Validating Cohesion Metrics by Mining Open Source Software Data With Association Rules

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A dissertation submitted for the fulfillment of the requirement for the degree of Masters in Information Technology

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Declaration

I, Pariksha Singh declare that this dissertation represents research work carried out by myself and that it has not been submitted in any form for another degree at any university or higher learning institute. All information used from published or unpublished work of others has been acknowledged in the text.

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Pariksha Singh Date

Dedication

To my spouse Surendra, parents Premlall and Vanitha, siblings Varsha and Vedanth, and children Yadav and Shriya thank you for your love and support.

Acknowledgements

I would like to express my sincerest and deepest gratitude to all the people who supported me throughout my research.

I am particularly grateful to my supervisor Dr Eyono Obono for his thoughtful and creative comments, and especially for exploring with me the boundaries of the study. I am indebted to him for his unbounded enthusiasm and infectious energy.

I like to thank Professor D Petkov for his significant input and intriguing ideas.

My deepest gratitude goes to Pieter Germishuys and Nolan Naidoo for their assistance in helping program the software used by this study.

My appreciation also goes to Nareen Gonsalves for her critical evaluation and editing of the dissertation.

I wish to thank Anusha Govender and the IT department for the fruits of several valuable discussions held throughout the course of this work.

I thank my spouse, Surendra, for his forbearance whilst I have spent hundreds of hours working. A special thanks to family members who have continually offered advice, support and encouragement throughout my study.

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Abstract

Competitive pressure on the software industry encourages organizations to examine the effectiveness of their software development and evolutionary processes. Therefore it is important that software is measured in order to improve the quality. The question is not whether we should measure software but how it should be measured. Software measurement has been in existence for over three decades and it is still in the process of becoming a mature science. The many influences of new software development technologies have led to a diverse growth in software measurement technologies which have resulted in various definitions and validation techniques.

An important aspect of software measurement is the measurement of the design, which nowadays often means the measurement of object oriented design. Chidamer and Kemerer (1994) designed a metric suite for object oriented design, which has provided a new foundation for metrics and acts as a starting point for further development of the software measurement science.

This study documents theoretical object oriented cohesion metrics and calculates those metrics for classes extracted from a sample of open source software packages. For each open source software package, the following data is recorded: software size, age, domain, number of developers, number of bugs, support requests, feature requests, etc. The study then tests by means of association rules which theoretical cohesion metrics are validated hypothesis: that older software is more cohesive than younger software, bigger packages is less cohesive than smaller packages, and the smaller the software program the more maintainable it is.

This study attempts to validate existing theoretical object oriented cohesion metrics by mining open source software data with association rules.

Glossary of Terms

Attribute: - A data item encapsulated in a class. Other names include instance variable, data member, and state variable

Class: - A term that denotes the encapsulation of data and behavior into a single package or unit. Class is the template from which many objects are instantiated.

Independent Variables: - Variables that do not depend on one another

Measurement: - The process by which numbers or symbols are assigned to attributes of entities in the real world according to clearly defined rules

Methodology: - Comprehensive guidelines to follow for completing an activity including specific models, tools and techniques

Methods: - How behaviors are implemented in object oriented languages. Similar to functions found in other languages.

Metrics: - The aspect being measured.

Private Methods: - Methods that are accessible only within the body of a class.

Public Methods: - Methods with no access limitation.

Object: - Instance of a class.

Object Orientation

Approach: - An approach to system development that views a program as a collection of interacting objects that work together to accomplish required tasks.

Variables: The representation of an area in the computer memory in which a value of a particular data type can be stored.

List of Acronyms

CAMC: - Cohesion among methods in a class

CBO: - Coupling between objects

GNU: - Not Unix

Co: - Connectivity

CVS: - Concurrent versioning system

GQM: - Goal question metrics

Ich: - Information – flow based cohesion

Lcc: - Loose class cohesion

Lcom: - Lack of cohesion Metrics

MNC: - Number of methods in a class

NAS: - Number of associations

OO: - Object Oriented

OSS: - Open source software

RFC: - Response for a class

Tcc: - Tight class cohesion

TCO: - Total cost of ownership

Chapter One - Introduction

1.1 Background

Software engineering is the process of developing software through successive phases in a methodical way. This process includes the groundwork of the user requirements definition and analysis, the design of what is to be coded, the actual writing of software code, and the testing of the developed software to ensure that it meets the requirements. Before systems development methods came into being, the development of new systems or products was often carried out using the experience and intuition of management and technical personnel. Among systems development methods, object oriented programming within the unified model is the state of the art software development model. It is difficult to perform measurements on proprietary software due to its closed nature, but the emergence of Open Source Software has opened new opportunities to measure software features. One of theses features is software quality. But software quality must be considered in the broader context of the software project's scope.

1.1.2 Software Project Scope

A project scope encompasses these three concepts: quality, cost and time.

1.1.2.1 Quality

While it is obvious that determining what truly represents software quality in the customer's view can be elusive, it is equally apparent that the number and regularity of problems and defects associated with a software product are inversely proportional to the quality of the software. Software problems and defects are among the few direct measurements of software processes and products. Flora (1996) states that "Problem and defect measurements are also the basis for quantifying several significant software quality attributes, factors, and criteria-reliability, correctness, completeness, efficiency, and usability among others" .

1.1.2.2 Cost and Maintenance

The amount of rework is an important cost factor in software development and maintenance. The number of problems and defects connected with the product are direct contributors to this cost. Measurement of defects can assist one to realize where and how the problems and defects arise, provide an insight to methods of fault detection, fault prevention, and fault prediction, and keep expenditure under control. Maintenance of software is also considered an immense cost in the software development process.

It is difficult to measure the quality of software code but evaluating why code is difficult and time consuming to maintain is very important. According to Wise (2005) maintenance problems fall into one of the following categories: poor specifications, complex design and bad code.

a) Poor specification

Poor specification is usually a result of poor planning and communication between the users/management and the developer/architect.

b) Complex Design

When the code is required to do really complicated things, its structure and reliability also become complex.

c) Bad code

Bad code seems to be linked to programming experience. The following questions are used when it comes to bad coding. Are the developers not following coding standards? Do developers have a fundamental misunderstanding of how to write clean code? Are they junior developers who are performing tasks for the first time?

The above categories (a, b, c) have an impact on the maintenance of software code.

1.1.2.3 Schedule

The primary driver of projects schedules is the tracking of workload, people and processes. But it is also useful to measure defects in tracking project progress in order to identify process inefficiencies, and to forecast obstacles that can jeopardize scheduled commitments.

If software development is no longer seen as an 'art', but as a craft or a science, then we must be able to measure the characteristics of a software product. We can pursue this by using metrics. Metrics can provide the feedback we need during the software life cycle in order to evaluate software complexity, and to avoid its inherent consequence which is defective software.

1.1.3 Object Oriented Programming

Currently, software development environments quite often form a methodological and technical framework for the realization of complex software systems. Because of the demand for tool integration, tool management, communication support, and process modeling, etc., the conception and realization of such development environments becomes quite a difficult undertaking. A distinct software process is required to provide organizations with a reliable framework for performing and improving their work. An overall modeling framework simplifies the task of producing process models, permits them to be customized to particular requirements, and facilitates process evolution. It is often claimed that the object oriented programming paradigm allows a faster development pace and higher quality of software. A number of metrics have been proposed to measure object oriented systems. Chidamber and Kemerer (Chidamber et al, 1994) made one of the first attempts at developing software metrics for object oriented systems. They proposed a set of six oriented design metrics. Object oriented systems development is one of the

major aspects of modern software engineering.

Certain aspects of object orientation require a fundamental reconsideration of basic concepts of development environments as well as their technical realization. Emphasis is placed on a realistic consistent object oriented software development environment and on the concepts for integrating an object oriented generic process model into a software development environment.

1.1.4 Open Source Software

Open Source software is a system whose source code is freely available to the general public for use and/or modification from its original design. Open source code is usually produced as a collaborative attempt in which programmers enhance upon the code and disclose the changes. The open source definition denotes that the origins of a product are freely available in part or in full.

1.1.5 Software and Cohesion Metrics

A metric is defined as a process by which numbers are assigned to attributes of entities in the real world to describe them according to clearly defined rules (Fenton, 1994). There are relatively new metrics, called 'object oriented' metrics and the older metrics, which are now referred to as "traditional" or "conventional" metrics. Then there is another distinction, namely, there are metrics that measure the written code, and there are metrics for software design.

The study of metrics was established in the 1960s and developed further in the 1970s. The earliest software metric is the measure LOC (lines of code) (Park, 1992). This metric was subjected to lots of criticism for the reason that the program length is not a good way to determine program characteristics like reliability and ease of maintenance.

That criticism gave birth to a great deal of metrics and measurement ideas. For example, the metrics proposed by McCabe (1989) and Halstead (1997) were created in the middle of the 1970s, and are still heavily discussed today. In (McCabe, 1989), cyclomatic metric is presented; it uses graph theory to measure software complexity. It looks at a program's control flow graph and determines the minimum number of paths in that graph. McCabe argued that this number determines the complexity (cyclomatic complexity) of a program. Halstead devised a metric, which is based on two quantities: the number of distinct operators in the program and the number of distinct operands in the program. From these numbers one can construct the "Halted Length" which is the measure of the complexity of a program. Usually the "Halted length" is calculated after the code is written but is also used for the measurement of programming effort. McCabe and Halstead complexity measures were deemed to be inconsistent due to the following:

a) The measure is independent on physical size.
b) The measure fails to distinguish between different kinds of control flow structure.
c) The measure does not account for the level of nesting of various control structures and for this measure three loops in succession and three nested loops are equivalent. Such nesting however, may affect the psychological complexity of the program.
d) The cyclomatic complexity increases with each application of structuring transformation like node splitting.

These inconsistencies urged different researchers to improve the science of metrics. Weyuker (1998) proposed her desirable properties for metrics; these properties are discussed and elaborately explained by Misra and Misra (2007). Weyuker properties are accepted by numerous authors as been very robust.

Recent works by Chidamber and Kemerer (1994) outline the most important Object oriented metrics. These metrics are summarized by Briand, Daly, and Wust (1999).

1.1.6 Data Mining

Data mining, also known as knowledge discovery, is the practice of analyzing data from diverse perspectives and summarizing it into constructive information. Data mining software is an analytical tool for analyzing data. It allows users to analyze data from many diverse dimensions or angles, categorize it, and summarize the relationships recognized. Data mining is the process of finding correlations or patterns among thousands of fields in large relational databases.

1.1.6.1 Data Mining Algorithms

Frequent item set mining (FIM) has only being in existence from 1993 according to Agrawal, Imielienski and Swami (1993). These authors describe and explain the way association rules works when mining databases with a large number of item sets. Agrawal, Imielinski and Swami (1993) introduced an algorithm called *AIS*. Later Agrawal and Srikant (1994) proposed two new algorithms, called *Apriori* and *AprioriTid* that are fundamentally different from the previous one. The algorithms achieved significant improvements over *AIS* and became the core of many new algorithms for mining association rules.

Cheung (1996) proposed an algorithm called FUP (Fast Update Algorithm) for finding the frequent item sets. The word item set was invented specially for data mining and it means a set of items, a group of elements that represents together a single entity. The major idea of the FUP algorithm is to reuse the information of the old frequent item sets and to integrate the support information of the new frequent item sets in order to reduce the pool of candidate item sets to be re-examined. Along with the item sets, a negative border, proposed by Toivonen (1996) was maintained. A negative border consists of all the item sets that are candidates of the Apriori algorithm that do not have sufficient support.

Another approach to incremental mining of frequent item sets was presented by Thomas et al (1997). The algorithm that was introduced required only one database

pass and was applicable not only for expanded but also for reduced databases. Nag (1999) introduced the issue of interactive mining of association rules and the concept of *knowledge cache* was introduced. The cache was designed to hold frequent item sets that were discovered while processing other queries. Several cache management schemas were proposed by Aggarwal and Yu (1998), Han (1998) and Hidber (1999) and their integration with the Apriori algorithm was analyzed. An important contribution as stated by Nag (1999) was an algorithm that used item sets discovered for higher support thresholds in the discovery process for the same task, but with a lower support threshold. The notion of data mining queries or knowledge discovery in databases was introduced by Imielinski and Mannila (1996). The need for Knowledge and Data Management Systems (KDDMS) as second generation data mining tools was expressed. The ideas of application programming interfaces and data mining query optimizers were also mentioned. Several data mining query languages that are extensions of SQL were proposed by Ceri, Meo and Psaila (1996), Han et al (1996), Imielinski and Mannila (1996) and Morzy, Wojciechowski z and Zakrzewicz (2000).

1.2 Problem Statement

Cohesion metrics intend to measure software quality, but they only apply to software classes. Ideas have been put forward as to how to derive the cohesion of a software package from the cohesion of its classes but the validity of those ideas is still to be proven.

The concept of class cohesion provides an interesting link between object oriented programming and software metrics, but it is even more interesting to study that link in the specific context of open source software.

These are possible research ideas that can exhibit the contribution of object oriented programming, open source software and software metrics (cohesion) to software quality.

1.3 Research Questions

The relationship between software quality, object oriented programming, software metrics, and open source software, calls for several questions.

For example one may want to examine the correlation between software quality as measured by cohesion metrics and software attributes such as software size, software domain, software age and the number of developers. What is the correlation between these independent variables and cohesion? Can software metrics conclusively measure software quality?

Since object oriented cohesion metrics are only defined for classes, how can the cohesion of a software package be calculated?

This research is an attempt to answer the above questions.

1.4 Research objective

The objective of this study is to design a methodology to test the validity of software cohesion metrics.

In pursuing the above-defined objective, the following tasks must be completed.

a) Document existing metrics within the object oriented development environment.
b) Develop software that calculates cohesion metrics for a sample of open source software.
c) Data Mine these metrics to test the hypothesis as outlined in this study.

1.5 Rationale

The Linus's law states, "Given enough eyeballs, all bugs are shallow". More formally:

> "Given a large enough beta-tester and co-developer base, almost every problem will be characterized quickly and the fix obvious to someone" (Torvalds, 2003).

The driving force of Linus' Law is less about security than it is the general process of assuring quality in software. This certainly resonates with the existing deliberation amongst open source advocates, that having source code accessible for analysis and audit helps make certain that potentially unsafe bugs are more easily neutralized.

This law states that the greater number of people to view the developed code that is developed the easier it is to discover bugs and problem areas. With proprietary software only the testing team has access to test the source code therefore some problems may not be unearthed. Due to open source software being available to all eyes, this software can be revised until it is deemed perfect by all associated parties.

This study can contribute to the testing the validity of the Linus Law in the sense that it assesses open source software quality based on the calculation of cohesion metrics of open source software. Threats to validity include construct validity, External validity and internal validity.

Construct Validity is defined as the extent to which the independent variables and dependent variables precisely measure the concept they intend to measure.
Internal Validity is defined as the degree to which conclusion can be drawn about the causal effect of the independent variables on the dependent variables.
External validity is defined as the degree to which the results of the research can be generalized to the population under study and other research settings.

The study focuses on construct validity since cohesion values are compared to independent variables e.g. age, size, category, programming language, etc.

1.6. Research Methodology

The research methodology comprises of the research method, research population and research sample.

1.6.1 Research method

It is important to know that the present study is a survey. The population and sampling of the survey is defined below.

1.6.2 Research population

The research population is made up of open source software. All necessary data can be gathered and downloaded from the *url* http://www.Sourceforge.org. The size of the population of open source software packages as at December 2006 was 65549 and these increases daily.

1.6.3 Sampling

Data gathering for the sample is performed on historical data available from open source software that is on the Internet within software categories. The reason for this is to prove the theory of Linus' Law as stated in the rationale. The sampling method and sample size is defined below.

1.6.3.1 Sampling Method

The sampling method used is randomization within a stratified group. The population referred to above has been stratified into 13 different domains; the sample in each of these domains is randomly chosen. Each software domain is considered as a strata. For example the category "software development" is a strata; Software packages from this category is randomly selected and downloaded. This method is used for the entire sample.

1.6.3.2 Sampling Size

The size of the sample used to test the hypothesis is 68 i.e. 68 software packages are downloaded and their data form the basis of the study. The calculation of the sample size is given in chapter 3.

1.6.4 Data processing

In chapter 4, software data from the 68 software packages is mined using association rules in order to determine the correlation between cohesion and software independent variables.

1.6.5 Hypothesis

The following hypotheses are assumed.

a) There is a correlation between software size, software support requests, software feature requests, software patches and cohesion.
b) Software cohesion does not depend on the software domain.
c) Highly cohesive software contains few errors.

1.7 Scope and constraints

There are different metrics for object oriented design e.g. depth of inheritance tree, weighted average method per class, coupling, lines of code, etc. This study deals exclusively with cohesion metrics, especially the one defined by Chidamber and Kemerer. While the study does discuss cohesion metrics in general, it does however exclusively focus on the cohesion metrics proposed by Chidamber and Kemerer (1994). Software written in a traditional programming language is excluded since this study is based on the object oriented software paradigm.

Another limitation is on the data collected. Data is solely collected from open source

software. The reason for choosing Open source software is because proprietary software or off the shelf software is expensive and their code is not available.

All software studied is written in programming languages in the .net environment (Example C#.net, J#.net, Visual Basic.net, etc)

1.8 Conclusion

A cohesive program is one in which the modularisation of functionality is performed ‘correctly'. More precisely, a cohesive module or function should perform only closely related tasks. The principle is mirrored in object-oriented programming by the concept of encapsulation: well-encapsulated objects contain all necessary data and function members within themselves.

The motivation for measuring and assessing the cohesiveness of programs rests upon claims that highly cohesive code is easier to maintain, modify and reuse.

Open source software is relevant in today’s ever-changing world of information technology and we need to know if the millions of open source code available can be trusted for deployment. One way of measuring whether this open source software code is reliable is through the measurement of quality. One measurement of software quality used today is software cohesion. Cohesion can confirm if software quality is high, medium or low and if software reuse is a dependable approach.

This study comprise of five chapters and is broken down into 3 three sections. In the first section, which is chapters one and two, an overall context for the study is provided, as well as an in-depth literature review on the mining of software engineering data.

In the second section, which comprises chapter three, a description of the research methodology is given with the aim of explaining the entire research process from the data collection to the production of association rules. The design of software programs is written for the calculation of cohesion metrics are presented.

Finally, in chapter four, the association rules are analyzed and the results of that analysis are presented and interpreted. Chapter five concludes the study.

Chapter Two - Literature review

2.1 Introduction

Validation of software measures and prediction models are based on the following questions documented by Zeus (1991):

a) Is it possible to predict the error-proneness of a system using software measures from its design phase?
b) Is it possible to extract quantitative features from the representation of a software design to enable us to predict the degree of maintainability of a software system?
c) Are there any quantifiable, key features of the program code of a module that would enable us to predict the degree of difficulty of testing for that module, and the number of residual errors in the module after a particular level of testing has occurred?
d) Is it possible to extract quantifiable features from the representation of a software design to enable us to predict the amount of effort required to build the software described by that design?
e) What properties of software measures are required in order to determine the quality of a design?
f) Are there features in order to predict the size of a project from the specification phase?
g) What are appropriate software measures to underlie the software quality attributes of the ISO 9126 norm by numbers?
h) What are the criteria for the internal and external validation of software measures? What are the criteria for prediction models?

These questions may form the basis of a software measurement theory whose importance according to Zeus will become more and more obvious with time.

Metrics is not just important in software development but imperative since metrics can measure different aspects of a software program, like quality. Cohesion metrics measures software quality by measuring how closely related classes are in a software package. This is known as cohesion of a software package.

The Lcom metric was one of the six metrics proposed in a draft suite of measurements theory based software metrics in 1991 by Chidamber and Kemerer. The metric was interpreted by Li and Hendry (1993, 1995), which was later refined by Hitz and Montazeri(1996). Chidamber and Kemerer (1994) also later proposed a revised definition for Lcom. The multiple interpretations of the Lcom metrics can result in different values for a particular class (Hitz and Montazeri, 1996) (Etzkorn, Davis and Li, 1998). However, in spite of its many definitions, the Lcom metric is still currently the most widely used metric for measuring cohesiveness of a class. The Lcom metric uses class data attributes access patterns to compute the lack of cohesion. The metrics determines the set of methods that have one or more attibute access in common in the implementation of the methods of a class. The number of set of non-overlapping attributes gives the Lcom measure of a class. Using the Chidamber and Kemerer revised definition, the Lcom value for completely cohesive classes is zero and can be as high as (2^n) for a class with *"n"* methods. With the Li and Hendry (1993) interpretation, the Lcom provides a number that indicates the number of classes with which a non-cohesive class should be replaced with. In an article (Etzkorn, Davis and Li, 1998) which compares the various implementations of Lcom by Chidamber and Kemerer and the extensions made by Li and Hendry provide the best interpretation of lack of cohesion in methods of a class. A framework for the measurement of cohesion was agreed upon by several authors, this framework is used to test the validity of cohesion metrics in this study (Briand, Daly and Wust, 1998).

> "In the future, theory building (hypotheses about reality) becomes more and more important. The axiom systems of measurement theory can help here to get a better understanding of what's behind software quality and cost." – [Zeus, 1989; 24]

2.2 Software Measurement

Many object-oriented metrics have been proposed over the last decade. A few of these metrics have undergone empirical validation, and in reality metrics are being used by corporations as functional effort to manage software quality. Accurate prediction of fault prone modules in software development process enables effective discovery and detection of defects. Such prediction models are valuable for comprehensive systems, where verification experts need to focus their attention and resources to problem areas in the system under development. The assessment of the changeability of software systems is of concern for purchases of the huge systems found in fast-moving domains. An approach to this problem is to examine the dependency between the changeability of the software and its design, with the purpose of discovering design properties that can be used as changeability indicators.

The usage of metrics in the analysis and design of object oriented (OO) software can aid designers make improved decisions is gaining relevance in software measurement area. Moreover, the necessity of having early indicators of external quality attributes, such as maintainability, based on early metrics is growing.

2.2.1 Prediction of fault-proneness

Basili, Briand and Melo (1996) experimentally investigated the suite of Object Oriented (OO) design metrics introduced by (Chidamber and Kemerer, 1994), with the aim of assessing if metrics can predict fault-prone classes. Data on the development of average-sized information management systems based on evenly balanced requirements were collected and a controlled study was run over four months. Data was also collected on defects found in Object-Oriented classes from graduate students. The students were randomly grouped into eight teams. Each team developed medium-sized management information systems that support the rental/return process of a hypothetical video rental business with a customer and video database. Based on this data it was confirmed experimentally how much fault-proneness is influenced by internal (e.g., size, cohesion) and external (e.g., coupling)

design characteristics of OO classes. From the results, five out of the six Chidamber and Kemerer's OO metrics are effective to forecast class fault-proneness during the initial phases of the life-cycle. This empirical validation presents some empirical evidence indicating that the majority of these metrics can be effective quality indicators. In addition the results show these metrics to be complementary.

Benlarbi, Emam and Goel (1999) investigated the empirical validation of object-oriented metrics by assessing each metric (Weighted Method Per Class, Coupling Between Objects, RFC, LCOM) against class fault-proneness. Data was collected from 174 classes in a C++ system. The method of analysis used was logistic regression. The results showed that size can have an important confounding effect on the validity of object-oriented metrics.

2.2.2 Prediction of changeability

Kabaili et al (2001) goal was to validate cohesion metrics as changeability indicators. LCC and LCOM were chosen as cohesion metrics. Data was collected about these metrics on three different industrial systems. For each metrics minimum, maximum, mean, median and standard deviation statistics were collected, to test the relationship between cohesion and the coupling metrics. The Pearson correlation coefficient was used to measure the degree of relationship between variables. Investigation of classes that was weakly cohesive showed that the metrics used do not capture all the facets of class cohesion. The conclusion was that cohesion metrics such as LCC and LCOM should not be used as changeability indicators.

Esperanza, Genero and Piattini (2003) used three controlled experiments to ascertain if any correlation exists between the structural complexity and the size of UML class diagrams and their maintainability, using eight metrics for measuring the structural complexity of class diagrams and three metrics to measure their size. The obtained results show that the metrics related to associations, aggregations, generalizations and dependencies, are validated whilst those related to size seem to be redundant. The result also shows a strong relationship between maintainability and principal components (Independent Variables).

In an Empirical study by Bhadri and Bhadri (2004), the main goal of the research was to validate the introduced criterion which focuses on interactions between class methods and their approach for class cohesion assessment. The results showed clearly that based on a combination of the proposed criteria, there are more pairs of connected methods than the existing cohesion metrics, particularly the ones implicitly taking into account the interactions between methods (such as Connectivity, Tight Class Cohesion and Loose Class Cohesion metrics). A cohesion measurement tool was developed for Java programs to automate the computation of the major existing class cohesion metrics presented by Chidamber and Kemerer (1991). In order to demonstrate the effectiveness of the new criterion and the proposed metrics for class cohesion, a case study of more than 2000 Java classes was analysed. The results proved that their analysis constitutes an improvement of class cohesion assessment. Existing class cohesion metrics are essentially based on instance variables, this criterion is important but not sufficient to capture all the connections among members within a class according to Bhadri and Bhadri (2004). In order to capture additional characteristics of classes and to better measure the cohesion property of classes, Bhadri and Bhadri (2004) introduced new class cohesion criteria, based on methods invocation.

The goal of research by Muskens, Chaudron and Lange (2004) was to develop industry-proof software architecture and design metrics. They identified a number of problems that occur in computing software architecture and design metrics in industrial settings that were not encountered in computing source-code metrics. These problems include the absence of a single, unifying representation for architectures and they arise from the fact that architecture diagrams are used in an informal manner. They evaluated models based on the object oriented paradigm for representing architecture and the results documented that software architecture has significant impact on the quality, cost and development time of software projects; hence the quality of software architecture needs to be evaluated in the early stages of the development process.

Counsell, Swift and Turner (2006) attempted to clarify the contributing factors to an OO cohesive class. Twenty four test subjects were used and 322 C++ classes were tested in their study to test if:-

a) Smaller classes are more cohesive than larger classes
b) Classes with relatively large number of comment lines are more cohesive than those without and
c) There is a relatively large difference in the rating of cohesion made by developers with IT experience and those developers without IT experience.

The cohesion metric used in the study was Number of Methods in a class (NMC), Coupling between objects (CBO) and Number of Associations (NAS). The results showed that smaller classes are not more cohesive than larger classes and it is not true that classes with relatively large numbers of comment lines are generally deemed more cohesive than those with fewer comment lines. There was not enough evidence to support the difference in rating between novice and experienced developers in IT.

2.2.3 Independence of cohesion metrics

Lethbridge and Anquetil (1998) applied cohesion metrics to various decomposition of a large system of about 4500 files. The results revealed that no matter which method was used to compute similarity, roughly the same information about the coupling and cohesion subsystems were recorded. Results also recorded correlation between cohesion and coupling. Thus Lethbridge and Anquetil believed that these metric should not be thought of as completely independent indicators of quality.

Kabaili et al (2001) also looked at the correlation between cohesion and coupling metrics. The metrics used for the study was Coupling Between Objects (CBO) and Response For a Class (RFC). They experiment showed no correlation between cohesion and coupling metrics chosen. Cohesion metrics used in their experimentation did not reflect the real cohesion of a class. An investigation carried

out using manual classes with low cohesion metric values were analysed and the results proved although some classes have low LCC and/or high LCOM values, these classes are actually cohesive. Based on these results the authors concluded that cohesion metrics cannot be trusted as changeability indicators and further concluded that as measures, LCC and LCOM do not reflect the cohesion property of a class.

2.2.4 Prediction of maintainability

Li and Henry's (1993) research implemented object oriented metrics to predict maintenance effort. This research used one dependent variable representing software change, and ten independent variables. Change is a measure of maintenance effort. All the independent variables are metrics values. The metrics used were Depth of inheritance tree (DIT), Number of Children (NOC), Response for a class (RFC), Lack of cohesion of class (LCOM) and Weighted Method per class (WMC). The study tested if there is a strong relationship between object oriented metrics and the maintenance effort as measured and if size has any correlation with maintainability. The results of their analysis proved that

a) There is a strong relationship between metrics and the maintenance effort in the object oriented systems. Ninety-percent (90%) of the total variance in the maintenance effort is accounted for by metrics.
b) The maintenance effort can be predicted from the combinations of metrics collected from source code
c) Size can account for a large portion of the total variance in the maintenance effort.
d) Metrics are very useful predictors of maintenance.

Bansiya et. al. (1998) compared the Lack of cohesion (LCOM) metrics with Coupling Among Methods of a Class (CAMC). CAMC is a metrics representing the cohesion among methods in a class. A sample size of 17 classes was used in the analysis. As part of their study LCOM was statistically correlated with CAMC and the results proved that the CAMC metric shows significant potential as an early way to assess

the cohesiveness of classes in a design but it needs to be validated using a set of projects from various domains.

In a paper by Harrison, Councell and Nithi (1998), two coupling metrics are analyzed: the metrics proposed by Chidamber and Kemerer's (Coupling between Objects) and Number of Association between classes (NAS) metric developed through the use of the Goal-Question-Metrics. Five systems were tested and the results showed a strong relationship between Chidamber and Kemerer's metrics and NAS metrics, implying that only one of these metrics need be used to access systems design.

2.3 Mining Software Data

Inderpaul et al (1993) effectively introduced the attribute-focusing technique to the software engineering community. It discusses the use of association discovery for exploring defective software and process improvement. The authors discuss the results of their technique in an extensive case study which was executed at IBM. Inderpaul et al (1994) also present work on attribute focusing that is more oriented to software engineering practitioners. It focuses on the data analysis methodology and the lesson learned by the authors. The major lessons learned from Inderpaul et al. is that machine-assisted data exploration of classified defect data can readily lead a project team to improve their process during development. Such analysis focuses the team on the immediate experience of development and helps them correct process problems as well as to validate whether those problems have indeed been corrected. Such analysis can complement current practices of in-process improvements.

De Oca and Carver (1998) describe data mining techniques as having been used previously, for identification of subsystems based on associations. This approach provides a system abstraction up to the program level as it produces a decomposition of a system into data cohesive subsystems by detecting associations between

programs sharing the same files. Results show that data mining can identify data cohesive subsystems without any previous knowledge of the subject system. Furthermore, data mining can produce meaningful results regardless of system size making this approach especially appropriate to the analysis of large undocumented systems.

Manoel et al (1998) discusses two approaches for improving existing measurement and data analysis techniques in software organizations. The first approach works top-down based on goal oriented measurement planning. The second approach works bottom-up by extracting new information from the legacy data already available in the organization. For the latter approach, the authors use association discovery to gain new insights into the data that is already present in the organization. These approaches were used to analyze the customer satisfaction (CUSTSAT) survey data at the IBM Software Solutions Division Laboratory. The CUSTSAT data are collected annually through surveys carried out by an independent party. Their purpose is to evaluate customer satisfaction with products of IBM's Software Solutions Division and competing products. IBM surveys a large number of customers from several different countries. All the data are stored in one database. Currently, this database stores CUSTSAT data collected over several years. The studies main objectives were: (1) better understanding of the user groups' needs with respect to the CUSTSAT measurement, and (2) better exploration of the data already stored in this database. The results showed that the Goal Question Matrix (GQM) - and AF-based approaches are complementary and can work in synergy. The GQM structures help us to choose and organize data for AF analyses. The new knowledge gained through the AF analyses can be fed back into the measurement goals and used to revise GQM structures.

Data mining has appeared as one of the tools of choice to better explore software engineering data as described by Brand and Gerritsen (1998). The constant increases in software and hardware infrastructures only increase the availability of data in software organizations. Brand and Gerritsen carried out analysis on data collected in telecommunications. The results showed that association algorithms can only operate

on categorical data. If non-categorical is used, the non-categorical data must be binned into ranges, and each range would have to represent an attribute.

Rousidis and Tjortjis (2005) described clustering that is used to support software maintenance and systems knowledge discovery. Rousidis and Tjortjis describe in a paper the method for grouping Java code elements together according to their similarity. It focuses on achieving a high-level system understanding. This method derives system structure and interrelationships, as well as similarities among systems components. This is done by applying cluster analysis on data extracted from source code in order to better understand similarities among program elements in support of software maintenance. This methodology used an input model and a clustering algorithm. It correctly recognized data about software packages, classes, methods and parameters. A tool was developed to assess this fully automated approach, and the experimental results showed that the tool successfully revealed similarities among Java code elements.

An approach for evaluation of dynamic clustering was presented by Xiao and Tzerpos (2005). The scope of this work was to evaluate the usefulness of providing dynamic dependencies as input to software clustering algorithms. This method was applied to Mozilla, a large open source software system with more than a four million lines of C-Sharp (c#) source code. In this experiment, the clustering produced by the dynamic process to the ones produced by the static one was compared. Results show that the static process performs usually better. However, there are cases where the dynamic clusterings are the ones with the higher quality. Also, the average difference between the static and dynamic clustering was less than 5%.

Michail (2000) discussed how data mining could be used to discover reuse patterns in existing applications. This work improves upon his earlier research using "association rules" by taking into account the inheritance hierarchy using "generalized association rules". Michail explains by browsing generalized association rules, a developer can discover pattern in usage in a way that takes into account

inheritance relationships. Michail's research illustrated the approach using the tool, CodeWeb, by demonstrating characteristic ways in which applications reuse classes in the Knowledge Desktop Environment application framework. The results showed that some important rules would not have been found without taking into account the inheritance hierarchy.

Recently Xie, Pei and Hassan (2007) presented in a tutorial the latest research in mining Software Engineering data, discusses challengers associated with mining software engineering, highlights software engineering mining success stories, and gives future direction of Data mining. This paper outlines the types of Software Engineering data that is available to be mined, which software engineering tasks can be helped using data mining and how are data mining techniques used in software engineering.

Data mining can be effectively performed on open source software since open source software is transparent.

2.4 Open Source Software

The free software movement was launched in 1983. In 1998, a group of individuals advocated that the expression "free software" be replaced by open source software (OSS) as an expression which is less ambiguous and more comfortable for the corporate world (Raymond, 1998). Software developers want to publish their software with open source software license, so that any person can also cultivate the same software or understand how it functions. Open source software usually permits anyone to develop a new version of the software, port it to new operating systems and processor architectures and distribute it to others or promote it. The purpose of open source is to let the software developed be more understandable, modifiable, duplicatable, reliable or simply accessible, while it is still marketable.

The open source software (OSS) model represents a disruptive paradigm in the software industry. Compared with traditional proprietary software development, OSS is a radically new paradigm (Moody, 2001; Raymond, 2005; Sharma, Sugumaran and

Rajagopalan, 2002). With OSS, software source code is freely available for anyone to view, download, modify and redistribute as long as it is under the same open source license. Most open source software projects rely entirely on the voluntary efforts of a community of developers (although some projects are coordinated and led by commercial entities). Such a voluntary community process keeps the cost of development and testing low. The nearly zero total cost of ownership (TCO) gives open source software a strong competitive edge. A few of the projects initiated by the OSS community, such as GNU, Linux, Apache, MySQL and PHP, have achieved extraordinary success. However, except for these few successful projects, the majority of the open source projects lack performance, with little development momentum behind them (Thomas et al, 2004). A Dutch Maastricht Economic research Institute (MERIT) in 2005 presented the results of an open source software survey at the O'Reilly open source Convention in Amsterdam. A total of 955 participants from twelve countries were consulted via phone and web- based survey. The study found that 49% of organizations are using open source software within their IT environments and about 70% of open source users wanted to increase their open source use. Furthermore the results also showed that IT administrator's efforts can be reduced by adopting open source software environments i.e. maintenance would be reduced considerably.

2.4.1 Comparison of open source software and closed software

A study by Samoladas et al. (2004) examined five active and popular open source software projects that comprised of 5,856,873 lines of code. For each project the number of major releases was measured, obtaining a history of the evolution of the source code quality. This was compared to closed source code (Proprietary Software) and the results showed that open source software code compared to be equal and in some cases better than the quality of closed source software code implementing the same functionality. Results also showed that open source software code quality suffers the same problem as closed source software. Maintainability deterioration over time is a typical phenomenon and produces legacy closed source software systems. Similar behavior was exhibited with open source software projects as they

age: the open source systems approach will produce legacy systems in much the same way as closed source systems has done.

Zhou and Davis (2005) collected data on bug tracking from eight popular open source software projects from sourceforge.org and investigated the time related bug reporting patterns from them. The results indicate that along its development cycle, open source projects exhibit similar reliability growth pattern with that of closed source projects. Bug arrivals of most open source projects will stabilize at a very low level, even though in comparison, no formal testing activities are involved.

2.5 Cohesion of open source software

Research carried out by Koch and Schneider (2000) into open source development was to use existing data on the projects available to the public. Therefore the CVS-repository of the GNOME project was used for the collection of data. The research aim was to identify if there was any correlation between Lines of Code and programming effort. The results could not confirm any correlation.

A paper written by Gyimothy, Ferenc and Siket (2005) on the validation of object oriented metrics on open source software for fault proneness aim was to calculate and validate the object oriented metrics suite given by Chidamber and Kemerer (1994) for fault prone detection from the source code suite of "Mozilla". Using the calculated metrics, Mozilla's predicted fault proneness changed over seven versions covering one and a half years of development. The results showed that the correctness of the LCOM metrics is good, but its completeness value is low.

Koru, Zhang and Liu (2007) presented a paper on modeling the effect of Size on Defect Proneness for Open Source Software. The objective of their study was to model the relationship between size and defect proneness while addressing the unique dynamic characteristics of Open Source Software. Defect fixes made to C++ classes in open source projects were modeled. Class size was measured in Lines of Code

excluding the blank and comment lines. The results showed that when change in module size and addition and deletion of software modules over time was related to defect-proneness, the functional form of size was logarithmic.

2.6 Conclusion

Many object oriented metrics have been proposed over the last decade. A few of these metrics have undergone empirical validation.

Factors related to cohesion are fault-proness, changeability, maintainability and other independent variables (such as the number of developers, number of bugs, etc). This chapter focused on the empirical validation of cohesion metrics as related to fault-proness, changeability, maintainability and other independent variables. The chapter starts with a review of existing literature on the empirical validation of cohesion metrics for software in general; a similar review for open source software is done.

Chapter Three - Research Design

3.1 Introduction

The purpose of this chapter is to present the methodology used for the assessment of validity of cohesion metrics with regard to the assumed hypothesis.

This chapter defines the research method, the population, the sampling size and sampling methods. The research variables are also described and the design of a software program that calculates the values of cohesion is documented. The chapter ends on the presentation of suitable data mining techniques for the testing of the hypotheses.

3.2 Research Method

This study is based on a survey. The purpose of the survey is to collect data on open source object oriented software packages. In the study the correlation between cohesion variables and other independent variables is tested.

3.3 Research Population - Open Source Software

The population of the survey is made of open source software packages. It is a very large population but this study only focuses on software written within the dot net framework. Open source software was chosen because by definition the source code of proprietary software is very difficult to obtain but the source code of open source software is freely available. The dot net framework is also becoming more popular for developers and analysts.

3.4 Data Sampling

It is impractical and virtually impossible to study every occurrence of currently available open source software packages. The study therefore needs a sampling technique to get a large enough cross section of the population. Sample size must be calculated and a sampling method must be designed.

3.4.1 Sample Size

A simple and reliable formula for determining sample size is:-

> Sample size = 0.25 * (Certainty factor/Acceptable error) ^{2} obtained from Bentley and Whitten (2000).

The certainty factor depends on how certain you want to be that the data sample will not include variations in the sample. The certainty factor is calculated from tables obtained from industrial engineering texts or statistics. For this study a 90% certainty factor is assumed and an acceptable error rate of 10%. Acceptable error rate is the maximum error rate that should be accepted by the test process. Therefore the study sample would be: -

$$\textbf{Sample size} = 0.25\,(1.645 / 10)^2 = 68$$

3.4.2 Stratification

Stratification is a systematic sampling technique that attempts to reduce the variance of estimates by spreading out the sampling – for example, choosing open source software by category and not excluding any category.

There are 14 categories (as at November 2006) that open source software belong to, and all 14 categories will be tested. The categories are as follows: -

a) Enterprise software
b) Clustering Software
c) Multimedia software

d) Database software
e) Financial software
f) Networking software
g) Desktop software
h) Entertainment software
i) Security software
j) Development software
k) Hardware software
l) Systems Administration
m) Storage software
n) Voice over internet protocol software.

3.4.3 Randomization

This sampling method randomization is a technique characterized as having no predetermined pattern or plan for selecting sample data. This study selects open source software randomly within a specific category

Within each of the above software categories, random sampling is used to select the packages on which the cohesion metrics software will be tested.

The following table shows the different categories together with the number of open source programs in that category. The percentage of programs is worked out in each category and the sample size determined from that. Since the sample size is a percentage it is not a whole number, the number is then rounded off to the nearest integer and the software downloaded according to the required sample.

Table 3.1 Open Source Software Population and sample.

Domain	Number	% of total	Total for sample	Rounded off Total
1) Enterprise software	1049	1.60	1.09	1
2) Clustering Software	451	0.69	0.47	0
3) Multimedia software	10482	15.99	10.87	11
4) Database software	5962	9.09	6.18	6
5) Financial software	1723	2.63	1.79	2
6) Networking software	4397	6.71	4.56	5
7) Desktop software	155	0.24	0.16	0
8)Entertainment software	12351	18.84	12.81	13
9) Security software	2876	4.38	2.98	3
10) Development software	18845	28.75	19.55	20
11) Hardware software	1627	2.48	1.69	2
12) Systems Administration	3295	5.03	3.42	3
13) Storage software	2017	3.08	2.09	2
14) Voice over internet protocol software.	319	0.49	0.34	0
Total	**65549**	**100**	**68**	68

As outlined in 3.1 above, open source software is classified into different domains. Data was obtained from Sourgeforge.net website in October/ November 2006. For each domain (e.g. Storage software), the number of recorded software packages for the domain is obtained (i.e. 2017 for storage software). This number is compared to the total size of open source software population recorded as 65549 (in November 2006). The size of the population of each domain is then calculated (e.g. storage software has a proportion of 3.08 % of the total number of open source software

population. This percentage is then used to calculate the sample size for each domain knowing that the total sample size for the study is 68. (E.g. storage software domain sample size is 2, that is 3.08% of 68).

3.5 Independent Variables used in this study

For each open source software package, the following data (3.5.1) is available from the sourceforge.net website. The following variables (3.5.2) are independent variables obtained from available information on open source software used in the study, which are compared to the values of cohesion.

3.5.1 Souceforge.net data

a) Name of Package

This is the name of the software as baptized by its authors.

b) Number of developers

This is the number of people used for the development of the package.

c) Category

This is the category in which the package falls into; this category can be one of the 14 categories listed under the domain column of table 3.1.

d) Total number of bugs

This is the total number of bugs that were found in the package by the open source community.

e) Total number of bugs still opened

This is the total number of bugs not yet solved.

f) Total number of support requests

This is the total number of help requests from the users for the package as reported by the sourceforge.net administrators.

g) Total number of support requests still opened

This is the total number of help requests for the package, not yet been solved.

h) Total patches and feature requests

Patches are used to solve security issues and feature requests are requests that are used to enhance the functionality of the software package. This aspect deals with the number of patches and feature requests made by users.

i) Total patches and feature requests still opened

It is the number of patches and feature requests not yet implemented.

j) Number of messages in a public forum

This is the number of messages posted by open source forum users about the package.

k) Mailing lists

The number of users in the packages mailing lists.

l) CVS Repository Commits

CVS stands for Concurrent Versions Systems. It is a tool used by many software developers to manage changes within their source code tree. CVS provides the means to store the current version of a piece of source code, and to record all changes (and who made those changes) that have occurred to that source code from its first version up to its current version. CVS repository commits are permanent changes made to a software version by developers. Here this study is interested in the total number of such commits.

m) CVS Repository Reads

Is the same as the above except that now this study is now interested in the number of times such changes have been read.

n) Size

It is the amount of disk space occupied by the package (e.g. Bytes, Kilobytes, Megabytes, etc).

o) Programming Language

It is the dot net language in which the software package is written (e.g. C#, J#, VB.net)

p) Age

It is the number of days the project has been in existence.

3.5.2 Class cohesion variables

a) Lcom1

Lcom1 counts methods implemented in a class that only reference attributes implemented in that class, therefore Lcom1 is the number of pairs of methods in the class using no attribute in common.

b) Lcom2

Lcom2 is the number of pairs of methods in the class using no attributes in common, minus the number of pairs of methods that do. If this difference is negative, however, Lcom2 is set to zero.

c) Lcom3

Lcom3 is defined as the number of connected components in a class. Values of 1 and greater are considered extreme lack of cohesion.

d) Lcom4

A value of 1 indicates a good cohesive class (Highly Cohesive). Values of 2 and greater are considered bad (lack of cohesion). Such a class should be split.

e) Lcom5

Lcom5 Counts for each attribute, how many methods access the attribute. Only direct connections between methods and attributes are considered. In a completely cohesive class, each attribute is accessed by every method.

f) Connectivity (Co)

The value for Co can either be 0 or 1, where 0 means tightly cohesive and 1 means loosely cohesive.

g) Tight Class Cohesion

Besides methods using attributes directly (by referencing them), this measure considers attributes *indirectly* used by a method. Method m uses attribute a indirectly, if m directly or indirectly invokes a method which directly uses attribute a. Two methods are said to be *connected*, if they directly or indirectly use common attributes. TCC is defined as the percentage of pairs of public methods of the class, which are connected, i.e., pairs of methods which directly or indirectly use common attributes.

h) Loose Class Cohesion (Lcc)

Lcc is the same as Tcc, except that this measure also considers pairs of *indirectly connected* methods. If there are methods m_1 m_2,... m_n, such that m_i and m_{i+1} are connected for $i=1,...,n-1$, then m_1 and m_n are indirectly connected. LCC is the percentage of pairs of public methods of the class which are directly or indirectly connected.

i) Information-flow-based cohesion (Ich)

Ich for a method is defined as the number of invocations of other methods of the same class, weighted by the number of parameters of the invoked method.
The Ich of a class is the sum of the Ich values of its methods.

3.5.3 Package cohesion variables

a) Cohesion Value – Maximum

This variable represents the maximum cohesion value among the classes of a package.

b) Cohesion Value – Minimum

This variable represents the minimum cohesion value among the classes of a software package.

c) Cohesion Value – Average

This variable represents the average cohesion value among the classes of a software package. The average is the sum of cohesion values for each class divided by the number of classes in that package.

d) Cohesion Value - Sum for package

This variable represents the sum of the cohesion values among the classes of software package.

3.6 Research Approach

Because data is mined using association rules, and because association rules require qualitative data, this can be described as qualitative research. However several variables above are described by quantitative data. There is therefore a need to convert quantitative data to qualitative data through data discretisation.

3.6.1 Qualitative Data

Only three variables have qualitative values namely package name, category of software and programming language.

3.6.2 Quantitative Data

Except for package name, category of software and programming language all other variables contain quantitative values: i.e. class cohesion values, packaged cohesion values as defined above

3.6.3 Data Discretisation

As stated in the preceding paragraphs, almost all variables contain quantitative data but association rules require qualitative data. This section explains how quantitative data is converted into qualitative data through the data discretisation process.

Data discretisation is a strategy for data reduction. Data reduction techniques are used in order to obtain a new representation of the data set that is much smaller in volume, but yet produces the same analytical results.

The most common strategies for data reduction are:

a) Data cube aggregation
b) Dimensionality reduction
c) Numerocity reduction
d) Concept hierarchy generation and
e) Data discretisation

Simply put, data discretisation is the conversion of quantitative data into qualitative data. The data discretisation algorithm used in this study is presented in the next section.

3.6.3.1 Data discretisation algorithm

The method used here assists in dividing the range of each variable into five segments: one segment to locate the average value of the range, two segments to locate values below average and two segments for values above average.

The division of the data range into segments is carried out according to the following algorithm.

Figure 3.2 Data Discretisation Algorithm

Variables

B: Array [1 .. n] of Int.

B=[3,1,2,8,4,1,1,3,1,2,1,1,1,1,1,1,1,1,11,2,1,3,1,4,1,1,1,2,1,2,1,1,1,1,1,1,2,1,1,1,1,13,1,1,2,1,1,7,3,1,2,3,1,12,3,1,1,1,1,1,1,1,1,2,1,6,1,2]

A: Set[1..m] of Integer

E1,E2,E3,E4 : Integer;

N1, N2, N3, N4 : Integer;

Position_min1, Position_min2 , Postion_Ave1 , Position_Ave2 ,Position_Ave3 : Int;

PMin1Plus, PMax1Plus, PositionAvePlus : Integer;

Min1, Max1 : Integer;

Ave1, Ave2, Ave3 , AvePlus: Real;

Segment1, Segment2, Segment3, Segment4, Segmen5, Segment6, SegmentX: Interval;

Pseudo code

B=[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,2,2,2,
2,2,2,2,2,2,3,3,3,3,3,3,4,4,6,7,8,11,12,13]

A = {1,2,3,4,6,7,8,11,12,13}

Min1 = A[1];

Position_min1;

Max1 = A[n];

Positionmax1 = n;

Ave1 = average of B[1..n]

E1 = Biggest element of A less than Ave1

PositionAve1 =Position in A of E1;

Ave2 = average of B[PositionMin1..PositionAve1] = Average of B[1..2]

E2 = Biggest element of A less than Ave2

Position_Ave2 = Position in A of E2 = 1

Ave3 = average of B[PositionAve1+1 ..PositionMax1]

E3 = Biggest element of A less than Ave3

Position_Ave3 = Position in A of E3 ;

Segment 1 = [PositionMin1 .. PositionAve2]

Segment 2 =]PositionAve2 .. PositionAve1]

Segment 3 =]PositionAve1 .. PositionAve3]

Segment 4 =]PositionAve3 .. PositionMax1]

Calculate N1, N2, N3, N4;

SegmentX = Most populated non singleton segment from Segment 1, 2, 3, 4

PMin1Plus = Beginning of SegmentX

PMax1Plus = End of SegmentX

AvePlus = average of B[PMin1Plus..Pmax1Plus]

E4 = Biggest element of A less than AvePlus

PositionAvePlus = Position in A of E4

Segment 5 = [PMin1Plus .. PositionAvePlus]

Segment 6 =]PositionAvePlus..Pmax1Plus]

The following section runs the data discretisation algorithm for the variable representing the number of developers. The dataset for the variables representing the number of developers is given below:
B={3,1,2,8,4,1,1,3,1,2,1,1,1,1,1,1,1,1,11,2,1,3,1,4,1,1,1,2,1,2,1,1,1,1,1,1,2,1,1,1,1,13,
1,1,2,1,1,7,3,1,2,3,1,12,3,1,1,1,1,1,1,1,1,2,1,6,1,2}

Figure 3.3 Example of data discretisation: (Number of Developers)

Variables

B: Array [1 .. n] of Int.

B=[3,1,2,8,4,1,1,3,1,2,1,1,1,1,1,1,1,1,11,2,1,3,1,4,1,1,1,2,1,2,1,1,1,1,1,1,2,1,1,1,1,13,
1,1,2,1,1,7,3,1,2,3,1,12,3,1,1,1,1,1,1,1,1,2,1,6,1,2]

A: Set[1..m] of Integers

E1,E2,E3,E4 : Integer;

N1, N2, N3, N4 : Integer;

Position_min1, Position_min2 , Postion_Ave1 , Position_Ave2 ,Position_Ave3 : Int.

PMin1Plus, PMax1Plus, PositionAvePlus : Integer;

Min1, Max1 : Int.

Ave1, Ave2, Ave3 , AvePlus: Real;

Segment1, Segment2, Segment3, Segment4, Segmen5, Segment6, SegmentX: Interval;

Pseudo code

```
B=[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,2,2,2,
2,2,2,2,2,2,2,3,3,3,3,3,3,4,4,6,7,8,11,12,13]
A = {1,2,3,4,6,7,8,11,12,13}
Min1 = A[1];                          Positionmin1 = 1;
Max1 = A[n] = 13;                     Positionmax1 =13;
Ave1 = average of  B[1..n] = 2.1618
E1 = Biggest element of A less than Ave1 = 2
PositionAve1 =Position in A of E1  = 2;
Ave2 = average of B[PositionMin1..PositionAve1] = Average of B[1..2] = 1.1852
E2 = Biggest element of A less than Ave2 = 1
Position_Ave2 = Position in A of E2 = 1
Ave3 = average of B[PositionAve1+1 ..PositionMax1]= Ave of B[3.. 13] = 5.9286
E3 = Biggest element of A less than Ave3 = 4
Position_Ave3 = Position in A of E3 = 4 ;
Segment 1 = [PositionMin1 .. PositionAve2] = [1..1]
Segment 2 = ]PositionAve2 .. PositionAve1] = ]1..2]
Segment 3 = ]PositionAve1 .. PositionAve3] = ]2..4]
Segment 4 = ]PositionAve3 .. PositionMax1] = ]4..13]
N1 = 44;   /* But segment 1 is a singleton i.e only made up of the element 1 */
N2 = 10; /* But segment 2 is a singleton i.e only made up of the element 2 */
N3 = 8;  /* But segment 3 is not a singleton i.e  made up of the elements  3 and 4 */
N4 = 6;  /*But segment 4  is not a singleton i.e  made up of the elements
6,7,8,11,12,13 */
SegmentX=Most populated non singleton segment from Segment 1,2,3,4 = Segment 3
PMin1Plus = Beginning of SegmentX = 3
PMax1Plus = End of SegmentX = 4
AvePlus = average of B[PMin1Plus..Pmax1Plus] = Average of B[3..4] = 3.3
E4 = Biggest element of A less than AvePlus = 3
PositionAvePlus = Position in A of E4 = 3
Segment 5 = [PMin1Plus .. PositionAvePlus] = ]3..3]
Segment 6 = ]PositionAvePlus..Pmax1Plus] = ]3..4]
```

Table No 3.3: Number of Developers –
(Part of the data columns from the study)

3	Average Minus
1	very low
2	Low
8	High
4	Average Plus
11	High
13	Very high
7	High
12	High
6	High

Data discretisation will be performed on all numeric rows in the study.

3.7 Data Processing Techniques

Data mining is the data processing technique used in this study. There are several data mining techniques e.g. Classification Trees; Association Discovery Techniques; Clustering Techniques; Artificial Neural Networks; Optimized Set Reduction and Bayesian Belief Networks

Classification or decision trees are induction techniques used to discover classification rules for a chosen attribute of a data set by systematically subdividing the information contained in this data set. They are one of the tools of choice for building classification models in the software engineering field. Association discovery extracts information from coincidences in the data set. Knowledge discovery takes place when these coincidences are previously unknown, non-trivial, and interpretable by a domain expert.

Clustering is group data records with similar attributes together so information can be abstracted. Neural networks have been one of the tools of choice for building predictive software engineering models. They are heavily interconnected networks of simple computational elements. Optimized Set Reduction (OSR) is a technique that was specifically developed in the realms of software engineering data analysis. Its approach is to determine what subset of data records provides the best characterization for the entities being assessed.

3.7.1 Data Mining

Generally, data mining (sometimes called data or knowledge discovery) is the process of analyzing data from different perspectives and summarizing it into useful information - information that can be used to increase revenue, cut costs, or both. Technically, data mining is the process of finding correlations or patterns among fields in large databases.

One of the ways of finding these patterns is through association rules. Data mining software is one of a number of analytical tools for analyzing data. It allows users to analyze data from many different dimensions or angles, categorize it, and summarize the relationships identified.

3.7.2 Association Rules

Association rules mining finds interesting associations and/or correlation among large sets of data items. Association rules shows attribute value conditions that occur frequently together in a given dataset. Algorithms for discovering large item sets make multiple passes over the data. In the first pass support of individual items is counted and those that are large i.e. have required minimum support are identified. Each subsequent pass starts with a seed set of item sets found to be large in the previous pass. This seed set is used for generating new potentially large item sets, called candidate item sets, and count the actual support for these candidate item sets during the pass over the data. At the end of the pass, the larger candidate item sets are determined, and they become the seed for the next pass.

This process continues until no new large item sets are found. The market basket analysis is one way in which association rules are used.

Market basket analysis is possibly the largest application for algorithms that discover association rules. These days, purchased items have bar codes that enable retail organizations to track the sale of items and if a retail organization issues 'loyalty cards' the organization can track the purchases made by customers. A typical customer will revisit the same supermarket many times throughout the year. A transaction refers to a single visit and associated with each transaction is a purchase date and the items purchased.

The term 'basket data' is used to refer to such transaction data. By analyzing basket data, retail organizations can extract information to drive their marketing strategy. For example, the data may show that customers who purchase baby products have a tendency to purchase ready-made meals. This information can then be used for target marketing (e.g., send promotional offers for take-away meals to customers who purchase baby products) (Agrawal and Srikant, 1994).

The application of association rules is not restricted to market basket analysis. The following section explains the Apriori algorithm as published by Agrawal, Imielinski and Swami (1993).

3.7.2.1 The Apriori Algorithm

The algorithm is given by the following pseudo code.

The Apriori Algorithm: Pseudo code

C_k: Candidate itemset of size

L_k: frequent itemset of size k

```
1)  L_1 = {large 1-itemsets};
2)  for ( k = 2; L_{k-1} ≠ ∅; k++ ) do begin
3)     C_k = apriori-gen(L_{k-1}); // New candidates
4)     forall transactions t ∈ D do begin
5)        C_t = subset(C_k, t); // Candidates contained in t
6)        forall candidates c ∈ C_t do
7)           c.count++;
8)     end
9)     L_k = {c ∈ C_k | c.count ≥ minsup}
10) end
11) Answer = ⋃_k L_k;
```

Join Step: C_k is generated by joining $L_{k-1}$with itself

Prune Step: Any *(k-1)*-itemset that is not frequent cannot be a subset of a frequent *k*-itemset

L_1= {frequent items};

One way to explain the algorithm is to run it with an example. Consider a database consisting of six records.

Table 3.4: Package Database

Package	No of developers	No of Bugs	Size
Package 1	High	Large	Very big
Package 2	Low	Small	Very Small
Package 3	Low	Small	Very Small
Package 4	High	Medium	Very Big
Package 5	High	Large	Very Big
Package 6	Low	Small	Very Big

Suppose the sequential minimum support is 2, meaning only associations supported by least 2 records will be considered. Let the minimum required confidence be 70%. The percentage of the confidence factor is according to how correct one wants the information to be.

Firstly, the large itemset called L_1 in the algorithm has to be determined. $L_1$is simply the list of all attributes values satisfying the required minimum support.

Table 3.5: Frequent Itemsets

Package	**Item Set**
Package 1	High, Large, Very big
Package 2	Low, Small, Very Small
Package 3	Low, Small, Very Small
Package 4	High, Medium, Very Big
Package 5	High, Large, Very Big
Package 6	Low, Small, Very Big

Table 3.6: Attribute Values

Item Set	Sup Count
{high}	3
{large}	2
{very big}	4
{low}	3
{small}	3
{very small}	2
{medium}	1

Attribute Values

Item Set	Sup Count
{high}	3
{large}	2
{very big}	4
{low}	3
{small}	3
{very small}	2

L1

In the algorithm it is said that C_2 = aprior_gen (L_1).
In other words the algorithm uses L_1 *cross-tabulate* L_1 to generate a candidate set of 2-itemsets, C_2.

Cross tabs are frequently used because:

- They are easy to understand. They appeal to people that do not understand the most sophisticated measures.
- They can be used with any level of data: nominal, ordinal, interval, or ratios cross tabs treat all data as if it is nominal.
- A table can provide greater insight than single statistics.
- It solves the problem of empty or sparse cells.
- They are simple to conduct.

Therefore, it can be said that: $\mathbf{C_2 = L_1 * L_1}$

Where the * represents cross tabulation.

Table 3.7: Itemsets

$C_2 = L_1 * L_1$

{high, large}	2
{high, very big}	3
{high, low}	0
{high, small}	0
{high , very small}	0
{large, very big}	2
{large, low}	0
{large ,small}	0
{large, very small}	0
{very big, low}	1
{very big, small}	1
{very big, very small}	0
{low, small}	3
{low, very small}	2
{small , very small}	2

C_2

L_2 is made of C_2 items with the require minimum support

Now moving on to $C_3 = L_2 * L_2$

Where * means the Join

Table 3.8: Items with minimum support

Item Set	Support Count
{high, large}	2
{high, very big}	3
{large, very big}	2
{low, small}	3
{low, very small}	2
{small , very small}	2

3 – Itemset **L3**	Support Count
{high, Large, Very Big}	2
{Low, Small, Very small}	2

Table 3.9 : - 3-Itemset

3 – Itemset	Support Count
{high, Large, Very Big}	2
{Low, Small, Very small}	2

L_3

Now moving on to $C_4 = L_3$ Join L_3

The two items in L_3 do not have a common value, so L_3 Join $L_3 = \theta$ therefore $C_4 = \theta$ and the algorithm stops. So the largest frequent item set is in L_3.

It is now time to generate associations from the largest itemset according to the following procedure.

Procedure:

For each frequent itemset "***I***", which generate all nonempty subsets of ***l.***
For every nonempty subsets **s** of ***I***, output the rule **"s →(I-s)"** if Support (I)/ Support(s) >= minimum support confidence.
Let's look at the example again.
For I = (Low, Small, Very Small) and I = {High, Large, very big}

If s = {Low} then l- s is (Small and very small)

Support (I) = 2
Support (s) = 3
Support (I) / Support (I - S) = 2/3 = 67%
That implies that if the number of developers is low then the number of bugs is small and the size is very small.

If s = {small} then 1-s is {Low, very small}
That implies that if number of bugs is small then the no of developers is low and the size is very small

If s = {very small} then 1-s is {Low, small}
That implies that if Size is very small then the no of developers is low and no of bugs is small.

If s = {High} then 1-s is {Large, very big}
That implies that if no. of developers is high then No. of bugs is Large and Size is very big.

If s = {Large} then 1-s is {High, very big}

That implies that if the number of bugs is large then the number of developers is high and the Size is very big.

If s = {very big} then 1-s is {High, Large}

That implies that if the Size is very big then number of developers is high and the number of bugs is large.

From the above this is the final set of association rules:

a) That if the number of developers is low then the number of bugs is small and the size is very small.

b) That if number of bugs is small then the no of developers is low and the size is very small

c) That if Size is very small then the no of developers is low and no of bugs is small.

d) That if no. of developers is high then No. of bugs is Large and Size is very big.

e) That if the number of bugs is large then the number of developers is high and the Size is very big.

f) That if the Size is very big then number of developers is high and the number of bugs is large.

3.8 Program Design

The purpose of this section is to explain the architectural design of the program used for the computation of the cohesion values of a package classes.

A package is made of different classes. There exists a C # structure that represents all the types of classes in a package. That structure is the assembly structure.

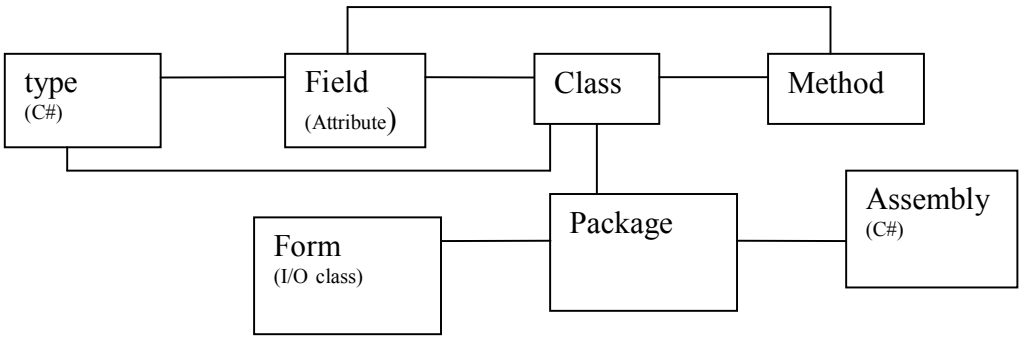
The different classes in the class diagram below can be constructed with their main attributes and methods as indicated in fig 3.1, 3.2, and 3.3.

3.8.1 Class Diagram

Below are the classes that are designed to write the program.

A class is made of attributes (fields) and methods (operations). In return, an attribute belongs to given class type and a method also accesses attribute. The user interacts with the program using a form. (See fig. 3.1)

Fig 3.1: System Class Diagram



The class type and assembly belong to C#. The main methods for type are getMethods and getFields. The main method for assembly is getTypes.

Fig. 3.2 Package outline

```
Class Package

fileName : String
classes: List of Class
assembly:       Assembly

Package (filePath):     Constructor
        fileName = FilePath
        Classes = 0
        assembly = Create New Assembly for the path "filepath"
        For each type_ in Assembly.getTypes
                {c = newclass(type_); Add c to classes}
```

Fig 3.3 Class Outline

```
class Class
type :   Type    /* C# data structure */
methods: List of Methods
fields: List of Fields
Class (type): Constructor
        type = type_
        methods = type.getMethods
        fields = type.getFields
Lcom1

        /* See algorithm in the next figure */
```

Fig 3.4 Lcom Outline for class c

```
L = 0
for each methodI in c.Method
        for each methodJ in c.Method
                fieldI = methodI. getReferenceFields
                fieldJ = methodJ. getReferenceFields
                L= L + (fieldi – fieldj)
        Lcom1 = L
```

3.8.2 Sequence Diagram

A system sequence diagram is used to show the flow of messages in the designed program. Diagram in figures 3.5 and 3.6 is a systems sequence diagram of the program design

Suppose a user wants to calculate the cohesion of all classes inside a package located in the file c:\xmas\solar.exe. A form is presented to the user from which he / she can locate the file c:\xmas\solar.exe. The form has an instance of a package but at this stage, that instance is not yet created. The form can now create the instance by passing to it the file name for which an assembly is created inside the package. This creation of that instance means that a list of instances of classes has been created for each type in the assembly of the package. Now that the package has been fully constructed, the calculation of cohesion values for each class in the package can now proceed, and the results of those calculations are output on the form.

3.8.3 Use Case Diagram

Once a user selects a package, the user can then request for the cohesion values of that package to be calculated. The program calculates the cohesion of each class of the selected package and displays the results. (Fig 3.6)

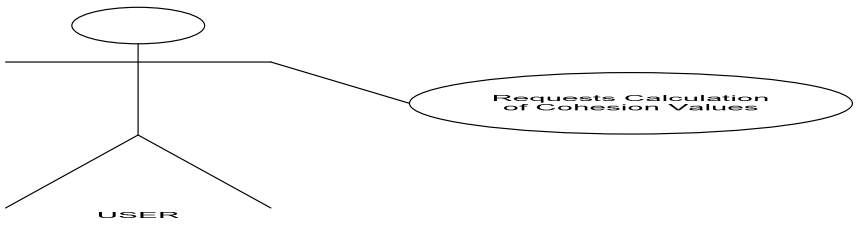


Fig 3.6 Use Case Description

Fig. 3.5 System Sequence Diagram

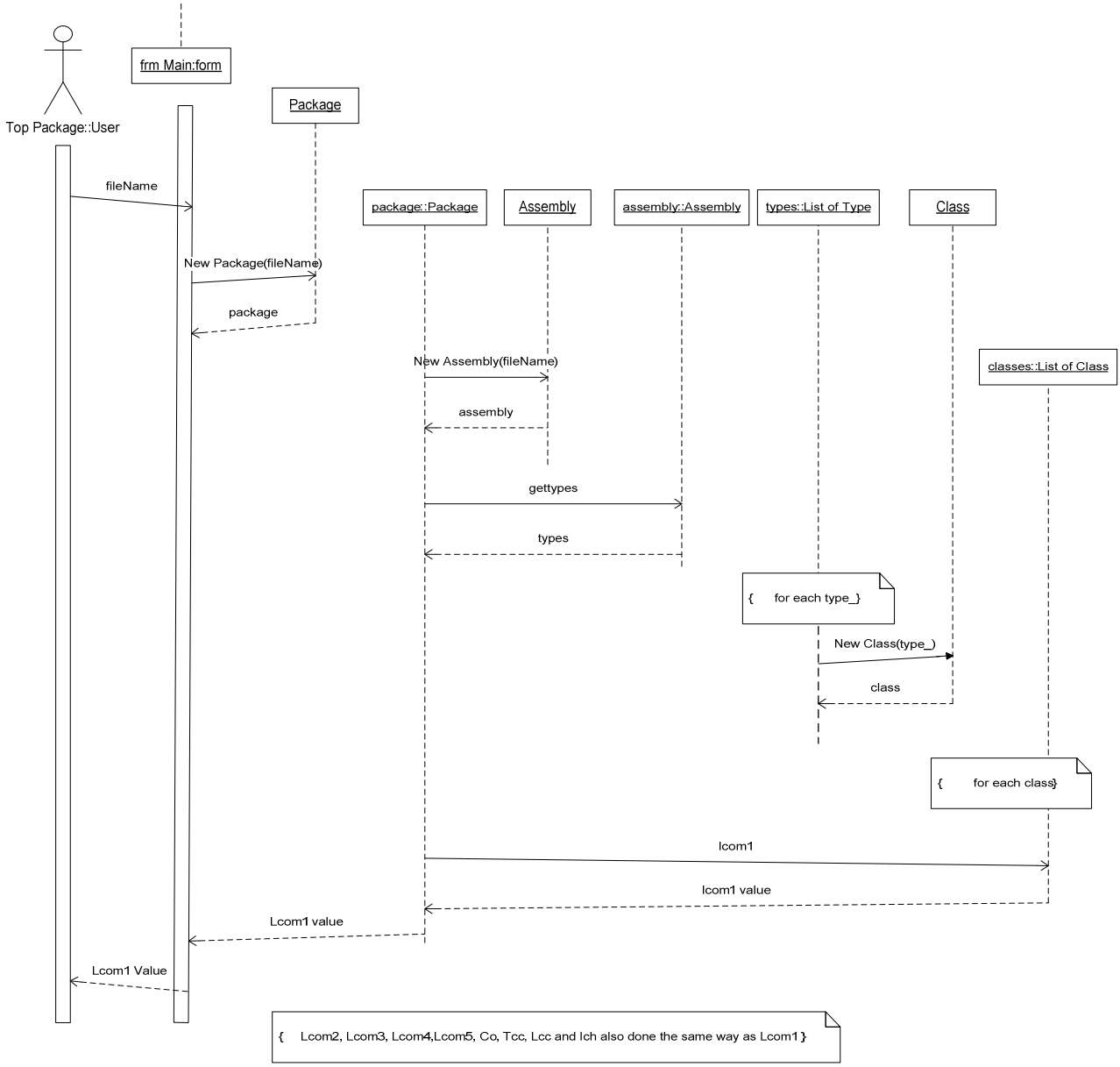
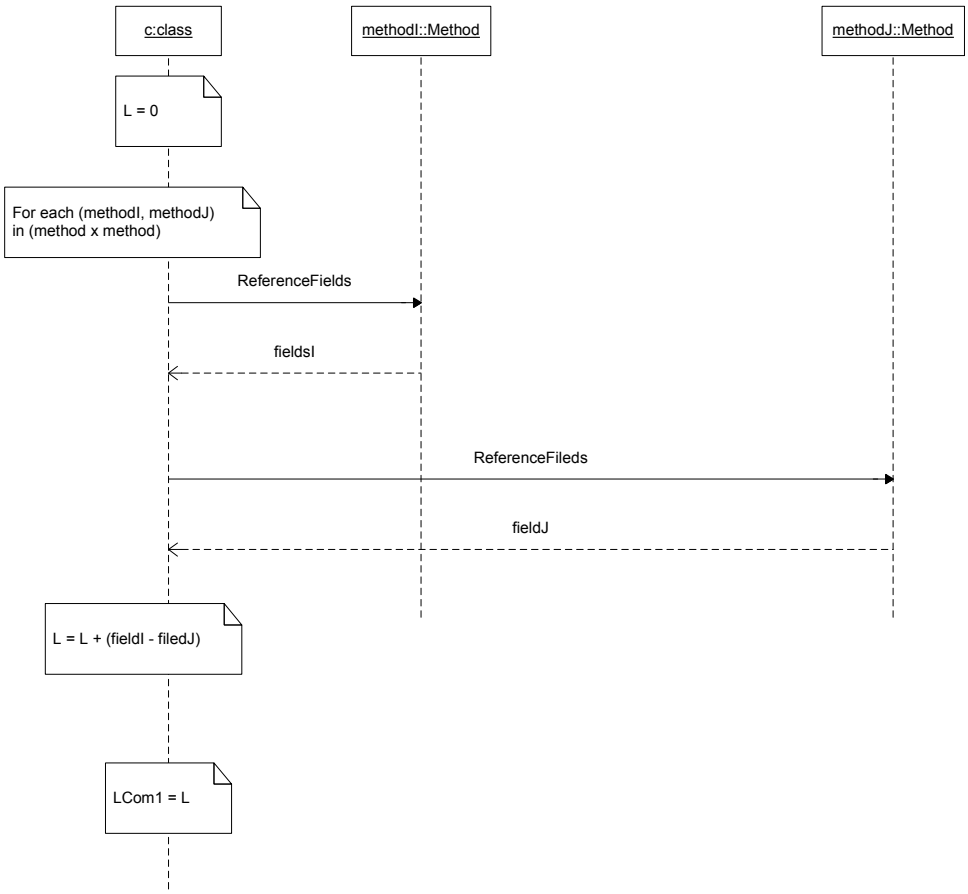


Fig 3.6 Lcom1 – Sequence Diagram



3.9 Conclusion

Chapter three described the research design for the rest of the study and for the program that has been written to test cohesion. Data mining and data mining techniques were discussed and in particular association rules which is used to determine correlation between different values.

The research design uses a survey of 68 randomized open source software programs within a stratified group. Each independent variable used in the study is compared to cohesion. All variables are presented as either being quantitative or qualitative. Data discretisation was performed on all collected data and the method of discretisation was explained using an example from the study. Data mining and the algorithm known as *Apriori* was discussed and explained using an example from the collected data.

The program design of classes is discussed to show how classes of the written software program are compiled.

In Chapter four the results obtained from the association rules of data mining using the *Apriori* algorithm will be discuss and analysed. In addition, the difficulties and future work for the study are then discussed.

Chapter Four - Results

4.1 Introduction

This chapter analyses and interprets the association rules obtained from the data collected. The chapter starts with a short definition of association rules.

The list of all association rules obtained from the data is then presented. That list is then cleaned with the view of eliminating meaningless rules once the criterion for rule selection has been defined. The chapter ends with a classification of the selected rules in accordance with the research hypothesis defined in the previous chapters.

4.2 Association Rules

Maqbool et al (1995) describes association rules as attributes value conditions that occur frequently together in a given dataset. Association rules provide information of this type in the form of "if-then" statements. These rules are computed from the data and, unlike the if-then rules of logic, association rules are probabilistic in nature. In addition to the antecedent (the "if" part) and the consequent (the "then" part), an association rule has two numbers that express the degree of uncertainty about the rule. The antecedent and consequent are sets of items (called itemsets) that are disjoint (do not have any items in common).

The legitimacy of each association with regard to the values in the whole dataset is described by two metrics: the support and the confidence.

The support represents the number of transactions whose attributes match both the antecedent and consequent parts of the rule.

Confidence of rule "B given A" is a measure of how much more likely it is that B occurs when A has occurred. It is expressed as a percentage, with 100% meaning B always occurs if A has occurred. Statisticians refer to this as the conditional probability of B given A. When used with association rules, the term confidence is

observational rather than predictive. (Statisticians also use this term in an unrelated way. There are ways to estimate an interval and the probability that the interval contains the true value of a parameter is called the interval confidence. So a 95% confidence interval for the mean has a probability of .95 of covering the true value of the mean.) (Two Crows Corporation, 2005)

4.3 Rules obtained from independent variables and cohesion values.

Having in mind the data set described in the previous chapter, it is now time to present the association rules obtained from the data. The rules are listed according to the following protocol. Rules with no mention of a cohesion variable are put in one section. Rules with mention of single cohesion variables are grouped under another section specific to those cohesion variables. Rules with mention of many cohesion values are not listed because the correlation between cohesion values is not studied here. The entire set of rules can be viewed in Appendix B

4.4 Criteria for rule selection

The criteria for the selection of rules are based on the hypothesis. If a rule confirms the hypothesis, then that rule is chosen. If a rule does not support any hypothesis then that rule is disregarded.

For example, if a rule states that the cohesion value is high when the software package size is small, then that rule is selected since it is in line with the studies hypothesis.

If a rule states the cohesion value is low for a software package easily maintainable, then that rule is discarded because it is not in line with this hypothesis. If a rule supports one hypothesis and that rule contradicts another hypothesis than that rule is discarded. The following rules are selected from the appendix of rules on the basis of the selection criteria.

4.5 Selected Rules

4.5.1 Rules with no cohesion variables.

Selected Rule 1 (Rule 67,69,71,73,81,1006,1012,1016, 1022,1029,1035)

Total no. of Support Requests=very_low_Plus 56 ==> Support requests still opened=very_low 56 conf:(1)

Selected Rule 2 (Rule 68, 70, 72, 74, 79, 82, 1004, 1009, 1014, 1020, 1026, 1033,)

Total patches and Feature Requests=very_low 56 ==> Total patches and Feature Requests still opened=very_low 56 conf:(1)

Selected rule 1 and 2 are obtained by mining Lcom1 with all independent variables, Lcom2 with all independent variables, Lcom3 with all independent variables, Lcom4 with all independent variables, Tcc with all independent variables, Lcc with all independent variables and Ich with all independent variables

Selected Rule 3 (Rule 76, 80, 83, 88)

Support requests still opened=very_low Total patches and Feature Requests=very_low 55 ==> Total patches and Feature Requests still opened=very_low 55 conf :(1)

Selected rule 3 is obtained by mining Tcc with all independent variables, Ich with all independent variables and Lcc with all independent variables.

Remark: Selected rule 3 summarizes selected rule 1 and selected rule 2 but the support is slightly different.

Selected Rule 4 (Rule 77, 86)

No of Bugs still opened=very_low 56 ==> Support requests still opened=very_low 55 conf:(0.98)

Selected rule 4 is obtained by mining Tcc with all independent variables and Lcc with all independent variables.

Selected Rule 5 (Rule 78)

Total no. of Support Requests=very_low 60 ==> Support requests still opened=very_low 58 conf:(0.97)

Selected rule 5 is obtained by mining Tcc with all independent variables.

Selected Rule 6 (Rule 84)

No of Bugs still opened=very_low Total no. of Support Requests=very_low_Plus 51 ==> Support requests still opened=very_low 51 conf:(1)

Remark: Selected rule 6 summarizes selected rule 4 and selected rule 5 but the support is different.

Selected rules 6 is obtained by mining Ich with all independent variables

Selected Rule 7 (Rule 85)

Total no. of Support Requests=very_low_Plus Total patches and Feature Requests still opened=very_low 51 ==> Support requests still opened=very_low 51 conf:(1)

Selected rules 7 is obtained by mining Ich with all independent variables

Selected Rule 8 (Rule 87)

Total patches and Feature Requests still opened=very_low 58 ==> Total patches and Feature Requests=very_low 56 conf:(0.97)

Selected rules 8 is obtained by mining Ich with all independent variables

Selected Rule 9 (Rule 89)

No of Bugs still opened=very_low Support requests still opened=very_low 53 ==> Total no. of Support Requests=very_low_Plus 51 conf:(0.96)

Selected rules 9 is obtained by mining Ich with all independent variables

Selected Rule 10 (Rule 90)

Total patches and Feature Requests still opened=very_low 58 ==> Support requests still opened=very_low 55 conf:(0.95)

Selected rules 10 is obtained by mining Ich with all independent variables

Remark: Contained in selected rule 7 but the support is different.

Selected Rule 11 (Rule 1003)

Total No of bugs=very_low 46 ==> No of Bugs still opened=very_low 46 conf:(1)

Selected rule 11 is obtained by mining Lcom1 with bugs

Selected Rule 12 (Rule 1005, 1010, 1015, 1021, 1034)

Total patches and Feature Requests still opened=very_low 58 ==> Total patches and Feature Requests=very_low 56 conf:(0.97)

Selected rule 12 is obtained by mining Lcom1 with total patches and feature requests, Lcom2 with total patches and feature requests, Lcom3 with total patches and feature requests, Lcom4 with total patches and feature requests and Ich with total patches and feature requests

Selected Rule 13 (Rule 1007, 1011, 1017,1023, 1030, 1036)

Support requests still opened=very_low 61 ==> Total no. of Support Requests=very_low_Plus 56 conf:(0.92)

Selected rule 13 is obtained by mining Lcom1 with support requests, Lcom2 with support requests, Lcom3 with support requests, Lcom4 with support requests, Tcc with support requests and Ich with support requests

Selected Rule 14 (Rule 1008, 1018, 1024, 1027, 1031, 1037)

CVS Repository - Commits=very_low 50 ==> CVS Repository - Read=very_low 49 conf:(0.98)

Selected rule 14 is obtained by mining Lcom1 with CVS Repository , Lcom3 with CVS Repository , Lcom4 with CVS Repository, Lcc with CVS Repository, Tcc with CVS Repository and Ich with CVS Repository

Selected Rule 15 (Rule 1013, 1019, 1025, 1028, 1032)

Total No of bugs=very_low 46 ==> No of Bugs still opened=very_low 46 conf:(1)

Selected rule 15 is obtained by mining Lcom3 with Bugs, Lcom4 with Bugs, Lcc with Bugs , Tcc with Bugs and Ich with bugs

4.5.2 Rules with one cohesion variable

4.5.2.1 Mining one cohesion variable against all independent variables

Obtained by mining Lcom1 with all independent variables

Selected Rule 16 (Rule 3)

Support requests still opened=very_low 61 ==> Lcom1 Value Minimum=high 60 conf:(0.98)

Selected Rule 17 (Rule 5)

Total patches and Feature Requests still opened=very_low 58 ==> Lcom1 Value - Minimum=high 57 conf:(0.98)

Selected Rule 18 (Rule 6)

Total no. of Support Requests=very_low_Plus 56 ==> Lcom1 Value - Minimum=high 55 conf:(0.98)

Selected Rule 19 (Rule 7)

Total patches and Feature Requests=very_low 56 ==> Lcom1 Value - Minimum=high 55 conf:(0.98)

Selected Rule 20 (Rule 8)

Total no. of Support Requests=very_low_Plus Support requests still opened=very_low 56 ==> Lcom1 Value - Minimum=high 55 conf:(0.98)

Obtained by mining Lcom3 with all independent variables

Selected Rule 21 (Rule 17)

CVS Repository - Read=very_low 55 ==> Lcom3 Value - Minimum=high 55 conf:(1)

Selected Rule 22 (Rule 20)

Support requests still opened=very_low 61 ==> Lcom3 Value - Minimum=high 59 conf:(0.97)

Selected Rule 23 (Rule 22)

Total patches and Feature Requests still opened=very_low 58 ==> Lcom3 Value - Minimum=high 56 conf:(0.97)

Selected Rule 24 (Rule 23)

Total no. of Support Requests=very_low_Plus 56 ==> Lcom3 Value - Minimum=high 54 conf:(0.96)

Selected Rule 25 (Rule 24)

Total patches and Feature Requests=very_low 56 ==> Lcom3 Value - Minimum=high 54 conf:(0.96)

4.5.2.2 Mining one cohesion variable against one independent variable

Obtained by mining Lcom1 with Bugs

Selected Rule 26 (Rule 93)

No of Bugs still opened=very_low 56 ==> Lcom1 Value - Minimum=high 53 conf:(0.95)

Obtained by mining Lcom1 with Age

Selected Rule 27 (Rule 100)

Age=new 17 ==> Lcom1 Value - Minimum=high 17 conf:(1)

Obtained by mining Lcom1 with Category

Selected Rule 28 (Rule 110)

Category=Development_software 20 ==> Lcom1 Value - Minimum=high 20 conf:(1)

Obtained by mining Lcom1 with Number of Developers

Selected Rule 29 (Rule 120)

Number of Developers=very_low 44 ==> Lcom1 Value - Minimum=high 43 conf:(0.98)

Obtained by mining Lcom1 with Mailing Lists

Selected Rule 30 (Rule 130)

Mailing Lists=low 53 ==> Lcom1 Value - Minimum=high 52 conf:(0.98)

Obtained by mining Lcom1 with number of messages in a public forum

Selected Rule 31 (Rule 140)

No. of messages in public forums=very_low_Minus 18 ==> Lcom1 Value - Minimum=high 18 conf:(1)

Selected Rule 32 (Rule 141)

No. of messages in public forums=very_low_Plus 30 ==> Lcom1 Value - Minimum=high 29 conf:(0.97)

Obtained by mining Lcom1 with total patches and feature requests

Selected Rule 33 (Rule 150)

Total patches and Feature Requests still opened=very_low 58 ==> Lcom1 Value - Minimum=high 57 conf:(0.98)

Selected Rule 34 (Rule 154)

Total patches and Feature Requests=very_low 56 ==> Lcom1 Value - Minimum=high 55 conf:(0.98)

Selected Rule 35 (Rule 156)

Total patches and Feature Requests still opened=very_low 58 ==> Total patches and Feature Requests=very_low Lcom1 Value - Minimum=high 55 conf:(0.95)

Obtained by mining Lcom1 with Programming Language

Selected Rule 36 (Rule 157)

Programming Language=C# 45 ==> Lcom1 Value - Minimum=high 44 conf:(0.98)

Obtained by mining Lcom1 with Size

Selected Rule 37 (Rule 166)

KiloBytes=very_low_Plus 19 ==> Lcom1 Value - Minimum=high 19 conf:(1)

Selected Rule 38 (Rule 167)

KiloBytes=very_low_Minus 24 ==> Lcom1 Value - Minimum=high 23 conf:(0.96)

Obtained by mining Lcom1 with Support Requests

Selected Rule 39 (Rule 176)

Support requests still opened=very_low 61 ==> Lcom1 Value - Minimum=high 60 conf:(0.98)

Selected Rule 40 (Rule 179)

Total no. of Support Requests=very_low_Plus Support requests still opened=very_low 56 ==> Lcom1 Value - Minimum=high 55 conf:(0.98)

Selected Rule 41 (Rule 180)

Total no. of Support Requests=very_low_Plus 56 ==> Lcom1 Value - Minimum=high 55 conf:(0.98)

Obtained by mining Lcom1 and CVS Repository

Selected Rule 42 (Rule 183)

CVS Repository - Commits=very_low 50 ==> Lcom1 Value - Minimum=high 50 conf:(1)

Selected Rule 43 (Rule 184)

CVS Repository - Commits=very_low CVS Repository - Read=very_low 49 ==> Lcom1 Value - Minimum=high 49 conf:(1)

Selected Rule 44 (Rule 188)

CVS Repository - Read=very_low 55 ==> Lcom1 Value - Minimum=high 54 conf:(0.98)

Obtained by mining Lcom3 with Bugs

Selected Rule 45 (Rule 302)

Total No of bugs=very_low 46 ==> No of Bugs still opened=very_low Lcom3 Value - Minimum=high 43 conf:(0.93)

Obtained by mining Lcom3 with number of developers

Selected Rule 46 (Rule 325)

Number of Developers=very_low 44 ==> Lcom3 Value - Minimum=high 43 conf:(0.98)

No rules were selected for Lcom2

Obtained by mining Lcom3 with mailing lists

Selected Rule 47 (Rule 335)

Mailing Lists=low 53 ==> Lcom3 Value - Minimum=high 52 conf:(0.98)

Obtained by mining Lcom3 with number of lists in a public forum

Selected Rule 48 (Rule 345)

No. of messages in public forums=very_low_Plus 30 ==> Lcom3 Value - Minimum=high 30 conf:(1)

Obtained by mining Lcom3 with total number of patches and feature requests

Selected Rule 49 (Rule 355)

Total patches and Feature Requests=very_low 56 ==> Total patches and Feature Requests still opened=very_low Lcom3 Value - Minimum=high 54 conf:(0.96)

Selected Rule 50 (Rule 356)

Total patches and Feature Requests=very_low Total patches and Feature Requests still opened=very_low 56 ==> Lcom3 Value - Minimum=high 54 conf:(0.96)

Selected Rule 51 (Rule 358)

Total patches and Feature Requests=very_low 56 ==> Lcom3 Value - Minimum=high 54 conf:(0.96)

Selected Rule 52 (Rule 360)

Total patches and Feature Requests still opened=very_low 58 ==> Total patches and Feature Requests=very_low Lcom3 Value - Minimum=high 54 conf:(0.93)

Selected Rule 53 (Rule 361)

Total patches and Feature Requests still opened=very_low 58 ==> Lcom3 Value - Minimum=high 56 conf:(0.97)

Obtained by mining Lcom3 with Programming Language

Selected Rule 54 (Rule 363)

Programming Language=C# 45 ==> Lcom3 Value - Minimum=high 43 conf:(0.96)

Obtained by mining Lcom3 with Size

Selected Rule 55 (Rule 373)

KiloBytes=very_low_Minus 24 ==> Lcom3 Value - Minimum=high 24 conf:(1)

Obtained by mining Lcom3 with Support Requests

Selected Rule 56 (Rule 384)

Support requests still opened=very_low 61 ==> Lcom3 Value - Minimum=high 59 conf:(0.97)

Selected Rule 57 (Rule 385)

Total no. of Support Requests=very_low_Plus 56 ==> Support requests still opened=very_low Lcom3 Value - Minimum=high 54 conf:(0.96)

Selected Rule 58 (Rule 386)

Total no. of Support Requests=very_low_Plus Support requests still opened=very_low 56 ==> Lcom3 Value - Minimum=high 54 conf:(0.96)

Selected Rule 59 (Rule 387)

Total no. of Support Requests=very_low_Plus 56 ==> Lcom3 Value - Minimum=high 54 conf:(0.96)

Obtained by mining Lcom3 with CVS Repository

Selected Rule 60 (Rule 391)

CVS Repository - Read=very_low 55 ==> Lcom3 Value - Minimum=high 55 conf:(1)

Selected Rule 61 (Rule 392)

CVS Repository - Commits=very_low 50 ==> Lcom3 Value - Minimum=high 50 conf:(1)

Selected Rule 62 (Rule 393)

CVS Repository - Commits=very_low CVS Repository - Read=very_low 49 ==> Lcom3 Value - Minimum=high 49 conf:(1)

Selected Rule 63 (Rule 397)

CVS Repository - Commits=very_low 50 ==> CVS Repository - Read=very_low Lcom3 Value - Minimum=high 49 conf:(0.98)

Obtained by mining Lcom4 with Category

Selected Rule 64 (Rule 414)

Category=Development_software 20 ==> Lcom4 Value Maximum=very_low 20 conf:(1)

Obtained by mining Lcom4 with number of Developers

Selected Rule 65 (Rule 424)

Number of Developers=very_low 44 ==> Lcom4 Value -Maximum=very_low 44 conf:(1)

Obtained by mining Lcom4 with Mailing Lists

Selected Rule 66 (Rule 434)

Mailing Lists=low 53 ==> Lcom4 Value -Maximum=very_low 53 conf:(1)

Obtained by mining Lcom4 with number of messages in a public forum

Selected Rule 67 (Rule 444)

No. of messages in public forums=very_low_Plus 30 ==> Lcom4 Value -Maximum=very_low 30 conf:(1)

Obtained by mining Lcom4 with total number patches and feature requests

Selected Rule 68 (Rule 454)

Total patches and Feature Requests still opened=very_low 58 ==> Lcom4 Value -Maximum=very_low 58 conf:(1)

Obtained by mining Lcom4 with programming Language

Selected Rule 69 (Rule 464)

Programming Language=C# 45 ==> Lcom4 Value -Maximum=very_low 45 conf:(1)

The selected rules obtained for Lcom4 is discarded because it does not match the hypothesis outlined in chapter 1. For example if selected rules 48 and 67 was

compared, a contradiction would have resulted. Therefore, the one that does not match the hypothesis, in this case it is selected rule 67, would have to be discarded.

No rules were selected for Lcom5, Co, Lcc, Tcc and Ich

4.6. Rules Interpretation

Lets interpret one of the above listed rules, for example, Selected Rule 2. Total patches and Feature Requests = very_low 58 ==> Total patches and Feature Requests still opened = very_low 58 conf :(1)
This rule means:- If the total patches and feature requests is very low that implies the total patches and feature requests that are still not resolved are also very low with a confidence factor of 100%, 58 records from the 68 records matched this rule. All the other rules can be interpreted in a similar way.

4.7 Results

The following results were obtained from the association rules.

4.7.1 Independence of variables

The following positive conclusion can be reached by the study with the rules that contained no cohesion variables

a) There is a correlation between the total number of support requests and the total number of support requests still opened. There is also a correlation between the total number of patches and feature requests, and the total number of patches and feature requests still opened. This is validated by selected rules 1, 2, 3, 5, 7, 8, 10, 12, 13. There is a correlation between the total number of bugs in a software program and the number of bugs in a program yet to be solved. This is validated by selected rule 11 and 15. A correlation exists between the CVS repository commits and the CVS repositories read. This is validated by selected rule 14.

b) A correlation exists between the number of bugs and the number of support requests. This is validated by selected rules 4, 6, 9

4.7.2 Validity of cohesion formulas

The following positive conclusion can be reached by the study with the rules that contained one cohesion variable against all independent variable.

There is empirical evidence that Lcom1 and Lcom3 are valid formulas for the calculation of cohesion when testing independent variables. This is validated by selected rules 16 to 69

4.7.3 Correlation between independent variable and cohesion

Bugs, Age, Number of Developers, Mailing Lists, number of messages in a public forum, total patches and feature requests, Programming Language, Size, Support requests and CVS Repository can be used as predictors of software cohesion when that cohesion is calculated using Lcom1 or Lcom3. This is validated by selected rules 16 to 64

4.7.4 Calculation of the cohesion of a package

There is empirical evidence that the cohesion of a package (set of classes) can be calculated as the minimum value for all cohesion values of the classes in the set.

4.7.5 Negative Results

The following negative conclusions are determined by the study.

a) There is no empirical evidence that Lcom2, Lcom4, Lcom5, Lcc, Tcc, Ich and connectivity (Co) must be used for the evaluation of software cohesion.
b) There is no empirical evidence that sum, maximum, and average must be used for the evaluation of software package cohesion.

4.8 Conclusion

An overview of all cohesion measures shows that the minimum value of cohesion for Lcom1 and Lcom3 are measurements that can be trusted. The measurement for Lcom2, Lcom4, Lcom5, Co, Lcc, Ich and Tcc cannot be validated as true refection of cohesion measurements.

The correlation between Lcom1 and Lcom3 and the independent variables of the study was proven to be successful when measuring cohesion. It was concluded that independent variables i.e. Support requests, Total patches and feature requests, Bugs, Age, Category, Number of Developers, Mailing Lists, messages in a public forum, patches and feature requests, programming language, size and CVS Repository used in study can be used as indicators of cohesion in any software program.

It is assumed that since cohesion is a measure of quality, the more cohesive a package is the higher the package quality. If a package is of a high quality then that package is easier to maintain.

Chapter 5 Conclusion and Recommendations

5.1 Comparisons with existing Literature

The objective of this study is to test the empirical validity of software cohesion metrics based on the mining of open source software data.

5.1.1 Software Size

The research reveals empirical evidence that smaller software is more cohesive than bigger software when Lcom1 and Lcom3 are used for the calculation of cohesion. That result complements a result found by Benlarbi, Eman and Goel (1999) in the same sense that both results are similar but on different types of software (proprietary software (for Benlarbi, Eman and Goel) versus open source software (that is used in this study)). Moreover, the results find differences in the behavior of the different cohesion metrics (Lcom1, Lcom2, Lcom3, Lcom4, Lcom5, Co, Tcc, Lcc and Ich) but Benlarbi, Eman and Goel results looks at Lcom as its research took place before the categorization of Lcom by many different authors. The methodologies used in the two cases are also different. In the study data mining is used, but Benlarbi, Eman and Goel used logistic regression of 174 classes in a C++ system and the study consisted of 68 packages with different number of classes in each package from the .net languages (C#, VB.net and J#)

On the other hand, Counsell, Swift and Turner (2006) could not find empirical evidence that smaller software is more cohesive than bigger software probably because the cohesion metrics used was Coupling Between objects, Number of Association and Number of Methods in a class.

5.1.2 Software Faults

Basili, Briand and Melo (1995) conducted a study on a medium size information system in which it was empirically shown that fault proness is influenced by size and cohesion. The results are in line with the work published by Basili, Briand and Melo

(1995) in the sense that the study also found empirical evidence that software faults expressed by software bugs, software support requests and patches and feature requests correlate with software cohesion. This is also confirmed by Gyimothy, Ferenc and Siket (2005) where research on the validation of object oriented metrics on open source software using Mozilla's proved that the Lcom metric is a good indicator of software fault proneness.

Moreover, Koru, Zhang and Liu (2007) presented a paper on the modeling of the effect of Size on Defect Proneness for Open Source Software. The results showed defect-proneness is a logarithmic pattern. The research does not reveal any empirical evidence linking size to defect proneness. This study also showed that there is a correlation between the number of bugs in a package and the Lcom1 and Lcom3 value, the lower the number of bugs the higher the cohesion. A correlation also exists between the category of development software and the cohesion values for Lcom1 and Lcom3, as long as the category is "development software" the cohesion value was high.

5.1.3 Software Changeability

Kabaili et al (2001) goal was to validate cohesion metrics as changeability indicators, and Lcc, and Lcom were chosen cohesion metrics. For each metric min, max, mean, median and standard deviation statistics were collected. The conclusion reached by Kabaili et al (2001) was that Lcc and Lcom should not be used as changeability indicators. The results however show that Lcom1 and Lcom3 can be used as changeability indicators represented by the number of software patches. Once again, the studies methodology is original and it relies on a wider data set compared to the methodology used by Kabaili et al (2001) that only applied to three industrial systems.

Furthermore, Li and Hendry (1993) research implemented object oriented metrics to predict maintenance effort. The results of their analysis proved that there is a strong

relationship between maintenance effort and size. This study shows a relationship between the total patches and feature requests (linked to maintenance) and cohesion values for Lcom1 and Lcom3. The lower the total patches and feature requests the higher the cohesion of Lcom1 and Lcom3. The study also revealed that if the CVS repository for commits or reads were low the Lcom1 and Lcom3 cohesion values were also high.

5.1.4 Results obtained that has not being recorded in literature

a) Team Size

If the number of developers is low in a package the values for Lcom1 and Lcom3 cohesion is high.

b) Software reviewers

If the mailing lists is low the values for Lcom1 and Lcom3 cohesion is also high.

If the number of messages in a public forum is low the value of Lcom1 and Lcom3 cohesion is high.

c) Software Maturity

If a software package was only a few days old the cohesion of that package was high for Lcom1 and Lcom3

d) Software Language

If the programming language was C# the cohesion of Lcom1 and Lcom3 was high

5.2 Future Work and Recommendations

There is a very rich body of object oriented measurement documented, but these frameworks for measurement have not been empirically tested. There is definitely a need for these measurements to be tested and validated to ensure good software packages that are easy to maintain, reliable and easily imported into ones own work.

Future work should also include identifying guidelines for the measurement of object oriented metrics measurement and a standardized framework should be established. There also exists a platform for the measurement of independent variables and object

oriented metrics. A platform also exists for developing a standardized framework of all metrics

5.2.1 Software Size

It is recommended to design software in small units rather than in big monolithic programs. It actually confirms the basic principal of modularization.

5.2.2 Software faults and Changeability

It is recommended to design highly cohesive software. This is possible at the design stage where the calculation of cohesion metrics should be done and appropriate decisions should be taken as to optimize software cohesion that will yield positive rewards during the maintenance phase as this study shows that cohesive software is less fault prone.

5.2.3 Team Size

It is recommended that teams should be kept small

5.2.4 Software Reviewers

Even though fewer software reviewers can guarantee higher software cohesion, it is still recommended to have a bigger set of software reviewers because the more the reviewers the more the faults will be discovered. It is a rectification of these faults that leads to low cohesion.

5.2.5 Software Maturity

There is nothing one can do about the maturity of a software package even though the results show that young software is more cohesive than old software.

5.2.6 General Recommendation

This study results shows that software cohesion only makes sense at the early state of the software life cycle. Therefore it is recommended to measure software cohesion

before the software is released for the first time to users. Once the software has been released, its maintenance seems to degrade software cohesion. The possible results for that cohesion degradation seems to be linked to the fact that changes are made under pressure and no time is given to the redesign of the software. It is therefore recommended to re-engineer the design of software every time that software is maintained.

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