZeroOne*. The mean of *LC* in *RInheritPlus* is

480.03 and 273.41 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have *LC* measure of about 480, while classes that are not reusable have about 273.

At $\alpha = 0.05$, the mean *NMS* value of classes in *RInheritPlus* is greater than the mean *NMS* value of classes in *RInheritZeroOne*. The mean of *NMS* in *RInheritPlus* is 132.23 and 60.29 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have about 132 message sends, while classes that are not reusable have about 60.

At $\alpha = 0.05$, the mean *NP* value of classes in *RInheritPlus* is greater than the mean *NP* value of classes in *RInheritZeroOne*. The mean of *NP* in *RInheritPlus* is 25.84 and 10.37 in *RInheritZeroOne*. Classes that are reusable based on their inheritance-based reuse value have about 26 parameters, while classes that are not reusable have about 10.

Section 4.1.1.2 shows that the mean metric values of the reusable group *RInheritPlus* and non-reusable group *RInheritZeroOne* are generally not the same. In summary, at $\alpha = 0.05$, the mean metric values of { *NDSub, NSub, NOM, NIM, NIV, NCMC, NIMC, NSup, CycC, NPubM, NPriM, CC, U, S, LOC, NOS, LC, NMS and NP* } are significantly different between classes in *RInheritPlus* and *RInheritZeroOne*. The mean metric values of *NCV* are **not** significantly different between classes in *RInheritPlus* and *RInheritZeroOne*.

4.1.1.2 Inter-application reuse by extension

Table 4.2 presents the t-test results for the groups *RExtPlus* and *RExtZeroOne*. A one-sided test gives the direction of the difference in the mean metric values of classes in

Table 4.2. RExt: T-test between classes that are reused (+) vs. classes that are not reused (0 and 1).

	Mean	Std Dev	Prob>|T|
NDSub			
0*	0.5814	5.0468	0.0283
+*	4.6535	29.3656	
Nsub			
0	1.38882	10.8487	0.0588
+	20.9055	163.7928	
NOM			
0	16.9549	25.1051	0.0001
+	57.0866	67.7375	
NIM			
0	13.9363	23.3679	0.0001
+	46.7165	58.3888	
NCV			
0	0.1955	0.9489	0.0001
+	0.7717	2.1253	
NIV			
0	2.2045	4.5017	0.0001
+	4.063	5.9587	
NCMC			
0	0.7538	0.6780	0.0001
+	1.7441	1.9483	
NIMC			
0	1.2152	1.3917	0.0001
+	3.2874	3.3362	
Nsup			
0	3.5442	1.9012	0.0002
+	3.0709	1.8294	
CycC			
0	5.9042	9.6956	0.0001
+	20.8780	31.1078	
NpubM			
0	7.6496	13.6086	0.0001
+	26.0079	39.9729	
NPriM			
0	9.3053	18.0840	0.0001
+	31.0787	39.8466	
CC			
0	41.2276	62.0049	0.0001
+	84.4843	83.4829	
U			
0	0.1398	0.1907	0.5522
+	0.1468	0.1730	
S			
0	0.7122	5.3884	0.0069
+	7.9073	42.0679	
LOC			
0	76.1955	188.6428	0.0001
+	230.5276	341.0489	
NOS			
0	129.7245	292.9132	0.0001
+	390.1653	556.4687	
LC			
0	258.4444	605.8115	0.0001
+	744.0858	1083.6628	
NMS			
0	59.1527	128.4950	0.0001
+	195.6890	268.8709	
NP			
0	10.0862	26.0351	0.0001
+	39.7913	55.2857	

*0 = RExtZeroOne, number of samples =1775

*+ = RExtPlus, number of samples = 254

RExtPlus and *RExtZeroOne*. The mean metric values may be used as a guide to judge whether a class will be reused in another application by extension at least two or more times.

At $\alpha = 0.05$, the mean *NDSub* value of classes in *RExtPlus* is greater than the mean *NDSub* value of classes in *RExtZeroOne*. The mean of *NDSub* in *RExtPlus* is 4.65 and 0.58 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about five direct subclasses, while classes that are not reusable have about one. The greater the number of direct subclasses of a class are, the more likely they will be reused by extension.

At $\alpha = 0.05$, the mean *NOM* value of classes in *RExtPlus* is greater than the mean *NOM* value of classes in *RExtZeroOne*. The mean of *NOM* in *RExtPlus* is 57.09 and 16.95 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about 57 methods, while classes that are not reusable have about 17.

At $\alpha = 0.05$, the mean *NIM* value of classes in *RExtPlus* is greater than the mean *NIM* value of classes in *RExtZeroOne*. The mean of *NIM* in *RExtPlus* is 46.72 and 13.94 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about 46 instance methods, while classes that are not reusable have about 14.

At $\alpha = 0.05$, the mean *NCV* value of classes in *RExtPlus* is greater than the mean *NCV* value of classes in *RExtZeroOne*. The mean of *NCV* in *RExtPlus* is 0.77 and 0.20 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by

extension value have about one class variable, while classes that are not reusable have about zero.

At $\alpha = 0.05$, the mean *NIV* value of classes in *RExtPlus* is greater than the mean *NIV* value of classes in *RExtZeroOne*. The mean of *NIV* in *RExtPlus* is 4.06 and 2.20 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about four instance variables, while classes that are not reusable have about two.

At $\alpha = 0.05$, the mean *NCMC* value of classes in *RExtPlus* is greater than the mean *NCMC* value of classes in *RExtZeroOne*. The mean of *NCMC* in *RExtPlus* is 1.74 and 0.75 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about two class method categories, while classes that are not reusable have about one.

At $\alpha = 0.05$, the mean *NIMC* value of classes in *RExtPlus* is greater than the mean *NIMC* value of classes in *RExtZeroOne*. The mean of *NIMC* in *RExtPlus* is 3.29 and 1.22 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about three instance method categories, while classes that are not reusable have about one.

At $\alpha = 0.05$, the mean *NSup* value of classes in *RExtPlus* is less than the mean *NSup* value of classes in *RExtZeroOne*. The mean of *NSup* in *RExtPlus* is 3.07 and 3.54 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about three superclasses, while classes that are not reusable have about four.

At $\alpha = 0.05$, the mean *CycC* value of classes in *RExtPlus* is greater than the mean *CycC* value of classes in *RExtZeroOne*. The mean of *CycC* in *RExtPlus* is 20.89 and 5.9 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have cyclomatic complexity about 21, while classes that are not reusable have about 6.

At $\alpha = 0.05$, the mean *NPubM* value of classes in *RExtPlus* is greater than the mean *NPubM* value of classes in *RExtZeroOne*. The mean of *NPubM* in *RExtPlus* is 26.01 and 7.65 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about 26 public methods, while classes that are not reusable have about eight.

At $\alpha = 0.05$, the mean *NPriM* value of classes in *RExtPlus* is greater than the mean *NPriM* value of classes in *RExtZeroOne*. The mean of *NPriM* in *RExtPlus* is 31.08 and 9.31 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about 31 private methods, while classes that are not reusable have about nine.

At $\alpha = 0.05$, the mean *CC* value of classes in *RExtPlus* is greater than the mean *CC* value of classes in *RExtZeroOne*. The mean of *CC* in *RExtPlus* is 84.48 and 41.23 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have a class coupling value of about 84, while classes that are not reusable have about 41. This result shows that the higher the *CC* value of a class, the more likely this class will be reused by extension two or more times.

At $\alpha = 0.05$, the mean *S* value of classes in *RExtPlus* is greater than the mean *S* value of classes in *RExtZeroOne*. The mean of *S* in *RExtPlus* is 7.91 and 0.71 in

RExtZeroOne. Classes that are reusable based on their inter-application reuse by extension value have specialization value approximately equal to eight, while classes that are not reusable have about one.

At $\alpha = 0.05$, the mean *LOC* value of classes in *RExtPlus* is greater than the mean *LOC* value of classes in *RExtZeroOne*. The mean of *LOC* in *RExtPlus* is 230.53 and 76.20 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about 231 lines of code, while classes that are not reusable have about 76.

At $\alpha = 0.05$, the mean *NOS* value of classes in *RExtPlus* is greater than the mean *NOS* value of classes in *RExtZeroOne*. The mean of *NOS* in *RExtPlus* is 390.17 and 129.72 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about 290 statements, while classes that are not reusable have about 130.

At $\alpha = 0.05$, the mean *LC* value of classes in *RExtPlus* is greater than the mean *LC* value of classes in *RExtZeroOne*. The mean of *LC* in *RExtPlus* is 744.09 and 258.44 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have *LC* measure of about 744, while classes that are not reusable have about 258.

At $\alpha = 0.05$, the mean *NMS* value of classes in *RExtPlus* is greater than the mean *NMS* value of classes in *RExtZeroOne*. The mean of *NMS* in *RExtPlus* is 195.69 and 59.15 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about 196 message sends, while classes that are not reusable have about 60.

At $\alpha = 0.05$, the mean *NP* value of classes in *RExtPlus* is greater than the mean *NP* value of classes in *RExtZeroOne*. The mean of *NP* in *RExtPlus* is 39.79 and 10.09 in *RExtZeroOne*. Classes that are reusable based on their inter-application reuse by extension value have about 40 parameters, while classes that are not reusable have about 10.

Appendix B presents the graphs of mean, median, standard deviation of the 20 metrics using the set *RExtPlus*.

To summarize Section 4.1.1.2, at $\alpha = 0.05$, the mean metric values of { *NDSub, NOM, NIM, NCV, NIV, NCMC, NIMC, NSup, CycC, NPubM, NPriM, CC, S, LOC, NOS, LC, NMS, and NP* } are significantly different between classes in *RExtPlus* and *RExtZeroOne*. The mean metric values of { *NSub, U* } are **not** significantly different between classes in *RExtPlus* and *RextZeroOne*.

4.1.1.3 Inter-application reuse as a server

Table 4.3 presents the t-test results for the groups *RServPlus* and *RServZeroOne*. A one-sided test gives the direction of the difference in the mean metric values of classes in *RServPlus* and *RServZeroOne*. The mean metric values may be used as a guide to judge whether a class will be reused in another application as a server at least two or more times.

At $\alpha = 0.05$, the mean *NOM* value of classes in *RServPlus* is greater than the mean *NOM* value of classes in *RServZeroOne*. The mean of *NOM* in *RServPlus* is 40.92 and 14.94 in *RServZeroOne*. Classes that are reusable based on their

Table 4.3. RServ: T-test between classes that are reused (+) vs. classes that are not reused (0 and 1).

	Mean	Std Dev	Prob>|T|
NDSub			
0*	0.6829	5.5090	0.0832
+*	2.1891	20.0761	
Nsub			
0	1.9675	17.6027	0.1439
+	8.8436	109.6776	
NOM			
0	14.9351	21.8703	0.0001
+	40.9200	54.9743	
NIM			
0	12.7052	20.4451	0.0001
+	32.3854	48.6040	
NCV			
0	0.0933	0.5131	0.0001
+	0.7363	2.0284	
NIV			
0	1.8404	4.1333	0.0001
+	4.0418	5.8062	
NCMC			
0	0.6842	0.6142	0.0001
+	1.3982	1.4979	
NIMC			
0	1.1582	1.1400	0.0001
+	2.3255	2.9380	
Nsup			
0	3.5693	1.8116	0.0022
+	3.2582	2.0992	
CycC			
0	5.2109	8.7275	0.0001
+	14.6836	23.8720	
NpubM			
0	6.5943	10.4519	0.0001
+	18.9655	32.6392	
NPriM			
0	8.3408	16.7466	0.0001
+	21.9545	33.0147	
CC			
0	40.8837	63.6089	0.0001
+	62.1291	71.9021	
U			
0	0.1209	0.1748	0.0001
+	0.1939	0.2126	
S			
0	1.0917	14.0364	0.0379
+	3.0146	19.9301	
LOC			
0	72.7721	196.9638	0.0001
+	156.6745	262.0116	
NOS			
0	124.3874	297.4761	0.0001
+	264.3527	441.4250	
LC			
0	250.3231	629.6258	0.0001
+	504.5616	841.4862	
NMS			
0	55.8661	123.7201	0.0001
+	131.0454	221.0812	
NP			
0	8.7485	17.3646	0.0001
+	27.4018	53.7599	

*0 = RServeZeroOne, number of samples =1479

*+ = RServePlus, number of samples = 550

inter-application reuse as a server value have about 41 methods, while classes that are not reusable have about 15.

At $\alpha = 0.05$, the mean *NIM* value of classes in *RServPlus* is greater than the mean *NIM* value of classes in *RServZeroOne*. The mean of *NIM* in *RServPlus* is 32.39 and 12.71 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have about 32 instance methods, while classes that are not reusable have about 13.

At $\alpha = 0.05$, the mean *NCV* value of classes in *RServPlus* is greater than the mean *NCV* value of classes in *RServZeroOne*. The mean of *NCV* in *RServPlus* is 0.73 and 0.09 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have about one class variable, while classes that are not reusable have about zero.

At $\alpha = 0.05$, the mean *NIV* value of classes in *RServPlus* is greater than the mean *NIV* value of classes in *RServZeroOne*. The mean of *NIV* in *RServPlus* is 4.04 and 1.84 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have about four instance variables, while classes that are not reusable have about two.

At $\alpha = 0.05$, the mean *NCMC* value of classes in *RServPlus* is greater than the mean *NCMC* value of classes in *RServOne*. The mean of *NCMC* in *RServPlus* is 1.40 and 0.68 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have about two class method categories, while classes that are not reusable have about one.

At $\alpha = 0.05$, the mean *NIMC* value of classes in *RServPlus* is greater than the mean *NIMC* value of classes in *RServZeroOne*. The mean of *NIMC* in *RServPlus* is 2.32 and 1.15 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have about two instance method categories, while classes that are not reusable have about one.

At $\alpha = 0.05$, the mean *NSup* value of classes in *RServPlus* is less than the mean *NSup* value of classes in *RServZeroOne*. The mean of *NSup* in *RServPlus* is 3.26 and 3.57 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have about three superclasses, while classes that are not reusable have about four.

At $\alpha = 0.05$, the mean *CycC* value of classes in *RServPlus* is greater than the mean *CycC* value of classes in *RServZeroOne*. The mean of *CycC* in *RServPlus* is 14.68 and 5.21 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have cyclomatic complexity about 15, while classes that are not reusable have about five.

At $\alpha = 0.05$, the mean *NPubM* value of classes in *RServPlus* is greater than the mean *NPubM* value of classes in *RServZeroOne*. The mean of *NPubM* in *RServPlus* is 18.97 and 6.59 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have about 19 public methods, while classes that are not reusable have about seven.

At $\alpha = 0.05$, the mean *NPriM* value of classes in *RServPlus* is greater than the mean *NPriM* value of classes in *RServZeroOne*. The mean of *NPriM* in *RServPlus* is 21.95 and 8.34 in *RServZeroOne*. Classes that are reusable based on their inter-

application reuse as a server value have about 22 private methods, while classes that are not reusable have about eight.

At $\alpha = 0.05$, the mean *CC* value of classes in *RServPlus* is greater than the mean *CC* value of classes in *RServZeroOne*. The mean of *CC* in *RServPlus* is 62.13 and 40.88 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have a class coupling value about 62, while classes that are not reusable have about 41. This result shows that the higher the *CC* value of a class, the more likely this class will be reused as a server two or more times.

At $\alpha = 0.05$, the mean *U* value of classes in *RServPlus* is greater than the mean *U* value of classes in *RServZeroOne*. The mean of *U* in *RServPlus* is 0.19 and 0.12 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value reuse ratio value approximately equal to 0.19, while classes that are not reusable have about 0.12.

At $\alpha = 0.05$, the mean *S* value of classes in *RServPlus* is greater than the mean *S* value of classes in *RServZeroOne*. The mean of *S* in *RServPlus* is 3.01 and 1.09 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have specialization value approximately equal to three, while classes that are not reusable have about one.

At $\alpha = 0.05$, the mean *LOC* value of classes in *RServPlus* is greater than the mean *LOC* value of classes in *RServZeroOne*. The mean of *LOC* in *RServPlus* is 156.67 and 72.77 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have about 157 lines of code, while classes that are not reusable have about 73.

At $\alpha = 0.05$, the mean *NOS* value of classes in *RServPlus* is greater than the mean *NOS* value of classes in *RServZeroOne*. The mean of *NOS* in *RServPlus* is 264.35 and 124.39 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have about 264 statements, while classes that are not reusable have about 124.

At $\alpha = 0.05$, the mean *LC* value of classes in *RServPlus* is greater than the mean *LC* value of classes in *RServZeroOne*. The mean of *LC* in *RServPlus* is 504.56 and 250.32 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have Lorenz complexity approximately equal to 505, while classes that are not reusable have about 250.

At $\alpha = 0.05$, the mean *NMS* value of classes in *RServPlus* is greater than the mean *NMS* value of classes in *RServZeroOne*. The mean of *NMS* in *RServPlus* is 131.04 and 55.87 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have about 131 message sends, while classes that are not reusable have about 56.

At $\alpha = 0.05$, the mean *NP* value of classes in *RServPlus* is greater than the mean *NP* value of classes in *RServZeroOne*. The mean of *NP* in *RServPlus* is 27.40 and 8.75 in *RServZeroOne*. Classes that are reusable based on their inter-application reuse as a server value have about 27 parameters, while classes that are not reusable have about 9.

In summary, at $\alpha = 0.05$, the mean metric values of { *NOM, NIM, NCV, NIV, NCMC, NIMC, NSup, CycC, NPubM, NPriM, CC, U, S, LOC, NOS, LC, NMS, and NP* } are significantly different between classes in *RServPlus* and *RServZeroOne*. The mean

metric values of { *NDSub*, *NSub* } are **not** significantly different between classes in *RServPlus* and *RservZeroOne*.

4.1.2 Nonparametric test

This section gives the results of analyzing the data using nonparametric test. Section 4.1.2.1 gives the results of comparing the groups *RInheritPlus* and *RInheritZeroOne*. Section 4.1.2.2 describes the results of comparing the groups *RExtPlus* and *RExtZeroOne*. Section 4.1.2.3 presents the results of comparing the groups *RServPlus* and *RServZeroOne*.

4.1.2.1 Inheritance-based reuse

For inheritance-based reuse, the results of the nonparametric tests were the same as those from the t-tests, except for *U*. Table 4.4 presents the nonparametric test results for the groups *RInheritPlus* and *RInheritZeroOne*. At $\alpha = 0.05$, the mean metric values of { *NDSub, NSub, NOM, NIM, NIV, NCMC, NIMC, NSup, CycC, NPubM, NPriM, CC, U, S, LOC, NOS, LC, NMS, NP* } are significantly different between classes in *RInheritPlus* and *RInheritZeroOne*.

The mean metric values of {*NCV, U*} are **not** significantly different between classes in *RInheritPlus* and *RInheritZeroOne*.

4.1.2.2 Inter-application reuse by extension

For inter-application reuse by extension, results from the t-tests and nonparametric tests were the same, except for *NDSub* and *U*. Table 4.5 presents the nonparametric test results for the groups *RExtPlus* and *RExtZeroOne*.

Table 4.4. RInherit: nonparametric test between classes that are reused (+) vs. classes that are not reused (0 and 1)

	Mean	Prob>|Z|
NDSub		
0*	791.11	0.0001
+*	1800.57	
NSub		
0	790.89	0.0001
+	1801.36	
NOM		
0	929.64	0.0001
+	1314.49	
NIM		
0	929.67	0.0001
+	1314.41	
NCV		
0	1008.13	0.0689
+	1039.10	
NIV		
0	951.64	0.0001
+	1237.31	
NCMC		
0	990.26	0.0001
+	1101.79	
NIMC		
0	946.62	0.0001
+	1254.92	
NSup		
0	1042.06	0.0001
+	920.02	
CycC		
0	961.42	0.0001
+	1202.98	
NPubM		
0	965.76	0.0001
+	1187.77	
NPriM		
0	927.49	0.0001
+	1322.03	
CC		
0	959.24	0.0001
+	1210.64	
U		
0	1006.61	0.2258
+	1044.43	
S		
0	792.06	0.0001
+	1797.23	
LOC		
0	951.99	0.0001
+	1236.08	
NOS		
0	951.56	0.0001
+	1237.58	
LC		
0	955.79	0.0001
+	1222.75	
NMS		
0	940.94	0.0001
+	1274.85	
NP		
0	934.41	0.0001
+	1297.75	

*0 = RInheritZeroOne, number of samples =1579

*+ = RInheritPlus, number of samples = 450

Table 4.5. RExt: nonparametric test between classes that are reused(+) vs. classes that are not reused(0 and 1)

	Mean	Prob>|Z|
NDSub		
0*	986.22	0.0001
+*	1216.05	
NSub		
0	986.21	0.0001
+	1216.12	
NOM		
0	939.43	0.0001
+	1543.05	
NIM		
0	942.95	0.0001
+	1518.44	
NCV		
0	991.91	0.0001
+	1176.32	
NIV		
0	978.66	0.0001
+	1268.92	
NCMC		
0	964.58	0.0001
+	1367.32	
NIMC		
0	931.72	0.0001
+	1596.96	
NSup		
0	1034.26	0.0001
+	880.37	
CycC		
0	956.69	0.0001
+	1422.42	
NPubM		
0	954.65	0.0001
+	1436.71	
NPriM		
0	944.12	0.0001
+	1510.32	
CC		
0	962.95	0.0001
+	1378.70	
U		
0	1003.37	0.0178
+	1096.27	
S		
0	985.72	0.0001
+	1219.56	
LOC		
0	967.9473	0.0001
+	1343.8130	
NOS		
0	966.49	0.0001
+	1343.81	
LC		
0	947.52	0.0001
+	1486.51	
NMS		
0	947.52	0.0001
+	1486.51	
NP		
0	937.69	0.0001
+	1555.20	

*0 = RExtZeroOne, number of samples =1775

*+ = RExtPlus, number of samples = 254

At $\alpha = 0.05$, the mean metric values of { *NDSub, NSub, NOM, NIM, NCV, NIV, NCMC, NIMC, NSup, CycC, NPubM, NPriM, CC, U, S, LOC, NOS, LC, NMS, and NP* } are significantly different between classes in *RExtPlus* and *RExtZeroOne*.

4.1.2.3 Inter-application reuse as a server

Except for *S*, results from the t-tests and nonparametric tests were the same for inter-application reuse as a server. Table 4.6 presents the nonparametric test results for the groups *RServPlus* and *RServZeroOne*. At $\alpha = 0.05$, the mean metric values of { *NOM, NIM, NCV, NIV, NCMC, NIMC, NSup, CycC, NPubM, NPriM, CC, U, LOC, NOS, LC, NMS, and NP* } are significantly different between classes in *RServPlus* and *RServZeroOne*.

The mean metric values of { *NDSub, NSub, and S* } are **not** significantly different between classes in *RServPlus* and *RServZeroOne*.

A summary of the results relative to the question "Are the population means of the reusable and non-reusable groups the same?" follows:

- Classes in *RInheritPlus* have significantly greater mean { *NDSub, NSub, NOM, NIM, NIV, NCMC, NIMC, CycC, NPubM, NPriM, CC, U, S, LOC, NOS, LC, NMS and NP* } metric values than those in *RInheritZeroOne*, at $\alpha = 0.05$.
- Classes in *RInheritPlus* have significantly lower mean { *NSup* } metric values than those in *RInheritZeroOne*, at $\alpha = 0.05$.
- The mean metric values of *NCV* are **not** significantly different between classes in *RInheritPlus* and *RInheritZeroOne*.

Table 4.6. RServ: nonparametric test between classes that are reused(+) vs. classes that are not reused(0 and 1)

	Mean	Prob>|Z|
NDSub		
0*	1006.51	0.1439
+*	1037.82	
NSub		
0	1006.10	0.1258
+	1038.92	
NOM		
0	884.85	0.0001
+	1364.98	
NIM		
0	920.27	0.0001
+	1269.73	
NCV		
0	959.37	0.0001
+	1164.58	
NIV		
0	931.43	0.0001
+	1238.36	
NCMC		
0	917.56	0.0001
+	1277.01	
NIMC		
0	927.63	0.0001
+	1249.93	
NSup		
0	1050.39	0.0001
+	919.80	
CycC		
0	913.29	0.0001
+	1288.49	
NPubM		
0	906.81	0.0001
+	1305.92	
NPriM		
0	905.33	0.0001
+	1309.90	
CC		
0	947.00	0.0001
+	1197.83	
U		
0	962.70	0.0001
+	1155.62	
S		
0	1006.00	0.1217
+	1039.18	
LOC		
0	932.07	0.0001
+	1237.98	
NOS		
0	932.72	0.0001
+	1236.23	
LC		
0	935.24	0.0001
+	1229.46	
NMS		
0	935.26	0.0001
+	1229.42	
NP		
0	923.69	0.0001
+	1260.5236	

*0 = RServZeroOne, number of samples =1479

*+ = RServPlus, number of samples = 550

- Classes in *RExtPlus* have significantly greater mean { *NDSub, NOM, NIM, NCV, NIV, NCMC, NIMC, CycC, NPubM, NPriM, CC, S, LOC, NOS, LC, NMS, and NP* } metric values than those in *RExtZeroOne*, at $\alpha = 0.05$.
- Classes in *RExtPlus* have significantly lower mean { *NSup* } metric values than those in *RExtZeroOne*, at $\alpha = 0.05$.
- The mean metric values of { *NSub, U* } are **not** significantly different between classes in *RExtPlus* and *RextZeroOne*.
- Classes in *RServPlus* have significantly greater mean { *NOM, NIM, NCV, NIV, NCMC, NIMC, CycC, NPubM, NPriM, CC, U, S, LOC, NOS, LC, NMS, and NP* } metric values than those in *RServZeroOne*, at $\alpha = 0.05$.
- Classes in *RServPlus* have significantly lower mean { *NSup* } metric values than those in *RServZeroOne*, at $\alpha = 0.05$.
- The mean metric values of { *NDSub, NSub* } are **not** significantly different between classes in *RServPlus* and *RServZeroOne*.

4.2 Stepwise Regression

Next we answer the question: Are there object-oriented metrics that can predict *RInherit, RExt* and *RServ*? The results of stepwise regression for the dependent variables *RInherit, RExt* and *RServ* are discussed in Sections 4.2.1 through Section 4.2.3.

4.2.1 Inheritance-based reuse

The results of the last step of stepwise multiple linear regression for the dependent variable *RInherit* are presented in Table 4.7 and a summary is presented in Table 4.8. From Table 4.7, the p-value, labeled "Prob>F" is 0.0001. Since p-value is less than 0.05, there is sufficient evidence to reject H_0.

Table 4.7. Last step of stepwise procedure for dependent variable inheritance-based reuse.

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Step16 Variable CC Entered R-square = 0.89196816 C(p) = 15.11696922

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	12	4994984795506.6	416248732958.89	300.68	0.0001
Error	437	604973811187.39	1384379430.6348		
Total	449	5599958606694.0			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	-15386.07158669	3347.12834226	29252696465.355	21.13	0.0001
NSub	799.88213316	20.71722391	2063687864941.1	1490.70	0.0001
NIM	774.04365437	145.03961130	39428730369.861	28.48	0.0001
NCV	-4373.31798700	1816.84575721	8021233010.7308	5.79	0.0165
NIV	-2378.22161683	460.36115259	36945576272.156	26.69	0.0001
NCMC	-3978.68692592	1712.30847259	7474302321.8468	5.40	0.0206
NIMC	3417.28244033	915.79063491	19276336177.371	13.92	0.0002
CycC	359.77148421	144.49322711	8582496442.6577	6.20	0.0131
CC	58.85814993	31.25448665	4909571753.3785	3.55	0.0603
U	45284.30961131	14435.87221083	13622743580.242	9.84	0.0018
S	-874.85088834	64.22157869	256898316268.96	185.57	0.0001
NMS	-77.00737049	21.05161586	18524600584.884	13.38	0.0003
NP	-196.27268875	98.05520000	5546686524.6399	4.01	0.0459

Bounds on condition number: 15.8281, 551.2057

All variables left in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable INHERIT

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	NSub		1	0.7982	0.7982	374.3511	1771.7635	0.0001
2	S		2	0.0659	0.8641	108.3912	216.8356	0.0001
3	NIMC		3	0.0132	0.8773	56.6992	48.0182	0.0001
4	NPubM		4	0.0034	0.8807	44.8397	12.7206	0.0004
5	NSup		5	0.0014	0.8821	41.0931	5.3257	0.0215
6	NIV		6	0.0011	0.8833	38.4278	4.3563	0.0374
7	NIM		7	0.0027	0.8860	29.2996	10.6165	0.0012
8		NPubM	6	0.0000	0.8860	27.4888	0.1805	0.6712
9	NMS		7	0.0011	0.8871	24.9782	4.3437	0.0377
10	U		8	0.0009	0.8880	23.4069	3.4583	0.0636
11		NSup	7	0.0000	0.8879	21.5782	0.1658	0.6841
12	NCV		8	0.0008	0.8887	20.5215	2.9789	0.0851
13	CycC		9	0.0009	0.8896	18.9065	3.5433	0.0604
14	NCMC		10	0.0007	0.8902	18.1458	2.7164	0.1000
15	NP		11	0.0009	0.8911	16.6806	3.4286	0.0647
16	CC		12	0.0009	0.8920	15.1170	3.5464	0.0603

Table 4.8. Summary of stepwise procedure for dependent variable inheritance-based reuse.

Variable	Parameter Estimate	Model R^2	Prob > F
Intercept	-15386.1		
NSub	799.9	0.7982	0.0001
S	-874.8	0.8641	0.0001
NIMC	3417.3	0.8773	0.0001
NIV	-2378.2	0.8833	0.0374
NIM	774.0	0.8860	0.0012
NMS	-77.0	0.8871	0.0377
U	45284.3	0.8880	0.0636
NCV	-4373.3	0.8887	0.0851
CycC	359.8	0.8896	0.0604
NCMC	-3978.7	0.8902	0.1000
NP	-196.3	0.8911	0.0647
CC	58.9	0.8920	0.0603

n=449

There is sufficient evidence that the dependent variable *RInherit* is linearly related to a subset of the 20 metrics. Inheritance-based reuse can be predicted by using the 12 metrics *NSub*, *S*, *NIMC*, *NIV*, *NIM*, *NMS*, *U*, *NCV*, *CycC*, *NCMC*, *NP*, and *CC*. The prediction equation is

$$\text{Predicted } RInherit = -15386.1 + 799.9*NSub - 874.8*S + 3417.3*NIMC - 2378.2*NIV + 774*NIM - 77*NMS + 45284.3*U - 4373.3*NCV + 359.8*CycC - 3978.7*NCMC - 196.3*NP + 58.9*CC. \quad (4.1)$$

The coefficient of determination R^2 represents the variation in the dependent variable that is explained by the model [Mye90]. From Table 4.7, $R^2 = 0.8919$. This value means that 89% of the variability of inheritance-based reuse is accounted for by the independent variables in the multiple regression model. *NSub* with partial $R^2 = 0.7982$, contributed most heavily to the model R^2. *S* is the second largest contributor with a partial R^2 contribution of 0.0659. This finding suggests that the number of all subclasses of a class is a good predictor of inheritance-based reuse. A two-variable regression model using *NSub* and *S* as independent variables was fitted. From Table 4.9, the model R^2 is 86% and the two-variable prediction equation is

$$\text{Predicted } RInherit = -267.68 + 911.01 * NSub - 969.49 * S. \quad (4.2)$$

4.2.2 Inter-application reuse by extension

The results of the last step of stepwise multiple linear regression for the dependent variable *RExt* are presented in Table 4.10 and a summary is presented in Table 4.11. From Table 4.10, the p-value is 0.0001 < 0.05. This implies that there is sufficient evidence to reject H_0. The dependent variable *RExt* is linearly related to a subset of the

Table 4.9. Summary of 2-variable stepwise procedure for dependent variable inheritance-based reuse.

RInherit SUMMARY OUTPUT - 2-Variable Regression (NSub and S)

Regression Statistics

Multiple R	0.929569988
R Square	0.864100363
Adjusted R Square	0.86349231
Standard Error	41261.76449
Observations	450

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	4.83893E+12	2.42E+12	1421.096	1.8806E-194
Residual	447	7.61032E+11	1.7E+09		
Total	449	5.59996E+12			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-267.6771379	1991.820325	-0.13439	0.8931561	-4182.174083	3646.8198	-4182.1741	3646.81981
NSub	911.0980634	17.33586803	52.55566	1.89E-193	877.0281216	945.16801	877.028122	945.168005
S	-969.4893633	65.83817414	-14.7253	2.696E-40	-1098.880217	-840.0985	-1098.8802	-840.09851

Table 4.10. Last step of stepwise procedure for dependent variable interapplication reuse by extension.

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Step 9 Variable CycC Entered R-square = 0.84991673 C(p) = 25.05823826

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	9	6816.09456597	757.34384066	153.53	0.0001
Error	244	1203.62590647	4.93289306		
Total	253	8019.72047244			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	-0.22327699	0.36657288	1.83007533	0.37	0.5430
NDSub	0.03354981	0.00591503	158.69657987	32.17	0.0001
NIV	-0.13740894	0.02936779	107.99139389	21.89	0.0001
NCMC	0.28420266	0.09759085	41.83499823	8.48	0.0039
NIMC	1.15073851	0.05747153	1977.64991203	400.91	0.0001
NSup	-0.22422644	0.07934297	39.39657599	7.99	0.0051
CycC	0.01352812	0.00591373	25.81387248	5.23	0.0230
NPubM	0.02229792	0.00557672	78.86288181	15.99	0.0001
CC	0.00961716	0.00200557	113.42839447	22.99	0.0001
NP	-0.01181594	0.00466422	31.65779761	6.42	0.0119

Bounds on condition number: 3.410369, 153.6375

All variables left in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable INTERAPP

Step	Variable Entered	Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	NIMC		1	0.7126	0.7126	246.0701	624.8445	0.0001
2	NCMC		2	0.0680	0.7806	130.6589	77.8279	0.0001
3	NDSub		3	0.0283	0.8089	83.8931	36.9557	0.0001
4	CC		4	0.0100	0.8189	68.5658	13.8035	0.0003
5	NIV		5	0.0122	0.8311	49.5163	17.9074	0.0001
6	NPubM		6	0.0096	0.8407	34.9467	14.8854	0.0001
7	NSup		7	0.0033	0.8440	31.2628	5.1928	0.0235
8	NP		8	0.0027	0.8467	28.6142	4.3040	0.0391
9	CycC		9	0.0032	0.8499	25.0582	5.2330	0.0230

Table 4.11. Summary of stepwise procedure for dependent variable interapplication reuse by extension.

Variable	Parameter Estimate	Model R^2	Prob > F
Intercept	-0.2233		
NIMC	1.1507	0.7126	0.0001
NCMC	0.2842	0.7806	0.0001
NDSub	0.0335	0.8089	0.0001
CC	0.0096	0.8189	0.0003
NIV	-0.1374	0.8311	0.0001
NPubM	0.0223	0.8407	0.0001
NSup	-0.2242	0.8440	0.0235
NP	-0.0118	0.8467	0.0391
CycC	0.0135	0.8499	0.0230

n=253

20 metrics. Inter-application reuse by extension can be predicted by using the 9 metrics *NIMC, NCMC, NDSuB, CC, NIV, NPubM, NSup, NP, CycC*. The prediction equation is

$$\text{Predicted RExt} = -0.22 + 1.15*NIMC + 0.28*NCMC + 0.03*NDSuB + 0.01*CC - 0.14*NIV + 0.02*NPubM - 0.22*NSup - 0.01*NP + 0.01*CycC. \quad (4.3)$$

From Table 4.10, $R^2 = 0.8499$. This value means that 85% of the variability of inter-application reuse by extension is accounted for by the independent variables in the multiple regression model. *NIMC* with partial $R^2 = 0.7126$, contributed most heavily to the model R^2. It suggests that programmers should logically group instance methods within a class by categorizing them since *NIMC* can be used to predict inter-application reuse by extension. *NCMC* is next with partial R^2 contribution = 0.0680. A two-variable regression model using *NIMC* and *NCMC* as independent variables was fitted. From Table 4.12, the model R^2 is 78% and the two-variable prediction equation is

$$\text{Predicted } RExt = -1.36 + 0.81 * NIMC + 1.25 * NCMC. \quad (4.4)$$

4.2.3 Inter-application reuse as a server

The results of the last step of stepwise multiple linear regression for the dependent variable *RServ* are presented in Table 4.13 and a summary is presented in Table 4.14. From Table 4.13, the p-value is 0.0001 < 0.05. This result implies that there is sufficient evidence to reject H_0. The dependent variable *RServ* is linearly related to a subset of the 20 metrics.

Since $R^2 = 0.059$ is small, the variability in the dependent variable RServ cannot be fully explained by the independent variables. Predicting inter-application reuse as a

Table 4.12. Summary of 2 variable regression procedure for dependent variable interapplication reuse by extension.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.883531
R Square	0.780627
Adjusted R Square	0.778879
Standard Error	2.64749
Observations	254

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	6260.410896	3130.205	446.5852	2.08195E-83
Residual	251	1759.309576	7.009201		
Total	253	8019.720472			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-1.35965	0.252360233	-5.38772	1.64E-07	-1.856660541	-0.86263	-1.856661	-0.8626334
NCMC	0.809201	0.091725261	8.822012	1.94E-16	0.62855207	0.989851	0.6285521	0.98985067
NIMC	1.252544	0.053566039	23.38317	5.7E-65	1.147047648	1.35804	1.1470476	1.35804007

Table 4.13. Last step of stepwise procedure for dependent variable interapplication reuse as a server.

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Step 3 Variable NDSub Entered R-square = 0.05902977 C(p) = 6.74591680

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	3	302150.78970285	100716.92990095	11.42	0.0001
Error	546	4816466.6648426	8821.36751803		
Total	549	5118617.4545455			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	-4.33521823	6.31572019	4156.34972174	0.47	0.4927
NDSub	-0.49063005	0.23387769	38820.99069411	4.40	0.0364
NCMC	13.99922709	2.95378659	198146.22620030	22.46	0.0001
NIMC	4.19052617	1.50641306	68262.92399119	7.74	0.0056

Bounds on condition number: 1.372059, 11.42824

All variables left in the model are significant at the 0.1500 level.

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No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable SERVER

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	NCMC		1	0.0432	0.0432	11.9775	24.7423	0.0001
2	NIMC		2	0.0082	0.0514	9.1688	4.7550	0.0296
3	NDSub		3	0.0076	0.0590	6.7459	4.4008	0.0364

Table 4.14. Summary of stepwise procedure for dependent variable interapplication reuse as a server.

Variable	Parameter Estimate	Model R^2	Prob > F
Intercept	-4.3352		
NCMC	13.9992	0.0432	0.0001
NIMC	4.1905	0.0514	0.0296
NDSub	-0.4906	0.0590	0.0364

n=549

server by using a linear regression model is not meaningful. There is a possibility that the relationship of *RServ* with the 20 metrics is not linear. Hence, a second order regression equation was fitted with the stepwise regression procedure summary in Table 4.15. However R^2 is still small with a value of 0.1.

To summarize, H_0 is rejected for inheritance-based reuse and inter-application reuse by extension and H_0 is not rejected for inter-application reuse as a server. Also, it was shown that the number of all subclasses of a class is a good predictor of inheritance-based reuse and that the number of instance method categories is a good predictor of inter-application reuse by extension. Inter-application reuse as a server, on the other hand, does not have a significant linear relationship with the 20 metrics.

4.3 Statistical Validation

We answer the question: Are the prediction equations from Section 4.2. empirically valid? We list these prediction equations again as follows:

$$\text{Predicted } RInherit = -267.68 + 911.01 * NSub - 969.49 * S. \quad (4.2)$$

$$\text{Predicted } RExt = -1.36 + 0.81 * NIMC + 1.25 * NCMC. \quad (4.4)$$

Table 4.16 shows the results of a simple regression analysis with predicted $RInherit_{predicted}$ from the two-variable regression equation (4.2). as the dependent variable, and $RInherit_{actual}$ from the new set of data as the independent variable. The resulting regression equation with $R^2 = 0.9155$ is:

$$\text{Predicted } RInherit_{predicted} = 1651.3 + 0.3161 * RInherit_{actual} \quad (4.5)$$

Table 4.15. Summary of second order multiple regression procedure for dependent variable interapplication reuse as a server.

Step 8 Variable METRIC16 Entered R-square = 0.10076030 C(p) = 0.80711921

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	8	515753.41241198	64469.17655150	7.58	0.0001
Error	541	4602864.0421335	8508.06662132		
Total	549	5118617.4545455			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	-16.82748626	7.79529110	39646.48553235	4.66	0.0313
NSub	-0.36643805	0.17886208	35710.46325782	4.20	0.0410
NIV	-1.54294601	0.86708950	26940.42792553	3.17	0.0757
NCMC	12.75529190	3.02993257	150780.70133615	17.72	0.0001
NIMC	17.47128154	4.04041491	159084.72282758	18.70	0.0001
LOC	-0.24090502	0.09289691	57216.33760640	6.72	0.0098
LC	0.08386972	0.02825005	74989.88869095	8.81	0.0031
NSub*NSub	0.00030570	0.00009216	93617.42737624	11.00	0.0010
NIMC*NIMC	-1.17784438	0.31166703	121513.62572120	14.28	0.0002

Bounds on condition number: 38.57608, 1421.334

All variables left in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

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Summary of Stepwise Procedure for Dependent Variable SERVER

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	NCMC		1	0.0432	0.0432	20.9122	24.7423	0.0001
2	NIMC		2	0.0082	0.0514	18.0266	4.7550	0.0296
3	NIMC*NIMC		3	0.0107	0.0622	13.6596	6.2563	0.0127
4	NSub*NSub		4	0.0086	0.0708	10.5772	5.0309	0.0253
5	NSub		5	0.0070	0.0778	8.4235	4.1353	0.0425
6	NIV		6	0.0052	0.0830	7.3556	3.0659	0.0805
7	LC		7	0.0066	0.0896	5.4302	3.9441	0.0475
8	LOC		8	0.0112	0.1008	0.8071	6.7250	0.0098

Table 4.16. Empirical validation regression for RInherit.

Regression Statistics								
Multiple R	0.956837							
R Square	0.915536							
Adjusted R Square	0.915348							
Standard Error	30204.45							
Observations	450							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	4.43E+12	4.43E+12	4856.046	1.5E-242			
Residual	448	4.09E+11	9.12E+08					
Total	449	4.84E+12						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1651.304	1427.353	1.1569	0.24793	-1153.83	4456.44	-1153.83	4456.44
Actual	0.316132	0.004537	69.68534	1.5E-242	0.307216	0.325047	0.307216	0.325047

Known data points correlated highly with predicted values. The graph of Figure 4.2 shows that the prediction equation (4.2) performed satisfactorily since the line corresponding to equation (4.5) is almost similar to the line

$$RInherit_{predicted} = RInherit_{actual} \quad (4.6)$$

Equation (4.6) is the ideal case when the *RInherit* values obtained from the two-variable prediction equation (4.2) accurately predicted the new *RInherit* values from the new set of data.

Table 4.17 shows the results of a simple regression analysis with predicted $RExt_{predicted}$ from the two-variable regression equation (4.4) as the dependent variable, and $RExt_{actual}$ from the new set of data as the independent variable. The resulting regression equation with $R^2 = 0.7042$ is:

$$\text{Predicted } RExt_{predicted} = 2.436 + 0.937 * RExt_{actual} \quad (4.7)$$

Known data points correlated highly with predicted values. The graph of Figure 4.3 shows that the prediction equation (4.4) performed satisfactorily since the line corresponding to equation (4.7) is almost similar to the line

$$RExt_{predicted} = RExt_{actual} \quad (4.8)$$

Equation (4.8) is the ideal case when the *RExt* values obtained from the two-variable prediction equation (4.4) accurately predicted the new *RExt* values from the new set of data.

To summarize, the prediction equations (4.2) and (4.4) were compared with known data points and were shown to be correlated. Equations (4.2) and (4.4) are empirically valid.

Table 4.17. Empirical validation regression for RExt.

Regression Statistics								
Multiple R	0.839194							
R Square	0.704247							
Adjusted R Square	0.703073							
Standard Error	2.710604							
Observations	254							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	4408.873	4408.873	600.061	1.3E-68			
Residual	252	1851.538	7.347374					
Total	253	6260.411						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.435928	0.184211	13.22357	1.13E-30	2.073139	2.798718	2.073139	2.798718
Actual	0.936754	0.038241	24.49614	1.3E-68	0.861441	1.012066	0.861441	1.012066

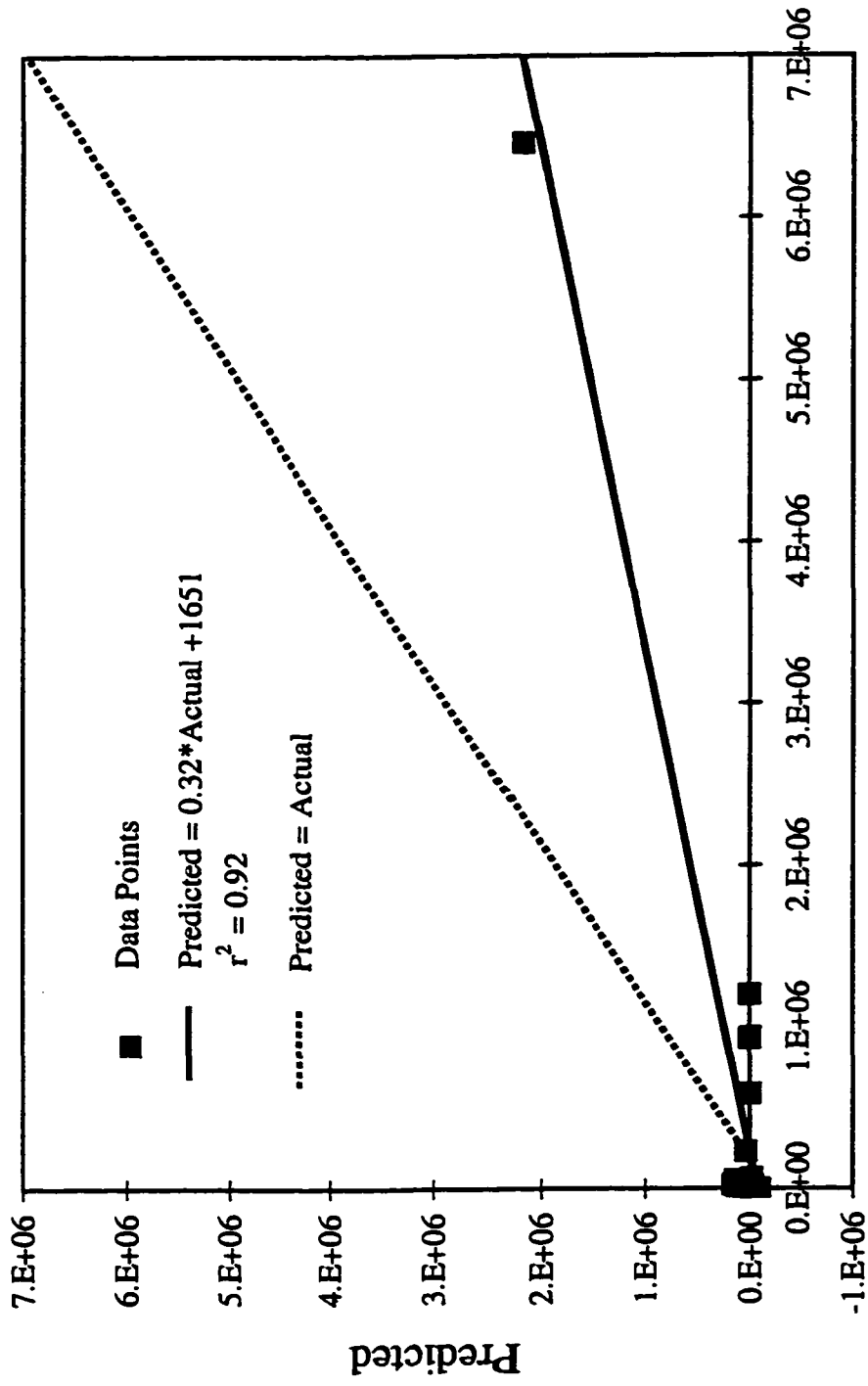

Figure 4.2. RInherit empirical validation regression graph.

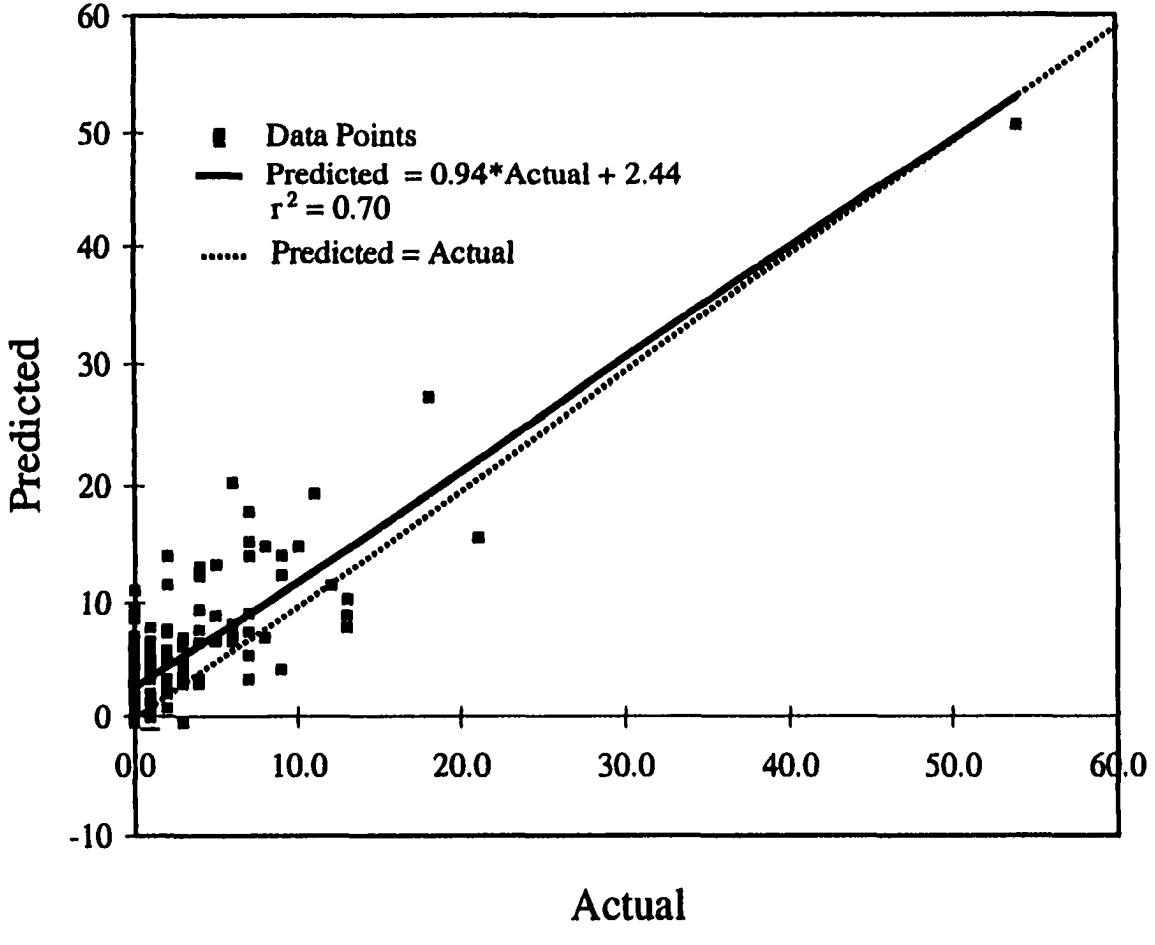

Figure 4.3. RExt empirical validation regression graph.

4.4 Other Statistical Analysis

Section 4.4 answers the following questions:

1. Are any of the 20 metrics in the reusable groups correlated?
2. Are *RInherit*, *RExt* and *RServ* correlated?.

4.4.1 Correlation Among the Metrics in Group RInheritPlus

Table 4.18 shows the correlation coefficients r of the 20 metrics and *RInherit*. The metric pairs listed in Figure 4.4 have r values greater than 0.8.

RInherit is positively correlated with *NSub*. *LOC* is sufficient to measure size, since it is highly correlated with *NOS* and *NMS*, which are harder to compute. In the traditional procedural programming paradigm, studies show that defects correlated with *LOC* and Cyclomatic complexity [Wal79, Ram85, Cur79, Kan95]. In this study, *LOC* is positively correlated with *LC*. As the number of message sends by a class increases, its *LC* also increases.

CycC is positively correlated with *LC* with $r = 0.673$. *CycC* is also positively correlated with *LOC* with $r = 0.645$.

The results from this section do not support [Lor94] claims that reuse encourages lower levels of coupling and inheritance encourages higher levels of coupling.

4.4.2 Correlation Among the Metrics in Group RExtPlus

Table 4.19 shows the correlation coefficients r of the 20 metrics and *RExt*. The metric pairs listed in Figure 4.5 have r values greater than 0.8. These results are very similar to results for *RInherit* given in Figure 4.4. *NIMC* is positively correlated with *RExt*, as was also shown in Chapter 4.2.2.

Table 4.18. Pearson correlation coefficients of metrics in RInheritPlus.

	NDSub	*NSub*	*NOM*	*NIM*	*NCV*	*NIV*	*NCMC*	*NIMC*	*NSup*	*CycC*
NDSub	1									
NSub	0.836978	1								
NOM	0.399393	0.416114	1							
NIM	0.267543	0.361406	0.936277	1						
NCV	0.059153	0.041233	0.446206	0.395884	1					
NIV	-0.06866	-0.05089	0.518929	0.558221	0.248661	1				
NCMC	0.44744	0.299907	0.438291	0.185693	0.125715	0.016102	1			
NIMC	0.404206	0.535285	0.550709	0.596263	-0.00921	0.227529	0.30289	1		
NSup	-0.08872	-0.10836	-0.02424	-0.01967	-0.11072	0.055987	-0.07211	0.013322	1	
CycC	0.238905	0.16569	0.75289	0.596638	0.483901	0.417314	0.520654	0.343789	0.076042	1
NPubM	0.346955	0.324339	0.832242	0.755992	0.34197	0.279061	0.424745	0.400479	-0.10159	0.563787
NPriM	0.33294	0.380326	0.866452	0.832147	0.413075	0.587239	0.325744	0.529254	0.052324	0.708895
CC	0.099945	0.014473	0.467046	0.376791	0.220545	0.271389	0.330326	0.104603	0.18661	0.464882
U	-0.11471	-0.10417	-0.08695	-0.05752	0.029478	0.064804	-0.04208	-0.04018	-0.46559	-0.1191
S	0.337636	0.433629	0.245367	0.121053	0.056467	-0.06039	0.349517	0.126096	-0.17181	0.215454
LOC	0.104897	0.150968	0.815527	0.880212	0.459957	0.542506	0.110621	0.447091	0.133503	0.645058
NOS	0.091818	0.140122	0.80484	0.866012	0.448724	0.548681	0.128543	0.470704	0.14785	0.675918
LC	0.078238	0.12143	0.784988	0.842926	0.447202	0.518972	0.125937	0.446167	0.172161	0.67305
NMS	0.100824	0.149361	0.824293	0.894308	0.397844	0.541612	0.107341	0.464565	0.114706	0.594015
NP	0.285013	0.367033	0.850559	0.902832	0.336585	0.397265	0.175233	0.563433	-0.06919	0.547104
RInherit	0.739348	0.893407	0.442635	0.433225	0.027287	-0.01909	0.222774	0.60457	-0.09509	0.171492

(Table continued)

Table 4.18 continued

	NPubM	*NPriM*	*CC*	*U*	*S*	*LOC*	*NOS*	*LC*	*NMS*	*NP*	*RInherit*
NPubM	1										
NPriM	0.444301	1									
CC	0.348792	0.440607	1								
U	-0.00086	-0.13972	-0.05672	1							
S	0.236575	0.183449	0.060522	-0.14469	1						
LOC	0.627313	0.752905	0.474043	-0.06651	0.042996	1					
NOS	0.593937	0.765691	0.474257	-0.06479	0.040009	0.98761	1				
LC	0.58428	0.742309	0.486453	-0.07837	0.03944	0.985534	0.995708	1			
NMS	0.64746	0.748926	0.446966	-0.03625	0.046125	0.952221	0.952345	0.941749	1		
NP	0.725817	0.720807	0.346322	-0.06672	0.179153	0.792903	0.76616	0.762581	0.785334	1	
RInherit	0.347605	0.40223	0.044904	-0.03336	0.156047	0.222298	0.20912	0.187011	0.218601	0.413083	1

NSub and *NDSub*	*NIM* and *NOS*
NSub and *RInherit*	*NIM* and *LC*
NOM and *NIM*	*NIM* and *NMS*
NOM and *NPubM*	*NIM* and *NP*
NOM and *NPriM*	*LOC* and *NOS*
NOM and *LOC*	*LOC* and *LC*
NOM and *NOS*	*LOC* and *NMS*
NOM and *NMS*	*NOS* and *LC*
NOM and *NP*	*NOS* and *NMS*
NIM and *NPriM*	*LC* and *NMS*
NIM and *LOC*	

Figure 4.4. Pairs in RInheritPlus with r-values > 0.8.

Table 4.19. Pearson correlation coefficients of metrics in RExtPlus.

	NDSub	*NSub*	*NOM*	*NIM*	*NCV*	*NIV*	*NCMC*	*NIMC*	*NSup*	*CycC*
NDSub	1									
NSub	0.892212	1								
NOM	0.442065	0.425385	1							
NIM	0.291331	0.370706	0.928241	1						
NCV	0.023427	0.003991	0.4226	0.383162	1					
NIV	-0.07022	-0.05523	0.521739	0.547585	0.246774	1				
NCMC	0.448255	0.268586	0.377026	0.126283	0.153835	-0.02414	1			
NIMC	0.502985	0.608676	0.458516	0.50409	-0.01412	-0.03133	0.364049	1		
NSup	-0.12006	-0.13666	-0.09446	-0.09846	-0.20321	0.028234	-0.13573	-0.11215	1	
CycC	0.207183	0.11802	0.655281	0.50739	0.437204	0.430522	0.365538	0.160067	-0.03617	1
NPubM	0.351368	0.303566	0.849154	0.789082	0.324727	0.296525	0.362143	0.394175	-0.13103	0.482931
NPriM	0.39901	0.418609	0.84811	0.786387	0.392646	0.589469	0.277636	0.384032	-0.02914	0.629487
CC	0.113863	-0.0009	0.479802	0.384215	0.19092	0.369461	0.290894	0.042257	0.006529	0.383289
U	-0.11786	-0.1022	-0.01869	0.011388	0.202882	0.08449	0.033786	0.04816	-0.46298	0.058487
S	0.341135	0.413206	0.227999	0.091145	-0.00473	-0.05998	0.320364	0.121383	-0.1783	0.156394
LOC	0.081472	0.123315	0.778139	0.848276	0.453426	0.646262	0.035752	0.259599	-0.0196	0.563974
NOS	0.074365	0.116233	0.779992	0.844643	0.452662	0.63442	0.055337	0.273812	-0.02045	0.594639
LC	0.054749	0.09379	0.760244	0.822443	0.458454	0.623642	0.051638	0.254917	-0.00637	0.585202
NMS	0.092547	0.137818	0.801165	0.873691	0.427942	0.557898	0.029787	0.296497	-0.00254	0.509544
NP	0.278793	0.361576	0.82235	0.883588	0.319438	0.435479	0.123569	0.471194	-0.17857	0.476309
RExt	0.636014	0.62731	0.521887	0.4432	0.045856	-0.10223	0.550227	0.84416	-0.18959	0.271971

(Table continued)

Table 4.19 continued

	NPubM	*NPriM*	*CC*	*U*	*S*	*LOC*	*NOS*	*LC*	*NMS*	*NP*	*RExt*
NPubM	1										
NPriM	0.440355	1									
CC	0.367438	0.44704	1								
U	0.039928	-0.07182	0.031102	1							
S	0.199504	0.187453	0.060399	-0.14618	1						
LOC	0.641294	0.679476	0.448913	0.12072	0.008979	1					
NOS	0.629471	0.694486	0.455396	0.124296	0.007773	0.99063	1				
LC	0.616044	0.674385	0.451282	0.124787	0.005707	0.988328	0.996526	1			
NMS	0.706258	0.653449	0.441508	0.085673	0.014196	0.957447	0.962718	0.957678	1		
NP	0.722666	0.673002	0.365464	0.074143	0.135877	0.788451	0.783352	0.782241	0.779315	1	
RExt	0.495266	0.390349	0.21016	0.01747	0.24008	0.213743	0.219342	0.20235	0.257976	0.418017	1

NSub and *NDSub*	*NIM* and *NMS*
NOM and *NIM*	*NIM* and *NP*
NOM and *NPubM*	*NIMC* and *RExt*
NOM and *NPriM*	*LOC* and *NOS*
NOM and *NMS*	*LOC* and *LC*
NOM and *NP*	*LOC* and *NMS*
NIM and *LOC*	*NOS* and *LC*
NIM and *NOS*	*NOS* and *NMS*
NIM and *LC*	*LC* and *NMS*

Figure 4.5. Pairs in RExtPlus with r-values > 0.8.

4.4.3 Correlation Among the Metrics in Group RServPlus

Table 4.20 shows the correlation coefficients r of the 20 metrics and *RExt*. The metric pairs listed in Figure 4.6 have r values greater than 0.8. These results are very similar to for *RInherit* and *RExt* as shown in Figures 4.3 and 4.4

4.4.4 Correlation Among the Reuse Measures

Table 4.21 shows the correlation coefficients r of the proposed reuse measures *RInherit*, *RExt* and *RServ* among each other. The computation is based on the intersection of the sets *RInheritPlus*, *RExtPlus* and *RServPlus*, meaning that the data points used are those with *RInherit*, *RExt* and *RServ* values greater than 1. *RInherit* and *RExt* are correlated with $r = 0.732158$.

Table 4.22 shows the correlation coefficients r of the proposed reuse measures *RInherit*, *RExt*, *RServ*, and Henderson-Sellers' reuse ratio U, among each other. Data points used are those with *RInherit*, *RExt* and *RServ* values greater than 1 and U values > 0.1. *RInherit* and *RExt* are slightly positively correlated with $r = 0.556036$. *RInherit* and U are slightly negatively correlated with $r = -0.36918$.

In summary, the following metric pairs are correlated: *NSub* and *NDSub*, *NSub* and *RInherit*, *NOM* and *NIM*, *NOM* and *NPubM*, *NOM* and *NPriM*, *NOM* and *LOC*, *NOM* and *NOS*, *NOM* and *NMS*, *NOM* and *NP*, *NIM* and *NPriM*, *NIM* and *LOC*, *NIM* and *NOS*, *NIM* and *LC*, *NIM* and *NMS*, *NIM* and *NP*, *LOC* and *NOS*, *LOC* and *LC*, *LOC* and *NMS*, *NOS* and *LC*, *NOS* and *NMS*, *LC* and *NMS*, *NIMC* and *RExt*, *NIMC* and *RExt*.

Finally, *RExt* and *RInherit* are positively correlated.

Table 4.20. Pearson correlation coefficients of metrics in RServPlus.

	NDSub	*NSub*	*NOM*	*NIM*	*NCV*	*NIV*	*NCMC*	*NIMC*	*NSup*	*CycC*
NDSub	1									
NSub	0.90106	1								
NOM	0.401425	0.391323	1							
NIM	0.269519	0.336361	0.937761	1						
NCV	0.020773	0.011007	0.354377	0.263483	1					
NIV	-0.04496	-0.03321	0.531022	0.567912	0.167354	1				
NCMC	0.412524	0.256341	0.328736	0.103018	0.152117	-0.06433	1			
NIMC	0.413111	0.49968	0.522096	0.574958	-0.02195	0.236678	0.25692	1		
NSup	-0.07632	-0.08137	-0.04348	-0.03825	-0.20557	0.020931	-0.10169	0.040989	1	
CycC	0.210431	0.132955	0.635589	0.495458	0.339877	0.365389	0.372382	0.23864	0.021297	1
NPubM	0.318625	0.280116	0.835282	0.78335	0.287263	0.280339	0.299901	0.360874	-0.10647	0.444697
NPriM	0.353431	0.374681	0.839365	0.78707	0.306094	0.60708	0.250904	0.512597	0.032864	0.61871
CC	0.121989	0.032893	0.430053	0.331422	0.159109	0.238861	0.294726	0.145722	0.123171	0.410051
U	-0.0871	-0.06935	-0.09633	-0.06644	0.089849	0.040745	-0.0507	-0.03499	-0.5745	-0.08162
S	0.462782	0.413979	0.350052	0.181629	0.033283	-0.03669	0.416716	0.177834	-0.13754	0.267447
LOC	0.107464	0.142512	0.818436	0.882119	0.300227	0.582392	0.028066	0.451541	0.024769	0.551193
NOS	0.09644	0.131992	0.788135	0.845798	0.283299	0.586356	0.041922	0.474861	0.041609	0.579313
LC	0.082202	0.114482	0.788873	0.845828	0.288563	0.554914	0.041743	0.447302	0.050634	0.571072
NMS	0.109572	0.147408	0.816236	0.87745	0.301117	0.574984	0.032738	0.481746	0.029509	0.505816
NP	0.227375	0.281147	0.795403	0.850771	0.194605	0.322384	0.087674	0.429691	-0.07437	0.370314
RServ	0.040251	0.025738	0.067425	0.044942	0.010768	-0.03238	0.207846	0.141158	0.003072	0.106093

(Table continued)

Table 4.20 continued

	NPubM	*NPriM*	*CC*	*U*	*S*	*LOC*	*NOS*	*LC*	*NMS*	*NP*	*RServ*
NPubM	1										
NPriM	0.402242	1									
CC	0.291022	0.428389	1								
U	-0.02154	-0.13911	-0.13223	1							
S	0.292261	0.293951	0.155267	-0.12465	1						
LOC	0.640365	0.729736	0.400759	-0.07291	0.095639	1					
NOS	0.568873	0.749957	0.415984	-0.07483	0.091175	0.980777	1				
LC	0.597702	0.722686	0.419697	-0.07797	0.088636	0.98506	0.992324	1			
NMS	0.62066	0.745553	0.403653	-0.06152	0.102023	0.946549	0.955394	0.946779	1		
NP	0.797564	0.53597	0.229229	-0.00891	0.201848	0.713732	0.63414	0.683702	0.664109	1	
RServ	0.06899	0.044066	0.091566	-0.04695	0.021939	0.051713	0.068534	0.076453	0.058785	0.068814	1

NSub and *NDSub*	*NIM* and *NMS*
NOM and *NIM*	*NIM* and *NP*
NOM and *NPubM*	*NIMC* and *RExt*
NOM and *NPriM*	*LOC* and *NOS*
NOM and *LOC*	*LOC* and *LC*
NOM and *NMS*	*LOC* and *NMS*
NOM and *NP*	*NOS* and *LC*
NIM and *LOC*	*NOS* and *NMS*
NIM and *NOS*	*LC* and *NMS*.
NIM and *LC*	

Figure 4.6 Pairs in RServPlus with r-values > 0.8.

Table 4.21. Pearson correlation coefficient of RInherit, RExt and RServ.

	RInherit	*RExt*	*RServ*
Rinherit	1		
Rext	0.732158	1	
Rserv	-0.02852	0.024705	1
n=61			
RInherit, RExt, RServ > 1			

Table 4.22. Pearson correlation coefficient of U, RInherit, RExt and RServ.

	U	*RInherit*	*RExt*	*RServ*
U	1			
RInherit	-0.36918	1		
RExt	-0.12006	0.556036	1	
RServ	0.027779	0.057251	0.278479	1
n = 16				
RInherit, RExt, RServ > 2				
U > .1				

4.5 Summary

In sixteen out of twenty OO metrics, there are significant mean differences between the mean metric values of classes that have reuse values greater than one and classes that have reuse values equal to zero or one. The only exceptions are: *NCV* for inheritance-based reuse; *U* for inter-application reuse by extension; *NDSub* and *NSub* for inter-application reuse as a server. Results show that the higher the values of { *NOM, NIM, NIV, NCMC, NIMC, CycC, NPubM, NPriM, CC, S, LOC, LC, NMS, NP* }, the class is at least two times more likely to be reused through inheritance, by extension from another application, and as a server. On the other hand, the lower the values of *NSup*, the class is at least two times more likely to be reused through inheritance, by extension from another application, and as a server.

We found that object-oriented metrics have a statistical relationship with inheritance-based reuse and inter-application reuse by extension. Two prediction equations were derived relating these two reuse measures with OO metrics. The contribution of *NSub* to the inheritance-based reuse model's R^2 is large, suggesting that this metric should be calculated for inheritance-based reuse studies. For inter-application reuse by extension, the major contributor to R^2 is *NIMC*. This result suggests that the number of logical grouping of methods within a class should be investigated when studying inter-application reuse by extension. Inter-application reuse as a server does not have a linear statistical relationship with the OO metrics in this study. Validation results show that it is possible to predict whether a class from one application can be reused by extension in another application. Lastly, *LOC* is positively correlated with *LC*; *CycC* is positively correlated with *LC*; and *RInherit* and *RExt* are positively correlated.

Chapter 5. Summary and Conclusions

The role of measurement in any engineering discipline is important. In the software engineering discipline however, the progress of research in software measurement has been either slow or lacking in theoretical basis. Added to this scenario is the recent birth of the OO paradigm which is unlike the traditional procedural paradigm. Proponents of OOP claim that reusability is an added benefit of the paradigm. Software metrics for the traditional paradigm are abundant, but are criticized for having little or no solid theoretical basis. Moreover, these metrics do not support new OO concepts. The OOD metrics in [Chi94] are one of the most comprehensive and successful attempts to provide a metrics suite for OOD. The feasibility of gathering and statistically analyzing empirical data was also shown by recent studies.

This research investigated whether reusable classes can be characterized by OO software metrics. The investigation was carried out by:

- proposing three quantitative measures of reuse in the object-oriented paradigm (*RInherit, RExt, RServ*)
- collecting metrics data from Smalltalk applications using an automated tool
- investigating the statistical relationship between object-oriented and traditional metrics with the reuse measures
- deriving prediction models for measuring reusability using the object-oriented metrics
- validating these prediction models with empirical data

For most of the OO metrics, there are significant mean differences between the mean metric values of classes that have reuse values greater than one and classes that

reuse values equal to zero or one. The only exceptions are: *NCV* for inheritance-based reuse; *U* for inter-application reuse by extension; *NDSub* and *NSub* for inter-application reuse as a server. It was shown that the higher the values of { *NOM, NIM, NIV, NCMC, NIMC, CycC, NPubM, NPriM, CC, S, LOC, LC, NMS, NP* }, the class is at least two times more likely to be reused through inheritance, by extension from another application, and as a server. Moreover, it was shown that the lower the values of *NSup*, the class is at least two times more likely to be reused through inheritance, by extension from another application, and as a server.

Object-oriented metrics were shown to have a statistical relationship with inheritance-based reuse and inter-application reuse by extension. Two prediction equations were derived relating these two reuse measures with OO metrics. The contribution of *NSub* to the inheritance-based reuse model's R^2 is large, suggesting that this metric should be calculated for inheritance-based reuse studies. For inter-application reuse by extension, the largest contributor to R^2 is *NIMC*. This suggests that the number of logical grouping of methods within a class should be considered when studying inter-application reuse by extension. Inter-application reuse as a server does not have a linear statistical relationship with the OO metrics in this study.

Validation results show that it is possible to predict whether a class from one application can be reused by extension in another application.

Lastly, the following metric pairs are correlated: *NSub* and *NDSub*, *NOM* and *NIM*, *NOM* and *NPubM*, *NOM* and *NPriM*, *NOM* and *LOC*, *NOM* and *NOS*, *NOM* and *NMS*, *NOM* and *NP*, *NIM* and *NPriM*, *NIM* and *LOC*, *NIM* and *NOS*, *NIM* and *LC*, *NIM* and *NMS*, *NIM* and *NP*, *LOC* and *NOS*, *LOC* and *LC*, *LOC* and *NMS*, *NOS* and *LC*, *NOS*

and *NMS*, *LC* and *NMS*, *CycC* and *LC*, *NSub* and *RInherit*, *NIMC* and *RExt*, *NIMC* and *RExt*, *RInherit* and *RExt*.

5.1 Contributions Of This Research

To summarize, the contributions of this research are as follows.

- Three quantitative measures of reuse (*RInherit*, *RExt*, *RServ*) in the object-oriented paradigm were defined. These measures are based on OO concepts such as inheritance and extensibility and hence, are appropriate in measuring class reuse.
- Linear regression results show that *NSub* can be used to predict reuse through inheritance.
- Linear regression results show that *NIMC* can be used to predict inter-application reuse by extension.
- A class metric collector (CMC) tool was implemented that can automatically collect 20 metrics and *RInherit*, *RExt*, *RServ*.
- T-test results can be used as guidelines in writing new reusable classes.

5.2 Future Work

This dissertation research can be extended in the following ways:

- Use other OO metrics and correlate them with *RInherit*, *RExt*, *RServ*
- Use Java packages instead of Smalltalk applications and define *RInherit* as was defined here, *RExt* as inter-package reuse by extension, *RServ* as inter-package reuse as a server.

- Refine the definition of *RInherit* to factor in the number of times a method from a superclass *C* is actually used by *C*'s subclasses.
- Replicate this study in other Smalltalk environments.

In summary, this research can be extended by: using other OO metrics to correlate with *RInherit*, *RExt*, *RServ*; refining the definition of *RInherit*; and replicating this study in other Smalltalk environments; using Java packages instead of Smalltalk applications.

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Appendix A

Glossary

application. - A collection of defined and extended classes that provides a reusable piece of functionality. An application contains and organizes functionally related classes. It also can contain subapplications and specify prerequisites.

class. The specification of an object, including its attributes and behavior. Once defined, a class can be used as a template for the creation of object instances. "Class," therefore, can also refer to the collection of objects that share those specifications. A class exists within a hierarchy of classes in which it inherits attributes and behavior from its superclasses, which exist closer to the root of the hierarchy. See also inheritance, metaclass, polymorphism, defined class, extended class, private class, public class, visible class.

class extension. An extension to the functionality of a class defined by another application. The extension consists of one or more methods that define the added functionality or behavior. These methods cannot modify the existing behavior of the defined class; they can only add behavior specific to the application that contains the extended class.

class hierarchy. A tree structure that defines the relationships between classes. A class has subclasses down the hierarchy from itself and superclasses up the hierarchy from itself. The methods and variables of a class are inherited by its subclasses.

class instance variable. Private data that belongs to a class. The defining class and each subclass maintain their own copy of the data. Only the class methods of the class can directly reference the data. Changing the data in one class does not change it for the other classes in the hierarchy. Contrast with class variable.

class method. A method that provides behavior for a class. Class methods are usually used to define ways to create instances of the class. Contrast with instance method.

class variable. Data that is shared by the defining class and its subclasses. The instance methods and class methods of the defining class and its subclasses can directly reference this data. Changing the data in one class changes it for all of the other classes. Contrast with class instance variable.

containing application. The application to which a class definition belongs. A class can only be defined in one application in the image. Also referred to as the defining application.

defined class. A new class that a containing application adds to the system. It consists of a textual definition (which defines elements such as instance variables) and zero or more methods (which define behaviors). Contrast with extended class.

defining application. The application to which a class definition belongs. A class can only be defined in one application in the image. Also referred to as the containing application.

expression. In Smalltalk, the syntactic representation of one or more messages. An expression can consist of subexpressions representing the receiver and arguments of the message. The expression can also cause the assignment of its result to one or more variables.

extended class. An class that uses and extends the functionality of a class defined by another application. It consists of one or more methods that define the added functionality or behavior. These methods cannot modify the existing behavior of the defined class; they can only add behavior specific to the application that contains the extended class. Contrast with defined class.

image. A Smalltalk file that provides a development environment on an individual workstation. An image contains object instances, classes, and methods. It must be loaded into the Smalltalk virtual machine in order to run.

inheritance. A relationship among classes in which one class shares the structure and behavior of another. A subclass inherits from a superclass.

instance. An object that is a single occurrence of a particular class. An instance exists in memory or external media in persistent form.

instance method. In Smalltalk, a method that provides behavior for particular instances of a class. Messages that invoke instance methods are sent to particular instances, rather than to the class as a whole. Contrast with class method.

instance variable. Private data that belongs to an instance of a class and is hidden from direct access by all other objects. Instance variables can only be accessed by the instance methods of the defining class and its subclasses.

keyword message. A message that takes one or more arguments. A keyword is an identifier followed by a colon (:). Each keyword requires one argument, and the order of the keywords is important. 'hello' at: 2 put: $H is an example of a keyword message; at: and put: are keyword selectors, 2 and $H are the arguments. Contrast with binary message, unary message.

library. A shared repository represented by a single file. It stores source code, object (compiled) code, and persistent objects, including editions, versions, and releases of software components.

literal. An object that can be created by the compiler. A literal can be a number, a character string, a single character, a symbol, or an array. All literals are unique: two literals with the same value refer to the same object. The object created by a literal is read-only: it cannot be changed.

Appendix B

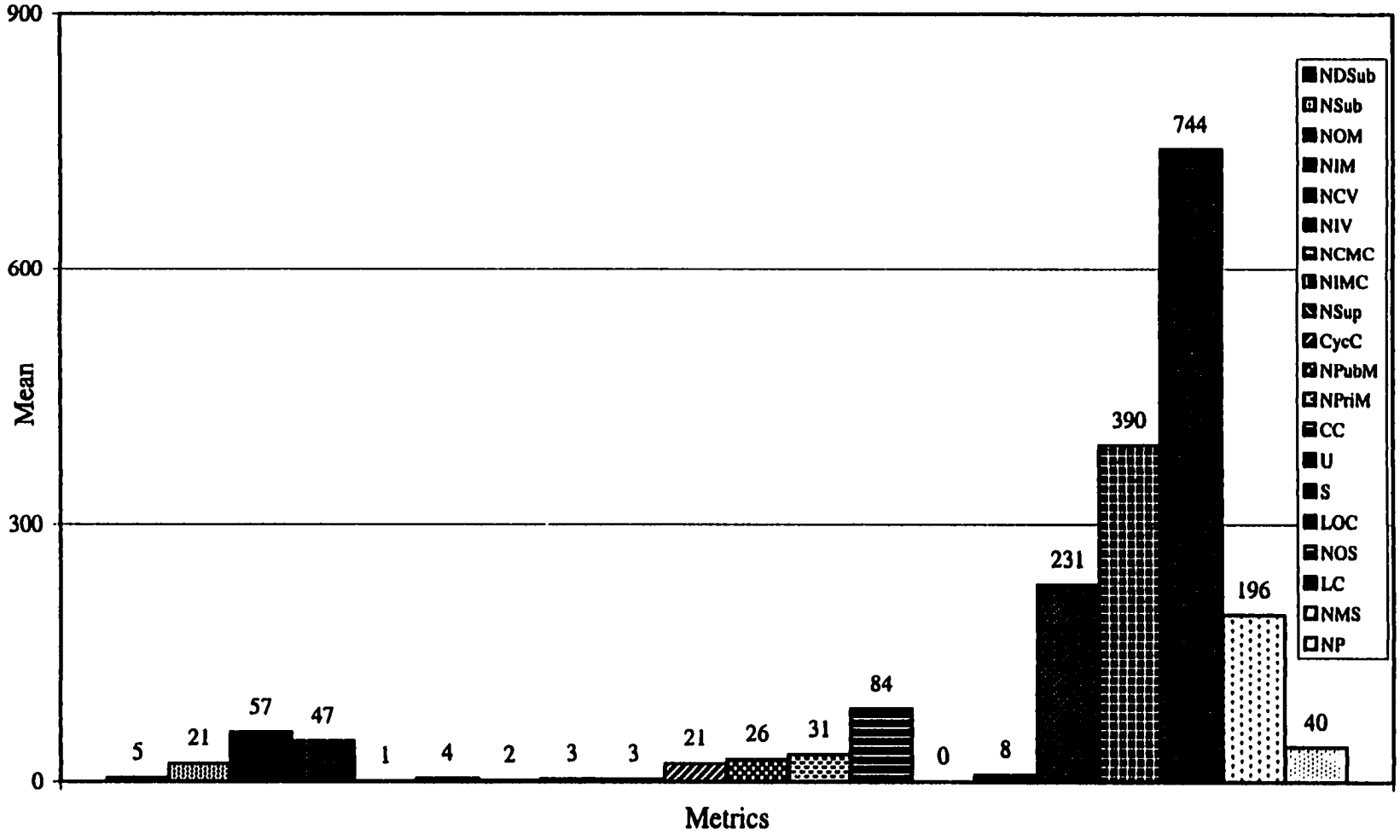


Figure B.1. Mean of the RExtPlus Group.

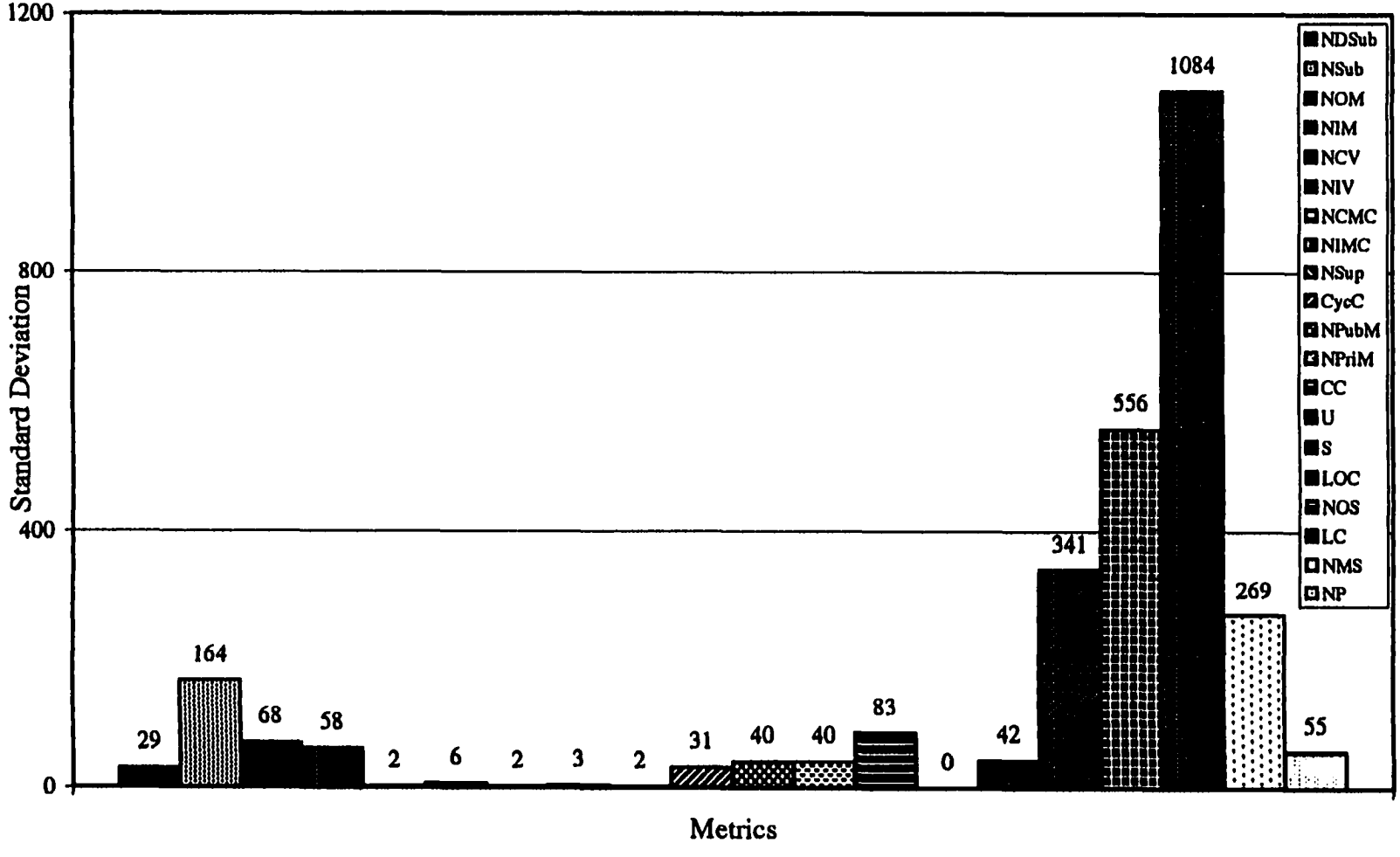


Figure B.2. Standard deviation of the metrics RExtPlus Group.

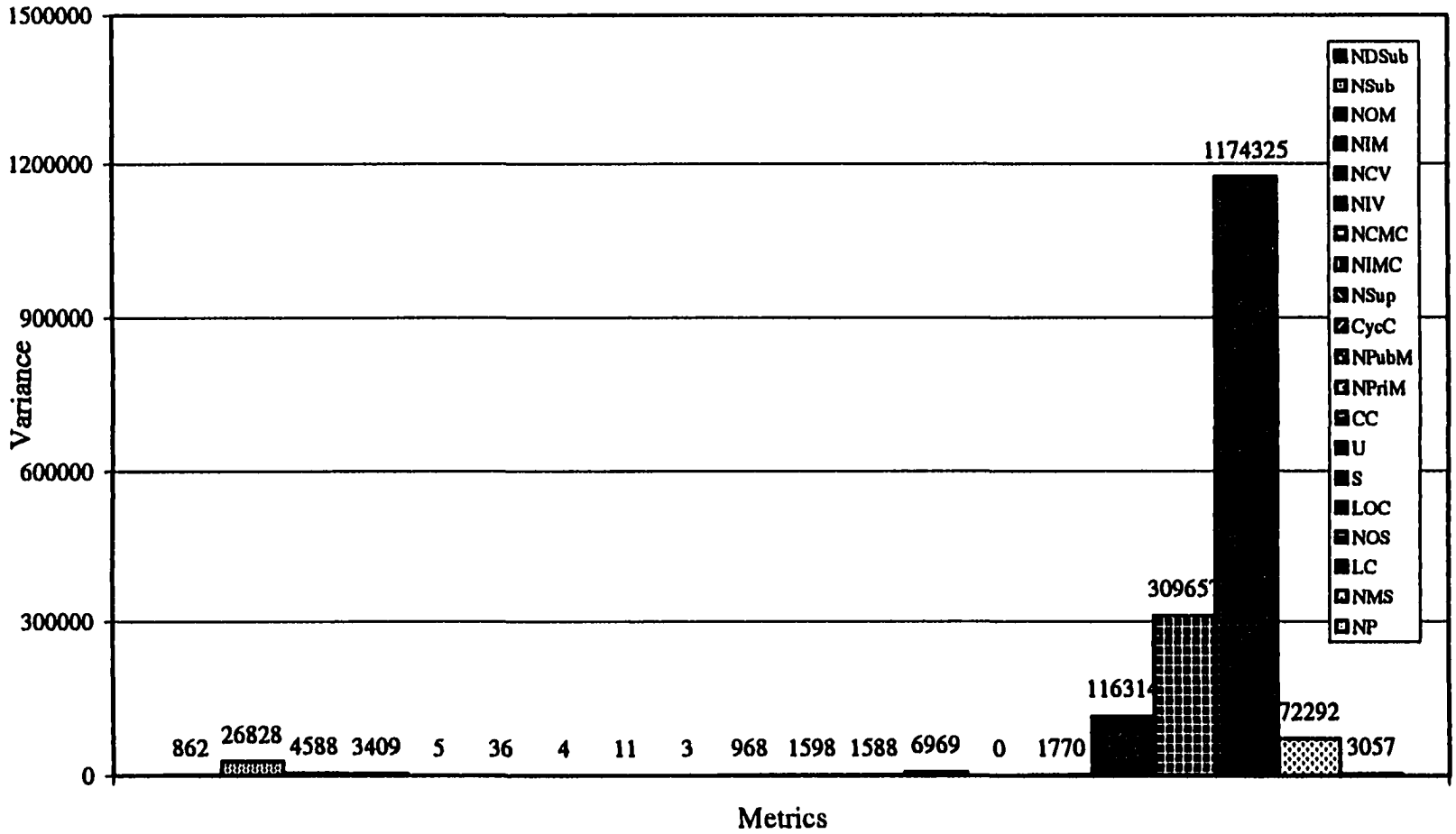


Figure B.3. Variance of the metrics RExtPlus Group.

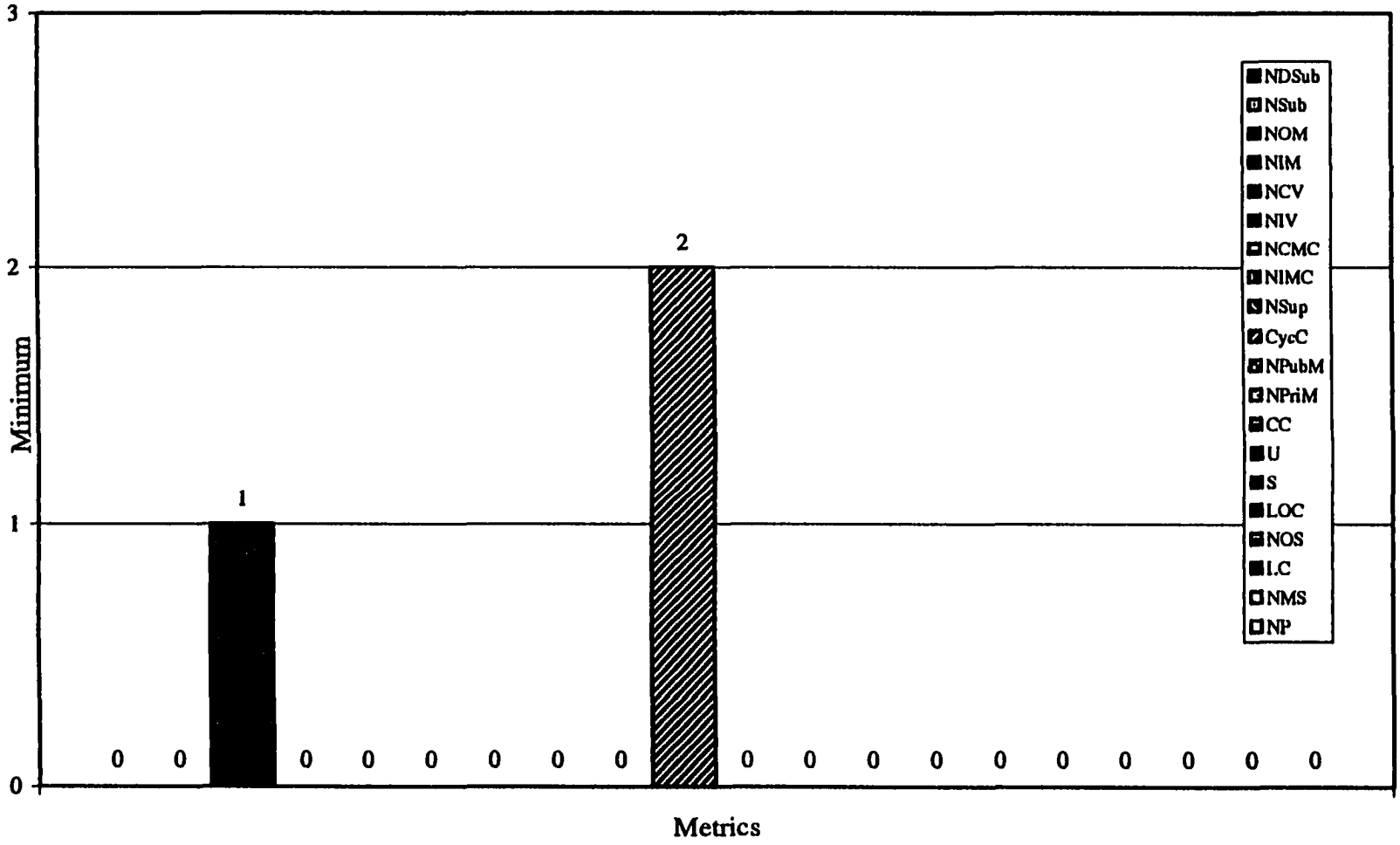


Figure B.4. Minimum of the metrics RExtPlus Group.

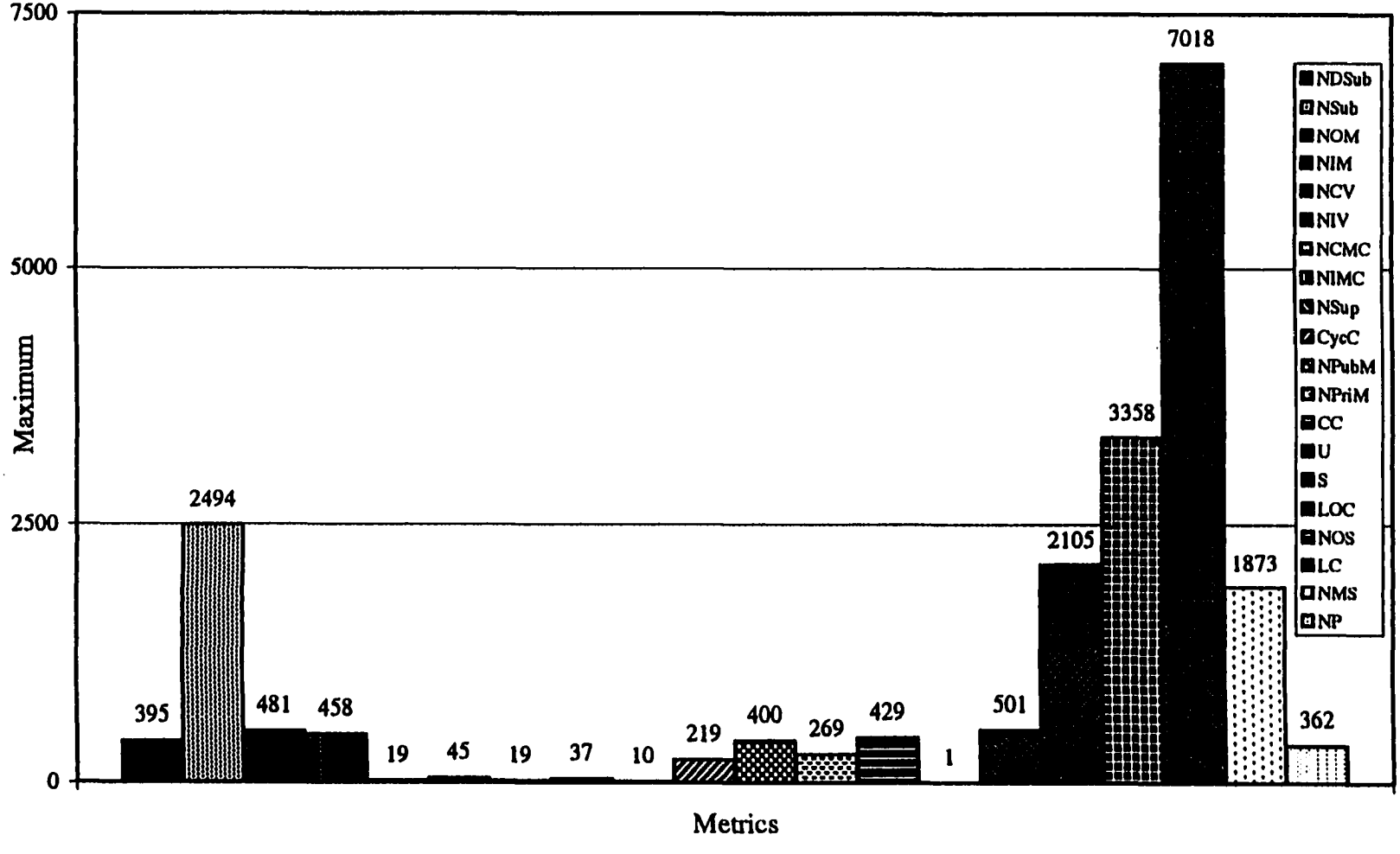


Figure B.5. Maximum of the metrics RExtPlus Group

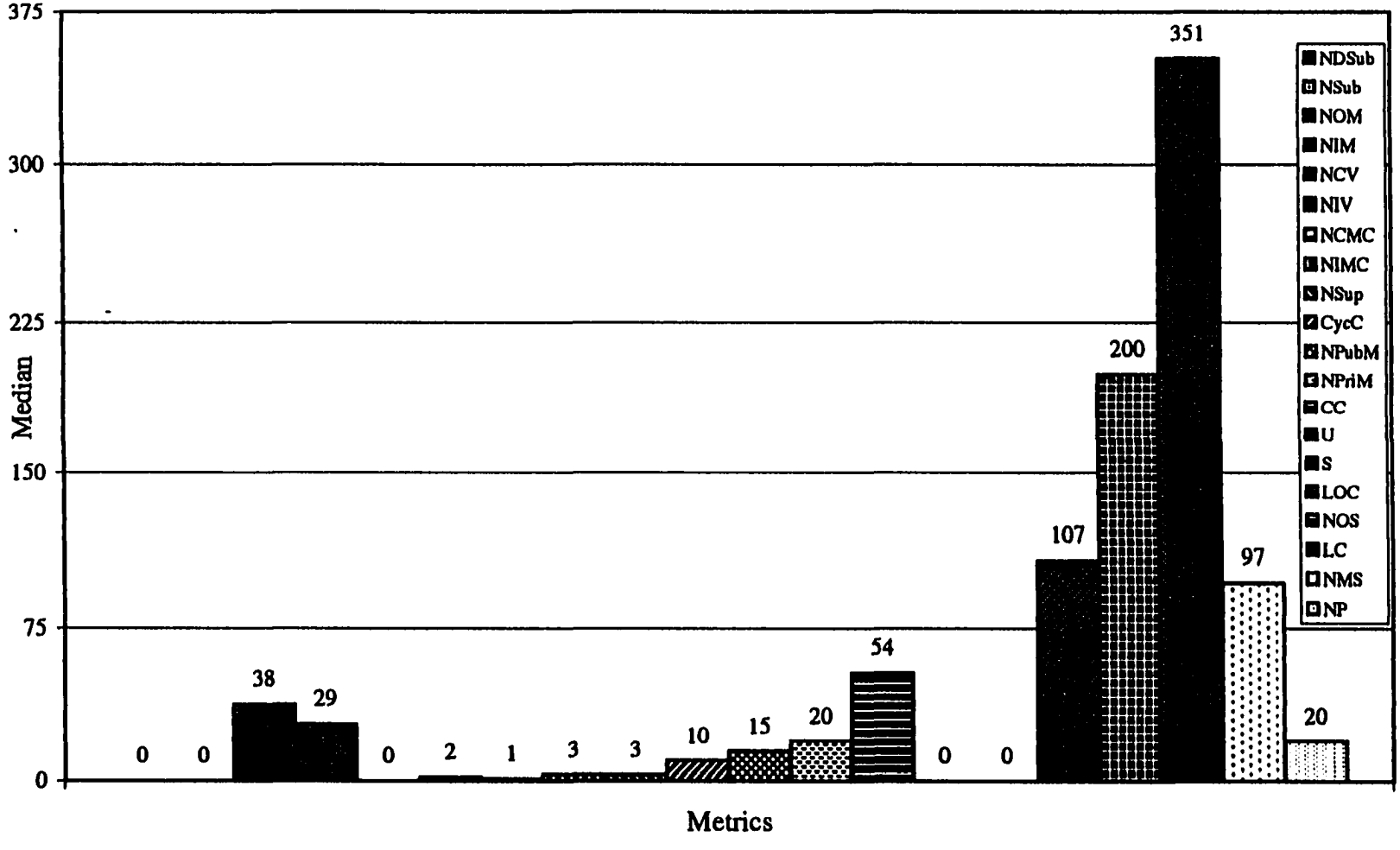


Figure B.6. Median of the metrics of RExtPlus Group

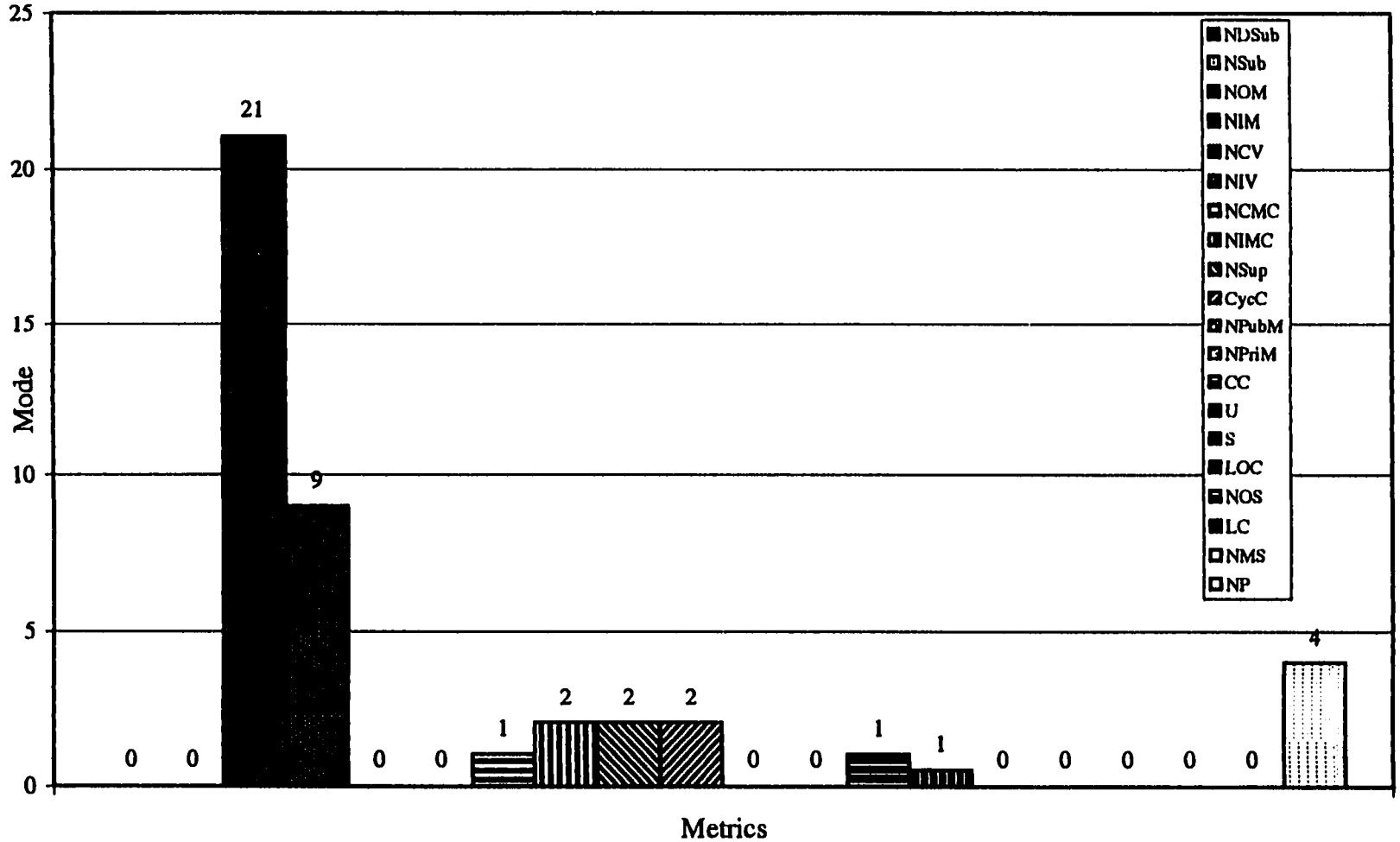


Figure B.7. Mode of the metrics RExtPlus Group.

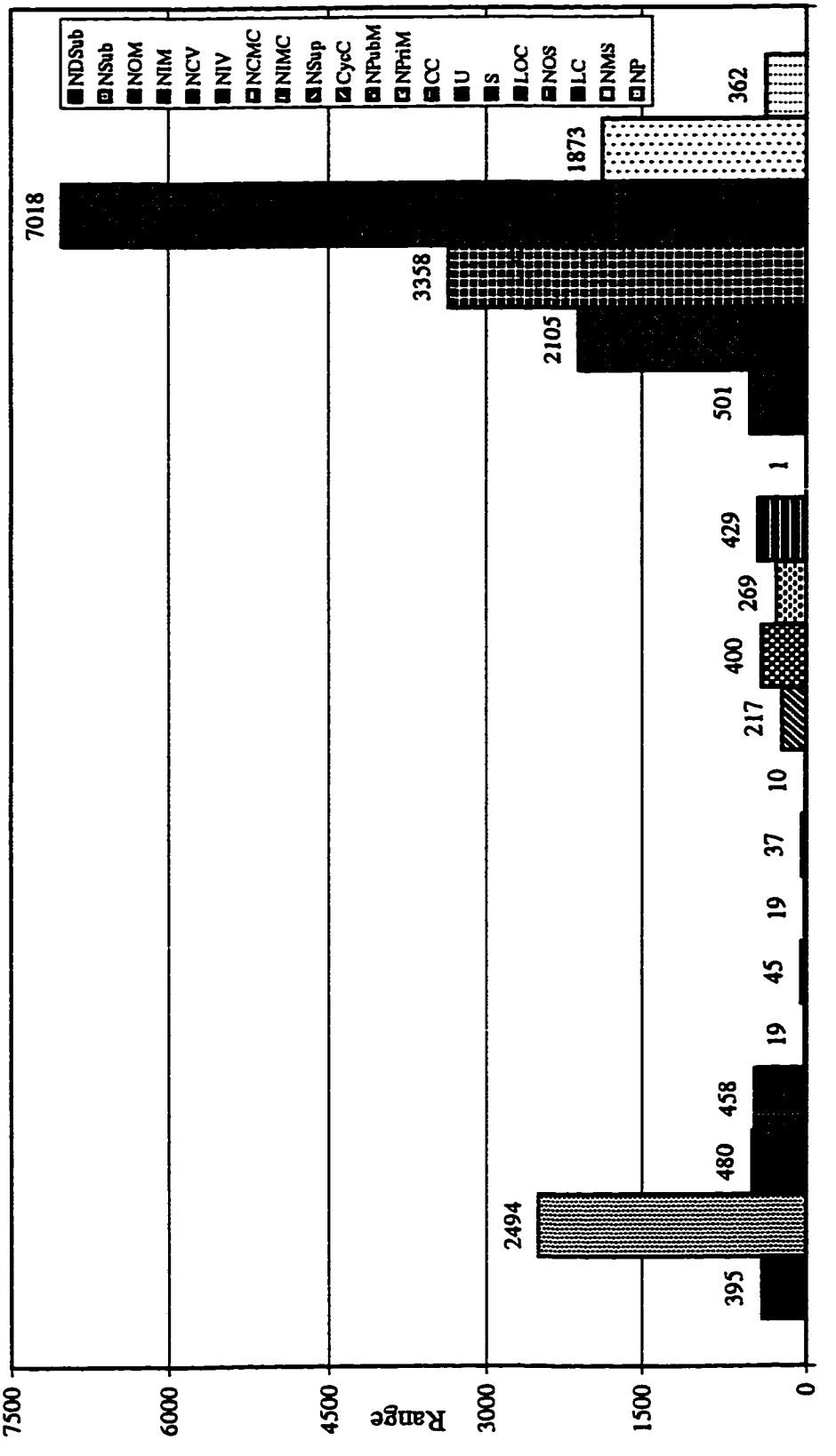


Figure B.8. Range of the metrics RExtPlus Group

Vita

Maria Lorna Bacarisa Reyes was born in Abra, Philippines. She is the second of seven children born to Anatolio Bacarisa, Sr., and Natividad Agaloos Bacarisa. Lorna is married to Manuel Reyes Reyes, and has a teenage son, Manuel Miguel Reyes, Jr.

In 1980, Lorna took her bachelor of science degree in Mathematics from the University of the Philippines at Los Banos (UPLB), Laguna, Philippines. She taught at the Institute of Mathematical Sciences and Physics, UPLB, from 1984 – 1986. Lorna then moved to teach at the Department of Mathematics at the University of the Philippines in Diliman, Quezon City. In 1988, she pursued a master of science degree in Applied Statistics at the Bowling Green State University, Bowling Green, Ohio, U.S.A. In the Spring of 1991, Lorna started her doctoral in Computer Science at Louisiana State University, Baton Rouge, Louisiana. Lorna is now working at IBM, Research Triangle Park, North Carolina, as a Staff Software Engineer. She is with the VisualAge for Java and VisualAge for Smalltalk validation team.

DOCTORAL EXAMINATION AND DISSERTATION REPORT

Candidate: Maria Lorna Reyes

Major Field: Computer Science

Title of Dissertation: Assessing the Reuse Potential of Objects

Approved:

Major Professor and Chairman

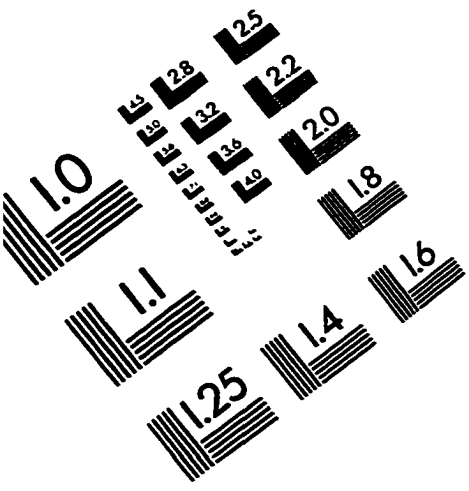
Dean of the Graduate School

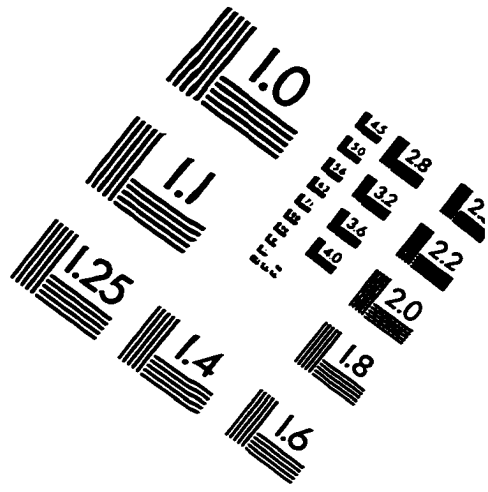
EXAMINING COMMITTEE:

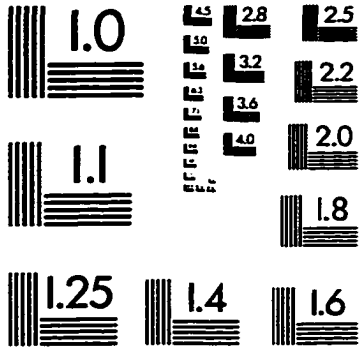
Date of Examination:

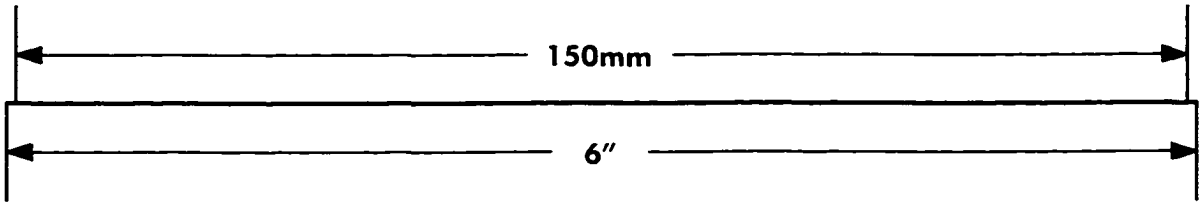
11/3/98

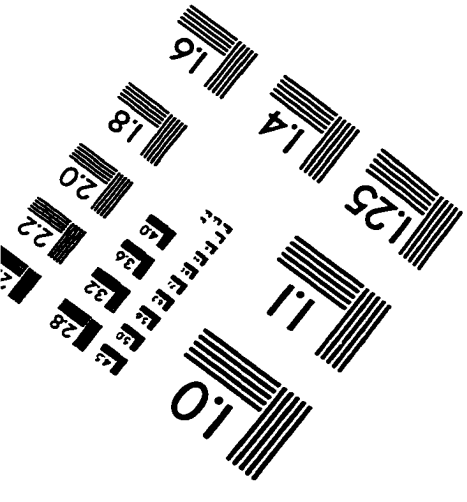
IMAGE EVALUATION TEST TARGET (QA-3)

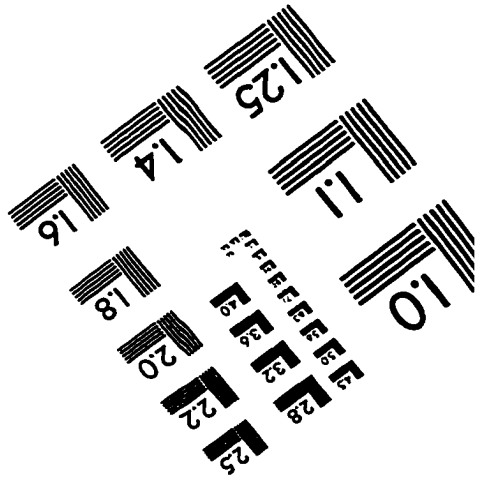












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