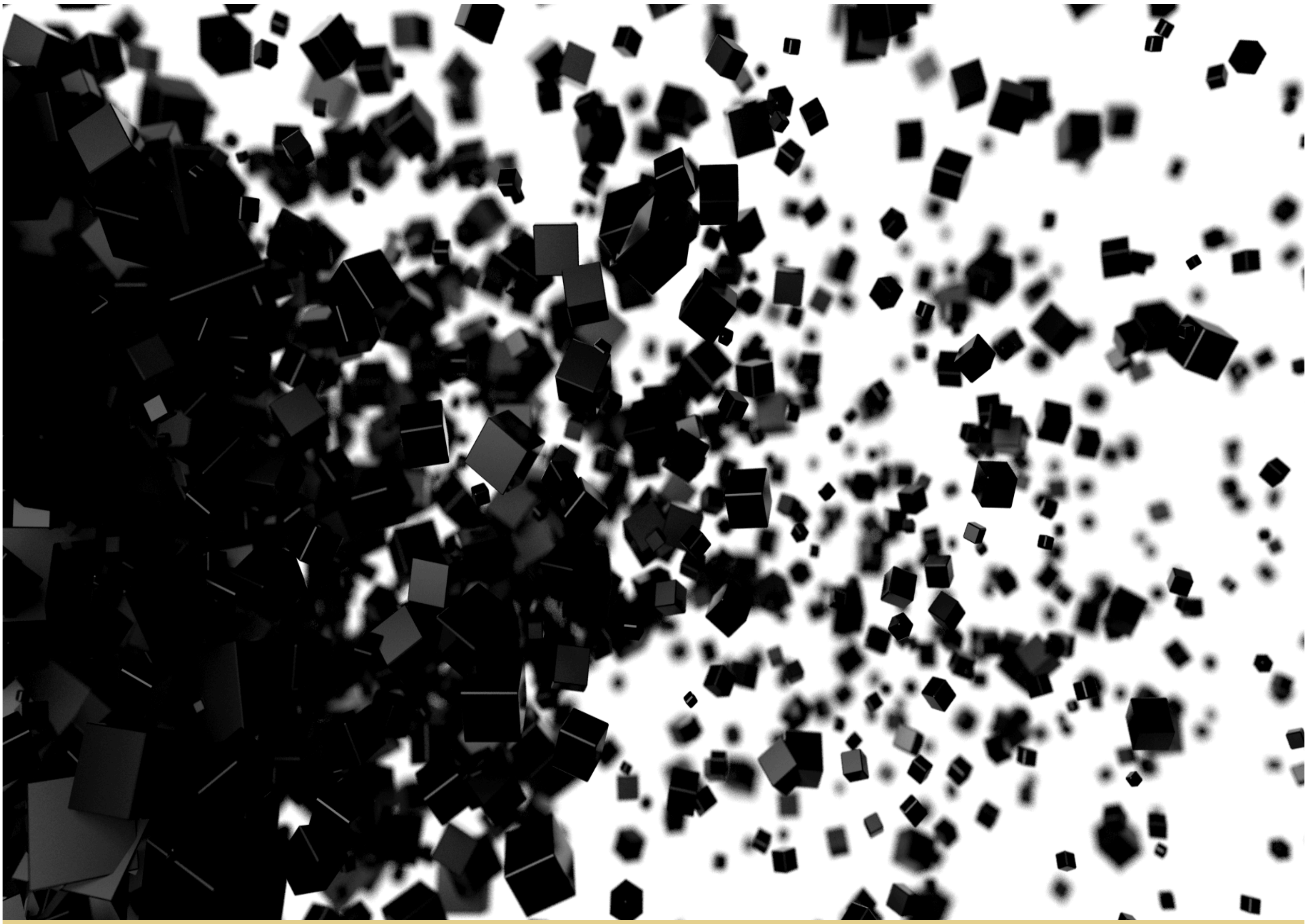

Eudisley Gomes dos Anjos

ASSESSING MAINTAINABILITY IN SOFTWARE ARCHITECTURES

THE ELUSIVE SOCIO-TECHNICAL DIMENSIONS OF MAINTAINABILITY

Tese de doutoramento
do Programa de Doutoramento em Ciências e Tecnologias da Informação
orientada pelo Professor Doutor Mário Alberto da Costa Zenha-Rela
e apresentada ao Departamento de Engenharia Informática
da Faculdade de Ciências e Tecnologia da Universidade de Coimbra

Janeiro de 2017

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UNIVERSIDADE DE COIMBRA

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Assessing Maintainability in Software Architectures

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PhD Thesis Submitted to the University of Coimbra

Tese de Doutoramento submetida à Universidade de Coimbra

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List of Publications

- Eudisley Anjos & Mário Zenha-Rela.A Framework for Classifying and Comparing Software Architecture Tools for Quality Evaluation. In Computational Science and Its Applications - ICCSA 2011, volume 6786 of Lecture Notes in Computer Science, pages 270 - 282. Springer Berlin Heidelberg, 2011. [Anjos 11]

- Eudisley Anjos, Ruan Gomes & Mário Zenha-Rela. Assessing Maintainability Metrics in Software Architectures Using COSMIC and UML. In Computational Science and Its Applications - ICCSA 2012, volume 7336 of Lecture Notes in Computer Science, pages 132 - 146. Springer Berlin Heidelberg, 2012. [Anjos 12b]

- Eudisley Anjos, Ruan Gomes & Mário Zenha-Rela. Maintainability Metrics in System Designs: a case study using COSMIC and UML. In International Journal of Computer Science and Software Technology, volume 5 of Lecture Notes in Computer Science, pages 91 - 100. International Science Press, 2012 [Anjos 12a]

- Eudisley Anjos, Fernando Castor & Mário Zenha-Rela. Comparing Software Architecture Descriptions and Raw Source-Code: A Statistical Analysis of Maintainability Metrics. In Computational Science and Its Applications ICCSA 2013, volume 7973 of Lecture Notes in Computer Science, pages 199 - 213. Springer Berlin Heidelberg, 2013 [Anjos 13]

- Braulio Siebra, Eudisley Anjos & Gabriel Rolim. Study on the Social Impact on Software Architecture through Metrics of Modularity. In Computational Science and Its Applications - ICCSA 2014 - 14th International Conference, Guimaraes, Portugal, June 30 - July 3, 2014, Proceedings, Part V, pages 618 - 632, 2014 [Siebra 14].

- Eudisley Anjos, Francielly Grigorio, Daniel Brito & Mário Zenha-Rela. On Systems Project Abandonment: An Analysis of Complexity During Development and Evolution of FLOSS Systems. In ICAST 2014, 6TH IEEE International Conference on Adaptive Science and Technology, Covenant University, Nigeria, 29 - 31 October 2014, Nigeria, 2014. [Anjos 14]

- Francielly Grigorio, Daniel Brito, Eudisley Anjos, and Mário Zenha-Rela. Using Statistical Analysis of FLOSS Systems Complexity to Understand Software Inactivity. In Covenant Journal of Informatics and Communication Technology - CJICT, volume 2, pages 1 - 28, December 2014 [Grigorio 14].

- Eudisley Anjos, Pablo Anderson de L. Lima, Gustavo da C. C. Franco Fraga & Danielle Rousy da Silva. Systematic Mapping Studies in Modularity in IT Courses. In Computational Science and Its Applications âĂŞ ICCSA 2015, volume 9159 of Lecture Notes in Computer Science, pages 132 - 146. Springer International Publishing, 2015 [Anjos 15].

- Gabriel Rolim, Everaldo Andrade, Danielle Silva, Eudisley Anjos. Longitudinal Analysis of Modularity and Modifications of OSS. 7th International Symposium on Software Quality - ISSQ 2015, volume 9790 of Lecture Notes in Computer Science, pages 363 - 374, Springer International Publishing, 2016 [Gabriel Rolim 16].

- Eudisley Anjos, Jansepetrus Brasileiro, Danielle Silva, Mário Zenha-Rela. Using Classification Methods to Reinforce the Impact of Social Factors on Software Success. 16th International Conference on Computational Science and Its Applications, ICCSA 2016, volume 9790 of Lecture Notes in Computer Science, pages 187 - 200, Springer International Publishing, Switzerland, 2016 [Anjos 16].

Resumo

Esta tese lida com um dos aspectos mais evasivos da engenharia de software, a manutenibilidade do software. Esse caráter fugidio parece resultar da sua dependência de uma multiplicidade de factores, desde os puramente técnicos —a forma como o software está estruturado a diferentes níveis—aos de natureza social —a estrutura da organização que o criou—passando pela capacidade humana de compreensão, nomeadamente a forma como o código-fonte está documentado e a adesão a convenções de programação.

Após uma extensa revisão da literatura científica sobre a manutenibilidade e conceitos relacionados, nomeadamente requisitos não funcionais, atributos de qualidade e arquitectura de software, na primeira parte deste estudo procurámos perceber como esta propriedade era caracterizada e quantificada nas representações mais abstratas do software, nomeadamente ao nível da arquitectura. Para isso foi feita uma análise sistemática das ferramentas de desenho arquitectural mais relevantes, e estudada a forma como abordam a manutenibilidade. Este estudo permitiu-nos concluir que estas ferramentas quantificam esta propriedade do software quase exclusivamente a partir do código-fonte, usando uma composição de métricas envolvendo a coesão, acoplamento, complexidade e dimensão.

Uma vez que o nosso trabalho estava integrado num projecto cujo objectivo era disponibilizar aos arquitectos de software um conjunto de metodologias e ferramentas que lhes permitissem trabalhar a evolução do software preservando, ou mesmo melhorando, a manutenibilidade para não prejudicar a sua longevidade, era-nos relevante adoptar uma representação mais abstrata desta propriedade que não estivesse tão directamente associada ao código-fonte. Para isso propusemos um mapeamento entre a representação UML do sistema e a notação mais abstracta adoptada pela COmmon Software Measurement International (COSMIC). A validade deste mapeamento foi realizada comparando os valores de manutenibilidade extraídas a partir do código-fonte de 39 versões do Apache Tomcat e as respectivas métricas na notação COSMIC.

Contudo, quando esta primeira análise foi alargada para outros sistemas de grande dimensão, a correlação entre as métricas de manutenibilidade extraídas a partir do código-fonte e as extraídas a partir da sua representação arquitetural reduziu-se significativamente. Estas observações levaram-nos a concluir que o pressuposto de que todos os atributos de qualidade podem ser mapeados ao nível arquitectural não se verifica, pelo menos no que à manutenibilidade diz respeito. Uma análise manual e um inquérito a gestores de projecto na indústria levou-nos a concluir que uma das possíveis causas para este desalinhamento se deve à existência de muita informação presente ao nível do código-fonte (por exemplo, comentários, adopção de convenções de programação, documentação), que manifestamente promovem a manutenibilidade e que estão omissas nas representações mais abstractas do software, nomeadamente ao nível arquitectural.

Perante a evidência desta natureza multidimensional da manutenibilidade, na segunda parte deste estudo focámo-nos numa terceira perspectiva, a dimensão social da estrutura do software e o seu impacto na manutenibilidade.

A primeira etapa foi procurar identificar projectos que manifestamente possuíssem altos valores de manutenibilidade, por forma a poder identificar os factores que os caracterizam. Para isso assumimos o pressuposto de que projectos de código-aberto (OSS) com grande longevidade teriam de estar necessariamente correlacionados com valores altos de manutenibilidade. Se assim não fosse, teriam grande dificuldade em se manter activos, bem como grande dificuldade em atrair e reter colaboradores. Ademais, a própria natureza voluntária e distribuída da colaboração em projectos de código-aberto promove a modularidade, uma das propriedades intrínsecas da manutenibilidade.

Após analisar cerca de 160.000 projectos de código-aberto concluímos que existe efectivamente um pequeno conjunto de parâmetros que podemos designar como 'sociais' (número de voluntários, número de *commits*, número de *issues* registados,...) que têm um impacto decisivo nas probabilidades de sucesso do projecto. De um modo informal podemos então afirmar que quanto mais 'activo' um projecto estiver, maiores as suas probabilidades de sucesso (activo nos dois anos seguintes). Complementarmente, também podemos afirmar que quanto menos manutenível um projecto, menos voluntários irá atrair, menor será o número de contribuições/commits, e consequentemente terá uma reduzida capacidade e motivação para produzir código mais modular e mais facilmente compreensível por uma comunidade alargada.

No final deste estudo sobre a natureza da manutenibilidade, podemos concluir que esta relevante propriedade intrínseca do software tem uma natureza marcadamente socio-técnica, nas suas múltiplas dimensões i) humana, ii) social e iii) estrutural e portanto, qualquer tentativa para a gerir considerando apenas uma dimensão tem reduzidas possibilidades de sucesso.

Keywords: manutenibilidade, atributos de qualidade, arquitectura de software, OSS.

Abstract

This thesis deals with a most elusive aspect of software engineering, the maintainability of software. Such elusiveness derives from its high dependence of multiple orthogonal factors, from the purely technical —the way software is structured at different levels—to the social dimension —the structure of the organization that manages the software system—but also depends on raw human understanding, namely how source-code is documented, and programming conventions adhered.

After a thorough review of the literature on maintainability and the related concepts of software quality attributes and software architecture, in the first part of this study we tried to identify how the maintainability quality of software was characterized and quantified at a more abstract, architectural level. In this context, a systematic review of contemporary software architecture design tools was performed, and its underlying principles identified in order to understand how maintainability was handled by such tools. It was much to our surprise to realize that every tool analyzed extracted its maintainability metrics from source-code whenever this quality attribute was involved, mostly through a few proxy variables (cohesion, coupling, complexity, and size).

Since our initial goal was to provide software architects with tools and methodologies to evolve software systems preserving, hopefully increasing, its maintainability, we proposed a mapping from the UML description of a software system into the Common Software Measurement International (COSMIC) notation. This mapping was validated by an extensive analysis of the evolution of 39 consecutive versions of a major open-source software product (Apache Tomcat).

However, after extending this analysis to other large software systems, the correlation between the maintainability metrics collected at the source-code and at the more abstract architectural level dropped significantly. This observation lead us to conclude that the assumption that quality attributes can be mapped at architectural level does not hold for maintainability, i.e. there is relevant maintainability-related information at the source-code (e.g. readability, adherence to code-conventions, documentation) that is not present at the more abstract architectural level.

Faced with this multidimensional nature of maintainability, in the second part of this study we addressed it from a third orthogonal perspective, the social dimension of software structure, and its impact on maintainability.

The first step was to identify a set of projects characterized by high maintainability, so that we could analyze its intrinsic social factors and how they differ from other projects. It seems plausible that long-term successful OSS projects do have to posses high maintainability, otherwise they would not achieve long-term success. So, having previously concluded that maintainability cannot be explained solely on the basis of structural/product characteristics, it is reasonable to assume that successful OSS projects do possess those elusive properties that lead to maintainable software. Thus, in the second part of our study we focused on identifying the long-term OSS success predictors, so that light can be shed on the social factors that promote highly maintainable software.

After analyzing about 160.000 OSS projects available in public repositories we could conclude that a few social parameters do have a direct impact on the odds of success of a software system. To state it in simple terms, the more 'alive' a project is (number of contributors, number of commits, number of issues), the more maintainable it will tend to be. The opposite also holds, i.e. the harder to maintain is a software system, the less contributors it will attract, leading to a reduction on the number of contributions, and thus a lower concern on producing easily readable/understandable code for a larger community.

So, after this study on the nature of maintainability, we can conclude that this relevant software property has an intrinsic socio-technical nature, due to its multiple dimensions, i) human, ii) social and iii) structural, thus any attempt to address it considering only one dimension will seldom be successful.

Keywords: maintainability, quality attributes, software architecture, OSS.

Science is but a perversion of itself unless it has as its ultimate goal the betterment of humanity.

Nikola Tesla, 1919

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List of Acronyms

AC	Aferent Coupling
ADL	Architecture Description Language
ATAM	Architecture Trade-off Analysis Method
CASE	Computer Aided Software Engineering
CBAM	Cost Benefit Analysis Method
CBO	Coupling Between Objects
CC	McCabe Cyclomatic Complexity
CCC	Coupling, Cohesion and Complexity
CCN	Cyclomatic Complexity Number
EC	Efferent Coupling
FAAM	Family-Architecture Analysis Method
FFC	Fan-in and Fan-out Complexity
FLOSS	Free Libre Open Source Software
FSF	Free Software Foundation
LCC	Loose Class Cohesion
LCOM	Lack of Cohesion of Methods
NBD	Nested Block Depth
NC	Number of Classes
NI	Number of Interfaces
NOAM	Net-based and Object-based Architectural Model
NOPK	Number of Packages
NORM	Number of Overridden Methods
IEEE	Institute of Electrical and Electronics Engineers

IETF	Internet Engineering Task Force
ISO	International Organization for Standardization
OMG	Object Management Group
OO	Object Oriented
OSSD	Open Source Software Development
OSS	Open-Source Software
RF	Reasoning Framework
RFC	Response For Class
ROC	Receiver operating characteristic
SAAM	Software Architecture Analysis Method
SwA	Software Architecture
TCC	Tight Class Cohesion
TLOC	Total Lines of Code
UI	User Interfaces
WMC	Weighted Methods per Class

Chapter 1

Introduction

This thesis deals with one of the most elusive aspects of software engineering, the maintainability of software. Maintainability is a quality attribute of software and as such it is expected to be determined at its architectural level. Therefore in this thesis we shall address the related concepts of maintainability, non functional requirements, quality attributes and software architecture.

The initial phase of this study was carried out integrated in a EU/USA project, AFFIDAVIT, involving universities from Portugal (University of Coimbra and Madeira Interactive Technology Institute) and the USA (Carnegie Mellon University). This project also involved the largest Portuguese software development company, Novabase, which from the outset selected availability, reliability and maintainability as the most relevant quality attributes that most concern a software services company. So, our study was focused on maintainability while other researchers targeted availability and reliability. The early field surveys (outside the scope of this thesis) confirmed that maintainability was one of the most relevant quality attributes considered during software design and evolution, and that it should be addressed at architectural level to be manageable. Moreover, maintainability is highly related to other quality attributes (e.g. extensibility, portability) which adds to the relevance of this research. In the initial phase of this work we were very focused on the structural dimension of maintainability, namely through the related concepts of modularity, complexity, cohesion and coupling.

The observations from this initial study contradicted the common assumption that software quality attributes are mostly determined at the architectural level. This observation, valuable by itself, led to a refocus of our research. Thus, in the second part of our research we addressed the social dimension of maintainability, namely through the identification of success predictors of Open Source Software projects.

This second part of our study was carried out in a collaboration, ARENA, between the Informatics Centre at the Federal University of Paraíba, Brazil, and CISUC, the research center of the Informatics Engineering Department at the University of Coimbra, Portugal.

1.1 Research questions

The initial goal of this thesis was to provide the software architect with methods and tools that help her assess maintainability properties so that software can be designed and evolved without hindering future changes, thus contributing to its long term success. The research questions pursued in this phase can be stated as:

1. Is it possible to extract a maintainability index from a software architectural description?

The goal addressed by this research question was to be able to provide software architects with a quantified –even if multidimensional– maintainability index, so that they could assess architectural alternatives when designing new systems or at major system updates. However, this research question involves addressing first the following question:

2. Is it actually possible to comprehensively map the multiple maintainability dimensions into an architectural description?

In fact, before defining any maintainability index at architectural level, it is necessary to ensure that maintainability itself can be properly mapped from source code into a more abstract representation. Since maintainability is a quality attribute of software we were looking for this mapping, expecting to find multiple complementary dimensions of maintainability. This research questions lead us to analyze state-of-art architectural evaluation tools in order to understand how is this mapping currently performed.

These research questions were addressed through our first hypothesis:

Source-code based metrics can be adapted to more abstract metrics and applied to assess maintainability at architectural level. [H1]

Along this work in fact we gathered evidence that supports the multidimensional nature of maintainability, its high dependence of multiple orthogonal factors, from the purely technical —the way software is structured at different levels—to the social dimension —the structure of the organization that manages the software system—but also depends on raw human understanding, namely how source-code is documented, and programming conventions adhered.

Thus, in the second part of this thesis new research questions were stated:

3. Is it possible to predict a software projects success from metrics related to its ’social’ dimension?

4. Which are the ’social’ variables that have the highest impact in the long term software project success, assuming that successful projects implicitly embed high maintainability.

These new research questions were addressed through the second hypothesis stated in this thesis:

Social factors play a significant role in the success (longevity) of OSS projects. [H2]

1.2 Contributions

To synthesize our major contributions to this research field we can state that we found evidence that contradict the common assumption that maintainability –a software quality attribute– is mostly determined at the architectural level. Moreover, we have shown that there is a significant correlation among social factors and the future success of OSS projects, which supports our claim that maintainability is a multidimensional property of software, therefore cannot be assessed solely at the architectural level. Thus, the major contributions of this thesis can be enumerated as follows:

Contribution (i): we proposed a framework to classify software architecture tools in order to be able to map source-code maintainability into the more abstract architectural representation of software.

We then used this framework to compare state-of-art tools, in order to understand how is maintainability addressed by them.

Related paper:

A Framework for Classifying and Comparing Software Architecture Tools for Quality Evaluation

In this paper we proposed a framework allowing a comparison to be made that throws light on the key attributes that are needed to help categorize the different tools for evaluating a software architecture. This is of value to the researchers and practitioners in the area, as there are a growing number of methods and tools and it is easy to be overwhelmed by the seemingly wide range of choices. Moreover, since this thesis research was directly involved in an international project (EU/USA) to build a comprehensive architectural support tool (AFFIDAVIT), it was necessary to examine the current approaches and tools to identify their main strengths and learn from their weaknesses.

The features outlined in this paper are essentially as follows: a) the ability to handle multiple modelling approaches, b) their integration with the industrial standard UML, but also specific ADL whenever needed, c) support provided by a trade-off analysis of multiple competing quality attributes and, of utmost importance, d) an opportunity to reuse knowledge by building up new architectural solutions.

Contribution (ii): we proposed and assessed a mapping between an architectural description using the COSMIC standard notation and the corresponding source-code originated UML description in order to assess whether it would be possible to extract a meaningful maintainability index from a (standardized) software architectural description.

Related papers:

Assessing Maintainability Metrics in Software Architecture using COSMIC and UML.

Software systems are subject to constant change. The evolution of these systems requires a trade-off between specific attributes to ensure the quality of the system architecture remains acceptable. Highly maintainable systems are needed since maintainability is one of the most important software quality attributes. However, the analysis of the changes in software architectures is hindered by a lack of common metrics. There are many software metrics to assess the maintainability from the source code but if the system yet has no source-code available, it is unfeasible an analysis of its maintainability properties. However, the COmmon Software Measurement International Consortium (COSMIC) has already defined standards and measurement models for analyzing Software Architectures (SwA). The SwA assessment proposed relies on COSMIC and UML, relating Object-Oriented (OO) metrics to the source-code, in particular Complexity, Coupling and Cohesion (CCC), which are linked to the methods and notations defined by COSMIC, and employ metrics-based models to evaluate CCC in SwA diagrams.

Maintainability Metrics in System Designs: A Case Study using COSMIC and UML.

This paper illustrates the use of COSMIC and UML applied to a small case study. Furthermore, we examined the evolution a complex architecture, thirty-nine versions of Apache Tomcat, showing that the correlations between the two types of metrics hold as the system evolved.

Contribution (iii): we provided evidence that maintainability metrics present at source code level might not be correlated to maintainability at architectural level.

Related papers:

Comparing Software Architecture Descriptions and Raw Source Code: A Statistical Analysis of Maintainability Metrics.

Most scientific literature on architectural evaluation methods is mainly concerned with scenario-based methods. Most of them employ surveys, meetings and interviews, and do not carry out the evaluation through an application of automatic metrics. Other works provide more extensive surveys but do not include architecture-level metrics either. Before it is possible to predict any quality attribute from an architectural description, we need to define which information we have available. In the case of software code metrics, the lexical rules and the grammar of the language already takes care of this and there are a large number of studies in this field. But software architecture has no standard language or standard definition and we should be careful not to use data that is not clearly a part of software architecture. In this paper we show that the type of information obtained from code metrics and from architectural metrics might not be correlated.

Contribution (iv): We provided evidence that the social dimension of the organizations that develop software, not only impact its maintainability, but also that a few social variables are good predictors of project success.

In this second part of the thesis we assumed that long-term successful OSS projects do need to posses high maintainability, otherwise they would not have achieved such success.

Related papers:

Study of the Social Impact on Software Architecture through Metrics of Modularity.

The "divide and conquer" (separation of concerns/modularity) principle that is used for managing complexity can be applied during the architectural design process and reinforces the belief that the concept of modularity is very effective in dealing with complex architectures. Thus, modularity can be understood as a way of improving maintenance. The idea of breaking a system into modules and allowing concurrent development, has led researchers to compare the structure of the organization that develops the software with the structure of the software itself, a research known as addressing the 'Mirroring Hypothesis' (informally also known as 'Conway's Law'). Thus the similarity of these structures has attracted the interest of academia, which is addressing the impact of multiple factors inherent in this relationship. Among other factors, in our study we focused on the number of people who collaborate in a project, the geographic location of developers, the number of commits into the project repository, and showed that these provide us with the relevant social dimension that can impact maintainability.

On Systems Project Abandonment: An Analysis of Complexity During Development and Evolution of FLOSS Systems.

In recent years, Open Source Software (OSS) has increasingly attracted the attention of the developer community. The main idea is very simple: the first version of a system is developed locally by a single developer, or a small team of developers, and is freely available over the Internet, so that other developers and contributors can read, modify, document and debug the source code.

Even though there is a great commitment to nurturing OSS projects, it is not unusual to find projects in which the lead developer(s) has lost the interest in it. Evidence for this was shown by the large number of "inactive" or "dormant" projects hosted by SourceForge.net and other repositories. Occasionally, there are contributors who are willing to continue the development, but its complexity (hinting a lack of maintainability) makes it more feasible for them to start a new project as a replacement to the original. Sometimes even the lead developer(s) realizes that the code has become so unmanageable that it is more cost-effective to rewrite large parts of the software, or even to rewrite it entirely from scratch, than spend time enhancing the existing code.

The relation between software metrics and "abandonment" has shown to be a fruitful area of research. Several studies have shown that in the SourceForge repository, the average complexity of inactive projects has grown substantially along the years. The complexity of the first version of the project contrasts markedly with its last version. At the same time, active projects were found to be more controlled, and had an almost constant and lower degree of complexity. This inability to handle the extra work needed to control the system's complexity, might be the factor that causes the abandonment of a software project, as predicted by one of Lehman's empirical laws of software evolution [Lehman 80]: there seems to be a correlation between the abandonment of projects and its complexity.

Using Statistical Analysis of FLOSS Systems Complexity to Understand Software Inactivity.

A statistical analysis using Pearson's correlation coefficient extracted from many projects using SonarQube showed behavioural variants in the features of the projects and software complexity metrics. Some projects, such as those of Jaxen and IdeaVim, have a strong correlation between all the diverse complexities (class, file and function) and the total complexity. Others, such as Jo! and Gilead, have a really weak correlation between all of the three variations and the total complexity. On the basis of this, we decided to study the question further, and then examined what had happened to each project separately. Despite the fact that the IdeaVim project showed an increasing growth in complexity until its 4th released version, later, its development team managed to keep this complexity under control. When we accessed its website, we found that it had been incorporated into another application.

These results lead us to conclude that although the complexity may be a contributory factor in the software abandonment, since an uncontrolled complexity requires a greater amount of work from contributors, it requires extra information about the project so that decisions can be made to improve its activity. In view of this, it is mandatory to evaluate the external factors that may interfere with the evolution of the software. We believe that the results of this study can be helpful for practitioners of OSS projects, since it provides them with an explanation for the decrease in involvement from its contributors. We also believe that this work can underpin future works in the area of OSS projects, particularly in the area of discontinued projects, which still needs further investigation.

Longitudinal Analysis of Modularity and Modifications of OSS

Open source software systems are always evolving with the additions of new features, bug fixes and the collaboration of many developers around the world. The modularity of the system provides a better understanding of the main features of the system and promotes the quality of the software. In this paper, we sought to compare the evolution of some software metrics, in particular complexity and coupling, with the evolution of the number of bug fixes, additions and contributory features from developers of different software versions. An attempt has been made to show that bug fixes when adding new features and the number of developers exert a strong influence on the improvement of those metrics.

Using Classification Methods to Reinforce the Impact of Social Factors on Software Success

Defining the path to success in software development can be an arduous task, especially when dealing with OSS projects. In this case, it is extremely difficult to have control over all the stages of the development process. Many researchers have adopted different approaches to identify factors (whether social or technical) that have had some effect on the success or failure of software. Despite the large number of promising results obtained, there is still no consensus about which types of attributes are more successful. Thus, after determining the technical and social factors that influence the success of OSS using data-mining techniques in about 20.000 projects with data from GitHub, this study aimed to compare them to determine how far the OSS project has been successful. The results show that it is possible to establish the status (active or dormant) in more than 90% of the projects, largely on the basis of its social attributes.

Other works in this area are currently being submitted to conferences and journals, the most advanced being :

Determining OSS Factors to Support Architectural Enhancements Towards a Project's Success

The constant modifications being made to software and the unsuitability of many of the alternative replacement systems, means that there is a demand for software that is highly maintainable. However, although systems must allow quick and easy changes in the long term, ensuring a high level of maintenance for architectural projects is still a very complex task. The study addressed by this work focuses on the problem of evaluating software architectures through activity indicators to determine the success of open source systems. The purpose of understanding these indicators is to identify which factors, (with regard to maintainability), are more effective as predictors of the project's success. Several experiments were performed on about 160,000 open source systems to identify the key factors that are best predictors of OSS projects success.

Classifying the Importance of OSS Using Socio-Technical Factors

This is one of the ongoing follow-ups of this thesis which has already reached an advanced stage. It involves determining taxonomies and frameworks that classify several project 'states' from inactive to active, which are subsequently analysed and compared. Most of this work do not involve OSS, and the attributes that have been evaluated are not known or make no sense in an open-source approach.

1.3 Document organization

This thesis is organized as follows. In the next chapter we present the main concepts and tools regarding maintainability and the related concepts of non functional requirements, quality attributes and software architecture. A survey on how this software quality is handled by contemporary architecture design and assessment tools will drive the first part of this study, presented in chapters 3, the experimental design, and chapter 4, the observations and its discussion. In the second part of this thesis we turn our focus onto the identification of success predictors of OSS projects; thus, in chapter 5 the new experimental setup is presented, followed by the discussion of observation results in chapter 6. Finally, in chapter 7 we briefly summarize the whole research path, the major contributions and the ongoing work that derives from this thesis.

Chapter 2

Concepts and Tools

This chapter addresses the main concepts and tools regarding maintainability, quality attributes and software architecture. When designing a software architecture there are decisions that will impact the final system for many years or even for its whole life-cycle, namely how easy it will be to maintain and evolve. However, maintainability is just one of the many quality attributes that will have to be embedded in the software architecture, and whose competing trade-offs must be balanced by the architecture designer. The concepts covered here reflect the different understanding of researchers on software architecture and quality attributes, with a particular focus on maintenance of software.

2.1 Relevance of Maintainability

It is a well known fact that software maintenance takes up a huge amount of the overall software budget. Several surveys have presented evidence that maintenance is one of the most expensive phases in software development [Schneidewind 87, Benaroch 13]. Some studies have addressed the ratio of maintenance costs versus initial software development costs [Buchmann 11, Galorath 06]. These studies conclude that at least 50% of the total life cycle is devoted to maintenance, from about 50% for a pharmaceutical company, to 75% for an automobile company. Several technical and managerial problems are added to the costs of software maintenance.

Two significant examples of its weight in the software development life cycle are shown in [Bennett 00]. *A posteriori* of most of the work in this thesis, it is interesting to note that besides structural characteristics, these studies refer explicitly the contribution of social factors to the maintainability effort required:

Case 1:

> *[in 2000]The city of Toronto lost out on nearly $700,000 in pet fees because nearly half of Toronto's dog and cat owners were never billed due an outdated computerized billing system. The staff who knew how to run the computerized billing system was laid off. [...] Only one city employee ever understood the system well enough to debug it when problems arose, and that employee was also laid off in 2000 due to downsizing, leaving no one to get things going again when the system ran into trouble and collapsed.*

Case 2:

> *The Associated Press today [April 14, 1997] reports that Robin Guenier, head of the UK's TaskForce 2000, estimates that Y2K reprogramming efforts will cost Britain $50 billion dollars, three times the guesstimates of business consultants and computer service companies. Guenier suggested that 300,000 people may be required to tackle the problem. Coincidentally, that number is roughly equivalent to the number of full-time computer professionals in the UK.*

Furthermore, many failures of software products can be attributed to maintenance problems. Sneidewind [Schneidewind 87] after an extensive study on project abandonment, concludes that "*'the main problem in doing maintenance is that we cannot do maintenance on a system which was not designed for that'*. Even if a system is carefully designed, there are inherent difficulties in performing maintenance, the intrinsic nature of software and its production process that make software maintenance an unequalled challenge [Canfora 95]. Brooks [Brooks 87] identifies complexity, domain conformity, changeability, and invisibility, as four inherent difficulties of developing and maintaining software. [Rajlich 10] adds discontinuity (*small changes of input can result in huge changes of output*) to this list.

Owing to these difficulties of maintaining software systems, maintenance activities should be well planned and maintainability should be embedded in the software structure itself. This is why it should be given special attention during the whole software development lifecycle. A system with a high degree of maintainability leads to either low total maintenance costs, or improved functionalities at the same total cost [Wang 02]. Therefore the sooner decisions are made to improve the level of maintainability, the lower the maintenance costs incurred. This is the rationale for addressing maintainability right at the architectural design phase, leading to systems designed to lower the maintenance, thus capable of dealing with the many constraints, new requirements or new problems that will eventually appear.

All these aspects underline the motivation for our research along with countless works that have emerged in an attempt to define new directions, approaches, assessments and guidelines for a better understanding of maintainability, a concept with very concrete impact on systems design, operation and longevity, but whose definition remains somehow elusive.

2.2 Maintainability Defined

The lack of a unique definition of the term maintainability is the first difficulty we face when addressing this research topic. This also hints that as we try to precisely define this concept, the more complex its nature is revealed. As we shall see, maintainability is mostly defined by its characterizations, a set of intertwined properties, rather than by a concise, but mostly nonoperational definition.

Maintainability is the term used to describe the quality attribute concerned with software maintenance. In ISO/IEC 9126 [ISO/IEC 01] maintainability is described as *'a set of attributes that have a bearing on the effort needed to make specified modifications'*. The IEEE standard computer dictionary [Board 90] defines maintainability as *'the ease with which a software system or component can be modified to correct faults, improve quality attributes, or adapt to a changed* *environment'*. In the standard ISO/IEC 14764 [ISO/IEC 06] software maintenance is linked to software engineering and is defined as *'the modification of a software product after it has been delivered to correct faults and improve performance or other attributes'*.

So, both for ISO and IEEE, maintainability is defined as the capability of the software product to be modified. On what concerns the motivations, these modifications may be due to corrections, new requirements, functional specifications, improvements, or the adaptation of software to changes in the environment. On what concerns type of modifications, these standards identify four categories of maintenance: corrective, preventive, adaptive and perfective.

- **Corrective Maintenance:** refers to carrying out modifications of a software product after delivery to correct faults or defects and thus satisfy system requirements. A defect can result from design errors, logic errors and coding errors [Erdil 03]. Examples of corrective maintenance include correcting a failure to test for all possible input conditions, or a failure to process the last record in a file [Martin 83].
- **Preventive Maintenance:** refers to modifications to detect and correct latent faults in the software product before they become operational faults. This involves carrying out activities to increase the system's future maintainability such as updating documentation, adding comments, and improving the modular structure of the system [Lassing 00]. Examples of preventive change include restructuring and optimizing code (code refactoring), and updating documentation.
- **Adaptive Maintenance:** refers to activities to adapt a software system to a changed or changing environment. The need for adaptive maintenance can only be recognized by monitoring the environment [Bensoussan 09]. An example is implementing a database management system for an existing application and making a modification to two programs so that they can use the same record structures [Martin 83].
- **Perfective Maintenance:** is concerned with accommodating new or changed user environments. It requires modifying a software product to detect and correct

> latent faults before a failure occurs. Examples of perfective maintenance include modifying a payroll program to incorporate a new union settlement, adding a new report to a sales analysis system, improving a terminal dialogue to make it more user-friendly, or adding a contextual help functionality.

The corrective and preventive types are classified as correction types while those that are adaptive and perfective are enhancement types, although some authors also include preventive maintenance as an enhancement type. The correction type is considered to be a 'traditional' kind of maintenance while enhancement types are tightly related to the concept of Software Evolution [Chapin 01].

While the ISO/IEC and IEEE maintainability definitions presented above (*the capability of a software product to be modified*) frame our research topic, they are somehow tautological, and are not much helpful to characterize its intrinsic nature and underlying properties. Another way of reasoning about maintainability is to link it to other software properties. For example, performance can be improved by maintenance, or security can be improved by fixing errors that might allow unauthorized accesses. In fact, when Avizienis [Avizienis 04] classifies dependability as having a set of six sub-attributes, availability, reliability, safety, confidentiality, integrity and *maintainability*, maintenance is understood as a property of a dependability. This taxonomy has the significant disadvantage of requiring the description of other descriptions to define what maintainability actually is.

However, maintainability can be also classified as a quality attribute on its own. According to ISO 9126, quality attributes are classified as functionality, reliability, usability, efficiency, *maintainability* and portability. This is our understanding and in this thesis we shall address maintainability as a quality attribute on its own.

2.3 Maintainability Properties

Having considered maintainability as a core quality attribute of software, there are several properties that characterize it. Gilb [Gilb 08] considers ten properties (referred as 'patterns') of highly maintainable systems:

- **Adaptability:** Time needed to adapt a system from a defined initial state to a defined final state using defined means.
- **Flexibility:** Ability of the system to adapt to suitable conditions or be adapted by its users (without any fundamental change to the system by system development).
- **Connectability:** The cost of connecting the system to its environment, enabling the system to be connected to different interfaces.
- **Tailorability:** The cost of altering the system to suit its conditions.
- **Extendibility:** The cost of adding a defined extension class and a defined extension quantity using a defined extension mean.
- **Interchangeability:** The cost of modifying use of system components.
- **Upgradeability:** The cost of radically changing the system; either by installing it or changing the system components.
- **Installability:** The installation costs in defined conditions.
- **Portability:** The cost of moving from one location to another.
- **Improvability:** The cost of enhancing the system.

While this characterization can be useful to distinguish different kinds of change that might occur in software, in our perspective these are properties that *emerge* from a maintainable system, i.e. are dependent properties, they do not help us characterize maintainability itself.

In a very different perspective, Gustavsson and Osterlund [Gustavsson 05] address maintainability properties based on the software development phase (architecture, design construction, etc.) they need to be addressed at. They argue that identifying the associated software development phase makes it possible to classify the types of changes in the system. Their categorization is described as:

- **Documentation:** To document how the system is designed and implemented can be of great value when carrying out maintenance tasks.

- **Architecture and Design:** The chosen software architecture and the design of a system will affect its maintainability, and thus it may be important to have built-in maintainability requirements from the start.
- **Source Code:** Complying with coding standards and having comments in the source code might benefit maintainability.
- **Environment by Third-parties:** The environment where the software operates is often made up by several items from third parties, such as programming languages, databases, code-libraries and operating systems.
- **Test Cases:** Having a suite of regression test cases can be a way to reduce the risk of introducing faults when carrying out maintenance.
- **Running Systems:** Maintainability requirements for the running systems include requirements about availability when carrying out maintenance, (e.g. a limit saying how long a version change may take).
- **Maintenance Organization:** One approach to handling maintenance is to require somebody else to handle it, i.e. to have the system delivered together with some kind of maintenance services.
- **Process:** Requirements can be made on how the system should be developed. For example: requiring certain stages to be followed such as formal inspections with a focus on maintainability.
- **Crosscutting Systems:** Some maintainability requirements are not tied to a specific entity, but rather crosscut the whole system.
- **Ownership:** Before being allowed to carry out maintenance on the system it might be necessary to require ownership of various items, such as the source code and documentation.

This software development life-cycle based characterization is very interesting in that the *process* is the defining criteria for maintainability activities. This is a very unique perspective, as the code structure, modularity and related concepts are not explicitly addressed. While this perspective might be useful from a management point-of-view, it is not so useful from an engineering standpoint.

[Hashim 96] presents a model where maintainability has seven properties: modularity, readability, programming language, standardisation, level of validation and testing, complexity, and traceability. The model can be used to highlight the need to improve the quality of the product so that maintenance can be carried out properly and efficiently. The maintainability properties of Khairuddin's classification are described as follows:

- **Modularity:** decomposition of a system into functional units, imposing hierarchical ordering on functional usage so that data abstractions can be deployed and useful systems developed independently.
- **Readability:** the degree to which a reader can quickly and easily understand the source code.
- **Programming Language:** adequacy of the programming language to the problem domain (fitness-for-purpose).
- **Standardisation:** adoption of coding standards to act as a guide in source-code construction to avoid idiosyncrasies among the developers.
- **Level of Validation and Testing:** Ratio of effort spent on design validation, inspections and software testing, versus the total development effort.
- **Complexity:** refers to the intrinsic complexity of the problem, reflected in the software artifact developed.
- **Traceability:** the ability to trace a design representation or actual program components back to its requirements and vice-versa.

It is very enlightening to realize that these properties can be grouped in different dimensions: the *structural* nature of the software artifact (modularity, complexity), *development process* related (programming language, standardization, level of validation and testing, and traceability). Readability could be considered as a *human intelligibility* dimension on its own, or included as part of the later, as it is promoted by standardization.

From the above overview, it seems almost impossible to make a general claim about which maintainability properties should be taken into account when designing or evolving a maintainable system. The nature of the maintainability properties seems to depend on the type of system and development phase that is being assessed, or on emerging properties from maintainability itself. Furthermore, the maintainability requirements depends on the specific software development process adopted. For example, if there is a requirement that eXtreme programming should be used, this might imply that documentation may be minimal but test cases must be explicitly managed [Gilb 08].

This discussion should be enough for the reader to understand why maintainability is such an elusive property of software systems. To avoid this elusivenss many authors have focused their efforts on the maintainability characteristics of specific programming paradigms [Al-Hudhud 15] or to the relationship between software design and maintainability [Malhotra 13]. Since our major goal is to provide software architects with tools and methodologies to maintain or improve maintainability during design and evolution, we need to define this elusive concept in concrete, objective terms. Thus, we shall now turn our focus into how can maintainability be quantified.

2.4 Maintainability Metrics

For the purposes of this thesis, we identified maintenance metrics from academic research, some of which have also been adopted by commercial tools. The most common metrics explicitly addressing maintenance are extracted from structural properties of source-code, namely WMC (Weighted Methods per Class), NORM (Number of Overridden Methods), AC (Afferent Coupling), EC (Efferent Coupling), CC (McCabe Cyclomatic Complexity), LCOM (Lack of Cohesion of Methods), but there are many others [Fernández 11, Al-Ajlan 09, Fenton 98, Colomo-Palacios 14].

Actually we can oberve that all those metrics have at its core the concept of modularity. A more modular organization of software offers many advantages in facilitating maintenance by promoting understandability, and by constraining the impact of changes to the module modified, and reducing or eliminating the impact on other modules [Bertolino 13]. This is one of the reasons why modularity has been adopted in many different areas, from hardware, software, social organization, and so forth. Therefore in the next subsections we will focus on modularity and describe the main modularity and related metrics that will be used in the experiments for the remaining of this thesis.

2.4.1 Modularity

The IEEE defines modularity as *'the degree to which a system is composed of discrete components where a change to one component has a minimum effect on the other components'* [ISO/IEC/IEEE 10].

In fact, the larger a system is the more difficult it is to understand and maintain. This 'divide and conquer' strategy –along with abstraction and reuse– is a paradigmatic approach to manage complexity that has also been applied to software design. Its underlying principle is that dividing large problems into smaller ones –or systems into components– makes large software systems more manageable.

Seminal works such as [Parnas 72] emphasized the idea of modules being independent through both cohesion and coupling. A modular system consists of other smaller and nearly independent parts, the modules, which cooperate and communicate with each other through a common interface, and where changes in one module only minimally affect the others. However, despite all the known benefits of modularity, its practical use is not always simple as sometimes cohesion and coupling have to be traded-off.

2.4.2 Cohesion

A module is said to have high cohesion when the relationships between its elements are tight and the module provides a single functionality. The higher the module's cohesion, the easier it is for the module to be developed, maintained, and reused. Moreover, there is empirical evidence that supports the importance of cohesion in structured design

[Card 86]. Thus, every software engineering text describes high cohesion as a very desirable property of a module [Chae 04, Pressman 10].

Numerous cohesion metrics have been proposed, most of them for object-oriented languages [Briand 01, Chae 00]. Researchers have always extracted cohesion metrics from the OO methods' structure [Chae 04]. It must be noted that cohesion metrics have not been applied to software architecture designs which prevents its application in a more abstract way. The reason for this is that the architectural descriptions normally do not specify behavior so they do not possess the internal content of a component that could be used as input for current cohesion metrics. So, the (code-based) cohesion metrics adopted in this thesis are presented below:

Tight and Loose Class Cohesion (TCC and LCC): TCC and LCC metrics provide a way to measure the cohesion of a class. In the case of TCC and LCC only visible methods are considered (methods that are not private). TCC represents a density of attribute-sharing relationships between public methods in a class. LCC represents extended relationships, which are constructed by the transitive closure of attribute-sharing relationships. The higher TCC and LCC are, the more cohesive the class is [Bieman 95].

Lack of Cohesion (LCOM): Defined by Chidamber and Kemerer [Hitz 96], this metric acts as a role model for many other proposed cohesion metrics and few other metrics have been used to redefine LCOM. This metric counts the number of "method pairs" that do not directly share their attributes [Al Dallal 11]. A lower LCOM value indicates high cohesion and vice versa. LCOM is widely applied and compared to other metrics in both a theoretical and empirical way [Al Dallal 12], [Briand 98].

2.4.3 Coupling

Coupling is one of the attributes of modularity with most influence on software maintainability. Coupling metrics are used in tasks such as impact analysis [Briand 01], assessing the fault-proneness of classes [Yu 02], fault prediction [Thongmak 09], re-modularization [Abreu 00], identifying software components [Lee 01], design patterns [Antoniol 98], assessing software quality [Briand 01], etc. In general, the main goal in the software design is to obtain the lowest coupling possible. In OO, classes that are strongly coupled are affected by changes and defects in other classes [Poshyvanyk 06]. Modules with high coupling have a considerable detrimental effect on software maintenance and thus need to be identified and restructured. The coupling metrics adopted in this thesis are the following:

Coupling Between Object (CBO): This is one of the initial metrics proposed by Chidamber and Kemerer (CK) [Hitz 96] and used to measure the coupling between classes. It has two inputs: the number of classes within a package and the relationships between these classes with others in different packages. Later, other parameters were added such as the number of methods in the class relationships, and the inheritance relationships between classes.

Response For Class (RFC): Another CK metric, it calculates the number of distinct methods and constructors invoked by a class. It is the number of methods in a particular class plus the number of methods invoked in other classes. Each method is counted just once, even if that method has many relationships with methods in other classes.

Afferent Coupling and Efferent Coupling (AC/EC): The Afferent Coupling (AC) metric determines the number of classes and interfaces from other packages, depending on the number of classes in the analyzed package. It is also known as Incoming Dependencies. The Efferent Coupling (EC) or Outgoing Dependencies includes all the packages that the classes in the current package depend upon.

2.4.4 Complexity

According to the IEEE, *'complexity is the degree to which a system or component has a design or implementation that is difficult to understand and verify'* [ISO/IEC/IEEE 10]. This definition assumes that complexity is a structural property of the software artifact. It is self-evident that the more complex the structure of a software architecture or the internal structure of modules, the harder it is to understand, change, and reuse, and therefore also more prone to defects. We present below the complexity metrics adopted in our work:

Cyclomatic Complexity Number (CCN): This was one of the first complexity metrics [McCabe 76]. This metric is obtained by counting the number of independent execution paths inside a method or function. If the code is represented as a directed-graph, CCN is also the number of disjoint regions. This metric is extensively used both in the academia and industry.

Fan-in and Fan-out Complexity (FFC): Henry and Kafura [Henry 81] consider fan-in (number of calls from a software module) and fan-out (number of calls into a software module) as a complexity measure, also referred as information flow. The fan-in and fan-out metrics by themselves are regarded by some authors as coupling metrics, since they also measure afferent and efferent coupling respectively.

Nested Block Depth (NBD): This metric represents the maximum number of blocks of code nested in a particular method of a class.

Weighted Methods per Class (WMC): According to Rosemberg [Rosemberg 98], this metric measures the individual complexity of a single class. In fact, the number of methods of a class and their complexities are indicators of the time and effort required for the development and maintenance of that class.

2.4.5 Size

Size metrics might not seem very relevant if compared to more obvious maintainability issues but they can be very useful as simple dependent variables especially when they correlate positively with other attributes [Fenton 14]. It is reasonable to expect that a million LOC software system, is clearly more difficult to maintain than one with 1000 LOC, therefore we expect evidence of a positive correlation between size and complexity. Below we present the metrics used in this thesis to account for software size.

Total Lines of Code (TLOC): The total number of lines of source-code, excluding empty (blank) lines. There are many variations of this metric such as logical source lines of code (SLOC-L), comment lines of code (CLOC), method lines of code (MLOC) lines with both code and comments (CSLOC), and more.

Number of Packages (NOPK): The number of packages refers to the ’packages count’ that of the software that is subject to analysis. This metric also includes all the sub-packages. It is very useful in planning when design diagrams are subject to inspections or revisions.

Number of Classes and Interfaces (NC and NI): This metric also indicates how extensible a package is. It considers the number of both concrete and abstract classes (and their interfaces).

§§§

We have now a set of metrics that can be used to assess maintainability through its constituent properties, modularity (cohesion and coupling), complexity and size. Not surprisingly, these metrics have originated from source-code.

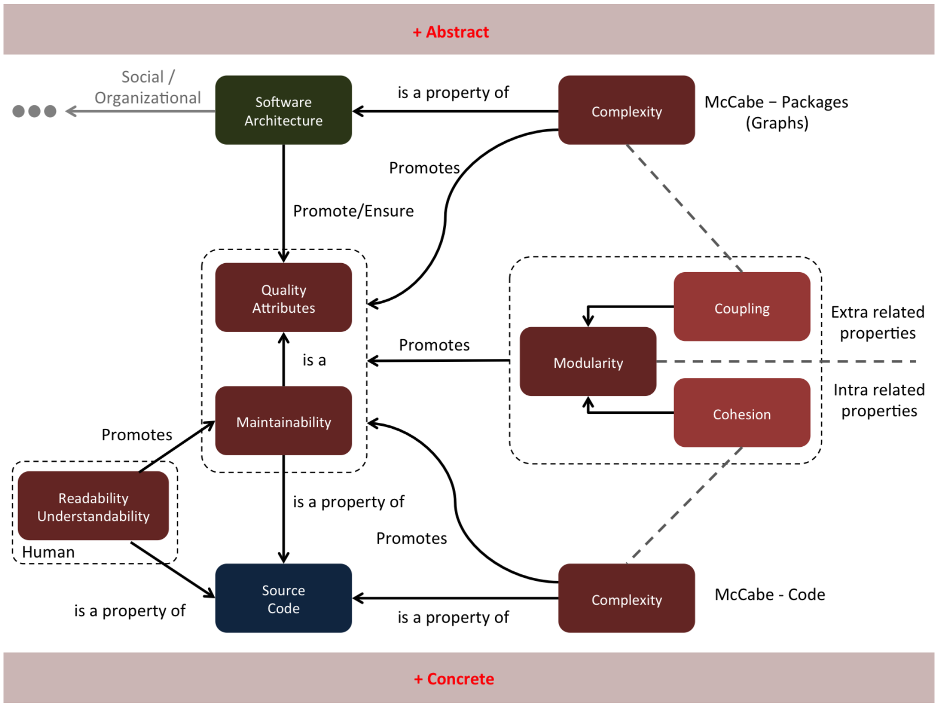


Figure 2.1: Quantifying Maintainability.

2.5 Quality Attributes

Up to this point we have been discussing maintainability and referred it as a quality attribute of software. But what exactly do we mean by quality and in particular by a *quality attribute* of software? In this section our concern is with quality attributes, their definition and relationship with software architecture so that we later we can study its impact on maintainability.

Software quality refers to several attributes that contribute to fully characterize a software system as it is not enough to ensure that the functional requirements of that system are satisfied. Depending on its nature, there is also a need to meet domain specific quality requirement, e.g. critical systems are mostly concerned with availability and performance, banking system are mostly concerned with security, etc. [Barbacci 95]. Regardless of what are its most relevant functions, the system should maintain a level of quality that allows it to be used in a satisfactory way. This means that the quality of a system can be defined as the degree to which its required quality attributes are met.

According to the IEEE Standard 1061 [IEEE 98], software quality is *'The degree to which a system, component, or process, meets specified requirements, customer, user needs or expectations'* while the ISO/IEC 9126 [ISO 01] standard, describes the software quality of a product as *'The totality of the characteristics of an entity that have a bearing on its ability to satisfy stated and implied needs'*. So, although different definitions for software quality have been proposed, the need for conformance with expectations (requirements, either functional and non-functional) can be found in all of them.

We can find in the literature different classifications and models for quality attributes. These definitions use different names (e.g. characteristics, parameters, attributes, etc.) to refer to indicators of software quality. The ISO 9126 standard [ISO 01] defines them as *'A feature or characteristic that affects an item's quality'* and, [Eisenbarth 03] as *'A property of a work product or goods by which its quality will be judged by some stakeholder or stakeholders'*. Indeed, the characterization of a quality attribute, in simple terms, refers to specific features that influence the global perceived quality of a system.

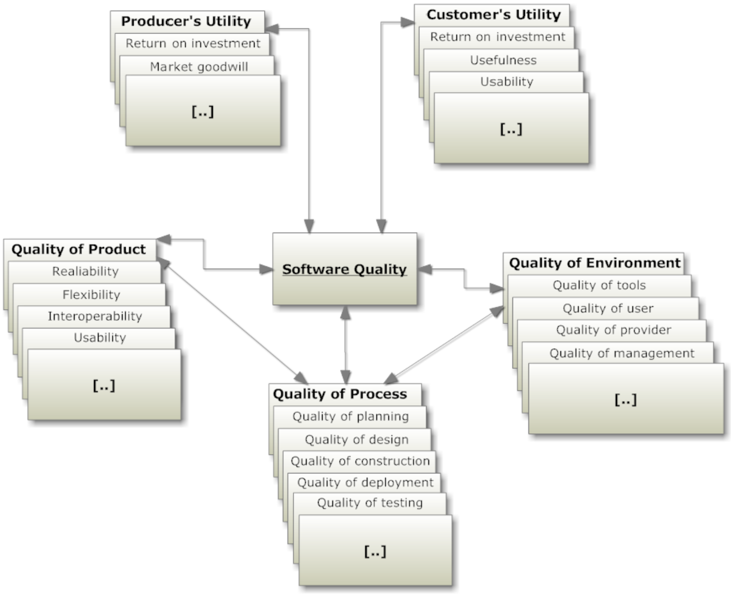


Figure 2.2: Software Quality Groups (adapted from [Malik 08])

According to [Malik 08] software quality can be divided into five groups (producer's utility, customer's utility, quality of product, quality of process and quality of environment) as shown in Figure 2.2. The producer and customer utility are obtained through the achievement of the quality of the product, process and environment. The quality of the product is related to all the attributes that can be experienced while using or seeing the product. Quality of process indicates the ability of a process to develop a quality product, and quality of environment is related to all the environments in which the software is embedded, including the tools used to develop and also the system management.

In the ISO 9126 standard [ISO 01], the quality model is classified in a structured set of characteristics. Each characteristics is further divided into sub-characteristics. In this model, the attribute is regarded as an entity of a software product which can be measured. In the case of ISO 9126, the characteristics and sub-characteristics are fixed in the definition while the attributes can vary between the different software products. The main characteristics and sub-characteristics according to ISO 9126 are depicted in Figure 2.3. The attributes can be tuned to meet the requirements of the project, which means that not all of the sub-characteristics or their attributes have to be addressed in the design.

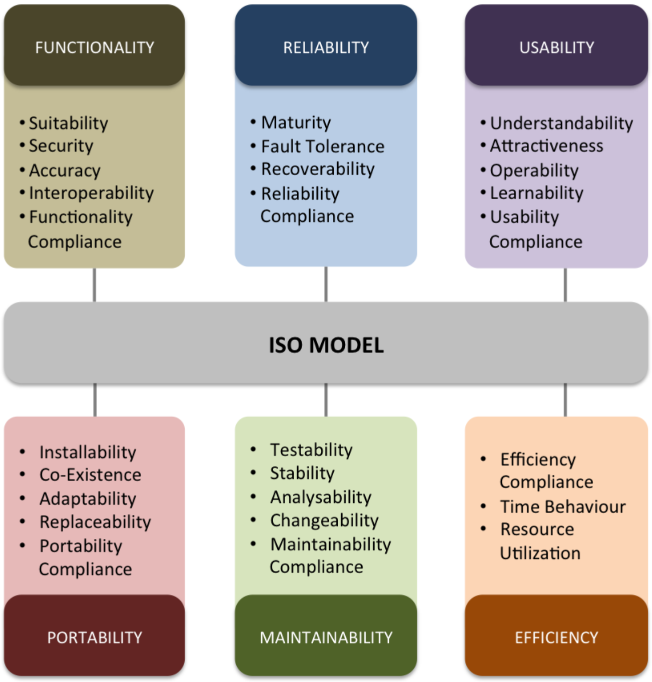
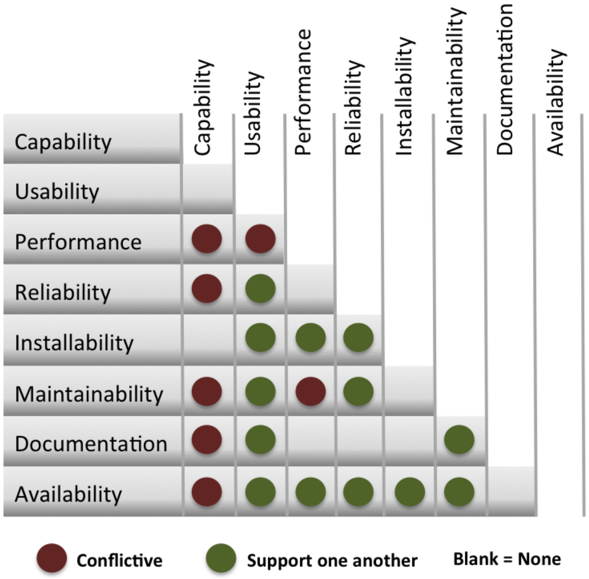


Figure 2.3: ISO Characteristics / Quality Attributes

2.6 Quality Attributes and Software Architecture

Quite often quality attributes are not congruous with each other, for instance, security versus usability or performance versus maintainability [Hohmann 03]. Thus, depending on the type of software and its customers, different weighting factors are needed for different quality attributes. Figure 2.4 shows the possible relationships between the quality attributes proposed by [Kan 03] and highlights the conflicting attributes and the cases when one quality attribute promotes another.

This is why, according to Barbacci [Barbacci 95], a core activity of the software architect is to analyze the trade-offs between the multiple conflicting quality attributes and still meet the user's requirements. The aim is to evaluate the trade-offs amongst the competing quality attributes so that a better overall system can be achieved, i.e. the best compromise for a given context. It should be stressed that is difficult to add quality as an afterthought; it has to be built into the system from its inception. Thus, the quality attributes are major drivers for the architectural structure for any software system where it is necessary to balance amongst competing quality requirements. It is therefore relevant to define precisely what we do mean by *software architecture*.



	Capability	Usability	Performance	Reliability	Installability	Maintainability	Documentation	Availability
Capability								
Usability								
Performance	🔴	🔴						
Reliability	🔴	🟢						
Installability		🟢	🟢	🟢				
Maintainability	🔴	🟢	🔴	🟢				
Documentation	🔴	🟢				🟢		
Availability	🔴	🟢	🟢	🟢	🟢	🟢		

🔴 Conflictive 🟢 Support one another Blank = None

Figure 2.4: Quality attributes relationship (adapted from [Kan 03])

Perry and Wolf [Perry 92] define a software architecture as a group of processing elements, data elements, and connecting elements. Hohmann [Hohmann 03] includes specific technology choices and the required capabilities of the desired system. According to [Aagedal 02], the architecture of a system consists of structures of the system, which comprise software elements, the externally visible properties of those elements, and the relationships between them. Fielding [Fielding 00] defines software architecture as a set of architectural elements that have a particular form, and propose the software architecture as a set of elements, forms and its rationale. Garlan and Shaw [Garlan 94] define a system for an architecture model as being a collection of computational components and connectors. The architecture of a software system is thus defined in terms of components and interactions between components. A structural element can be a subsystem, a process, a library, a database, a computational node, a legacy system, an off-the-shelf product, and so on. Systems can contain more than one structure and some structures are much more closely involved with interaction at runtime and are thus able carry out the system's function. Again, each of these elements can be instantiated in a variety of ways. For example, a connector might be a socket, synchronous or asynchronous, or combined with a particular protocol [Aagedal 02]. If a graph is used to indicate the features of an abstract architectural description, the nodes represent the components and the arcs represent the connectors between them. The connectors represent the interactive elements such as procedure call, event broadcast, database queries, and pipes. Thus, an architectural style is a ’vocabulary’ of components and connectors that can be used in instances of that style, together with a set of constraints that determine how they can be combined.

Garlan goes even beyond this ’operational’ view, stating that the definitions for the design level are concerned with issues that go beyond algorithms and data structures, and defines software architecture as an evolution of design over time [Garlan 94, Garlan 95]. According to the IEEE definition, *’Architecture is the fundamental organization of a system embodied in its components, their relationships to each other and the environment, and the principles guiding its design and evolution* [IEEE 00], a definition that seeks to provide a common frame of reference within which it is possible to codify common elements between the different views of architectural descriptions. This definition has become influential and used as a baseline for architectural description frameworks, for instance within OMG (Object Management Group). In 2007 this standard was also adopted by ISO/IEC as a standard (ISO/IEC 4201, ’Systems and software engineering: recommended practice for the architectural description of software-intensive systems’ [ISO/IEC 07]). Figure 2.5 shows a graphical representation of the IEEE conceptual model of an architectural description.

The standard also defines the following concepts that are tightly related to the definition:

- **System:** is a collection of components arranged to accomplish a specific function or set of functions. The term system encompasses individual applications, systems in the traditional sense, subsystems, a system of systems, product lines, product families, whole enterprises, and aggregations of interest.
- **Environment:** also referred as ’context’, it determines the setting and circumstances of developmental, operational, political, and other influences upon that system.
- **Mission:** is a use or operation for which a system is intended by one or more stakeholders to meet a set of objectives.

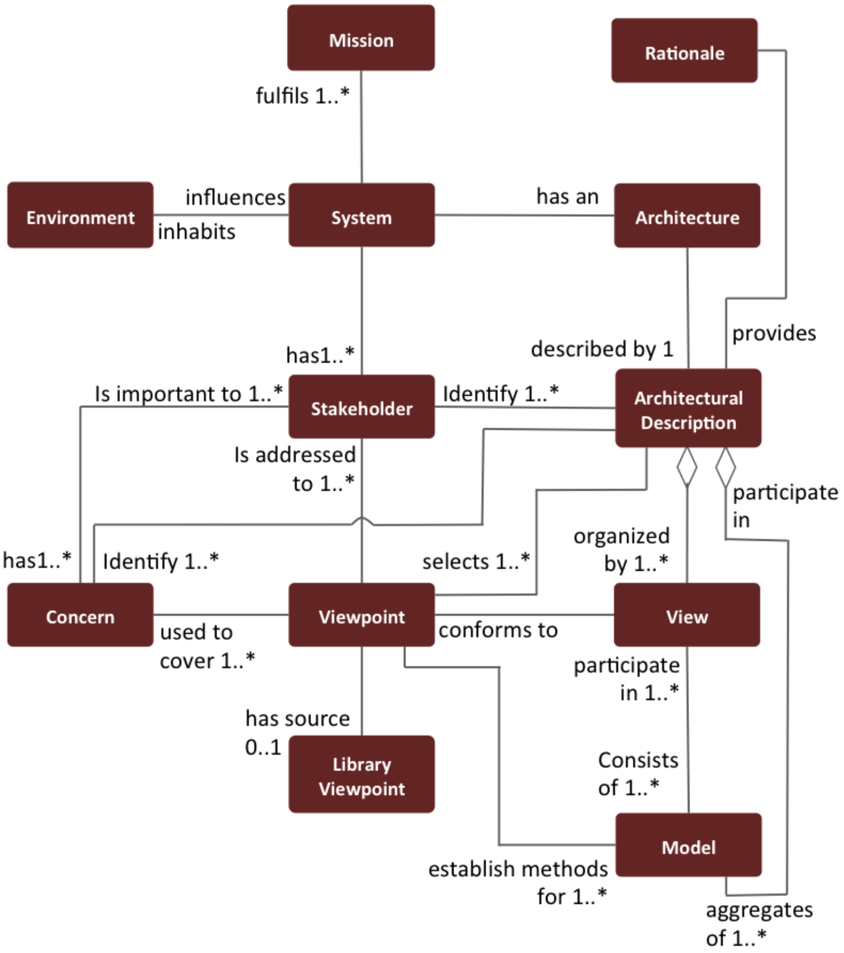


Figure 2.5: Conceptual model of architecture description from IEEE [IEEE 00]

- **Stakeholder:** is an individual, team, or organization with interests in, or concerns about a system.

Although the ISO terminology has mostly been employed to describe systems and their environments, the IEEE standard is also concerned with architectural descriptions, architectural views and viewpoints. As a systems' architecture is the result of a set of business and technical decisions there are many influences on its design and an awareness of these influences will impact a specific architectural design namely due to factors such as technology, user knowledge, the market, the environment, and so forth, in which the architecture is required to perform.

Architectural design is considered to be so complex that even with the same requirements, hardware, support software, and human resources available, an architect designing a system today is likely to design a different system from what might have been designed five years ago. Thus, while the definitions used in the ISO/IEEE standards are general enough to cover many types of software architectures they do not provide architects and developers of large-scale systems with detailed guidelines.

Bass [Bass 98] in *'Software Architecture in Practice'*, proposes a set of methods for quality evaluation in software architectures. The rationale for this evaluation assumes that the architect relies heavily on the quality of communication to improve the results. Without information being exchanged between the stakeholders and architect, it is difficult to understand a large and complex system well enough to make a decision. In [Bass 03], the terms 'structure' and 'view' are adopted to define the term 'architecture'. A view is a set of architectural elements and consists of a representation of the elements and the relations between them. A structure is the set of elements itself as they exist in software or hardware. Thus, the architect is concerned about how to employ a strategy that can achieve all of the stakeholders goals and provide a common language to express different ideas and concepts at a level that is intellectually suited to the different parts by expressing the system under different views. Figure 2.6 provides a graphical representation of a model depicting different elements - the lights represent the views and the groups of elements represent an architectural structure.

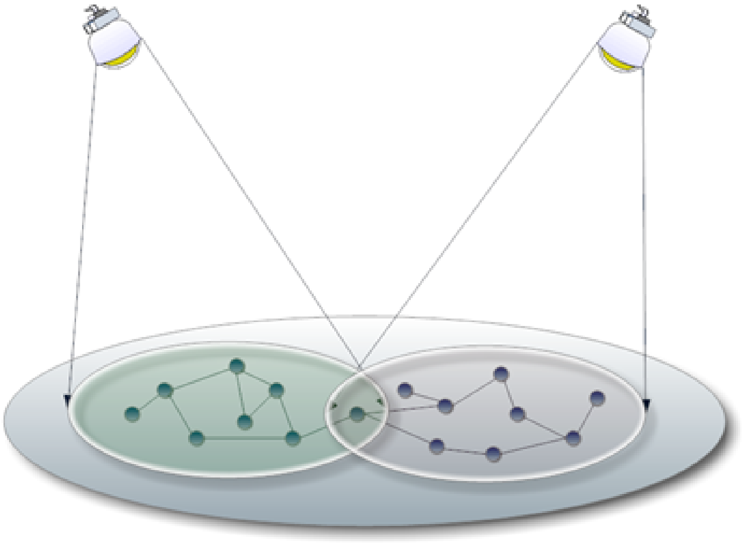


Figure 2.6: View points and Architecture Structure [Bass 03]

From the above discussion it is apparent that most of the architectural evaluation methods include some sort of trade-off analysis as a means of assisting the architect to achieve the most adequate balance between competing quality attributes on the system being designed. This is why the development of systematic ways of embedding quality attributes into the architecture of a system provides a solid basis for making objective decisions about design trade-offs. This enables architects to make reasonably accurate predictions about a system's attributes without following trends or making assumptions [Barbacci 95]. One way used to represents quality in architecture is to employ a model with quality profiles and/or architectural styles and patterns: quality profiles attach quality properties to a model whereas styles and patterns embody the desired quality requirements in the structure [Matinlassi 05]. There are many definitions of architectural styles. According to [Garlan 97] an architectural style is what supports the building of classes of architectures in a specific domain. For Perry and Wolf [Perry 92], an architectural style consists of components and the relationship between them (with the constraints imposed on their application) and the combined composition and design rules needed for their construction. Furthermore, according to Bass [Bass 03] an architectural style is a set of architectural patterns and consists of a few features and rules for combining them as a means of preserving the architectural integrity. In this way, an architecture can adopt an architectural style, and thus achieve specific architectural qualities.

A different perspective uses 'quality profiles', i.e. map the quality requirements into an architecture, a mapping that could support automated or semi-automated architectural evaluation [Immonen 05]. One way to implement quality profiles is to use UML profiles. A UML profile is a language extension mechanism that allows metaclasses from existing metamodels to be extended to adapt them for different purposes [OMG 03]. That is, UML may be tailored (e.g. to model different platforms or domains) and it has already been extended, especially to represent quality in the software model [Matinlassi 05]. Examples include also a UML profile for modeling quality of service and fault tolerance characteristics and mechanisms [OMG 08], a UML profile for schedulability, performance and time specification [OMG 03], a reliability profile [Rodrigues 04] and a quality profile for representing the reliability and availability requirements in architectural models [Immonen 06].

We can find several studies in the literature that compare or categorize architectural styles and profiles [Shaw 95, Levy 99, Keshav 98]. In the last decade several works have proposed new categorizations, such as in [Glinz 05] where the authors divide the non-functional attributes into kind, representation, satisfaction and role. However, there is no common understanding or agreement about this subject. For example, there is no consensus about which quality attributes should be supported by different styles, although some studies have begun to address this problem [Andersson 01,Niemelä 05]. In [Morasca 15] there is a discussion about the need to rethink the question of how quality attributes should be categorized. He criticizes the decision to divide them into external and internal categories as this causes several problems and sets out the main issues that arise from the current approaches. Moreover, this work makes some interesting points about new categorizations, and analyses attributes from a macro perspective and argues that they will always be liable to different interpretations.

§§§

From the above description is manifest that there are still many open issues involved in the characterization of quality attributes and its mapping into architectural descriptions. A core problem is objectively quantifying each system quality. This problem is further exacerbated by the fact that many characteristics can only be measured at run-time or after the system has been fully developed, which makes nearly impossible to assess them during the architectural design phase (e.g. usability and maintainability).

Despite all this uncertainty there are already a few tools that assist the architect in designing and evaluating the quality of software architectures, which, as we have already seen, involves selecting the 'best' trade-off among competing quality attributes. Therefore one of the first tasks of our research, was to establish a framework that could enable us to compare how different architectural design tools assess quality attributes, namely maintainability.

2.7 A Tools View on Maintainability

Several tools and methodologies have been proposed to help the architects design and evaluate the system requirements right from an early architecture model.

There are several methods in literature to evaluate software architecture quality namely: SAAM, Software Architecture Analysis Method [Clements 01, Kazman 94], with a focus on modifiability; ATAM, Architecture Trade-off Analysis Method [Clements 01, Barbacci 98], mainly used to modifiability but also applied to other quality attributes evaluation and trade-off verification; ARID, Active Reviews for Intermediate Design [Clements 01], CBAM, Cost Benefits Analysis Method [Kazman 01], FAAM, Family Architecture Assessment Method [Dolan 01]. Most of these methodologies describe a set of steps that should be followed in order to check and evaluate the quality of an architectural design.

Therefore, the architect can select one of the existing evaluation tools to support the application of a specific method in order to reduce the effort on analysis and improve the results of the evaluation process. These tools perform different types of evaluation depending on the method used and which design features are the focus of assessment. Many such architecture evaluation tools have been proposed but most of them are limited to a specific purpose (e.g. for deployment only) or support a generic approach but providing only a subset of possible functionalities for demonstration purposes. Some researchers have proposed a taxonomy framework to classify and compare software architecture evaluation techniques, selecting key features of each methodology to categorize them. In [Babar 04] a framework is proposed to compare and assess eight software architecture evaluation methods (most of them scenario-based) and demonstrate the use of the framework to discover the similarities and differences among these methods. In [Zhang 10] are described the main activities in model checking techniques defining a classification and comparison framework and, in [Mattsson 06], the focus is on evaluation of ten models to assess performance, maintainability, testability and portability. These works focus essentially on model checking, simulation-based or scenario-based approaches.

Some researchers have also tried to assess architecture tools based on the evaluation techniques adopted and comparing them across different tools. However, little work has been done to classify and compare evaluation tools from a generic perspective, describing the main characteristics and assisting the perception of which are the relevant features these tools should provide.

Below we present a comparison framework that highlights a set of relevant attributes to help categorize the different architecture evaluation tools. This is necessary to understand how these most well-know/mature tools deal with quality attributes, namely the one that is in our focus, maintainability.

2.7.1 Architecture Evaluation Methods

Any serious software architecture evaluation process needs to consider and categorize several different architectural aspects of the system's requirements (e.g. kind of requirements, architectural description, etc.). Depending on how these aspects are addressed by the evaluation methods, it is possible to identify different evaluation methods categories. Regardless of category, the evaluation methods can be used in isolation, but it is also possible and common to combine different methods to improve the insight and confidence in the architectural solution to evaluate different aspects of the software architecture, if needed. After deciding for a specific evaluation method, the architect has to select the Architecture Description Language (ADL), tool and the best suited technique to her or his specific project.

In this survey we classified the architecture evaluation methods according to the categorization presented in [Mattsson 06] and [Bosch 00]. The authors consider four evaluation categories: *scenario-based*, *formal-modeling*, *experience-based* and *simulation* based. Other authors (e.g. [Zhang 10]), use model-checking to address techniques which verify whether architectural specifications conform to the expected properties. Since in our study we are category agnostic since our focus is maintainability, we considered all presented categories that can be used to assess an architectural model. Model-checking was not considered as it as a different evaluation category.

Below we present a brief characterization of each category adopted to classify the tools analyzed:

- **Scenario-Based:** Methods in this category use operational scenarios that describe the requirements to evaluate the system quality. The scenarios are used to validate the software architecture using architectural tactics and the results are documented for later analysis including for system evolution, maintenance and the creation of a product line. There are several scenario-based evaluation methods namely SAAM [Clements 01, Kazman 94], ATAM [Clements 01, Barbacci 98], CBAM [Kazman 01], FAAM [Dolan 01].

- **Formal-Modeling:** Uses mathematical proofs for evaluating the quality attributes. The main focus of this category is the evaluation of operational parameters such as performance. An example of formal-modeling is NOAM (Net-based and Object-based Architectural Model) [Deng 97]. Usually, the use of formal-modeling and simulation-based methods can be joined to estimate the fulfillment of specific qualities.

- **Experience-based:** The methods in this category use previous experience of architects and stakeholders to evaluate the software architecture [del Rosso 06]. The knowledge obtained of previous evaluations is maintained as successful examples to design new similar solutions and drive further architecture refinements.

- **Simulation-based:** Uses architectural component implementations to simulate the system requirements and evaluate the quality attributes. The methods in this category can be combined with prototyping to validate the architecture in the same environment of the final system. Examples include LQN [Aquilani 01] and RAPIDE [Luckham 95].

It is important to notice that the evaluation categories are not directly linked to the evaluation tools. They specify how to apply the theory behind the tools and commonly define steps to assess the architectural quality. Some tools support different methods to get a better insight. In fact, very few ADLs, like Aesop [Garlan 94], Unicon [Shaw 95] and ACME [Garlan 10], provide support for different evaluation processes. They are closely serving as an evaluation tool themselves and assist in modeling specific concepts of architectural patterns, although unfortunately in most cases these are applicable to very restricted purposes only.

2.7.2 Architecture Evaluation Tools

The diversity of techniques focusing on restricted contexts and attributes turns the selection of an architectural method into a complex task. Architects typically need to adapt several models and languages depending on the attributes they want to evaluate. Thus, it is necessary to know different description languages, scenarios specification, simulation process, application contexts and others method's features to make the best choice and perform the intended evaluation process. While generic tools do not become widespread, we have observed that architects tend to adopt the methods, tools and ADLs that they have previously been in contact with.

Many evaluation methods (e.g. ATAM), describe a sequence of manual activities that the architect should perform to identify the main issues concerning quality assessment. Based on these descriptions or instructions, software tools are used to automate only parts of the evaluation process, such as architectural scenario definition, analysis of architectural components relationships and others. Automating the whole validation of architectural quality requires the mediation of the architect to tailor the model according to the requirements and to solve errors and conflicts detected by the tools.

ADLs have also evolved and new features were assembled to aid the architect. According to [Medvidovic 00] the tools provided by ADLs are the canonical components (also referred as *ADL toolkit* [Garlan 98]). Among these components we can mention the *active specification*, which that guides the architect or even suggests wrong options in the design and *architectural analysis*, which is the evaluation of the system properties detecting errors at the architectural phase and reducing costs of corrections during the development process. We have take into account that most tools have consraints that hinder the use of an ADL already known by the architect, forcing the learning of new architecture description languages or require designing the model directly at the interface of the tool.

Many characteristics have to be managed and balanced by the architect, thus selecting the best tool is not a simple task. Sometimes, it is necessary that the architect knows how the tool works to decide whether it is useful in a specific project. The system requirements guide the architect about the type of tool to be used but still lack specific information about methods and features or this information is dispersed, preventing a sound and informed *a-priori* evaluation by the architect.

There are few studies to assist the architect in the selection of the best tool to support the architectural quality evaluation. In [Tang 10] for example, the authors compare different knowledge management tools to understand architectural knowledge engineering and future research trends in this field. The knowledge about how to assess a particular kind of system requires that the architect knows which characteristics the tool should have.

In order to understand how maintainability is handled by actual tools, we surveyed different types of architecture evaluation tools and classified them according to the six dimensions presented in Table 2.1 below. Our goal was to identify significant dimensions from where to analyze the applicability of an evaluation tool in a particular context to a specific goal, but also to understand how each tool and the related 'enforced' methodology assessed or handled the specific software attribute of maintainability.

Method	The evaluation method used. One tool can support several methods.
ADL	Assess if the tool has its own ADL, use another know ADL or if the architect must describe the architecture manually using the tool interface.
Qualities	Indicate which quality attributes are covered by the tool.
Trade-off	The ability of the tool to understand and measure the trade-offs between two or more quality attributes.
Stakeholder	Whether the tool supports the participation of stakeholders (beyond the architect) during the architecture evaluation or somewhere during the architectural design.
Knowledge	Evaluate if the tool preserves the knowledge (e.g. architectural patterns) since the last architectural evaluation for performing new designs.

Table 2.1: Dimensions used for the evaluation of the tools

2.7.3 Assessment of Tools

A major criteria on the tool selection was to cover different methods of architectural evaluation, and in fact several tools use multiple methods to achieve the proposed objectives. This is especially true when the tool is more generic, therefore supports

Method	This tool uses a scenario-based method, but each RF can have its own evaluation method.
ADL	There is no specific ADL linked with this tool, only the XML file used as *manifesto*.
Qualities	All quality attributes can be evaluated, depending on which RF is used. There are no predefined RFs for all QAs.
Trade-off	The trade-off among different RFs uses a 'traffic-light' metaphor to indicate potential scenario improvements when applying different tactics.
Stakeholder	It is an architect-focused tool; other stakeholders are only involved when scenarios are identified.
Knowledge	ArchE does not build knowledge from past evaluation (architectural patterns) to apply in new projects.

Table 2.2: Dimensions evaluated for ArchE

different techniques depending on the quality attribute to be evaluated. The tools have also been selected based on their maturity and relevance in the scientific literature. It must be stressed that most of these tools are research prototypes even if also used in industry. After an extensive literature survey, and according to the above criteria, we selected five tools that we considered the more representative of the current state-of-art on architectural design and evaluation. Thus we selected ArchE design assistant [Diaz-Pace 08], Architecture Evaluation Tool (AET) [Thiel 03], Acme Simulator [Schmerl 06], ArcheOpterix [Aleti 09] and DeSi [Mikic-Rakic 04].

ArchE Design Assistant

This tool is an Eclipse plug-in that manages **reasoning frameworks** (RF) to evaluate software architectures. The evaluation models are the knowledge sources and the Architecture Expert (ArchE) baseline tool manages their interaction. A relevant point of this *'assistant'* is that a researcher can focus on the modeling and implementation of a reasoning framework for the quality attribute of interest. The tool has no semantic knowledge and consequently supports any reasoning framework. So, ArchE is an assistant to explore quality-driven architecture solutions.

Method	This tool use scenarios as main method for evaluation. It uses both dynamic and static (experience-based) evaluation types.
ADL	There is no ADL linked with this tool. The data is inserted directly using the tool interface.
Qualities	All quality attributes can be evaluated as it is a mostly manual operation.
Trade-off	The trade-off is performed based on the data introduced by the architect and stakeholders during the achievement of quality attributes and scenarios. The tool combines this information to guide the architect showing the risks and the impact of changes.
Stakeholder	In the initial steps of data gathering, the tool requires that stakeholders participate to fill the quality requirements scenarios.
Knowledge	The knowledge (experience repository) is stored in the databases as input to new evaluations.

Table 2.3: Dimensions evaluated for AET.

The ArchE receives from each RF a *manifesto*. This *manifesto* is a XML file that lists the element types, scenarios and structural information handled by the reasoning framework. In ArchE many actors collaborate to produce the solution of a problem. In this case, the actors are the RF and every other actor can read information provided by other RFs. This communication can produce new information useful to some of them.

The flexibility of ArchE is its major strength but also its major weakness: researchers and practitioners are able/forced to develop or adapt their own quality-attribute model if not already supported. An input conversion for non supported ADLs might also be necessary.

It is significant that ArchE is most useful during the assessment phase of architectural development and, as ArchE authors state, *ArchE is not intended to perform an exhaustive or optimal search in the design space; rather, it is an assistant to the architect that can point out "good directions" in that space.*

Architecture Evaluation Tool (AET)

AET is a research tool developed at BOSCH to support the evaluation team in documenting results and managing information during an architecture review. AET has two databases to assist the architect with the information management: General, (i.e. static data) and Project (i.e. dynamic data) databases. This tool is present during the gathering of quality attributes information and architectural scenarios. So, the information obtained from stakeholders is stored in AET databases. The information is used in the current project and storage in the general database for new architectural projects. Although this tool was initially developed to evaluate performance and security, the project is still under development to include more attributes. This tool is focused in the initial phases of requirements gathering and quality attributes trade-off analysis.

Acme Simulator

This tool is an extension of AcmeStudio and uses its existing features for defining architectural models. It also provides specific architectural styles to specify relevant properties and topology to the kind of analysis. This tool uses ’Acme’ as design ADL to model the software architectures and it is clearly focused on architectural assessment and evolution. The Acme simulator as originally developed supported security and performance analysis using Monte Carlo simulation to evaluate the properties under predefined assumptions about their stochastic behaviour. An extension for reliability and availability was also developed [Franco 13, Franco 14]. Since the simulator is embedded in the AcmeStudio framework (an Eclipse plug-in) it allows flexible extensions.

ArcheOpterix

This tool provides a framework to implement evaluation techniques and optimization heuristics for AADL (Architecture Analysis and Description Language) based specifications. The algorithms should follow the principle of model-driven engineering, allowing reasoning about quality attributes based on an abstract

Method	A Monte-Carlo simulation using specifically designed scenarios (behavior model trees) for evaluation.
ADL	Acme Simulator is linked with AcmeStudio, thus Acme ADL is necessary to model the architecture design before the evaluation.
Qualities	Initially only *performance* and *security* were supported using Monte Carlo simulation. *Availability* and *Reliability* have been added later [Franco 13, Franco 14] using stochastic approaches. This framework is general enough to be extended to other quality attributes, but it requires that the adequate extension is developed.
Trade-off	The trade-off is presented as a table; the comparison is realized manually with the information provided by the tool. The authors plan to support the comparison directly.
Stakeholder	The stakeholders do not participate during the use of this tool.
Knowledge	No knowledge is explicitly preserved to new projects.

Table 2.4: Dimensions evaluated for Acme Simulator

architecture model. The focus of ArcheOpterix is embedded and pervasive systems (AADL is extensively used in the automotive indistry).

The quality evaluation is represented using AttributeEvaluator modules that implements an evaluation method and provides metrics for a given architecture. This tool can evaluate all quality attributes as long as there are suitable evaluation algorithms. The two initial attribute evaluators use mathematical methods to measure the goodness of a given deployment, data transmission reliability and communication overhead. Thus, this tool was classified as formal, although the AttributeEvaluator may use different methods.

DeSi

DeSi is presented as an environment that supports flexible and tailored specification, manipulation visualization and re-estimation of deployment architectures for

Method	Although the tool uses formal modeling to evaluate the attributes, the *AttributeEvaluator* which contains the algorithm can adopt other methods.
ADL	Uses the AADL standard to describe the architecture to be evaluated.
Qualities	All quality attributes can be evaluated as long an algorithm exists. Currently two quality attributes have been evaluated: data transmission reliability and communication overhead.
Trade-off	The tool uses an architecture optimization module to solve multi-objective optimization problems using evolutionary algorithms.
Stakeholder	The stakeholders do not participate during the use of this tool.
Knowledge	ArcheOpterix does not preserve the knowledge of evaluations to be used in new projects.

Table 2.5: Dimensions evaluated for ArcheOpterix

large-scale and highly distributed systems. Using this tool it is possible to integrate, evaluate and compare different algorithms improving system availability in terms of feasibility, efficiency and precision.

This tool was implemented in the Eclipse platform. Its architecture is flexible enough to allow exploration to other system characteristics (e.g., security, fault-tolerance, etc.). DeSi was inspired in tools for visualizing system deployment using UML descriptions for improving support to specifying, visualizing and analyzing different factors that influence the quality of a deployment.

2.7.4 Support for Maintainability

In Table 2.7, we present a summary of dimensions analyzed for the selected tools, with a synthesis of the most relevant aspects that are required to assess its nature, applicability and usefulness for a specific goal.

As can be seen, although every tool claims to be devoted to architectural assessment their focus can be very distinct. While ArchE, AET and ArcheOpterix

Method	Formal, DeSi uses algorithms to improve system availability.
ADL	The data is input directly in DeSi interface and the tool does not use any ADL.
Qualities	Availability, although, depending on the taxonomy, some of its features could be independently classified, namely security and performance. The tool allows the integration of new components to explore different quality attributes.
Trade-off	There is no trade-off function. DeSi simply provides a benchmarking capability to compare the performance of various algorithms.
Stakeholder	The stakeholders do not participate during the use of this tool.
Knowledge	No knowledge is preserved for future evaluations.

Table 2.6: Dimensions evaluated for DeSi

	ArchE	**AET**	**ACME**	**ArchOpterix**	**DeSI**
Method	Scenario	Scenario	Simulation	Formal	Formal
ADL	–	–	✓	✓	–
Quality Attr.	All	All	Perf., Secur., Avail., Reliab.	All	Availability
Trade-offs	✓	✓	✓	–	–
Stakeholder	–	✓	–	–	–
Knowledge	–	✓	–	–	–

Table 2.7: Overview of tools according to the relevant dimensions

goals cover every quality attribute (depending on whether the corresponding models are implemented), AcmeSimulator and DeSi have a specific focus. On the other hand, while ArchE, AET and AcmeSimulator support human guided trade-off analysis, Archepterix and DeSi provide absolute assessment metrics. Since our focus is on maintainability, it was clear from this survey that no tool addresses explicitly this quality attribute. In fact, tools using formal methods for assessment are best suited to analyze operational –runtime– quality attributes (e.g. performance), which is clearly not the case of maintainability, a 'static' property of software.

Nevertheless, we searched further to understand how was this attribute considered whenever a trade-off involving maintainability was to be analyzed by each tool. Much to our surprise we realized that, if the need arises, these tools simply import metrics from other tools (namely Eclipse plugins) that use modularity (cohesion and coupling), cyclomatic complexity, and size as proxy variables to quantify maintainability. So, since most of this tools are still mostly used in a research context –and maintainability is not been explicitly addressed– or if used in an industry setting, the practitioners revert mostly to code-based metrics using external tools. This insight was the driver for the next step in our study.

2.8 Summary

This section provided an overview of the baseline concepts used in our study: maintainability as a quality attribute, and software architecture as the context where quality attributes are enforced. Then, we presented a systematic review of contemporary software architecture design tools to identify its underlying principles in order to understand how maintainability was handled by such state-of-art frameworks. Much to our surprise we realized that every tool analyzed extracted its maintainability metrics from source-code whenever this quality attribute was involved, mostly through a few proxy variables (cohesion, coupling, complexity, and size).

Since our goal is to provide software architects with tools and methodologies that allow them to deal with maintainability at architectural level, in the next chapter we present our first step into mapping ’low-level’ structures into more abstract representations.

Chapter 3

Research Design

Assessing the mapping of source-code maintainability onto its architectural description

3.1 Introduction

During architectural design the first decisions are made about the essential structures of a system, but there are few means of evaluating those decisions until much later in the development process [Bosch 01]. In particular, it is extremely difficult to predict how maintainable is a system at the software architecture level of abstraction. Despite this, information about the estimated effort and costs incurred by the architecture is needed, so that the trade-offs on future maintenance effort can be compared. For instance, if it is claimed that a software architecture will have a maintenance effort equivalent to ten full-time engineers per year, this raises the question of whether and how an alternative architecture could reduce maintenance costs.

The impact of software architecture on maintainability, and the need for a maintenance evaluation while the architecture is being designed or modified, has led us to formulate the first hypothesis of this study and conduct several experiments to validate it. Our first hypothesis states that:

Source-code based metrics can be adapted to more abstract metrics and applied to assess maintainability at architectural level. [H1]

In this chapter we set the stage for the experiments performed aiming at validation the hypothesis stated above. We present and discuss the metrics adopted in the experiments and an overview of the experimental setup. The results and discussion are presented in the next chapter.

3.2 Metrics

As we referred above, most maintainability metrics identified were based on source-code. This prevents the assessment of maintenance during the software design phases, when the source code may not yet exist. Therefore we decided to map source code metrics into a more abstract, architectural level. Several assumptions have been made on how maintainability can influence software architecture. First, we adapted a set of metrics used to evaluate Object-Oriented source-code into metrics applied to package diagrams. The most common metrics were taken from academic works, as well as from estimation tools used to measure code quality (Eclipse plugins and SonarQube). The most common code attributes that were considered were Complexity by class, Number of files of project, Number of functions, Complexity by Function, Lines of Code, Complexity by file, Cyclomatic Complexity, Duplications, and Technical Debt. After an importance and relevance prioritization, and considering its potential of mapping into package diagram models, we selected McCabe Cyclomatic Complexity (CC), Afferent Coupling (AC), Efferent Coupling (EC) and Lack of Cohesion (LCOM) as the metrics on which our study was going to be based (Table 3.1).

CC	Cyclomatic Complexity
AC	Afferent Coupling
EC	Efferent Coupling
LCOM	Lack of Cohesion

Table 3.1: Source-code metrics adopted

We must stress that the metrics adopted have been extensively used to evaluate source-code, mostly for object-oriented systems. Other studies that address the impact of software changes in software architecture, e.g. [Bengtsson 98], have refered that it should be possible to adapt OO metrics to abstract levels of the system. Also the work presented in [Shen 08] demonstrates how evolution can increase the complexity of maintaining a software system, and the need for a quality evaluation before the changes required for the system evolution can be coded. In [Garlan 09] a tool named Ævol was developed to define and plan the evolution of systems by means of its architectural model. Zayaraz [Zayaraz 05] uses COSMIC to define architectural metrics in order to evaluate maintainability, reliability and usability. His work uses the sub-characteristics of maintainability –complexity, coupling and cohesion– as the target metrics. This is exactly the same approach we adopted.

The initial experiments were performed manually by analysing the connections between the packages so that the results between the code and software architecture could be compared. We realized that we were actually working with package diagrams and its connections, which could be treated as graphs. So, in trying to validate hypothesis 1 we applied these metrics to package diagrams extracted directly from the source code. This mapping was performed automatically using an external tool, Visual Paradigm [1]. We did not use independently produced package diagrams, as if we did, we could not ensure that the representation had the required fidelity. In fact, it is very common that the models are not reflected in the actual code. Moreover, we did not have 39 models, one for each version of Tomcat. Lest it suffice to say that some major version number changes had indeed a redesigned package diagram, an these agreed with our automatically generated model. We think that these models might have also been reverse-engineered from the source code.

To further abstract the diagrams we adapted the UML package diagrams into the COSMIC notation [ISO/IEC 11], so that the our metrics could be applied to different versions of architectural models or systems in a semi-automatic way. The COSMIC Full Function Point (FFP) uses Functional User Requirements (FUR) to measure the software size. It also quantifies the software's sub-processes, known as data movements, by measuring the functionality of the software as did Dumke [Dumke 11], which used COSMIC to unify the architectural notation that would be used by the

[1] www.visual-paradigm.com

code metrics. With the aid of COSMIC data movements, it is possible to classify the processes by means of COSMIC standard notation. The main data movements defined in COSMIC are as follows: E: Entry, X: Exit, R: Read, W: Write, N: Number of components, and L: Layer.

The adaptation of UML diagrams to the COSMIC notation allowed us to propose that our new metrics-based models can be used to evaluate the software architecture. Each package UML diagram can be regarded as an architectural layer and the COSMIC data movements are linked to diagram elements. It should be mentioned that each metric has a scope of application. For example, concerning the complexity metrics, a component which possesses sub-components, is viewed as only one element for the layer being evaluated. It has the whole diagram as its scope of application without taking account of the internal relations of the component. However, in the cohesion metrics, the elements of evaluation consists of the component itself, and thus, in this case, the sub-components are necessary for the measurement. If the component has no sub-components, the calculation of TCC and LCC may indicate it has the maximum cohesion. The formulas below show an example of the McCabe Cyclomatic Complexity for code and its adaptation for Software Architecture and the adapted formulas for the other used metrics: Fan-in Fan-out Complexity, Coupling Between Objects, Response For Class, Tight Class Cohesion, Loose Class Cohesion and Lack of Cohesion.

Cyclomatic Complexity (CCN) for code:

CCN = (E - N) + 2P

Where:

E: Number of edges

N: Number of nodes (vertices)

P: Number of independent graphs (usually P= 1)

CCN adaptation to package diagrams:

CCN = ((E + X + W + R) - N) + 2L

Where

E: Dependencies from the component

X: Dependencies to the component.
W: Interfaces provided by the component.
R: Interfaces used by the component.
N: Number of components in a diagram
L: Number of layers in a diagram

It must be stressed that for the remaining three metrics (Afferent Coupling, Efferent Coupling, and Lack of Cohesion), the formulas have been preserved, only the formula inputs have been adapted (using packages rather than classes).

3.3 Experimental Design

From the above description we can now present our approach to validate our first hypothesis (H1). First we had to selected a well known, widely used project in production for several years, so that a large number of versions were available. A private, restricted usage, unknown project, would not be as interesting an relevant as a very common one. We opted for a well know, widely used project to ensure relevance of the results. The choice fell on Apache Tomcat, the most widely adopted web server on the Internet. Moreover, Tomcat's source code is available, along with previous versions. Thus, we downloaded and analyzed 39 consecutive versions of Tomcat (from version to 6.0.0 a 7.0.26).

For each version we extracted the source-code metrics referred in the previous section. For each source-code version available, the corresponding package diagram using Visual Paradigm was generated and the mapping into COSMIC applied. Then, we applied our maintainability metrics adapted to this more abstract notation. Finally, the metrics extracted from code and the metrics from the abstract notation were compared using statistical correlation methods. Initially four methods were used, Pearson, Kendall, Spearman and Factorial Analysis. Later we used only Pearson Correlation to reduce the effort, as no significant additional insights were achieved by using the other statistical techniques.

3.4 Summary

In this chapter we set the stage for the experiments performed to validate our first hypothesis (H1), that states *Source-code based metrics can be adapted to more abstract metrics and applied to assess maintainability at architectural level*. Therefore, if the metrics used to assess maintainability at source code level are significantly correlated to its mapping applied to the more abstract representation of the same software system, we can conclude that the mapping is not only feasible, but meaningful. This would open the possibility of designing and comparing architectural alternatives on what future maintainability is concerned. In the next section the results of this first study are presented and discussed.

Chapter 4

Results and Analysis (I)

Mapping source-code maintainability metrics onto its architectural equivalent

4.1 Introduction

In this chapter we present and analyse the first experimental results of this thesis. It focuses on determining the correlation between source-code and architecture derived metrics with the intention of validating hypothesis 1 of this thesis, i.e. whether *source-code based metrics can be adapted to more abstract metrics and applied to assess maintainability at architectural level*.

4.2 Observations

As stated earlier, the purpose this study is to understand if it was possible to map code metrics into architectural metrics as a way to support maintainability-related decisions of the software architect. Automatically generated package diagrams in UML were adapted to COSMIC notation and its graph representation. The maintainability-related

	Complexity (Package)	Efferent Coupling (Package)	Afferent Coupling (Package)	Cohesion (Package)
Complexity (Code)	0.793 (0.000)	0.710 (0.000)	0.748 (0.000)	0.534 (0.000)
Efferent Coup (Code)	0.973 (0.000)	0.957 (0.000)	0.951 (0.000)	-0.727 (0.000)
Afferent Coup (Code)	0.973 (0.000)	0.957 (0.000)	0.951 (0.000)	-0.727 (0.000)
Cohesion (Code)	- 0.967 (0.000)	- 0.919 (0.000)	- 0.940 (0.000)	0.719 (0.000)

Table 4.1: Pearson's correlation and significance for **Tomcat**

metrics were applied to the same versions of the systems, both to code and diagrams. Then the correlation was analyzed by means of Pearson correlation.

In Table 4.1 we show the Pearson correlation and significance between the code and architecture for 39 versions of TomCat. The information show how is the correlation between source-code metrics and package diagrams. Coupling and complexity had the higher correlation, reaching more than 0.9 with a 100% of significance. This results were very encouraging, as they showed a clear correlation between the code and architectural metrics along the 39 versions of Tomcat. Thus would lead us to conclude that the code-to-architecture mapping is not only feasible, but meaningful. This opens the possibility of designing and comparing architectural alternatives on what concerns future maintainability.

However, during the analysis of the results, we noticed that some code metrics had a significant higher correlation than the other architectural metrics and which were also different of the others that were tested. From the example in Table 4.1, it can be seen that the architectural complexity (package) has a strong correlation with the coupling of the code, even greater than with the complexity of the code. This observation lead us to further develop our study, and select other complex software systems to understand this behavior, and whether the correlations hold, or if this correlation was specific of the Apache Tomcat.

Therefore, we performed exactly the same study, now extending it to two other complex software systems: JEdit and Vuze. JEdit is a Java editor and Vuze is a

	Complexity (Package)	**Efferent Coupling (Package)**	**Afferent Coupling (Package)**	**Cohesion (Package)**
Complexity (Code)	-0.940 (0.000)	0.110 (0.328)	0.946 (0.000)	0.314 (0.095)
Efferent Coup (Code)	0.955 (0.000)	0.056 (0.410)	-0.798 (0.000)	-0.248 (0.153)
efferent Coup (Code)	0.974 (0.000)	0.175 (0.237)	-0.777 (0.000)	-0.225 (0.177)
Cohesion (Code)	0.613 (0.003)	0.775 (0.000)	-0.151 (0.268)	0.015 (0.475)

Table 4.2: Pearson's correlation and significance for **jEdit**.

widespread peer-to-peer client (formely Azureus). Both are open-source software, so we could access multiple version of its source code.

jEdit results, presented in Table 4.2, again show high correlation values between code complexity and architectural complexity. It also shows a strong correlation between package complexity and the code coupling (afferent and efferent). However coupling in code shows a weak correlation with architectural coupling. The same occurs for cohesion. This lack of correlation can also be seen in the significance values. These observations indicate that the previous correlation results obtained for Apache Tomcat do not hold for some of the metrics, hinting that some metrics, namely cohesion, might be inherently different in source-code and at its architectural representation.

Vuze, the largest system of our case study (in number of components), finally showed few similarities between the metrics. The only significant results are the comparison between package complexity with coupling (afferent and efferent). The other comparisons are not meaningful since they show a low coefficient or a high significance value. These results are presented in the Table 4.3 and displayed graphically in Fig. 4.2.

We extended this analysis up to twenty OSS projects, which confirmed these findings.

	Complexity (Package)	**Efferent Coupling (Package)**	**Afferent Coupling (Package)**	**Cohesion (Package)**
Complexity (Code)	-0.028 (0.461)	0.207 (0.220)	-0.155 (0.290)	0.215 (0.221)
Efferent Coup (Code)	0.930 (0.000)	0.572 (0.013)	-0.530 (0.021)	0.547 (0.017)
efferent Coup (Code)	0.378 (0.001)	0.415 (0.062)	-0.363 (0.090)	0.384 (0.079)
Cohesion (Code)	0.469 (0.039)	0.282 (0.154)	-0.224 (0.211)	0.253 (0.182)

Table 4.3: Pearson's correlation and significance for **Vuze**

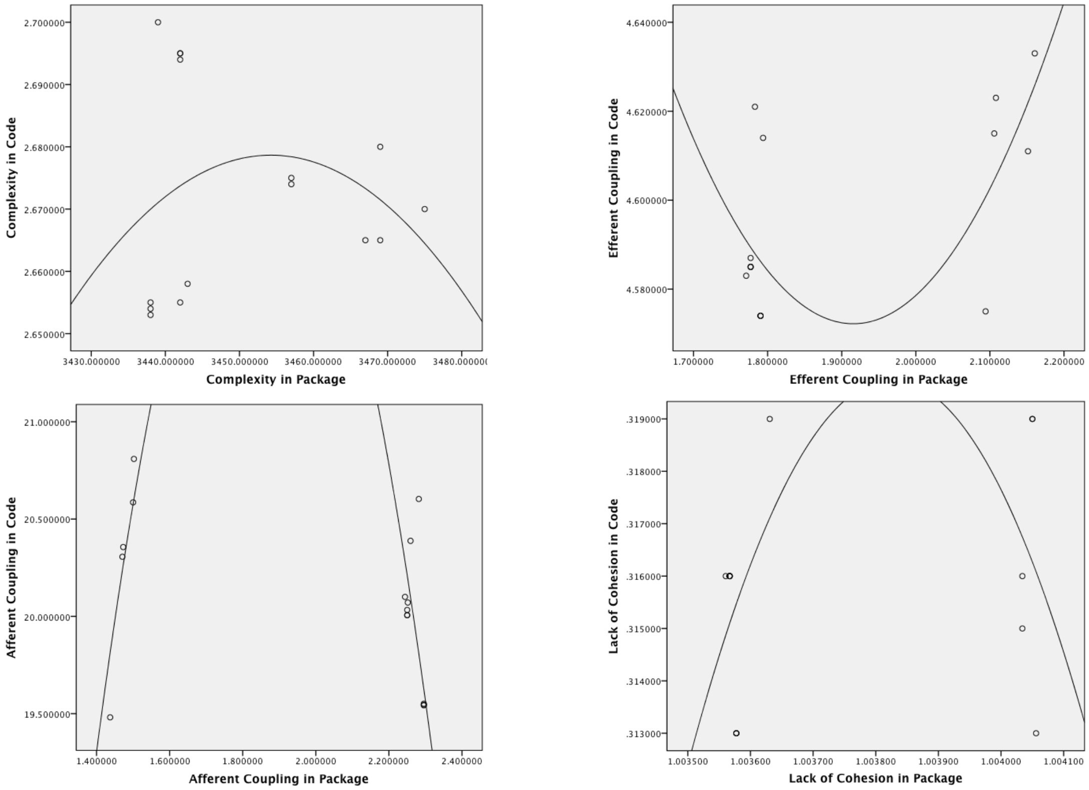


Figure 4.1: Vuze lacks meaningful code-to-architectural maintainability metrics correlation

At this point we were faced with the evidence that our metrics did not reflect at architectural level the source-code properties of a software system, i.e. the abstraction process clears information that is meaningful in what maintainability is concerned.

This observation suggests that there are quality attributes that are not apparent at more abstract levels of description. *This contradicts the widely held belief that maintainability –a quality attribute– is determined at the architectural level* and directed us to explore other complementary dimensions of maintainability.

4.3 A Field Survey on the Meaning of Maintainability

Up to this point our study considered that maintainability is an emergent property of modularity and the related concept of complexity. Our argument is based on the assumption that the more modular is a software system, the less complex it is, and therefore easier to maintain. This is the line followed by most of the literature, already discussed in chapter 2.

In order to further clarify this point, a field survey was conducted with software architects to understand what they understood was meant by architectural complexity as it relates to maintainability. In total, we surveyed 22 software architects with over 5 years experience from different countries, namely USA, Portugal, Brazil, Japan, Germany, Mexico, Spain and Italy. The survey confirmed that size, coupling and complexity were considered the most important metrics to assess maintainability. It was also found that developers tend to make constant checks of the size and level of complexity of the project, as they are concerned about the risk of the system being too complex, and therefore abandoned. The technical questions are shown in the Table 4.4[1]. Only 4 of the architects who responded to the survey agreed to the disclosure of their replies. These work for the following companies KVH (USA), NovaBase (PT), SESM Scarl (IT) and Compsis (BR).

This survey was answered only by 22 of the more than one hundred architects that have been contacted. Thus, we cannot extract solid quantified information from such a small sample of software architects. In fact, many respondents did not even fill the questionnaire, but rather sent their personal opinion about this issue in free form text.

A manual analysis and reflection on the feedback provided by this survey lead us to conclude that the conceptualization of maintainability, as perceived by the developers

[1] The remaining questions address socio-demographic aspects

Question	Description
Q1	How do team members communicate with each other regarding important aspects of design and architecture?
Q2	What kind of languages are used to describe the projects?
Q3	Do you agree that these languages are complete?
Q4	Is it possible to express everything that is relevant to the project using these languages?
Q5	What architectural aspects are hard to document using these languages?
Q6	How does your company check the non-functional requirements? (quality attributes)
Q7	How important do you think software architecture is on a project? (1-10)
Q8	Does your company have a preferred (or predominant) architectural style?
Q9	A modification of the system implies a modification of system architecture?
Q10	What quality attributes do you consider to be the most important ones?
Q11	What kind of methods/techniques are used to evaluate modularity (e.g. complexity, coupling, cohesion, etc.)?
Q12	Do you know some technique used to evaluate modularity in architectural phase? Which one?
Q13	Do you think the modularity evaluation during the architectural phase could reduce the cost of changes in the development and maintenance phases?
Q14	Would you adopt a new modularity evaluation technique if it could improve the level of maintainability of your systems?

Table 4.4: Core Survey Questions

and software architects alike, can be best described as the degree of “disorganization” of the modules, i.e. the *architectural entropy*, which in fact, reflects the degree of coupling of the different architectural components. This perspective –that is quite in line with our ’structural’ research line– was invariably linked with the perception that maintainability is addressed both at very low level (code conventions, meaningful comments) and at the ’social’ level, i.e. the organization itself can promote or hinder good maintainability practices.

Faced with the previous observations that support the limitations of constraining maintainability to a purely technical perspective, and the insight gathered from this survey, a new research line was then formulated: it seeks to understand whether maintainability is a multidimensional property of software and therefore whether it can only be fully grasped if these multiple dimensions are taken into account.

4.4 Summary

In this chapter we have presented and discussed the mapping of source-code level maintainability-related metrics into more abstract representations. While the first observations supported our hypothesis that it would be possible to map source-code metrics into more abstract, architectural ones, further observations have shown that the correlations did not hold for other systems analyzed. This was a very significant insight, as it means that not all quality attributes, namely maintainability, can be described solely from an architectural (structural) perspective.

Faced with the understanding that it would not be possible to fully map this quality attribute only at an abstract (architectural) level, the end-goal of providing the system architect with a set of tools and recommendations to help her/him evolve long-term software preserving maintainability for further evolution, lead us to surveying professionals responsible for software architecture from many different countries and companies. From this survey we concluded that there is a ’social’ dimension to maintainability. In fact, it is well known that the organization (architecture) of software artifacts reflect the structure of the organization that develops it. This is know informally as *Conway’s Law*, also referred in scientific literature as ’the mirroring hypothesis’ [Colfer 16].

Thus, in the second part of this thesis we turn our focus onto the social dimension of maintainability.

Chapter 5

Revised Experimental Setup

Assessing the impact of social factors on maintainable software projects

5.1 Introduction

The first results that are set out in the first part of this study motivated us to expand our analysis into the social dimension of maintainability.

Actually, in this second part of the thesis we are addressing a new hypothesis that can be stated as:

Social factors play a significant role in the success (longevity) of OSS projects. [H2]

This newly formulated hypothesis sets the groundwork to answer two complementary research questions:

- Is it possible to predict a software projects success from metrics related to its 'social' dimension?

- Which are the 'social' variables that have the highest impact in the long term software project success, assuming that successful projects implicitly embed high maintainability.

By identifying the social variables that impact the project longevity we provide the software architect/project manager with knowledge that can be actually used to drive successfully the project. This is perfectly aligned with the initial objectives, while embracing this new dimension.

The first challenge we faced was to identify a set of projects characterized by high maintainability, so that we could analyze its intrinsic social factors and how they differ from other projects. After a careful and informed reflection we realized the plausibility that long-term successful OSS projects do have to posses high maintainability, otherwise they would not achieve long-term success. Thus, in this second part of our study we will be focusing on identifying the long-term OSS success predictors, so that light can be shed on the social factors that promote highly maintainable software.

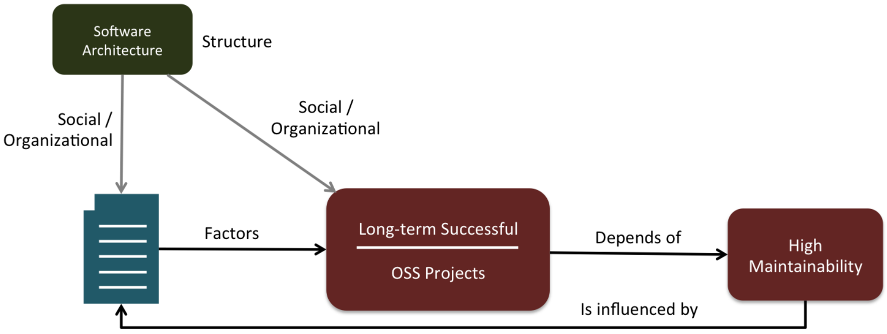


Figure 5.1: How social factors might impact maintainability.

In the next section we shall discuss the rationale behind the selection of OSS repositories. Then we present the experimental setup used in this second part of our study, describing the three phases of the experiments that were performed, after which the dataset and the classification methods used are presented.

5.2 OSS Data Repositories

The experiments in this second part will use the OSS projects available in several web repositories. However, the need to automate the validation process, demanded a comparison between them to support the choice best suited to our research. Amongst the most important repositories, we decided to use GitHub and SourceForge, both of which have already been used in many other research studies.

SourceForge was launched in 1999 and was one of the first repositories to work on managing the OSS system. For a long time, it was one of the leading and most reliable code repositories. Currently, SourceForge claims to have more than 430,000 projects and over 3.7 million registered users[1], but not all are active projects. SourceForge also allows integration of the projects with different version control systems: CVS, Git, Mercurial and SVN.

GitHub is a collaborative code hosting facility, which emerged in 2008. It is based on the Git version control software and was the first platform to support it. GitHub became one of the most popular repositories and currently has more than 11,000,000 users collaborating with more than 27,200,000 repositories[2]. It has a greater social emphasis than SourceForge, and allows users to follow updates from other repositories or users. Unlike SourceForge, GitHub only allows integration with the Git version control and partly with SVN.

In 2013, SourceForge experienced a popularity problem and as a result included advertising buttons inside the project's websites which made the users confused and reduced its usability. In response, many developers removed the download option from their project's website. At that time, SourceForge had 3 million registered users (700,000 less than today) while GitHub had approximately 2.5 million users in early 2013, reaching 3 million users in April 2013 and almost 5 million (with 10 million repositories) in December. Additionally, data extracted from Alexa.com shows the increasing popularity of GitHub in recent years, as SourceForge continues to decline. Furthermore, GitHub provides an access speed that is about 64% greater

[1] http://sourceforge.net/about

[2] Data from September 2015 on https://github.com/about/press

than SourceForge (1.117s vs 2.155s in average). Today, GitHub is among the top one hundred most visited Web sites (89th), while the SourceForge is at 272th.

One of the reasons for the extensive use of SourceForge in academic studies is the availability of free databases aimed at research, such as FLOSSmole, from Syracuse University (discontinued today), and the SourceForge Research Data Archive (SRDA) from University of Notre Dame. This database has been backing up instances of data from SourceForge for academic purposes for many years.

So, although GitHub has a large project database that is publicly available, there are some difficulties in using it for data mining, as demonstrated in [Kalliamvakou 14]. That may be the reason why so many academic researchers end up by choosing SourceForge which also explains the large number of references to it in our literature review, and also what first led us to choose SourceForge as a the main repository for analysis. However, Weiss [Weiss 05] found some problems with SourceForge, namely its unexpected categorization changes and high rate of abandonment. Furthermore, Rainer and Gale [Rainer 05] analysed the quality of SourceForge data and advised caution in the use of this data also due to the large number of abandoned projects. On the other hand, few studies have highlighted the quality of the GitHub data, and there is still a lack of information about what kind of methodology can be employed for its categorization.

Some attempts have already been made to make GitHub project data available on external databases namely through GHTorrent and GitHub Archive. However due to restrictions in their use, we had to design and build our own acquisition tools and analysis methods from the central GitHub repository. Thus, the choice of GitHub was threefold: the rising importance of this repository, the lack of academic work and the inclusion of social factors, some of them absent in SourceForge.

5.3 Phasing of Experiments

In this second study we shall use a large dataset from project data extracted from the OSS project repositories described above. The roadmap for these experiments is shown in Figure 5.2.

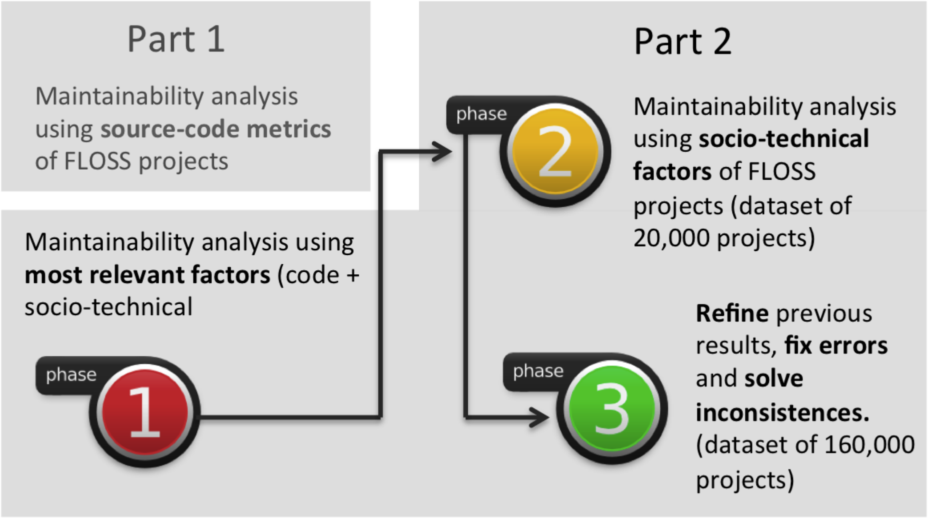

Part 1
Maintainability analysis using **source-code metrics** of FLOSS projects
Part 2
phase 2
Maintainability analysis using **socio-technical factors** of FLOSS projects (dataset of 20,000 projects)
Maintainability analysis using **most relevant factors** (code + socio-technical
phase 1
phase 3
Refine previous results, **fix errors** and **solve inconsistences.** (dataset of 160,000 projects)

Figure 5.2: Phases of the experiments

In phase 1 of this second part of our study, the same twenty projects used in the first experiments (Tomcat, Jedit, Vuze,...) were used, but now we extended the analysis to include the ’social’ parameters listed in Table 5.1. All the twenty Java systems analyzed confirmed that social factors are indeed relevant in predicting the future success of the OSS project. In phase 2, the most significant factors found in the previous phase were re-analyzed, but now using a larger number of systems –20,000 projects involving ten programming languages– to confirm the previous results. Finally, in phase 3, improvements were made since there was a need to increase the number of case studies in the dataset and conduct a more comprehensive experiment to account for language dependency bias. In this phase, about 160,000 OSS projects were used.

In the different phases of the study, the results were compared by using more than one correlation and classification technique determine which was the best evaluation model and to mitigate analysis bias. This is discussed in the next section.

Social Factors	Number of forks	Number of stars	Has pages
	Number of subscribers	Project size	Has wiki
	Number of contributors	Number of issues	Has downloads
	Number of commits	Open issues	Number of watchers
	Number of downloads	Branch attributes	URL and dates

Table 5.1: Social factors assessed during the experiments

Classification	J48	Simple Logistic	IBk (K=3)
	Bagging	Decision Table	Multilayer Perceptron

Table 5.2: Methods used to compare the results

5.4 Dataset and Classification Methods

The dataset used in the final (phase 3) experiments included 17 programming languages with different programming paradigms (scripting, procedural, and object-oriented). Initially the dataset had a larger number of languages but for different reasons, it was impossible to use all of them them. For example, the *Swift* language had no dormant project as the language was introduced by Apple in 2014 during the WWDC (Worldwide Developers Conference). Table 5.3 provides the distribution of the programming languages we used in the third phase of the experiments.

In this second part of our study, we used the Weka environment (Waikato Environment for Knowledge Analysis) [Frank 10] as a data analysis platform. Weka has all the models and algorithms needed to analyze the extracted datasets and allowed us to carry out a detailed analysis that otherwise would require independent tools.

In total, 4 attributes evaluation algorithms and 10 classification methods were used. However, owing to the significance of the results obtained in the preliminary experiments, after phase 2 we adopted only one attribute evaluation algorithm (Information Gain) and six classification methods (Table 5.2): Simple Logistics (mathematical functions), IBk (from the group of lazy classifiers), J48 (classification trees), Bagging (meta-learning algorithms), Decision Tables (from rule-based classifiers), and Multilayer Perceptron (from neural network).

Language	Dormant Projects	Active Projects	Ratio Act/Dor	Total Projects
Java	2371	13712	578%	16083
JavaScript	8984	36308	404%	45292
C	1972	7328	372%	9300
C++	1141	6511	571%	7652
C#	752	4029	536%	4781
Objective-C	3076	8765	285%	11841
Haskel	163	1021	626%	1184
Ocaml	41	267	651%	308
Shell	678	4282	632%	4960
Go	347	4629	1334%	4976
Arduino	32	203	634%	235
Assembly	27	146	541%	173
PHP	2734	11315	414%	14049
Ruby	6688	11278	169%	17966
Python	3716	15901	428%	19617
R	73	636	871%	709
Matlab	31	145	468%	176
Total	32826	126476	385%	**159302**

Table 5.3: Programming languages and number of projects used in Phase 3

5.5 Summary

This section sets the stage for the observations performed in the second part of this study. We present the rationale for using successful long-term OSS projects as plausible evidence of high levels of maintainability, then the present the OSS repositories from where project data was extracted, followed by the experimental phasing to be performed. Finally the dataset and the classification methods used in this part of the study are presented and justified. The results and analysis of the observations are presented in the next chapter.

Chapter 6

Results and Analysis (II)

6.1 Introduction

In this chapter we present and discuss the three phases of the second set of experiments aiming at assessing the impact of social factors on the success of OSS projects. On this second experimental phase, we compared the impact of code metrics versus social factors to determine its relative importance as project success predictors. This comparison was made using several distinct classifications algorithms. Due to the many parameters involved we tried to use as many systems as feasible for each step. So, all social-related information available in the repositories as well as an extensive list of source-code metrics were used.

6.2 Phase 1: SourceForge | 20 projects | Java

In the first step, after collecting all this project-related information from the OSS public repositories, we used several distinct statistical analysis algorithms to compare the data. The initial comparisons included all the project attributes presented in Table 6.1. In all the comparisons, the main objective was to analyse which factors were more effective to predict the success of the project. At this stage, 20 Java projects were tested and the code metrics were extracted using SonarQube [1].

These first results (Table 6.1) showed that the project's success is mostly influenced by social parameters. The code-related parameters (including complexity) were practically irrelevant and close to zero when compared with the former. This observation supports the argument of some researchers that OSS systems are intrinsically more modular [Baldwin 15], and therefore code attributes *per se* may not be a distinctive factor in determining the success or abandonment of a project.

Social Factor	**Consideration**	**Code Metrics**	**Consideration**
Forks	0.9612	Files	0.0000
Subscribers	0.9612	Duplicated lines density	0.0000
Stars	0.9611	Functions	0.0000
Number of contributors	0.5716	Complexity by file	0.0000
Size	0.3739	McCabe Complexity	0.0000
Number of commits	0.3217	Comment Lines Density	0.0000
Issues	0.3204	Directories	0.0000
Has page	0.1938	NLOC	0.0000
Has wiki	0.0328	Violations	0.0000
Has downloads	0.0276	TLOC	0.0000

Table 6.1: Attribute-based considerations using classification methods

It is also manifest that some of the social metrics have the greatest impact, namely forks, subscribers, and stars). These results also lead us to reflect on the influence of the specific repository that was being used to analyze the data. At this phase we were using a database extracted from SourceForge. So, despite the extensive use of SourceForge in most research papers, we decided to switch to GitHub as our main source of OSS project data to continue the experiments.

6.3 Phase 2: GitHub | 20K projects | 10 languages

As the initial experiments only considered 20 object-oriented OSS projects, we were concerned that these results could have been biased by the programming paradigm

[1] https://docs.sonarqube.org/

or the small sample size (number of projects). Thus, in the second phase of this set of experiments, we decided to increase the number of target systems significantly, as well as extend the programming languages and programming paradigms analyzed. Therefore we designed and built a tool to semi-automate the entire process, namely the information extraction using the GitHub API.

In this new setup we analyzed 19.994 projects (of which 9,995 considered dormant and 9,999 active) using 10 different programming languages: Java, Python, C, Shell, C++, C#, Objective-C, JavaScript, Ruby and PHP. During this second phase, we reduced the number of attributes tested, by using the most relevant attributes identified in Phase 1. This decision was motivated by the fact that the first preliminary results (of this second phase) confirmed their relevance was again very low for the subset tested. On the other hand, we increased the number and sophistication of the classification algorithms, in order to mitigate analysis tool bias, as might happen when complex systems are analyzed.

The results observed in this second phase confirmed the observations of phase 1. They strengthened the hypothesis that the social parameters are very effective predictors of OSS project success.

Table 6.2 presents the degree of accuracy, True Positives (TP) and False Positives (FP) of the classification algorithms applied on the second dataset. Accuracy is defined as the percentage of correctly classified instances, true positives are related to instances that are correctly classified as a given class and in the same way, false positives are instances that are falsely classified as a given class. Interestingly enough, source-code related attributes (complexity and programming language) have again shown to be the least relevant in the classification (Table 6.3).

The results presented on Table 6.3 draw our attention to the fact that the programming language was not assigned a significant weight as a success predictor. Moreover, the values of attributes relevance were smaller then in the first experiment. This information contradicts results found in other studies [Emanuel 10, Ghapanchi 14]. After a careful analysis of the results, we concluded that having merged all the datasets together might have concealed the relevance of language. Finally, we realized that in our global dataset (20K projects) the number of stars –the attribute with the greatest weight in the correlation– was biased. This was due

	Simple Logistic	J48	Bagging	IBk (K=3)	Multilayer Perceptron	Desicion Table
Accuracy	92.56%	96.25%	96.62%	93.72%	92.86%	95.05%
TP Rate Active Projects	91.00%	98.80%	99.50%	96.00%	93.50%	99.10%
FP Rate Active Projects	5.90%	6.30%	6.30%	8.60%	7.80%	9.00%
TP Rate Dormant Projects	94.10%	93.70%	93.70%	91.40%	92.20%	91.00%
FP Rate Dormant Projects	9.00%	1.20%	0.50%	4.00%	6.50%	0.90%

Table 6.2: Accuracy, true positive (TP) and false positive (FP) for the classification methods used in phase 2

Attribute	Importance
Stars	0.52531051
Subscribers	0.50602662
Forks	0.39342657
Number of contributors	0.35564825
Issues	0.25643352
Has pages	0.01838373
Has downloads	0.00001036
Language	0.00000109
Cyclomatic Complexity	0.00000000

Table 6.3: Importance of attributes

to the way the data is returned by the GitHub API. Even without using any data sort command, the API always returns first the projects with the larger number of stars. Since the number of active systems is much higher than that of the dormant systems and we had acquired the same number of dormant and active projects for each language, the set of active systems had considerably more stars than the set of dormant systems. These observations led us to refine the experiments, and in phase 3 we decided to consider the maximum number of projects by stars to ensure that the results obtained were not biased.

6.4 Phase 3: GitHub | 160K projects | 16 languages

When designing the phase 3 of experiments, we were very confident that our hypothesis would be confirmed. In this final step we collected data from the largest number of projects as possible from GitHub. This involved including all the projects available using the languages under consideration, while complying with an inclusion and exclusion criteria. These criteria were essential to ensure the dataset had no bias. Below, we describe the criteria used for the phase 3 experiments and in the next section we will outline the execution, analysis and results of these experiments.

Number of stars: Since GitHub has a free user profile, this repository has many small academic projects or "hobby-projects". To avoid including such projects in our experiments, we made use of a significant number of stars (a star shows the user's interest or satisfaction with regard to a project). After analysing the relevance of the number of stars, we found that many of the personal data projects had few stars and so it was decided not to include projects with less than 15 stars. This value was obtained after analyzing about 10.000 projects.

Active or dormant projects: Unlike SourceForge, GitHub has no tag to show if a project is not active. In view of this, as mentioned earlier and based on other works [Khondhu 13], we decided that if the last modifications of a project had been made earlier than 2 years before, it should be regarded as being dormant or abandoned i.e., in our criteria, 'not successful'. The date set for these last experiments was July 3rd, 2015.

Programming language: On the basis of our initial hypotheses, as well as the studies of other authors (e.g. [Cass 15]), we drew up a list of heterogeneous programming languages with the necessary characteristics. These are: Java, Python, C++, C#, PHP, JavaScript, C, Ruby, Assembly, Arduino, R, Shell, Haskel, Ocaml, Go and Matlab. Since there were similarities in the results, in the next sections we will single out those that are most relevant by examining some anomalous situations observed.

Classification models: We employed the same six classification methods used in Phase 2: Simple Logistics, J48, Bagging, IBk, Decision Table and Multilayer Perceptron. A brief explanation of each is given in the results section.

§§§

We must now take a brief pause and recall that the goal of this second study aims at identifying which factors are the most relevant as predictors of an OSS project success, as paradigms of projects possessing high maintainability. These factors are of great importance during architectural evolution as a lack of attention to them might be the root cause of project abandonment.

This section analyses the results of Phase 3, which is concerned with validating the second hypothesis after the experiments have been refined. In the validation process, different classification models were applied to the same dataset. The analysis of the results takes note of the strengths and weaknesses of each project attribute. Since our dataset is very large and the classification methods allow a wide range of analytical procedures, the results shown here are restricted to the most important sets of languages. Nonetheless, all the possible situations found in the analysis are covered.

The feasibility of predicting the success of the project was confirmed by carrying out classification experiments with popular machine learning algorithms in Weka. This contains a collection of algorithms, as well as preprocessing tools, and allows users to compare different methods and select the most appropriate for tackling the problem [Frank 10]. Each instance of the dataset is represented by the set of attributes (metadata) and its associated class (active or dormant). First we examined the most important attributes (i.e. the social factors) by means of algorithms used for attribute evaluation. This involved six different classifiers from different classes, as mentioned previously: Simple Logistics, J48, Bagging, IBk, Decision Table and Multilayer Perceptron. The default parameters adopted by Weka were used for all of them.

All the adopted methods employed a cross-validation model, using 10 folds during the application of the classification. In this approach the method is executed 10 times, using the proportion of 90% to train the classifier and 10% to test it. In each execution, different segments are used for training and testing. Cross-validation is regarded as a highly effective method for automatic model selection [Moore 94]. A more detailed explanation about how cross-validation works is beyond the scope of this thesis, and can be found in [Refaeilzadeh 09]. The key factor is that this choice enabled us to obtain more accurate results than other studies that relied on more common methods, such as the use of only one training set.

When applying the selected methods in Weka, a wide range of information is produced and provides many opportunities for interpretation as well as for future research. This information is described below:

Accuracy: Accuracy can be defined as the degree to which a result conforms to a correct value or standard. In Weka, there are several accuracy measures. Here it expresses the percentage of correctly classified instances (higher is better).

Precision: Precision is the probability that a retrieved sam+ple is important, when selected at random.

Recall: Also named 'sensitivity', reflects the proportion of instances classified as a given class divided by the actual total in that class. Precision and recall are usually combined (F-measure). They use the number of true positives, true negatives, false negatives and false positives in their calculation. In the last section, we showed these values for phase 2. In phase 3 we prefer to discriminate precision and recall to be more specific.

F-Measure: Precision and Recall can give different information in a single metric. If one of them excels the other, for example, the F-measure will reflect it. For that reason, F-measure can be a better combined metric. It is the weighted harmonic mean for precision and recall.

ROC: The Receiver Operating Characteristic, also known as the ROC curve, is a graph that illustrates the performance of a classifier system. This curve traces the behaviour of the classification rate when there is a variation in the classification threshold. The normal threshold for two classes is 0.5. If it is above this value, the algorithm classifies the date in one class, and if below in the other class.

Evaluating the Relevance of Attributes

The assessment of the projects' socio-technical attributes was initially based on an attribute evaluation algorithm. This type of algorithm is used to define the importance of each attribute in a dataset. The algorithm named 'Information Gain Attribute Evaluator', is available in Weka, and estimates the value of an attribute by measuring the information gain with respect to the class. Despite being a simple algorithm, it is very efficient [Karegowda 10] and has been adopted to train the classifiers used in our approaches.

The tests showed that all the languages included achieved almost the same results. The most important attributes were: Number of Contributors, Number of Subscribers, Number of Commits and Project Size, while 'Has Wiki', 'Has Issues' and 'Has Downloads' are less important as predictors. Table 6.4 shows these results for Python and Java. It should be noted that as cross-validation is used (with 10 folds), the algorithm is executed 10 times to show the mean average of the results and a margin of error.

Java			**Python**		
Average Merit		**Attribute**	**Average Merit**		**Attribute**
0.055	+-0.001	Number of subscribers	0.084	+- 0.001	Project size
0.054	+-0.001	Number of contributors	0.080	+- 0.001	Number of contributors
0.046	+-0.001	Number of commits	0.074	+- 0.001	Number of subscribers
0.040	+-0.001	Project size	0.063	+- 0.001	Number of commits
0.030	+-0.000	Number of watchers	0.037	+- 0.001	Number of open issues
0.030	+-0.000	Number of stars	0.032	+- 0.001	Number of forks
0.029	+-0.001	Number of open issues	0.025	+- 0.000	Number of stars
0.022	+-0.001	Number of forks	0.025	+- 0.000	Number of watchers
0.004	+-0.000	Has wiki	0.002	+- 0.000	Has wiki
0.000	+-0.000	Has issues	0.000	+- 0.000	Has downloads
0.000	+-0.000	Has downloads	0.000	+- 0.000	Has issues

Table 6.4: Average Attribute Merit for Java and Python

Although there were slight variations in the results for most of the languages, five of them, Assembly, R, Ocaml, Arduino and Matlab, had a completely different attribute evaluation. The observations for Assembly and Matlab can be seen in Table 6.5. When these results were compared with other languages, we realized that these languages had less than 1000 instances in the dataset, which suggests that this behavior is due to a lack of projects that are suitable for evaluation.

Assembly			Matlab		
Average Merit		Attribute	Average Merit		Attribute
0.061	+-0.005	Number of subscribers	0.097	+- 0.009	Number of contributors
0.007	+-0.001	Has issues	0.080	+- 0.004	Number of commits
0.007	+-0.004	Has download	0.014	+- 0.005	Has issues
0.001	+-0.001	Has wiki	0.003	+- 0.001	Has downloads
0.000	+-0.000	Number of watchers	0.022	+- 0.027	Number of open issues
0.006	+-0.017	Forks count	0.004	+- 0.004	Has wiki
0.000	+-0.000	Number of commits	0.000	+- 0.000	Number of forks
0.000	+-0.000	Number of stars	0.000	+- 0.000	Number of watchers
0.000	+-0.000	Number of open issues	0.000	+- 0.000	Number of subscribers
0.005	+-0.016	Number of contributors	0.000	+- 0.000	Number of stars
0.000	+-0.000	Project size	0.000	+- 0.000	Project size

Table 6.5: Average Attribute Merit for Assembly and Matlab

Despite these outliers for lack of representativeness, the average of attribute merits for all languages still suggests that contributors, subscribers, commits and project size are the most relevant success predictors. Table 6.6 presents the global average merit of different project attributes.

Attribute	Average Merit
Number of Contributors	0.097
Number of Subscribers	0.085
Number of Commits	0.064
Project Size	0.057
Number of Forks	0.047
Number of Open Issues	0.045
Number of Stars	0.027
Number of Watchers	0.027
Has Wiki	0.003
Has downloads	0.003
Has Issues	0.002

Table 6.6: Global Average of Attributes Merit (all languages)

From an analysis of these results, we can concluded that:

1) As the number of contributors increases, the prospect of success also increases. The reason for this may be that more people are working on the project, keeping it active or improving the development flow.

2) When the projects have many subscribers it is more likely that the project will remain active. Subscribers can help by giving feedback when they act as customers or even forking the repository and fixing bugs when they act as developers.

3) The number of commits is an indicator of development activity. Thus, if there is a reduction in the frequency of commits, it means that the project is declining or has become too mature and does not require frequent updates any more. This may lead the project to a state of dormancy.

4) It is not possible to make precise assumptions about the impact of project size on the project success, but there are signs that larger projects have a higher chance of success. Since large-sized projects are usually accompanied by a large number of contributors, commits and subscribers, it is reasonable to admit that size can have a indirect influence on the success of the project.

The importance of the attributes is supplied by the Information Gain Attribute Evaluation. In this way, it is possible to answer the main question which is whether an OSS project is active or dormant. Thus, the classification methods confirm that it is possible to classify projects using social factors.

We shall now present the observation results grouped by each the six algorithms used in the analysis of the about 160 000 OSS projects dataset.

Simple Logistic

Simple logistics is a kind of regression algorithm that fits a multinomial logistic regression model. In each iteration, it adds one Simple Linear Regression model per class into the logistic regression model. Logistic regression is a powerful statistical means of modeling a binomial outcome with single or multiple explanatory variables. One of the main advantages of this model is that it uses more than one dependent variable, and also provides a quantified value for the strength of the attributes association. However, a large sample size is needed and the variables must be carefully defined to ensure precise results. Table 6.7 shows the results of using this algorithm.

This algorithm displays a high degree of accuracy, more than 80% for almost all the languages. However, when other values were analysed, especially the ROC curve, there tended to be a considerable number of false positives. This is demonstrated by the low value obtained in this variable. To illustrate how the ROC curve is generated, Figure 6.1 shows the ROC curve of the Java and Shell languages. Java has the best ROC curve while Shell has the worst. Despite this, the accuracy, recall and precision values of the method are almost the same for both of them.

	Accuracy	**Precision**	**Recall**	**F-Measure**	**ROC Area**
Arduino	86.383%	0.746	0.864	0.801	0.5
Assembly	83.815%	0.711	0.838	0.77	0.609
C	78.7993%	0.833	0.788	0.695	0.725
C++	85.1365%	0.725	0.851	0.783	0.731
C#	84.09%	0.762	0.841	0.771	0.758
Go	92.9765%	0.864	0.93	0.896	0.603
Haskel	86.0899%	0.803	0.861	0.802	0.762
Java	85.0441%	0.873	0.85	0.782	0.744
JavaScript	79.6081%	0.767	0.796	0.711	0.737
Matlab	80.6818%	0.733	0.807	0.753	0.681
Objective-C	73.9748%	0.731	0.74	0.634	0.7
OCaml	87.3377%	0.847	0.873	0.848	0.868
PHP	82.4613%	0.801	0.825	0.752	0.776
Python	81.1082%	0.77	0.811	0.729	0.758
R	89.7616%	0.806	0.898	0.849	0.616
Ruby	73.872%	0.729	0.739	0.726	0.793
Shell	85.7204%	0.854	0.857	0.793	0.678

Table 6.7: Results for Simple Logistic Classifier

J48

J48 decision tree is an open-source implementation available on Weka and has a C4.5 algorithm developed by Ross Quinlan [Quinlan 93]. Both are an evolution from ID3

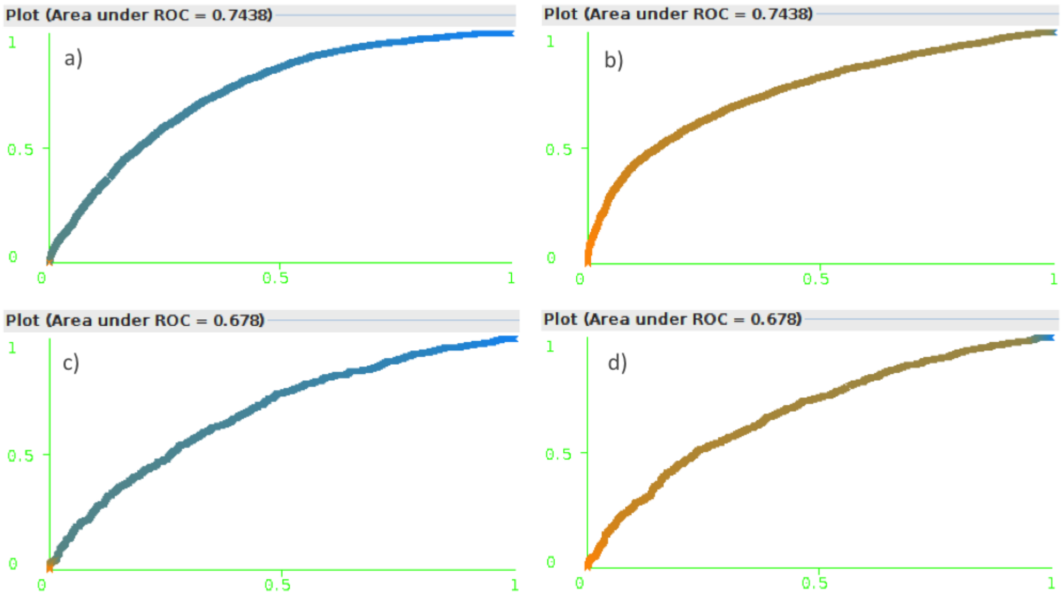


Figure 6.1: ROC curve for Java and Shell where: a) Java Dormants b) Java Actives c) Shell Dormants d) Shell Actives

(Iterative Dichotomiser 3) and adopt a "divide and conquer" approach to growing decision trees [Bhargava 13]. J48 is a classification algorithm where the division criterion is based on the standardized measure of lost information when a set A is used to approximate B, designated as 'information gain'. The attribute used to divide the set is the highest value of the information gain. The results for J48 are shown in Table 6.8.

This classifier behaved in a similar way to the Simple Logistics with regard to the ROC area. However, the J48 has a very poor performance when the dataset is too small, a behavior typical of tree-based algorithms. What happens is that even with high accuracy ratings, these languages will show a lot of false positives, and sharply reduce the area under the ROC curve. The results for Matlab, for example were under 0.5, which makes it completely random (thus unusable) for this subset.

	Accuracy	**Precision**	**Recall**	**F-Measure**	**ROC Area**
Arduino	86.383%	0.746	0.864	0.801	0.47
Assembly	84.3931%	0.712	0.844	0.773	0.51
C	79.2304%	0.761	0.792	0.765	0.712
C++	85.0065%	0.816	0.85	0.822	0.724
C#	84.153%	0.803	0.842	0.807	0.683
Go	92.4532%	0.891	0.925	0.901	0.602
Haskel	84.2239%	0.804	0.842	0.817	0.673
Java	85.8494%	0.829	0.858	0.826	0.726
JavaScript	80.9102%	0.779	0.809	0.774	0.739
Matlab	80.6818%	0.715	0.807	0.745	0.486
Objective-C	75.7064%	0.728	0.757	0.721	0.687
OCaml	85.3896%	0.824	0.854	0.834	0.606
PHP	85.1546%	0.834	0.852	0.835	0.774
Python	82.7038%	0.803	0.827	0.806	0.757
R	88.6396%	0.805	0.886	0.844	0.519
Ruby	76.5827%	0.76	0.766	0.76	0.793
Shell	86.5916%	0.84	0.866	0.84	0.676

Table 6.8: Results for J48 Classifier

Bagging

Bagging (Bootstrap Aggregating), creates separate samples of training datasets and classifies each sample, by combining them by average or voting[2]. Each trained classifier addresses the problem from a different perspective, and this increases the accuracy of the results. The advantage of Bagging is that it reduces variance and avoids overfitting[3]. The results for Bagging are shown in Table 6.9. One of the main advantages of bagging is its capacity of handling small datasets sets. Another factor is that this algorithm is less sensitive to noise or outliers.

The results for the Bagging classifier are very similar to J48, but in this case no language has a ROC area equal to, or below, a random guess of the threshold. It

[2] Voting is a well-known aggregation procedure for combining opinions of voters in order to determine a consensus, an agreement on a given issue, within a given time frame.

[3] It occurs when the data model fits too closely to the statistical model and causes deviations, normally due to undesirable consideration of measurement errors

	Accuracy	Precision	Recall	F-Measure	ROC Area
Arduino	85.9574%	0.746	0.86	0.799	0.548
Assembly	83.237%	0.711	0.832	0.767	0.504
C	80.6208%	0.78	0.806	0.779	0.784
C++	85.9428%	0.83	0.859	0.828	0.796
C#	84.5313%	0.809	0.845	0.809	0.759
Go	93.057%	0.908	0.931	0.908	0.826
Haskel	85.6658%	0.809	0.857	0.816	0.775
Java	85.99%	0.832	0.86	0.828	0.787
JavaScript	81.2451%	0.786	0.812	0.786	0.786
Matlab	82.9545%	0.795	0.83	0.775	0.698
Objective-C	75.2326%	0.723	0.752	0.722	0.718
OCaml	87.6623%	0.853	0.877	0.854	0.828
PHP	86.2113%	0.848	0.862	0.844	0.854
Python	83.7947%	0.818	0.838	0.815	0.811
R	89.3408%	0.805	0.893	0.847	0.682
Ruby	78.2033%	0.777	0.782	0.777	0.845
Shell	86.7828%	0.843	0.868	0.839	0.763

Table 6.9: Results for Bagging Classifier

must be noted that there has been a great improvement in the classification of Matlab repositories, from 0.486 to 0.698 (regarding the ROC Area).

IBk

The IBk (Instance Based KNN) is a Weka implementation of the K-Nearest Neighbour Algorithm. IBk generates a prediction for a just-in-time test instance which differs from other algorithms which build a prediction model. The IBk algorithm uses a distance measure that relies on k-close instances to predict a class for a new instance. In this way, it computes similarities between the selected instance and training instances to make a decision. The use of cross validation allows this algorithm to select appropriate values of k. Table 6.10 shows the results for this method.

These results were less satisfactory than all the previous methods. There was a marked increase in the randomness of the results, since all the ROC areas are close to

	Accuracy	Precision	Recall	F-Measure	ROC Area
Arduino	74.4681%	0.757	0.745	0.751	0.514
Assembly	75.1445%	0.755	0.751	0.753	0.575
C	72.6342%	0.725	0.726	0.726	0.588
C++	79.0897%	0.788	0.791	0.79	0.581
C#	78.5624%	0.781	0.786	0.783	0.59
Go	88.2069%	0.881	0.882	0.882	0.535
Haskel	81.4249%	0.811	0.814	0.813	0.597
Java	78.1989%	0.781	0.782	0.782	0.571
JavaScript	73.38%	0.731	0.734	0.733	0.587
Matlab	71.5909%	0.749	0.716	0.731	0.539
Objective-C	66.928%	0.67	0.669	0.67	0.576
OCaml	81.4935%	0.797	0.815	0.805	0.549
PHP	82.5709%	0.822	0.826	0.824	0.684
Python	75.0166%	0.749	0.75	0.75	0.591
R	82.0477%	0.833	0.82	0.826	0.568
Ruby	69.5057%	0.694	0.695	0.694	0.661
Shell	77.9006%	0.773	0.779	0.776	0.535

Table 6.10: Results for IBk Classifier

50%. In Ruby, which had featured prominently in other methods, there was a decline in performance for true positives, although it offers a very low value for false positives.

Decision Table

The Decision Table has two main components: a schema and a body. The Schema is a set of features and the body consists of labeled instances defined by the features in the schema [Kohavi 95]. When applied to unlabeled instances, the classifier searches the decision table using the features in the schema to find out in which class the instance will be classified. Table 6.11 shows the results for this classifier.

Again, for languages with few instances, this classifier (tree-based) obtained low values for the ROC area. the ’Go’ language provides a very high degree of Accuracy, but apart from the high TP, it’s FP is still too high, which means that such high rate of Accuracy does not necessarily imply it is a good classification.

	Accuracy	Precision	Recall	F-Measure	ROC Area
Arduino	86.383%	0.746	0.864	0.801	0.473
Assembly	84.3931%	0.712	0.844	0.773	0.47
C	80.3406%	0.774	0.803	0.766	0.748
C++	85.6177%	0.823	0.856	0.819	0.741
C#	84.0479%	0.793	0.84	0.794	0.739
Go	92.9765%	0.9	0.93	0.897	0.744
Haskel	86.0051%	0.821	0.86	0.826	0.715
Java	85.7216%	0.826	0.857	0.82	0.737
JavaScript	81.094%	0.783	0.811	0.773	0.757
Matlab	81.8182%	0.678	0.818	0.741	0.506
Objective-C	75.5686%	0.726	0.756	0.717	0.71
OCaml	86.3636%	0.751	0.864	0.803	0.546
PHP	84.2461%	0.82	0.842	0.817	0.796
Python	83.6061%	0.816	0.836	0.806	0.769
R	89.7616%	0.806	0.898	0.849	0.486
Ruby	71.2021%	0.714	0.712	0.713	0.768
Shell	86.7191%	0.842	0.867	0.841	0.686

Table 6.11: Results for Decision Table Classifier

Multilayer Perceptron

Multilayer Perceptron is an artificial neural network model that use layers between input and output and creates feedback flows between them. It is a logistic classifier that uses a non-linear transformation that has been learnt, by projecting input date into a space where it becomes linearly separable. It is known as a supervised network because it requires a desired output in order to the neural network learn. The results for Multilayer Perceptron are shown in Table 6.12.

In the case of this classifier, only Ruby obtained a satisfactory result. Despite it obtained an Accuracy value of 76% it was the only language where the value of TP was high, different from the others, and higher than FP by obtaining and as a result obtained a high ROC area, of approximately 0.81.

	Accuracy	Precision	Recall	F-Measure	ROC Area
Arduino	86.383%	0.746	0.864	0.801	0.617
Assembly	84.3931%	0.712	0.844	0.773	0.553
C	78.7778%	0.751	0.788	0.697	0.681
C++	85.1365%	0.725	0.851	0.783	0.682
C#	84.195%	0.709	0.842	0.77	0.708
Go	92.9765%	0.864	0.93	0.896	0.612
Haskel	86.0899%	0.789	0.861	0.799	0.733
Java	85.0377%	0.723	0.85	0.782	0.7
JavaScript	79.4293%	0.728	0.794	0.705	0.709
Matlab	81.25%	0.742	0.813	0.757	0.668
Objective-C	73.7767%	0.68	0.738	0.632	0.652
OCaml	85.3896%	0.75	0.854	0.799	0.739
PHP	82.2165%	0.768	0.822	0.744	0.739
Python	80.9655%	0.713	0.81	0.727	0.711
R	89.6213%	0.806	0.896	0.848	0.644
Ruby	76.7576%	0.763	0.768	0.755	0.815
Shell	85.6354%	0.805	0.856	0.79	0.632

Table 6.12: Results for Multilayer Perceptron Classifier

6.5 Discussion of the Results

The main objective in this second phase of our study was to determine which project attributes are most important to determine the success of an OSS project, with a focus on its social dimension. The first results showed it is possible to identify a certain pattern of significance for languages with more than 1000 projects. The attribute evaluation singled out four attributes as being important: number of contributors, number of subscribers, number of commits and size of the project. Most of the classifiers had a rate of accuracy higher than 80% for these projects with acceptable values in the ROC area, of more than 0.5. This shows that it is possible to predict if a project will remain active or becomes dormant in a time-span of two years on the basis of the created classification model. In the case of a few languages, for which had less than 1000 projects, the attribute evaluation was more random, due to the reduced number of samples. The tree-based algorithms were the worst of these cases. They produced very random results, with ROC area values close to 0.5.

When the classifiers were compared, IBk had the worst results, since its classification results were very close to random guess and had a relatively low rate of accuracy. On the other hand, Bagging showed the best results of all of them. It had acceptable results even for the smallest datasets. It should be noted that the comparison between two classifiers should not only be estimated in terms of accuracy. For instance, one classifier may be better than another when it obtains a high ROC area value but lower accuracy values, which makes it more realistic and reliable. Low ROC area value indicates randomness for the classifier and may lead to high accuracy, especially with short-term databases.

The use of data mining techniques to validate software engineering hypotheses about the success of software is addressed in many studies. In [Ramaswamy 12] several clustering algorithms are applied on a set of projects to predict success based on a count of defects. Their findings indicate that K-means algorithms are more efficient than other clustering techniques in terms of processing time, efficiency and reasonable scalability. Similarly, in [Wang 07] it is shown that the success of an OSS project can be predicted by just considering its first 9 month development data with a K-Means clustering predictor at a relatively high rate of confidence.

There are other studies where the authors apply concepts of machine learning to predict how healthy a project is at a given moment of time. In [Piggot 13], the authors claim they used machine learning to create models that can determine with reasonable accuracy the stage a software project has reached. When designing this model they took into account time-invariant variables such as type of license, the operating system the software runs on, and the programming language in which the source code is written. They also included time-variant variables such as project activity (number of files, bug fixes and patch releases), user activity (number of downloads) and developer activity (number of developers per project). The authors validated their model using two performance measures: the success rate for classifying an OSS project in its exact stage and the success rate when classifying a project in an immediately lower or higher stage than its actual one. In all the cases, they obtained an accuracy of above 70% with a “one way” classification (a classification which differs by one) and about 40% accuracy with an exact classification.

Along this line of using concepts from machine learning[4], our extensive set of

[4] It should be stressed that this study is not undertaken in the field of Artificial Intelligence (AI) or

experiments and techniques were very satisfactory. Classification models confirmed that social factors are effectively good predictors of OSS projects' success and it was possible to identify the six more relevant social attributes: number of contributors, number of subscribers, number of commits, project size, number of forks, and number of open issues.

The validity of these observations is constrained basically by the nature of projects, specifically whether they are OSS or commercial/closed source. The fact that we have used only OSS repositories constrains the validity of the results to OSS projects. It is not possible to generalize these conclusions to commercial software, as the voluntary nature of OSS contributions seems to have a determinant impact on the observations. This constraint is an interesting research topic that should be addressed in future studies. In what concerns the validity of data, we think that the large number of projects analyzed, the different programming languages targeted, and the adoption of several different techniques and models safeguard the validity of these results. Finally we should not forget that the *circa* 160.000 projects analyzed were extracted from gitHub, not SourceForge neither any other repository. This creates a significant dependence on the validity/applicability of these results, but due to the significant share of gitHub projects in the contemporary OSS landscape (section 5.2), we think this is clearly a minor threat to the validity of the results.

6.6 Summary

After observing in the first part of this study, that there is relevant maintainability-related information at the source-code that is not present at the more abstract architectural level (e.g. readability, adherence to code-conventions, documentation), we then turned our attention to the social dimension of software structure, and its impact on maintainability. Thus, in this second part of our study we focused on identifying the long-term OSS success predictors, so that light can be shed on the social factors that promote highly maintainable software.

Data Mining. Our aim on using different classifiers was to strengthen our confidence in the results and avoid classifier bias, it was not to compare mining algorithms or models created by them.

Our second hypothesis was that *'social factors play a significant role in the success (longevity) of OSS projects'*. Many decisions had to be made on the basis of well-controlled experiments to validate this hypothesis. These decisions range from the tools used for the extraction of the source-code metrics, from which OSS project repositories should we extract the information, and which programming languages should be selected, among others.

GitHub proved to be the best repository for the validation of this hypothesis. Among the reasons mentioned previously, we highlight the fact that it logs many social attributes and is on the rise in the market and academic world. Hence, the experiments started by analysing 20 projects from SourceForge and GitHub, then went through about 20,000 GitHub projects, and the last experiment collected data from about 160,000 OSS projects in different programming languages.

Although at the end of phase 2 we were very confident that our hypothesis was valid, the experiments performed in phase 3 served to further consolidate our assumptions and do some corrections. Thus, we collected data from projects of seventeen different languages. Then we applied an attribute selection algorithm in order to identify the most relevant attributes. Finally, six classifications algorithm were used in order to identify whether it was possible to classify projects in active or dormant based on these attributes. Moreover, using these models, it was possible to correctly classify such projects with an accuracy of more than 80% and an average high value for ROC area.

The results of these experiments were very satisfactory. Classification models confirmed that social factors are effectively good predictors of OSS projects' success and it was possible to identify the six more relevant social attributes: number of contributors, number of subscribers, number of commits, project size, number of forks, and number of open issues.

Chapter 7

Conclusions and future work

7.1 Scope and constraints

In this thesis we addressed the elusive nature of maintainability and we observed how this quality attribute is a multidimensional entity. On one hand, it has a solid structural dimension, promoted by the modularity of the components that make up a software system. On the other hand, it is also dependent on the human capacity to understand and modify existing source-code. While this later dimension is seldom addressed by software systems' researchers, it is the daily struggle of software professionals. Last but not least, the empiricism of Conway's Law, now a research topic on its own as the 'Mirroring Hypothesis', is starting to shed light on the correlation between architectural software structures with those of the organizations that build them. This third 'social' dimension has also been addressed in this thesis, under the assumption that long-term successful OSS projects are implicitly associated with software possessing high levels of maintainability. Thus, at least on what OSS projects are concerned, the nature of maintainability cannot be fully understood without considering both its structural (technical) dimension, as well as its human and social dimensions. This is the rationale behind our view of maintainability as a socio-technical property of software, which was a direct result of the research path followed along this thesis.

7.2 Research summary

In the first part of this thesis our goal was to understand whether it would be possible to quantify maintainability at an architectural level. This involved validating our first hypothesis, which stated that *source-code based metrics can be adapted to more abstract metrics and applied to assess maintainability at architectural level.*

This lead us to look for a mapping of source-code metrics related to maintainability into equivalent architectural metrics. This endeavour seemed feasible, as source-code is the ultimate reference of software-systems related information. Its architectural description, while more abstract, has necessarily to reflect the source-code structures and dimensions (e.g. complexity, cohesion, coupling).

After proposing a framework to classify software architecture tools in order to be able to map source-code maintainability into the more abstract architectural representation of software (Contribution (i)), we used this framework to compare state-of-art tools, in order to understand how is maintainability addressed by them.

Further, we proposed and assessed a mapping between an architectural description using the COSMIC standard notation and the corresponding source-code originated UML description in order to assess whether it would be possible to extract a meaningful maintainability index from a standardized software architectural description (Contribution (ii)).

Our observations contradicted a common held assumption (Contribution (iii)): while abstract models extracted from source code do reflect code structure, (both at component and interconnection levels) it became evident along our research that the abstraction process applied to source-code lead to a loss of information with meaningful impact on assessing the maintainability of software. It might be enough to refer that e.g. comments and the adherence to code-conventions are missing in architectural descriptions (and so should be). Thus, on what maintainability is concerned, the advantages of abstraction are achieved at the loss of 'low-level' information that is actually needed to fully characterize this software property.

Faced with the understanding that it would not be possible to fully describe this quality attribute only at an abstract architectural level, the end-goal of providing the system architect with a set of tools and recommendations to help her evolve long-term software while preserving maintainability for further evolution, directed us to explore the impact that the social dimension of software development might have on the maintenance capability. This goal was embedded in the second hypothesis explored in this thesis, *Social factors play a significant role in the success (longevity) of OSS projects.*

Thus, in the second part of this thesis we started with a reasonable assumption: that long-term successful projects do need to posses high maintainability properties. This was our axiom, whose demonstration is out-of-scope of this thesis, a topic to be addressed by further research, that served as the foundation to search for predictors of long-term software success. The rationale behind this further research line was that if maintainability has a social dimension, and long-lasting successful projects are characterized by high maintainability, it is of utmost importance to the software architect to understand this dimension so that it can serve as input when evolving a system so that it maintains or improves its maintainability level.

Due to the many factors involved in what characterizes a 'software project success' we tried to be as comprehensive as possible, and performed an extensive study on about 160 000 OSS projects. The use of OSS was a research constraint as we had no other feasible alternative to access such a large number of software projects.

After this extensive study, presented in chapter 6, we concluded that in fact a few 'social' variables (number of contributors, number of subscribers, number of commits, number of forks, number of open issues) were highly correlated with software success (Contribution (iv)). Our conclusions can be informally synthesized as 'lively projects tend to last longer'. Whether this is a cause or a consequence is irrelevant as there is an obvious feedback loop at play: lively projects tend to last longer, and long-lasting projects require a active community to move it forward. On what maintainability is concerned the same feedback loop applies: hard to maintain projects do not attract contributors, and a software system with low community involvement does not benefit from the motivation, neither has the resources to promote an easy to maintain system.

It is meaningful that, from a very different perspective, this same observation also holds: it is well known that long-lasting software projects (both OSS and proprietary), that undergoes successive updates, either to correct defects or add new functionality tend to become brittle, harder and harder to maintain. Indeed, we can observe a significant decrease on the number of ’activity’ and people involved during maintenance, when compared with the development phase.

While these social indicators should not be taken at face value, e.g. it seems unreasonable to enforce meaningless commits to promote maintainability, as it would be unreasonable to nano-decompose a module with the same goal, if used wisely they can actually serve as maintainability indicators and guide software architects –and project managers– to promote maintainability-inducing best practices. However, while structural properties can be directly measured and –to some extend– enforced, the same can not happen with its social dimension. We would say that a project ’successfulness’ predictor should account for both structural and social metrics: on one had the modularity, on the other hand the liveness of its community. If a decrease in activity is perceived, it can be balanced with an increase in structural modularity in order to facilitate the interest of new contributors; on the other hand a reduction on the structural maintainability properties should be addressed by requesting contributors to apply their effort into re-factoring and/or documenting the software so that it improves its ’attractiveness’ to current and new contributors.

We want to believe that the present research is a minor, but relevant step in the perception that maintainability, a paradigmatic ’evolution’ quality attribute –as opposed to ’execution’ quality attributes such as security and performance– can only be fully addressed by considering its multidimensional nature.

We do believe that researchers and practitioners alike have been struggling with the elusive nature of maintainability because it is being addressed either as a people issue (readability, understandability) or as a structural (modularity, complexity) system property. After this study we conclude it is both, and more, there is also a significant social dimension on it, to be fully grasped.

This is one of the major contributions of this thesis, providing evidence that contradict a widespread assumption of the software architecture community: that maintainability –a quality attribute– can be fully described solely at the architectural level.

The second major contribution, a much less hard-based fact as its common in the social sciences, is to highlight the importance that ’soft’ social factors can have on assuring the environment that fosters maintainability. In the end, what practitioners and researches are looking for, are guidelines to identify and monitor the right set of parameters that impact maintainability, irrespective of where they come from. We do believe that our work brought a sound, quantified, contribution to the consideration of maintainability in its multiple dimensions.

7.3 Future work

As part of the research team at Universidade da Pararíba, the candidate keeps working on the topics addressed in this thesis along three complementary research lines:

Coverage of non-OSS projects – as referred above, an immediate follow-up of this research is extending the results for non-OSS projects. It is questionable to state that these results can be extended to commercial and/or proprietary software even if a growing number of companies are using OSS-like software development models. As long as the voluntary nature of OSS is practiced in such contexts, we think these results might be applicable. However, most commercial software have an implicit structure in place that enforces authority and hierarchy as the management paradigm. Thus, while we cannot exclude a-priori that the same observations apply to commercial software, more research inside one or more large software organizations are be needed to conclude sensibly such hypothesis. Having a software factory integrated in the Federal University of Paraíba will provide us with the subjects to initiate such study.

Processualization of Software Evolution – since the work performed along this thesis lead us to understand that socio-technical factors have a considerable impact in maintainability, it should be possible to consolidate such insights into processes supporting architectural and managerial improvements during project evolution. However, we still need to make a more extensive study on how the emergent rules and indicators will be shown to architects and project managers. We will study whether ontology-based semantic annotations can be used as a means of creating flexible, and yet standardized, representations for architectural description languages, as well as supporting BPMN descriptions.

Validation support – the work performed along this thesis also open up new perspectives for validation metrics. Currently our team is designing a tool, *ArchEntropy*, that can support the activities of the software architect. Its main objective is to use the classification model devised earlier to allow an assessment and refinement of the project design in a semi-automatic fashion. This can expose irregularities and pinpoint improvements to be made.

7.4 Concluding statement

Maintainability is only one of the four software evolution qualities, along with testability, extensibility and scalability. Our work has just begun.

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