An Empirical Study Investigating the Predictors of
Software Metric Correlation in Application Code and Test
Code.

by

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A thesis submitted to the Faculty of Graduate and Postdoctoral
Affairs in partial fulfillment of the requirements for the degree of

Master of Applied Science

in

Electrical and Computer Engineering

Carleton University
Ottawa, Ontario

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Abstract

On non-trivial software, the large test code base needs adequate maintenance similarly to the application code. It has often been argued that test code should be simple, some authors even arguing that a test script should be reduced to a single control flow. If this is indeed what happens in practice, then we believe test code maintenance will be very different from application code maintenance, despite the fact that both are source code. Using a number of large open source software, we compare application code and test code by using a series of well-known source code complexity metrics. The results reveal that application code is, as expected, more complex than test code but not necessarily so much more complex. The study also confirms the assertion that test code is not as simple as it should be, at least as advocated in textbooks, and may therefore be very complex to maintain.

Using complexity metrics to determine the difference, our findings also reveal that, the kind of code determines the extent of monotonicity between the number of lines of code (LOC) and cyclomatic complexity (CC). While a number of authors hypothesize and experimentally confirm that CC has a very strong correlation with LOC, justifying the use of LOC in place of CC (and Halstead Effort), we believe that this strong correlation is prevalent only in production code as results from test code prove otherwise. In test code, there exist a very weak (or almost no) correlation between (a) LOC and CC, (b) Halstead Effort and CC, and (c) LOC and Halstead Effort. We therefore argue that the level of correlation depends on at least three factors namely: the kind of code, the kind of software and the kind of metric. Therefore, we believe it would be inappropriate, without considering these factors to substitute one metric with another using some generalized correlation hypothesis. The results gained thus far contradict the notion that some metrics are correlated (that is if the right factors are not considered).

Given the weak monotonicity between CC and LOC, CC and Halstead Effort for test code, we disagree that CC and Halstead metrics are redundant as some studies suggest. Rather, we advocate for the use of CC over LOC (or both or cyclomatic density) due to numerous advantages CC has over LOC such as the fact that CC is perceived to better reflect cognitive complexity, numerical complexity, adequacy of testing, interdependency and code refactoring that cannot be accounted for simply by LOC.

Acknowledgements

One great discovery of climbing mountains and winning battles is the realization of even greater mountains to climb and tougher battles to win. In doing so, we are faced with hard choices; one of which is flinching back, to the very least. The true test of our resilience is in our ability to ultimately win and endure climbing higher mountains. Without which many have lived their lives not having ever lived.

I am therefore grateful to Almighty God that this project is finally completed. A few years ago, a bleary-eyed stare at what lies in the future was unassuring, but the joining of the dots as time went on gives us this delight to be forever grateful and an assurance to be hopeful.

I owe special thanks most of all, to my supervisor, Prof. Yvan Labiche. Such a great inspiration. Everything he does, from what is believed to be conceptually complex to the least significant, are tackled with a great deal of perfection and a high level of academic proficiency. A mentor, a father, and a friend. You only get better by heeding to his advice. Very helpful, insightful and full of brilliance. I am privileged to work with him.

It was a great pleasure to collaborate with Prof. Natalia Stepanova at the School of Mathematics and Statistics for sharing ideas on complicated topics when organizing my thoughts on statistical principles and methodologies.

I feel so favored to enjoy special treatment from Jennifer Poll, Jenna McConnell and Darlene Hebert. Many thanks to them and members of the Department and Faculty. I am indebted to the many individuals who generously and without hesitation, supported in various ways.

The last stages of my masters had turmoil moments, to say the least. Thankfully, I had my fair share of great and reliable people who stood with me. A mentor Mr. George Cole, my sweetheart and good friend Abigail Oduro and a brother Eric Obeng.

I am grateful for the support and encouragement from my family, Samuel Afriyie, Mercy Afriyie and Isaac Afriyie. Where water fails, blood sticks better. I love you.

Table of Contents

Chapter 1 INTRODUCTION	1
1.1 Contribution of this Study	3
1.2 Summary of This Research	4
1.3 Organization of this Document.....	5
Chapter 2 RELATED WORK.....	6
Chapter 3 BACKGROUND INFORMATION	11
3.1 Cyclomatic Complexity, Lines of Code and Halstead Metrics.	11
3.2 On the Use of Maintainability Index	12
3.3 Measuring Correlation.....	13
3.3.1 Spearman’s Correlation Coefficient.....	14
3.3.2 On Pearson’s Correlation Coefficient	15
3.3.3 Kendall’s Correlation Coefficient	15
3.3.4 Conclusion on correlation tests	16
3.4 Test for Normality: Anderson Darling Test, Shapiro-Wilk, D’Agostino K-squared, Kolmogorov Smirnov	17
3.5 Homogeneity of Variance: T-Test and ANOVA.....	18
3.6 Statistical Analysis – Wilcoxon Rank Sum Test	19
3.6.1 Kolmogorov Smirnov Tests	20
Chapter 4 EXPERIMENTAL DESIGN	21
4.1 Selected Applications and Rationale	21
4.2 Measurement tool	24
4.3 Selected metrics.....	25
4.4 Selection of Statistical Methods	26
Chapter 5 RESULTS (ANALYSIS OF DATA)	28
5.1 Statistical Analysis of Extracted Data	28
5.1.1 Descriptive statistics on Lines of Code	28
5.1.2 Descriptive statistics on Cyclomatic Complexity	35
5.1.3 Descriptive statistics on Using Distributions, Graphs and Average Values for Cyclomatic Complexity.....	38
5.2 Inferential Statistics	54
5.3 On the Use of Non-Parametric Statistical Tests	57

5.4	On Correlation among Software Metric	59
Chapter 6 THREATS TO VALIDITY		65
Chapter 7 CONCLUSIONS		68
REFERENCES.....		71
APPENDICES		76
Appendix A Distributions of cyclomatic complexity values for objects.....		76
A.1	Sample representative distributions	76
A.2	Boxplots for all objects	78
Appendix B : Linear Scale Zoomed In On The Left Quadrant		80
B.1	Linear Scale Linear Scale Zoomed In On The Left Quadrant (Production Code)...	80
B.2	Linear Scale Zoomed In On The Left Quadrant (Production Code).....	85
Appendix C : Exporting Metric Values Using Scitols Version 4.0		90
C.1	Analyze Files or Directories Using SciTools Understand.....	90
C.2	Exporting Metric Summaries	93
C.3	Collecting General Metric Values about Code	93
C.4	Collecting more detailed Metric values for Different Programming Languages	94
C.5	Ancillary Metrics	96
Appendix D NORMALITY TEST USING SHAPIRO-WILK		97
Appendix E Collecting data from Understand.....		98
E.1	Export Metrics Using SciTools Understand Version 4.0	98
E.2	Basic Metrics with Methods Calls and Halstead using A Script.....	98

List of Tables

table 1. References Of Case Study Software Being Studied	23
Table 2. Simple Metric Values For Software Objects	32
Table 3. Metric Values (Cyclomatic And Halstead) For Software Objects	41
Table 4. Maximum Cyclomatic Complexity And Median Values, Results For Wilcoxon's Rank Sum Test, And Kolmogorov Smirnov Test.....	53
Table 5. Correlation Coefficient, P-Values And Statistic For Comparing Cyclomatic Complexity And Lines Of Code	63
Table 6. Correlation Of Loc Vs Cc And Cc Vs Halstead Effort For Test Code.....	64
Table 7. Normality Test For Shapiro-Wilk.....	97

List of Figures

Figure 1. Distribution of cyclomatic complexity values for Apache Httpd AC	39
Figure 2. Distribution of cyclomatic complexity values for Apache Httpd AC	76
Figure 3. Distribution of Cyclomatic complexity values for Apache Httpd TC (logarithmic scale)	76
Figure 4. Distribution of cyclomatic complexity values for JFreechart AC (logarithmic scale)	77
Figure 5. Distribution of cyclomatic complexity values for JFreechart TC (logarithmic scale)	77
Figure 6. Box Plot of CC for objects with method CC values in range [1, 100].	78
Figure 7. Box Plot of CC for objects with method CC values in range [1, 500].	78
Figure 8. Box Plot of CC for objects with method CC values in range [1, 1000].	79
Figure 9. Box Plot of CC for objects with method CC values in range [1, 10000].	79
Figure 10. Scatter Plot of LOC (x) vs CC (y) for Amorok, zoomed into the bottom left quadrant.....	80
Figure 11. Scatter Plot of LOC (x) vs CC (y) for Curl, zoomed into the bottom left quadrant.	80
Figure 12. Scatter Plot of LOC (x) vs CC (y) for Dita, zoomed into the bottom left quadrant.....	81
Figure 13. Scatter Plot of LOC (x) vs CC (y) for Handbrake, zoomed into the bottom left quadrant.....	81
Figure 14. Scatter Plot of LOC (x) vs CC (y) for Hibernate, zoomed into the bottom left quadrant.....	82
Figure 15. Scatter Plot of LOC (x) vs CC (y) for Hibernate ORM, zoomed into the bottom left quadrant.	82
Figure 16. Scatter Plot of LOC (x) vs CC (y) for Notepad++, zoomed into the bottom left quadrant.....	83
Figure 17. Scatter Plot of LOC (x) vs CC (y) for Onion, zoomed into the bottom left quadrant.....	83

Figure 18. Scatter Plot of LOC (x) vs CC (y) for VLC, zoomed into the bottom left quadrant.....	84
Figure 19. Scatter Plot of LOC (x) vs CC (y) for Open XML (PC), zoomed into the bottom left quadrant.	84
Figure 20. Scatter Plot of LOC (x) vs CC (y) for Amorok (TC), zoomed into the bottom left quadrant.	85
Figure 21. Scatter Plot of LOC (x) vs CC (y) for Curl (TC), zoomed into the bottom left quadrant.....	85
Figure 22. Scatter Plot of LOC (x) vs CC (y) for Curl (TC), zoomed into the bottom left quadrant.....	86
Figure 23. Scatter Plot of LOC (x) vs CC (y) for Handbrake (TC), zoomed into the bottom left quadrant.	86
Figure 24. Scatter Plot of LOC (x) vs CC (y) for Hibernate ORM (TC), zoomed into the bottom left quadrant.....	87
Figure 25. Scatter Plot of LOC (x) vs CC (y) for Hibernate (TC), zoomed into the bottom left quadrant.	87
Figure 26. Scatter Plot of LOC (x) vs CC (y) for Notepad ++ (TC), zoomed into the bottom left quadrant.	88
Figure 27. Scatter Plot of LOC (x) vs CC (y) for Onion (TC), zoomed into the bottom left quadrant.....	88
Figure 28. Scatter Plot of LOC (x) vs CC (y) for Open XML (TC), zoomed into the bottom left quadrant.	89
Figure 29. Scatter Plot of LOC (x) vs CC (y) for VLC, zoomed into the bottom left quadrant.....	89
Figure 30. Naming a new Project in Understand.....	90
Figure 31. Selecting Source Code Languages Understand should Export	91
Figure 32. Choosing How to Import Files and Settings.....	91
Figure 33. Add Project Directory for Analysis in Understand	92
Figure 34. Complete the Project Configuration and Settings for Analysis.....	92
Figure 35. Analysing and Extracting Source Code Information in Understand.	93
Figure 36. Exporting Metrics Summary for Source Code	94

Figure 37. Browse Detailed Metric Summary for Source Code	95
Figure 38. Extracting Detailed Metrics for Specific Programming Languages.....	95
Figure 39. Extract Ancillary Metrics from Understand.	96
Figure 40. Specifying file paths to Run a Script Using Command in Understand	99

Chapter 1 INTRODUCTION

In the past years, there has been reports and intense research activities on the relevance of test code and its positive impact on code quality in the software development. Schemes, hypothesis, and many algorithms have been developed to well maintain software. Verification of software by means of testing is the most common situation. On non-trivial software, software testing leads to a lot of test code. Depending on the context, anecdotal evidence indicates that one often needs to create one line of code (LOC) of test code for every LOC of application code and that this ratio can sometimes reach 1.5 or even in specific (e.g., safety critical applications) cases, four: in summary, one to four LOC of test code for every LOC of application code being tested. This large test code base needs maintenance, similarly to application code.

To adequately maintain test code, we need to understand it. Some authors argue that test code should be as simple as possible, sometimes limited to one straight sequence of statements (no control flow structure) [41], though this is not necessarily the case in practice. Additionally, test code can be expected to follow specific templates, the most common one being that a test case should include a set-up, some execution of the piece of software under test, some collecting of data for the oracle, an oracle assertion and a tear down. Last, some test cases are written with open source frameworks, such as xUnit, JUnit and the like, given their code a rather specific structure.

Maintaining application code often involves source code analysis techniques such as code smells or clone detection, which can lead to some refactoring of the code when this is warranted. Given the hypothesized differences mentioned above between application code and test code, we argue test code maintenance may look different to application code maintenance. For instance, assuming test code is indeed less complex than application code to the extent that a test code method is nearly a linear sequence of un-interrupted statements (no control flow), then a maintenance procedure that would prioritize refactoring based on high cyclomatic complexity values or the presence of for-loop statements (which have been shown to be less understandable than if statements [43]) would not be able to discriminate test methods and would be useless (i.e., the distribution of complexity values to prioritize from is flat). If, when maintaining test code, one wants to extend empirical results obtained by studying application code, for instance, to deploy some application code maintenance

techniques which have proved to be successful on application code, one must first evaluate whether test code is sufficiently similar to application code. (Note that this notion of similarity will need to be clarified and will necessarily be specific to the maintenance technique being considered. This kind of study is out of the scope of this work.)

This study is a first step towards identifying to what extent test code differs from application code. We stress here that this is a first step because we decided to focus on open source applications we collected online, and that we consider only one aspect of complexity as measured by standard metrics. Also, we do not distinguish between the different kinds of tests (e.g., unit/integration/system testing, functional/non-functional testing), which may also likely affect the linearity of the correlation of complexity metrics; for instance one may expect a unit test to likely be a linear sequence of statements whereas a non-functional (e.g., stress) test may require a complex set-up with complex control flow.

The results we discuss in this paper may therefore not (entirely) apply to industry software. We indeed expect industry code to lead to different results for two reasons (among others): the ratio test code LOC over application code LOC is likely higher in industry than in open source (e.g. we believe a 4:1 ratio is unheard of in open source whereas this is relatively common in industry, at least with the private organizations we engage with); some industry developed their own version of a test execution infrastructure that does not necessarily resemble xUnit, JUnit and the like, whereas these framework, that give a specific structure to test code, are pervasive in open source.

To identify whether and to what extent test code differs from application code, we turned to source code complexity metrics which have been shown to relate to maintenance tasks, source code understanding ... [3]. In this study, we therefore ask: How do application code and test code differ according to standard code complexity measures? How do these complexity software measures relate? If they do, to what extent are they related?

In the past years, there has been reports and intense research activities on software complexity, code maintenance and metric correlation using well-known metrics such as Cyclomatic complexity, Halstead metrics and Lines of Code, to predict code quality, bug proneness, and code maintenance, and this took place largely on production Code [66]. On the use of metrics such as Cyclomatic complexity, Lines of Code and Halstead Effort, numerous studies have been conducted to predict the extent to which some metrics are

correlated, and that, should they do, it would suffice to use one in place of the other(s). While these experimental results confirm some correlation, as confirmed by our results, this is somewhat specific to production code and not necessarily test code. Not much research has studied whether these metrics correlate also for test code. In our study, our investigation reveals that this hypothesis only holds when considering production code as it is the exact opposite in test code. We hypothesize that, the correlation that exist between some metrics does not merely depend on the type of metrics (size, complexity, cohesion, and coupling), rather, it depends more on the kind of software (open source application or industry application), and the kind of code (production code or test code).

One critical challenge that numerous studies and hypothesis [47], [48], [49], [50], [51] have not explored on correlation of metrics is the factors that affect the correlation being: the kind of code, the kind of software and the kind of metric. This is evident in the large-scale software study conducted by Landman and colleagues [49], the work of Maine and Miguel [47] and many others. The 1.2 million source files of C/C++ and Java production code analysed by Graylin and colleagues [51] present a verifiable evidence of a stable relationship between Lines of Code (LOC) and cyclomatic complexity (LOC) but lacks an analysis for test code and a quintessential lucid justification for advocating for the use of LOC over CC. Landman's work is limited to only Java methods, which is not a reflection of all programming languages. Also on Landman's work, the idea of data transformation is very arguable and does not reflect the authenticity and originality of the data collected. While we do agree that it really makes sense to transform non-normal data to a normal one, we are skeptical (disagree) with the results it produces as this can be very misleading [51], [52]. In addition, on the issue of normality, Landman presents a series of results gained from a transformed non-normal distribution, using parametric tests on the transformed data, which though this is a procedure accepted in the field, seems inappropriate and misleading. In our work, we investigate their claim by extending the work to 667,868 methods of 40 open source software applications and five Industry applications written in C, C++, C#, Python and Java.

1.1 Contribution of this Study

This research provides a unique contribution to test code maintenance by advancing the understanding of how Application Code and Test Code Differ. Previous literature

hypothesises a low complexity for test code and suggests test code should be as simple as possible, sometimes limited to one straight sequence of statements (no control flow structure). In contrast, our research shows this is not necessarily the case in practice. This research provides a fresh insight and clarity on the correlation of software complexity metrics. This study advances the theory of correlation by demonstrating that the strong correlation between complexity metrics (LOC, CC and Halstead metrics) is not a characteristic of the metrics but rather appears to depend on the kind of source code one measures. This research introduces the idea that the perceived strong correlation is only prevalent in application code and not test code and industry code. The degree of correlation relies on three factors namely: the kind of code (application vs. test code), the kind of software (obtained from an industry partner or online/open source) and the kind of metrics (LOC, CC, Halstead).

1.2 Summary of This Research

This thesis contributes to software maintainability and ways of analyzing application code and test code. In this study, we learn that:

- When measuring the extent of software complexity, Application Code is more complex than Test Code;
- Test Code is not as simple as it is supposed to be and can be extremely complex;
- The correlation between software metrics depends on factors such as the kind of software (open-source vs. industry), the kind of code (application vs. test code) and the kind of metric (LOC, CC, Halstead);
 - a) We confirm that there is a correlation between LOC, CC and Halstead Effort, however, this is only prevalent in application code
 - b) We identify that there is no such correlation for test code and therefore, the notion of correlation of LOC, CC and Halstead effort does not apply here.
 - c) The correlation for test code drops even further as we explore industry applications.
- Attempting to substitute one source code complexity metric with another should take into account the factors that affect the level of correlation between these metrics.

1.3 Organization of this Document

The remainder of the thesis is structured as follows. In Chapter 2, we investigate the depth of related work. We provide background on source code metrics and statistical analysis in Chapter 3. Chapter 4 describes the experiment we conducted. 0 discusses results. We discuss threats to validity in Chapter 6 and conclude in Chapter 7.

Chapter 2 RELATED WORK

A large number of authors have published on issues relating to software metrics largely due to their relevance when evaluating the quality of a piece of code. While we find most of them useful, not many have addressed salient issues regarding the extent of complexity that exist between different software artefacts. A select few of the several closely related studies are considered in this research work to gain a good understanding of the different facets of software quality, metric correlation and code complexity.

Related work in our context pertains to three different topics: (a) complexity measurement of code, including test code, (b) the correlation of complexity metrics and (c) the relative complexity of test code and the application code it tests.

We have not found any piece of work in our literature search on the Scopus database that discusses whether test code tends to have a different complexity than the application code it tests. There exist works on different notions of test quality, but these only look at test code, independently of the application code it tests. For instance, authors have discussed test patterns, that is, good design principles to code tests [39]. Others have tried to estimate test quality by considering the presence of assertions in code and the structural coverage of the application code achieved by the tests, among other things, thereby moving beyond the mere measurement of structural coverage of application code achieved by tests [40].

This chapter is not meant to be a systematic literature review or systematic mapping study about source code metrics, their definitions, their use... Instead we intend to report on a number of salient pieces of work which will shed some light on what we are doing and why.

Regarding code complexity, a plethora of source code metrics have been defined over the years [3]. Some are very simple, such as counting the number of lines of code (LOC), i.e. not counting comments and blank lines, or the number of lines of comments. Some are more complex to compute though there is tool support, such as the cyclomatic complexity. We can evaluate source code by collecting metric values for McCabe's cyclomatic complexity, Halstead's Effort, Difficulty, and Maintainability index, and other metrics such as the number of methods, the number of classes (in an object-oriented software) or the number of lines of code [33].

Through a systematic mapping study of 226 studies published from 2010 to 2015, Nuñez-Varela and colleagues show that some of the most used software metrics that are used to study various software engineering activities include Lines of Code (LOC) and cyclomatic complexity (CC), when one omits the metrics that are not common to different paradigms (e.g., after removing object-oriented metrics) [3].

Over the past decades, Cyclomatic Complexity (CC) has gained more attention in literature and has proven useful as a heuristic means of analyzing the cognitive complexity of a piece of code [3] rather than the traditional use of numerical complexity values reported by its counterpart, Lines of Code.

While some authors envision Cyclomatic Complexity as a tool to test the complexity of a source code, others focus on the use of traditional Lines of Code (LOC) as a better and much easier substitute to Cyclomatic Complexity due to the strong correlation that has been reported to exist between the two code quality metrics. We also note that there is an ongoing, unresolved debate about the usefulness of the Cyclomatic Complexity metric. While numerous research studies (e.g., [43], [44], [45], [48], [50]) have argued in favor of the existence of a strong correlation between Cyclomatic Complexity and Lines of Code, and therefore advocate for the use of only one of them, namely LOC because it is simpler to compute, some authors on the contrary claim that the correlation between CC and LOC is only moderate when the source code is analyzed in modules rather than as an aggregate unit (larger program) [49], [51] as claimed by the former. Though our intent is not to settle the ongoing debate, we, however, investigate these claims for application code and test code at the method level (lowest level of granularity for complexity metrics) and as an aggregate unit using large open source applications written in multiple programming languages to verify the validity of the claim for those two different kinds of code. We investigate the possible reasons for these claims, what is missing in the experiment leading to these varying hypotheses and what contributes to the differences in their outcomes.

Through the analysis of 1.2 million files written in C, C++ and Java, Jay and colleagues discover a strong linear relationship between Cyclomatic Complexity and LOC [51], to the extent that the authors argue the two metrics may likely be measuring the same source code complexity characteristics.

Meine and Miguel [47] investigate C and C++ programs under four common metrics (Lines of Code, Lines of comment, Halstead Effort, and Cyclomatic Complexity) using distribution graphs and density plots of LOC/Halstead Volume and LOC/CC. They find Lines of Code and Halstead Volume to be strongly correlated, and a higher (an even stronger) correlation between Cyclomatic Complexity and Lines of Code.

Similarly, Meulen and Revilla find that the Cyclomatic Complexity and Halstead volume metrics are correlated to LOC but not correlated to software dependability metrics [23].

Graylin and colleagues [51] strongly disagree with the reasons some practitioners prefer to use CC in place of LOC. Rather, they advocate substituting CC with LOC due to the perfect and stable linear relationship between CC and LOC across all platforms (C, C++, Java) they observe on 1.2 million source files randomly selected on SourceForge. With five select projects (from NASA), they justify the necessity of statistical analyses like distribution of variance and Persons Correlation coefficient in measuring the distinction between the two metrics. The work though presents a strong correlation between CC and LOC, however it claims CC but does not lay any strong justifiable reason why LOC should be preferred over CC as they believe CC and LOC measure the same property – which to some extent, is very arguable as CC rather presents a more convincing complexity measure that is helpful in cognitive complexity, numerical complexity, adequacy of testing, interdependency and code refactoring that cannot be accounted for simply by LOC. . With no clear justifiable reasons given, one could as well argue in favor of CC with the same set of data and analyses made, justifying why CC should be used instead, for a variable number of reasons, due to the strong correlation. The presence of a correlation between certain kinds of seemingly related software metrics does not always guarantee a substitution as they measure different properties. For example, Lines of Code may help in determining the number of test cases for 100% statement coverage and not branch coverage. Cyclomatic complexity on the other hand due to the number of linearly independent paths it measures, predicts the number of test cases need for 100% decision coverage which implies 100% branch coverage and 100% statement coverage. The same is for the cognitive complexity where the conceptual difference in understanding two different 100-line code with different CC makes CC a better substitute. These and many reasons, just to name a few.

Adnan and Enoiu [50] address the issue of complexity metrics and software testing and in their study, investigate whether the number of test cases in a test suite and the amount of time it takes to execute (test effort) are correlated with the software metrics they selected, on safety-critical industry control software. They report a moderate correlation between test effort and software complexity metrics (LOC, CC, Halstead complexity (HC) and Information Flow Complexity (IFC)). Also the size of a software highly affects the amount of test cases and execution time and therefore, directly affects the test effort required to maintain the software.

All these studies [43], [44], [45], [48], [50] report similar finding to what has already been said earlier, that is Lines of Code (LOC), cyclomatic complexity (CC) and Halstead Effort (HE) are correlated.

Henry and colleagues [46] in their measurement of the correlation between three complexity metrics, specifically Cyclomatic complexity, Halstead Effort and Henry and Kafura's information flow, observe CC and Halstead effort are linearly related whereas Henry and Kafura's Information flow is regarded as an independent complexity metric. Using a single UNIX Operating System as the sole case study, the results are somehow challenged due to the limited number of case studies presented in the paper and the exclusive use of correlation coefficient.

In another study [44], Abdullah Al Mamun and colleagues establish the relationship (inter-relationship and intra-relationship) between 25 software metrics, classified into size, documentation, complexity and duplication related metrics, in an empirical study on 20 open source software with 9,572 revision, from eight "well-known" companies. Results indicate a high correlation among size related metrics. Complexity related metrics and Documentation related metrics on the other are not as strongly correlated among themselves (intra-relationship), within the same category as they are with size related metrics. Duplication related metrics are more correlated with themselves (intra-relationship) than with metrics of other domains (inter-relationship).

Abdullah Al Mamun and colleagues use 21 open source applications to determine whether the hypothesized four different types of measurement (*cumulative*, *organic*, *density* and *average*) used in software correlation have some sort of influence on the correlation of the metrics they selected for these types [45]. The collinearity and correlation of software

metrics in a given project is strongly affected by the measurement approach being used. In their study, they identify the four categories of measurement that is “cumulatively”: a measure of the running sum of various revisions or commit of a single project whereas “organic” to describe a measurement where a single revision is taken into account and, if necessary sometimes, compared with previous versions. “Density” is a description of the per unit ratio of a given metric; for instance:

$$Comment_line_density = \frac{number_of_comment_lines}{LOC + number_of_comment_lines} * 100$$

$$Cyclomatic_Complexity_density = \frac{Cyclomatic\ Complexity\ (CC)}{Lines\ of\ Code\ (LOC)}$$

An “Average” gives the mean values of a given metric.

These results are somewhat refuted by the analysis of millions of Java and C functions conducted by Landman and colleagues [34]; the authors conclude that the relationship between Cyclomatic Complexity and LOC is not that strong and argue in favor of using the two metrics.

Chapter 3 BACKGROUND INFORMATION

In this chapter, we delve into software complexity metrics and common procedures for measuring and analyzing scientific data including statistical methods, metric correlation coefficients, normality tests and analysis of variance (homoscedasticity). We also describe the relevance of normality assumptions and its significance when constructing reference intervals and the choice of statistical procedures (parametric and non-parametric tests).

3.1 Cyclomatic Complexity, Lines of Code and Halstead Metrics.

Cyclomatic complexity (CC) is a well-known complexity measure and has proven useful as a standard metrics [3] for analyzing the cognitive complexity of a piece of code. It is often mentioned with Lines of Code and Halstead Effort.

The Cyclomatic Complexity [1] takes the approach of measuring the number of linearly independent paths in the code to determine its complexity. Linearly independent paths in the code are due to control flow structures such as if statements and loops. The Cyclomatic Complexity, denoted $V(G)$, of a piece of code represented by its control flow graph G with n vertices, e edges and p connected components is: $V(G) = e - n + p$. Code with a low Cyclomatic Complexity value has shown to be more stable than code with a high Cyclomatic complexity value [5]. Some authors provide guidance about the use of this metric [5]: A Cyclomatic Complexity value between 1 and 10 represents code that is simple, easy to test and modify with few risks due to the low number of paths and conditional statements; A Cyclomatic complexity value between 11 and 20 is for a piece of code that is understandable, maintainable and testable at a moderate level of risk; A Cyclomatic Complexity value between 21 and 50 represents code that is highly risky to maintain, test and modify; A cyclomatic complexity value above 50 means a practically unmaintainable piece of code.

Halstead instead envisions complexity [60] in terms of difficulty, effort needed to understand, algorithmic volume, by considering the number of distinct operands and operators. The program volume, V , is a measure of the (algorithmic) size of the program, and is defined as follows: $V = N_1 + N_2 \log_2(n_1 + n_2)$; where n_1 is the number of distinct operators, n_2 is the number of distinct operands, N_1 is the total number of occurrences of operators, and N_2 is the total number of occurrences of operands. The difficulty of handling

a program, D , is measured as: $D = \frac{n_1}{2} * \frac{N_2}{n_2}$. The Effort (E) required to understand the logic and algorithmic implementation of a program is given as a product function of the difficulty and the volume: $E = D * V$. Last, the Maintainability Index (MI) is calculated in terms of Halstead Volume, McCabe Cyclomatic Complexity and Lines of Code:

$$MI = 171 - 5.2 * \ln(V') - 0.23 * V(G)' - 16.2 * \ln(LOC') \\ + 50 \sin \sqrt{2.46 * RatioCommentToCode}$$

The choice on metrics is to construct a composite metric that factors the density of operators and operators (Halstead Volume), the logical complexity of code (cyclomatic complexity), the size of the code (Lines of Code) and the amount of comments [77].

3.2 On the Use of Maintainability Index

Maintainability index is a single-value index that measures the relative ease of maintaining a piece of code using a factored formula of Halstead Volume (V), Lines of Code (LOC) and cyclomatic complexity (CC) proposed by Oman and Hagameister [75]. In the estimation of Maintainability Index (MI) using regression models, Coleman-Oman [72] introduces the number-of-comments parameter in the Maintainability index equation and proposes a more satisfactory model (Model 2) [74] due to the sensitivity of the initial model of MI (Model 3, proposed by Oman [72], [75]) to large amounts of comments. This behavior has the tendency of increasing the Maintainability index especially for a small piece of code heavily doped with a large block of meaningful (relevant) comments. The introduction of a “threshold” value of 50 and the average comment lines per module (perCM) corrects this defect. In using the formula in Model 2, we observe a sinusoidal curve with an upper and lower limit of ± 50 . Welker and Oman [76] advocate using regression models 1 and 2 while ensuring that assumptions of using any [74] are satisfied (explained later). Aldo Liso [74] contributes to this by introducing a constant, K (in the Model 4 variant) that accounts for the peaks, decreasing paths, and the function path. Model 4 (a recent study) is a variation of Model 2 that introduces the multiplicative constant K for issues addressed in [74].

$$MI_1 = 171 - 5.2 \ln(V') - 0.23 V(G)' - 16.2 \ln(LOC') \quad (1)$$

$$MI_2 = MI_1 + 50 \sin \sqrt{2.46 \text{perCM}} \quad (2)$$

$$MI_3 = 171 - 3.42 * \ln(E') - 0.23 * V(G)' - 16.2 * \ln(LOC') + CM' \quad (3)$$

$$MI_4 = MI_1 + 50 \sin \sqrt{K * 2.46 \text{perCM}} \quad (4)$$

Where V' is the average Halstead Volume

$V(G)'$ is the average extended cyclomatic complexity

LOC' is the average Lines of Code.

perCM is the average percent of Lines of Comment per Module.

E' is the average Halstead effort and

CM' is the average number of comments per submodule or method.

MI_2 is a variant of MI relevant for situations where comments are an essential part of the code especially for code that is heavily loaded with such comments. It is important and worth noting the selection of MI more depends on the amount of comments contained in the code. For a piece of code with no comments or whose comments do not contribute to in any form to the code, MI_1 suffices. Else, MI_2 is recommended in all cases where comments are likely. Assumption of Model 2 are listed in [74][77]. Coleman and Oman [73] present thresholds for interpreting the results obtained for MI defined as:

$MI < 65$ as poor maintainability (difficult to maintain),

$65 \leq MI < 85$ as fair or moderate maintainability, and

$85 \leq MI$ as excellent maintainability.

A high value of MI (above 85) suggests a code with better maintainability while that below 65 is believed to be difficult to maintain. At this point it is right appropriate to observe the maximum, minimum, average CC and Halstead Volume (V) and compare with the MI if, perhaps, there is some sort of coherence in the level of complexity (as the polynomial of MI uses CC and V). The nature of the sinusoidal curve of the polynomial presented in the regression model 2 makes it is possible to have the median, mean and max MI values larger than the overall MI as the value depends on the variation of the values for the parameters (that is V , $V(G)$, and LOC) of the logarithmic function of MI.

3.3 Measuring Correlation

We first discuss separately three of the main correlation statistical tests and then conclude on their respective advantages and drawbacks. In this section, we explain some statistical concepts and provide useful information on Spearman's correlation coefficient in 3.3.1, Pearson's correlation coefficient in section 3.3.2, Kendall's correlation coefficient in section 3.3.3 and conclusions on correlation tests in section 3.3.4.

3.3.1 Spearman's Correlation Coefficient

In a quantitative analysis, the Spearman's Correlation, a non-parametric method, is used to establish whether a monotonic relationship exists between non-normal bivariate datasets using their ranked values. It measures the strength and the direction of the relationship to derive a correlation between the two variables. It requires ordinal data, interval variables with monotonic association. It is robust against outliers, skewed distributions, continuous data and cases where the assumptions of the widely used Pearson's coefficient are violated [55]. On a bivariate dataset it assigns ranks to one variable ignoring the others and vice versa to deduce what is known as the Spearman's rho, denoted by r_s .

The strength of the correlation measured is in the range of $-1 \leq r_s \leq 1$, where r_s represents the correlation coefficient [57]. A value of +1 indicates positive monotonic correlation (a perfect positive monotonic relationship), -1 represents negative monotonic correlation (a perfect negative relationship) and 0 represents no monotonic correlation. The closer the value is to +1 or -1, the stronger the monotonic correlation. Apart from these extreme cases, we need to describe the extent of correlation by a given r_s value. Prion and Haerling [56] describe a correlation coefficient in range [0.81, 1.00] as very high, range [0.61, 0.80] represents a high degree of correlation, range [0.41, 0.60] represents a moderate degree of correlation, range [0.21, 0.40] indicate a weak correlation and values that lie below 0.29 are regarded as small or negligible correlation.

The outcome of the relationship is grouped under three main categories [58]:

- Positive monotonic correlation—a correlation exists, as a positive increase in one variable causes a proportional increase in the other (or has a tendency to also increase);
- Negative monotonic correlation—for every positive increase in one variable, the other variable decreases or has a tendency to decrease proportionally;
- No correlation—This consist of a random set of values as regardless of any operation done on one variable, the other variable neither tends to increase nor decrease.

3.3.2 On Pearson's Correlation Coefficient

Pearson's Correlation is used to establish a linear relationship on a pair of independent variables. The correlation coefficient is used as a measure of the strength of the relationship given by the Pearson's R. It is usually used as a statistical measure on paired data to identify whether a linear relationship between two datasets exists using a line graph to represent the data. Pearson's correlation attempts to draw a line of best fit based on the data given, to measure the extent to which the homoscedastic (equal variance) pair of independent variable are close to or far from this line. The coefficient, R-value, is generated by dividing the covariance of the two variables by the product of their standard deviations. It should, however, be noted that this value, R, is not the same as the slope of the line in the line graph (or of the line of best fit). Richard Taylor outlines the interpretation of the degree of correlation in [59]: A value of R in range [0, 0.35] indicates a weak or low correlation, range [0.26, 0.67] indicates a moderate correlation, range [0.68, 0.89] indicates a strong correlation and range [0.90, 1] indicates a very high correlation.

Pearson's correlation requires that the two samples are bivariate [53], [55], normal, and dichotomous [54]. The Pearson's correlation test is sensitive to skewed distributions and outliers [52] and is not appropriate for non-normal and ordinal data as it may then lead to misleading [54] conclusions.

When attempting to use Pearson's coefficient on non-normal data, a transformation approach [78] like the Box Cox, Fisher transformation is required for a set of data that is approximately normal (or close to normal). However, a transformation on an extremely non-normal data (example with a p-value of $2.2e-16$) gives misleading results. The use of the Box Cox transformation, or other data transformation methods to do a monotonic transformation on non-normal data in order to obtain a normal distribution that satisfies the normality assumption of the Pearson's correlation tests, to then allow the use of Pearson's test, though acceptable, may lead to misleading results [55].

3.3.3 Kendall's Correlation Coefficient

Kendall's correlation, a non-parametric test measures the statistical association between columns of ranked data. Kendall's coefficient though does better on tied ranks (identical occurrences) than the Spearman's coefficient when the sample size is small and there are *not* many tied ranks [55]. It also generates narrower confidence intervals. It

requires ordinal or continuous data and a monotonic relationship to exist between the two variables. Similar to the Spearman's coefficient, it is a distribution-free (assumes no distribution) test of independence.

3.3.4 Conclusion on correlation tests

Spearman's correlation test is robust against outliers, skewed distributions, continuous data that is cases where the assumptions of the widely used Pearson's coefficient are violated [55]. Spearman's correlation test is preferred on non-normal data over Pearson's and Kendall's correlation tests due to its robustness against outliers [54] and skewed distributions, at which for instance the Pearson's coefficient fails [52].

For normally distributed datasets (or say transformed non-normal data sets), the Pearson's correlation is ideal [56] for accessing the linear relationship between the two variables while for non-normal data (skewed with outliers), the Spearman correlation is superior as it gives a monotonic relationship between the bivariate datasets, and does not assume any normality or linearity.

Transforming non-normal data sets and then using a Pearson's correlation test is possible when data sets are not extremely non-normal. This may however lead to misleading results. The preservation of the original data and the use of appropriate statistical methods (parametric for normal and non-parametric for non-normal) gives more genuine results, if possible, as sample averages and transformed data most often lead to different results for the same dataset.

A perfect Spearman correlation relates the two variables by a monotonic function whereas the Pearson's Correlation relates them with a linear function.

Spearman's coefficient does better than Kendall's coefficient on tied ranks with large sample sizes and is more sensitive on such samples [55] compared to the results gained using Kendall's coefficient which tends to drift from the desired level as the ties and sample sizes increase [55].

It is also worth noting that the absence of a correlation, say an r_s -value of 0, with either of the tests, does not suggest the two variables do not have any relation; it simply means there is no monotonic or linear correlation between the two variables. For instance, in the case of a quadratic equation such as $f(x) = y = x^2$, x and y have a relationship, yet the relation is neither linear nor monotonic and correlation tests return no correlation.

3.4 Test for Normality: Anderson Darling Test, Shapiro-Wilk, D'Agostino K-squared, Kolmogorov Smirnov

When working with statistical methods that assume the data to follow a particular distribution, typically a normal distribution, it is crucial to first perform a hypothesis test for normality (or another distribution) on the given data. The aim is to verify whether the (normality) assumption required for using the other test is satisfied as the validity of many statistical procedures depends on it. As E.S. Pearson [63] puts it: *...It is not enough to know a sample could have come from a normal population; we must be clear that it is at the same time improbable that it has come from a population differing so much from the normal as to invalidate the use of "normal theory" tests in further handling of the material.* A parametric test is then chosen for a normal distribution while a non-parametric test is for a non-normal distribution. Let us take a look at the various kinds of normality tests.

Common procedures for testing for normality suggested in literature are in the form of graphical methods (histogram, boxplots, QQ plots), numerical methods (skewness and kurtosis indices), and formal methods (Shapiro-Wilk test, Anderson-Darling test, Kolmogorov-Smirnov test, Lilliefors, D'Agostino skewness test). Though graphical methods suffice for assessing the normality of a given sample, however, they are unreliable as they do not provide sufficient convincing conclusion on whether or not the data is normal [55] for approximately (or almost) non-normal data. A good and complete statistical analysis will include the use of formal, descriptive and inferential statistical methods [62].

In testing for normality, the Anderson-Darling test, a widely used goodness of fit test, is a procedure used to determine whether a sample comes from a specified distribution (Gaussian distribution) for a given number of observations, more precisely, departures from normality in our case. Anderson-Darling is useful for normal, lognormal, Weibull and extreme value type I distributions. However, its counterpart, Shapiro-Wilk is superior, performs better [54], [55], and is used more often since, it exhibits high power and obtains good results for even a small number of observations. This research favors the use of the Shapiro-Wilk test due to its power over all others. D'Agostino's K-squared test is also a good alternative for Shapiro-Wilk but is mostly used in detecting departures from normality and whether a sample has a skewed distribution and kurtosis. D'Agostino and Belanger [61], [62] believe that the power of Kolmogorov Smirnov (Goodness of fit) test in

determining normality is so low that it should not be considered seriously. On a large study on investigating the power of statistical procedures on normality testing, Shapiro-Wilk emerges as the most powerful and most highly recommended solution [61] [62] [64].

3.5 Homogeneity of Variance: T-Test and ANOVA

The t-test is a parametric statistical method to make inferential decisions about the significant difference in the mean values of two variables. The Analysis of Variance (ANOVA) is a t-test equivalence for determining a difference between multiple experimental groups (two or more variables) or running multiple t-tests. In its simplest form, the t-test determines a difference in the mean of two data sets while the ANOVA is for multiple groups. The t-test assumes normality of the groups under comparison, homogeneity of variance (or equal variance). The t-test uses the *t*-statistic, the t-distribution and the degree of freedom to determine the probability value (p-value). For a test conducted on two variables, the t-test and the ANOVA will yield the same results, however, on three or more tests, the compounded effect will lead a t-test to create a Type I error (falsely rejecting a true null hypothesis when it is actually true and proceeding to accept the alternate hypothesis – false positive) [65],[67]. A Type II error occurs when the alternate hypothesis is true and the null hypothesis is falsely accepted when it should have been rejected (false negative). The fundamental principle of ANOVA requires the presence of a parametric dependable variable and multiple independent variables (factors).

The ANOVA test assumes that the subjects are randomly chosen, the response variable is normally distributed, and the population standard deviation is the same for all groups regardless of the differences in mean [67]. ANOVA and t-test are parametric tests and therefore, work very well on normally distributed data. However, with a violation to these normality and equal variance assumptions [65] the results are fairly trustworthy in the absence of non-parametric statistical methods given the sample size is “very large” and the number of subjects in each group are homoscedastic (property of having equal variance or homogeneity of variance). The largeness of a sample cannot be quantified per the central limit theorem [68] [69] and hence the validity of such an assumption requires a population that is not less than 30⁸. This will not work for a fixed population whose sample size cannot be further expanded.

We will not use ANOVA (as we have two variables) and t-test due to the violation of the normality and equal variance assumptions, and the presence of outliers, and skewed distribution. Non-parametric equivalence of ANOVA include the Kruskal-Wallis whilst that of the t-test is the Wilcoxon Rank Sum Test and Kolmogorov Smirnov Test.

3.6 Statistical Analysis – Wilcoxon Rank Sum Test

In hypothesis testing, a statistical data is often compared against a statistical synthetic data of an idealized model or a different statistical data and a hypothesis is inferred to confirm the existence of a relationship between the two datasets. A null hypothesis is initially assumed and accepted given the threshold of the significant level (probability value – p-value) is not exceeded. For a p-value that is lesser than the threshold probability (or the alpha significant level), the null hypothesis is rejected for an alternate hypothesis if the comparison reveals that the two datasets are statistically significant. The outcome will be used to infer whether the difference in the two datasets is by chance or statistically significant.

A normality test is initially conducted to establish if the data follows a particular distribution. This determines the choice of statistical method to use: parametric or non-parametric. A parametric statistical method is used for a dataset that follows a normal distribution (Gaussian distribution) while a non-parametric methods are used for a non-normal data. Among many non-parametric tests that compare the difference in seemingly similar means of two datasets, we have: Mann-Whitney U Test (Wilcoxon Rank Sum Test), Wilcoxon Rank Sign Test, Kruskal-Wallis, Mood's median test, Friedman test and Kolmogorov Smirnov Test.

The Wilcoxon Rank Sign Test requires that two samples be paired (paired variables have paired means with paired measurements). Kruskal-Wallis, which is an extension of the Mann-Whitney U Test [71] is used for three samples. The Wilcoxon Rank Sum Test and the Kolmogorov Smirnov Test [30] assume non-normal, non-parametric, independent and unpaired sets of data. They are the two most powerful non-parametric test to determine the difference in mean values between samples, thereby leading to more confirmatory conclusions. The Kolmogorov Smirnov test easily detects slight changes and shifts in the cumulative distribution of the samples while the Wilcoxon Rank Sum Test is more sensitive to changes in the median value rather than a shift in the cumulative distribution of the

samples [70]. These two tests are therefore complementary and give a better idea of the results gained from the data.

The Wilcoxon Rank Sum Test (Mann Whitney U Test) tests the median of two distributions with a null hypothesis on the basis that the two distributions are identical. An alternate hypothesis is used to gain evidence [31] against the null hypothesis if the probability value (level of statistical significance) is less than the well-accepted 0.05 level, i.e., with a specified alpha (α) level of 5%. The probability value (p-value) evaluates the probability that the observed results confirm the null hypothesis. A p-value smaller than α is evidence that the alternate hypothesis is true.

3.6.1 Kolmogorov Smirnov Tests

The Kolmogorov Smirnov Test (Goodness of Fit for one sample) is a non-parametric statistical method that is used to check for normality (for a single variable against a Gaussian or Laplace-Gauss distribution) or whether two datasets belong to the same distribution. For two sets of non-normal data, it is used to determine whether the two are drawn from the same distribution, by verifying whether there is a difference in the mean values or not. It calculates the maximum difference between the two cumulative distributions and gives a more accurate approximation than the t-test cannot see when detecting differences in a set of data. The Kolmogorov Smirnov Test makes no assumption about the distribution and is robust to the presence of outliers. It does not place a restriction on sample size. It has less power in detecting shifts in the median than the Rank Sum Test but is more powerful at detecting changes and shifts in the shape of the distribution given by the D statistic value.

Chapter 4 EXPERIMENTAL DESIGN

In this research, we select a number of software applications, developed with various programming languages and for which we have access to both the application code and the test code. We are interested in analyzing and comparing the complexity of application code and test code to evaluate whether indeed, test code is different to (e.g. is less complex than) application code and at the same time, what is the extent of such a difference (if any). This chapter described our selection of subject program to analyze (section 4.1), our selection of source code metrics (section 4.3), our selection of a software package, and its tailoring, to measure source code (section 4.2), and our statistical hypotheses and analysis (section 4.3).

4.1 Selected Applications and Rationale

For our analysis, we considered popular open source applications. These applications have received a credible level of acceptance by millions of users and contributors and have proven to be very useful to users, as evidenced by the number of contributors, commits and downloads. Then we wanted case study software that is (a) publicly accessible and can easily be retrieved for replication, (b) for which we can retrieve the code from the very source organisation, (c) which has a sizable number of commits, pulls and forks, with more than 10k for Application Code (we believed larger projects have a better chance of containing sufficient tests for our study). This is further explained in the threats to valid section (Chapter 6). We also considered criteria that others have identified for the selection of open source software, including perceived quality, user satisfaction [27], or cost [28].

We selected software for which we have access to both test code and application code, to compare one kind of code with the other for a given software, because we assume that both kinds of code for that software would be developed simultaneously (especially if agile methods are used), by approximately the same group of developers, who would therefore tend to program both kinds of code with similar coding principles. We also argue, although this would need to be confirmed, that, as the complexity of the application code increases, the complexity of its test code may also increase and that, therefore test code and application code for the same subject programs are required for our analysis. Last, we argue

that it would not make sense to compare the application code of one software with the test code of another software.

For the selection of case study software, we proceeded as follows. We first browsed a number of websites like Quora, Stack Overflow, Eclipse Community and Github, looking for the most used and popular open source projects. In doing so, we followed the process that has been identified as being typically used by users of open-source or free software [29]. For the many results we had, we proceeded to their respective websites in search for their source code (application code and test code). We were mainly interested in software that has the following characteristics: first and foremost, we wanted case study software that has both application code and test code and for which we can easily distinguish what is test code and what is application code to facilitate measurement. For instance we put aside Abiword as its distribution does not come with test code. Some applications were initially considered but were not selected in the end because they had test code files mixed with application code files thereby making it difficult to easily distinguish them from each other during measurement: examples are GCC, Linux 2.6, Guava, Columba 1.4, and Atom; With mixed application and test code, there is a higher risk that we consider an application code file when measuring test code and vice versa, which would be a severe threat to the validity of our results. A total of 500 open source software were considered.

In the end, we selected the 40 open source case study software of Table 1. The table also indicates the version software used and the URL from which the code from was obtained for each case study.

We then needed to distinguish application code from test code. We proceeded further to separate the application code from the test code and run the analyses on each one separately. Most of the packages we analyzed had the application code in the “src” directory while the test code was in a “test” directory, all within the same root directory. We used the Treemap functionality in Understand (which reveals all subfolders of source files in their parent folders at a glance) to observe the files and sub-directories contained in each directory to ensure we were not missing any misplaced file or sub-directory to adequately classify code as test code or application code.

Table 1. REFERENCES OF CASE STUDY SOFTWARE BEING STUDIED

Case study name	Version	URL	Case Study name	Version	URL
Amorok	2.9.0	https://github.com/KDE/amarok	Keepassx	2.0.3	https://github.com/keepassx/keepassx
Amule	1.28.0	https://github.com/Microsoft/vscode	Light GBM	2.2.1	https://github.com/Microsoft/LightGBM
Apache Ant	1.7.0	https://github.com/curl/curl	Mongo	r4.1.4	https://github.com/mongodb/mongo
Apache Httpd	2.2.8	https://github.com/apache/httpd	MPV Player	0.29.1	https://github.com/mpv-player/mpv
Audacity	2.3.1	https://github.com/audacity/audacity	Muscore	2.3.2	https://github.com/muscore/MuseScore
Bitcoin	0.15.1	https://github.com/bitcoin/bitcoin	Mypaint	1.2.1	https://github.com/mypaint/mypaint
Client		https://github.com/owncloud/client	NetData	1.10.0	https://github.com/firehol/netdata
Curl	7.56.0		NMap	7.7.0	https://github.com/nmap/nmap
Ditaa	0.11.0	https://github.com/stathissideris/ditaa	Notepad ++ (Scintilla 4.1.2)	7.5.9	https://github.com/notepad-plus-plus/notepad-plus-plus/tree/master/scintilla
Django	2.1.2	https://github.com/django/django	Onion	0.2.0	https://github.com/OnionIoT/source
FileZilla	3.0.0	https://github.com/basvodde/filezilla	PDF Creator	2.3.0	https://github.com/pdfforge/PDFCreator/tree/master/Source
Foundation DB	6.0.14	https://github.com/apple/foundationdb	Powershell	6.2.0	https://github.com/PowerShell/PowerShell
Handbrake	1.1.2	https://github.com/HandBrake/HandBrake	Rosegarden	10.02	https://github.com/nengxu/rosegarden
Hibernate ORM	5.3.7.Final	https://github.com/hibernate/hibernate-tools	Apache Shiro	1.4.0	https://github.com/apache/shiro
Hibernate	3.3.2.GA	https://sourceforge.net/projects/hibernate/files/hibernate3/3.3.2.GA/	Apache Sqoop	1.4.7-rc0	https://github.com/apache/sqoop
Inkscape	0.92.3	https://gitlab.com/inkscape/inkscape	Squirrel SQL	12	https://github.com/igorhvr/squirrel-sql/tree/master/sql12
Jfreechart	1.0.10	http://www.jfree.org/jfreechart/download.html	VLC	3.0.4	https://github.com/videolan/vlc-3.0
Jakarta JMeter	2.3.2	http://jmeter.apache.org/svnindex.html	Voldemort	1.10.26	https://github.com/voldemort/voldemort
JRuby	1.4.0	http://jruby.org/download	VSCode	1.28.2	https://github.com/Microsoft/vscode
			NASA WorldWind Java	2.1.0	https://github.com/NASAWorldWind/WorldWindJava

We also run a search for all files and folders that had the name “test” in it to reveal all potential test code. We inspected the packages of the source code to verify whether the application code and test code were in distinct directories by observing what is contained in every directory. We searched the individual directories (application code and test code) to see whether or not some test code files sneaked into the application code files and vice versa using the Treemap functionality of the Understand tool: the Treemap allows one to quickly and visually represent and dig into source code. We analysed the code by viewing a select number of source code in each package within Understand to ensure they really were application code or test code. We checked the naming convention used as some files and directory names (packages) suggest the kind of code included in packages or functions: for instance, we search for package/function names containing string “test”.

4.2 Measurement tool

To maintain consistency between measurements, and given the characteristics of the case study software presented in Table 1, we needed a source code analysis tool that can consistently measure the Cyclomatic Complexity and the Halstead complexity metrics on Java, C#, C++, Python and C. We evaluated a number of tools based on their support for these programming languages, their ability to run on tens of thousands of LOC, and the number of metrics they collect from the code.

These metrics can easily be extracted automatically with the use of a variety of tools that support a large number of different programming languages. The most frequently used [3] tools like Understand, CKJM, Authors’s tool, Metrics 1.3.6, Parasoft have been considered for use in our work and we finally decided to use Understand. Most of the tools considered are suitable for a single programming language and therefore, present a measurement challenge when dealing with an application written in multiple languages. Also, some tools have difficulties to handle large applications, at which Understand performed extremely well.

Scientific Tools Understand (Sci-Tools Understand) [18] fits our needs and appears to be a prime choice by others [3]. It was therefore preferred over other tools like Parasoft’s tools, Testwell, Author’s tool, Metrics 1.3.6. Some of these others tools, such as Parasoft’s tools, were however used, though results are not reported in this thesis, to confirm some of

the results obtained by using Understand. Understand was used to measure complexity metric values for functions/methods in application code and test code.

In order to collect exactly the information we needed, we developed scripts to execute in Understand. The information produced by Understand is collected in an Excel file. We also developed scripts to anonymize metric data; this was necessary when dealing with industry data in order to maintain confidentiality. All scripts are available in Appendix E .

4.3 Selected metrics

In this study we use software metrics to quantify the complexity difference and establish a correlation relation between the different software artefacts. Although we agree in part to seemingly strong correlation between the complexity metrics through the empirical results gained by some authors, we, however, believe that the results differ depending on the kind of code, the kind of metrics and the kind of software one is analysing.

Additionally, the cyclomatic complexity metric was shown to explain software development effort [35], [36], some authors also question the mere definition of these metrics and therefore their use [38].

Despite this debate, recognizing that the Cyclomatic Complexity is one of the most used [3] source code metrics as well as Lines of Code and Halstead Effort. We decided to also use the Halstead complexity metrics [23], because they are considered complementary [3], [37] to the Cyclomatic Complexity and are therefore often used together [37]. These two structural complexity metrics are somewhat strongly correlated but a combination of the two is practically useful for measuring data flow and control flow as illustrated by Yahya and colleagues [37]. Not only would we want to compare application code to test code using these complexity metrics but also, to verify the variable hypotheses on the correlation of these metrics.

One metric is not capable of giving a full perspective of how complex a program can be due to the different objectives achieved by each metric. However, using different metrics that are deemed complementary, popular and have gained a great level of impact in software quality [37] provides better results and less biased conclusions. Plus, since these metrics are often used by practitioners, the results we will obtain will be more directly

applicable to practitioners' contexts. Other metrics like Lines of Code (LOC), Number of Methods (NOM), and Number of Classes (NCLASS) will improve our analysis.

Other source code metrics could be used, such as those suggested by Henry and Kafura [25]. However, they have different interpretations [23] and it is difficult to find tool support.

We decided to therefore consider the following source code metrics: Lines of Code (LOC), McCabe cyclomatic complexity, Halstead Difficulty, Halstead Effort, Number of Methods (NOM), Number of Classes (NClass), and Maintainability Index which are all supported by Sci-Tools Understand. Apart from Maintainability which has different variants, Sci-Tools Understand preserves the definitions of all metrics as defined in section 3.1, and uses the Model 2 variant of Maintainability index defined in section 3.2.

4.4 Selection of Statistical Methods

When comparing test code complexity with application code complexity at the function/method level, we expect to obtain a very large number of data points which should allow us to conduct some statistical analysis. Knowing how software code is written, following coding principles that encourage short functions/methods, we expect to obtain a large number of data points with low complexity values. For instance, it is well recognized that the complexity of object-oriented software essentially comes from interactions between objects rather than complex function/method bodies. This will especially be the case when measuring the cyclomatic complexity of test code if our assumption, as advocated by prominent authors, that test code is limited to simple control flow, appears to hold. When plotting a frequency distribution with cyclomatic complexity values increasing on the x-axis, we expect to obtain a distribution that is skewed to the left with a possibly long tail of outliers to the right. In other words, we expect to obtain distributions that do not meet the assumptions of a normal distribution [32].

With such skewed and non-normal distributions, we have to resort to non-parametric statistical methods to test whether there is indeed a significant difference in the median values between application code and test code. Non-parametric tests perform better and are more powerful on non-normal data especially for a large size of discrete data [30]. We are also cognisant that with such skewed distributions, the mean values are strongly affected and may not be meaningful.

In this study, we will use Wilcoxon Rank Sum Test for determining whether two similar values (average complexity) for application code and test code for a given case study are statistically different or drawn from the same distribution. For our study, we define a null and an alternate hypothesis for Wilcoxon Rank Sum Test as follows:

- Null Hypothesis (H_0): The median complexity values of application code and test code are the same.
- Alternate Hypothesis (H_1): There is a difference between the median complexity values of application code and test code.

We define the null and alternate hypothesis for Kolmogorov Smirnov test as follows.

- H_0 : The two samples of application code complexity and test code complexity values are drawn from the same distribution.

H_1 : The two samples of application code complexity and test code complexity values are drawn from different distributions.

Also, on the correlation of software metrics, we will use Spearman's coefficient as our data is not normal and bivariate. We will not use of Pearson's coefficient, as all our dataset are non-normal.

Chapter 5 RESULTS (ANALYSIS OF DATA)

In this chapter, we discuss the metric values extracted using SciTools Understand. We start with providing and discussing some descriptive statistics results (Section 5.1) and then discuss inferential statistical results (Section 5.2). We then discuss the use of non-parametric tests (Section 5.3) and finally investigate the correlation between software metrics (Section 5.4).

5.1 Statistical Analysis of Extracted Data

We first provide and discuss some descriptive statistics results on Lines of Code (Section 5.1.1) and Cyclomatic complexity (Section 5.1.2). We also analyse the mean values of the data using frequency distribution, box plots and other graphical methods (Section 5.1.3).

5.1.1 Descriptive statistics on Lines of Code

Table 2 provides initial information about the application code (AC) and test code (TC) of the case study systems. Columns provide LOC details for each of AC and TC: the total number of LOC, the ratio of application code over test code, and the contribution of different programming languages towards the total LOC values. Last it provides the number of classes in the code (value 0 in case of procedural code), the number of methods in the code and the average size (LOC) of those methods.

The table shows that the selected case study software are developed with various programming languages, sometimes more than one programming language for one software and up to five different programming languages (eg. Foundation DB), with a predominance of C++ followed by C and then Java. Most of the applications are written in multiple languages. We manually verified and confirmed this was indeed correct output from Understand. It is not uncommon to find software with more one programming language, to achieve specific goals, including: Performance sensitive software and runtime performance favors the use of low level languages (C++, Rust, Go, C); Communicating with external libraries and APIs written in another language (Pearl, Python) and embedding scripting languages and interpreter (like Guile , Lua, Python) help improve the performance to generate faster executables; The need to include legacy code or legacy language.

For open source subjects, the largest AC is with Mango (2.3M LOC) while the smallest AC is Dita (6,568 LOC); the largest TC is with Mango (173,155 LOC) while the smallest TC is MPV Player (155 LOC). For Industry subjects, AC varies between 3,867 LOC and 83,710 LOC while TC varies between 27 LOC and 233,085 LOC.

Broadly speaking a values of the ratio of application code to test code strictly greater than one tells a different story than a ratio smaller than one; in the former case there is more AC than TC meaning that every line of TC essentially tests several lines of AC while in the latter case there is more TC than AC, meaning that each line of AC is essentially tested by more than one line of TC. When the ratio is strictly greater than one, it varies between 1.17 for PDF Creator and 2917.12 for Audacity, meaning that for each line of TC there is between 1.17 and 2917 lines of AC; one line of TC tests between 1.17 and 2917 lines of AC. Only two open source subjects have a ratio smaller than one: Django (0.58) and Hibernate ORM (0.88); one line of AC is tested on average by 1.72 (Django) and 1.13 (Hibernate ORM) lines of TC. Judging only by this ratio as a coarse-grained evidence of testing effort, we observe a huge variation of testing effort in these open source subjects. In comparison, the ratio is smaller than one for three Industry subjects (0.30, 0.36 and 0.86) and greater than one for two Industry subjects (11.65 and 14.29); for the former three, one line of AC is tested on average by 1.16, 2.78 and 3.33 lines of TC while for the latter two, one line of TC tests on average 11 or 14 lines of AC. We conclude that results obtained in our study from these open-source case studies may not generalize to Industry software.

The amount of LOC invariably has an *effect* on the proportion of test cases to be written. Therefore, a ratio of AC to TC of 1 or less suggests a thoroughly tested software over one that has a value greater than 1. While it is possible to predict that a higher amount of test code over application code suggests that for say a single line of application code, there exist two test code lines and therefore, one object seems more complex than the other by a mere observation of the ratios. Judging only by LOC, application code tends to be more complex than test code especially in open source subjects, but not in Industry subjects.

In analysing the table, there are a number of key observations that require a careful attention. We record extreme cases where the size of AC far exceeds the size of TC by a large multiplicand or factor. A critical observation of the amount of methods for these extreme cases also reveal a similar high ratio for AC and TC. Audacity is an example of this

extreme cases with 2,917.12 times more lines of AC than TC and 2,030 times more AC methods than TC methods. This is followed by MPV Player with 760 times more lines of AC than TC. Other instances include Apache Httpd whose AC is 360 times larger TC, with 203 times more AC methods than TC methods, Inkscape's AC is 213 times larger than its TC (LOC) with 203 times more AC methods than TC methods. Only a few of these objects show these wide differences in the amount of LOC for AC and TC. The LOC ratio for AC to TC (and ratio of AC to TC methods) for other example are: Powershell (148 and 149), Rosegarden (135 and 198), VLC (95 and 100), Shiro (36 and 154), VSCode (45 and 15) and JRuby (33 and 42). This suggests that the lines of code ratio of application code and test code almost invariably, increases or decreases with the AC to TC ratio of the number of methods. The higher the LOC AC/TC ratio, the higher the NOM AC/TC ratio.

Still on the relation between LOC and NOM, another interesting observation from Table 2 is that, some objects appear to have larger amounts of lines of test code than the application code it tests; i.e. with a ratio of AC to TC smaller than 1. An AC to TC ratio lesser than one implies test code has a higher size than application code. These objects still maintain a value for the NOM and LOC ratios (AC/TC). For example: Django has a LOC AC/TC ratio of 0.58, and a NOM AC/TC ratio of 0.65, Hibernate has a 0.88 AC/TC LOC ratio and a 1.17 AC/TC NOM ratio. While our observation suggests that most application code has a larger size than test code, some objects have an opposite ratio. This also implies that, envisioning complexity from a LOC point of view make test code more complex than is assumed. Similar instances that appear to have a very close range of values for the ratios of the amount of test code and production code are PDF creator and Sqoop which report 1.17 for LOC and 2.05 for number of methods, Curl has 1.89 for AC to TC ratio for LOC and 1.4 for number of methods, whilst Sqoop reports 2.0 for LOC ratio of AT to TC and 1.90 for number of methods. In this case, we observe similar LOC complexity levels and a software that seems to have an almost equal amount of test cases as the application. For such, if test code can be that high, then some test code is not that simple as it is assumed and can have an equal or even higher maintainability difficulties.

All other objects seem to relatively have larger ratio of AC/TC LOC and AC/TC number of methods. Audacity and MPV Player will therefore be discussed separately from

the other objects due to the less amount of test code size and methods, unless otherwise specified.

Table 2. SIMPLE METRIC VALUES FOR SOFTWARE OBJECTS

Application	LOC		LOC AC/TC Ratio	Java	C++	C	Python	C#	NCIASS	NOM	Method Avg size (LOC/NOM)
Amorok	AC	173639	9.91		171327	2237	75		1203	12952	13.41
	TC	17526			17526				128	995	17.61
Amule	AC	104106	27.75		100074	4032			404	5813	17.91
	TC	3752			3752				180	468	8.02
Apache ant	AC	100433	3.53	100299			94	40	1197	9339	10.75
	TC	28478		28411			47	20	392	2984	9.54
Apache httpd	AC	291321	359.66		7056	284153	112		0	5709	51.03
	TC	810				810			0	28	28.93
Audacity	AC	685524	2917.12		291926	393598			2289	32490	21.10
	TC	235			235				2	16	14.69
Bitcoin	AC	115726	2.79	438	106564	6329	2395		708	7448	15.54
	TC	41492			25528		15964		220	2131	19.47
Client	AC	108110	13.57		41891	65408	811		223	4597	23.52
	TC	7968			7664	304			54	585	13.62
Curl	AC	54253	1.89		4891	49362			0	1448	37.47
	TC	28641			314	13042	15285		301	981	29.20
Ditaa	AC	6568	13.24	6568					44	587	11.19
	TC	496		496					6	30	16.53
Django	AC	91746	0.58				91746		1620	10379	8.84
	TC	158125					158125		6544	15742	10.04
Filezilla	AC	101112	54.92		70538	30574			328	4399	22.99
	TC	1841			1841				4	27	68.19
FoundationDB	AC	214195	223.35	10139	130746	59542	10710	3058	694	14736	14.54
	TC	959					959		6	72	13.32
Handbrake	AC	121137	28.07		13831	73210	2126	31970	378	6577	18.42
	TC	4316			20	4296			0	42	102.76
Hibernate	AC	249226	3.04	249226					1591	14159	17.60
	TC	82106		82106					940	7196	11.41
Hibernate ORM	AC	15328	0.88	15328					198	1541	9.95
	TC	17387		17387					210	1087	16
Industry 1	AC	83710	0.36			83710			0	427	196.04
	TC	233085				233085			0	1281	181.96
Industry 2	AC	38914	0.86			38914			0	252	154.4
	TC	88794				88794			0	538	165.04
Industry 3	AC	44795	0.30			44795			0	395	113.40
	TC	144280				144280			0	743	194.18
Industry 4	AC	6036	11.77					6036		2001	3.01
	TC	513						513		38	13.50
Industry 5	AC	3867	143.22					3867		387	10

Application	LOC		LOC AC/TC Ratio	Java	C++	C	Python	C#	NCIASS	NOM	Method Avg size (LOC/NOM)
	TC	27						27		4	6.75
Inkscape	AC	488998	213.07		440119	46784	2095		1529	22357	21.87
	TC	2295			2295				19	110	20.86
Jfreechart	AC	108979	2.42	108979					609	7992	13.64
	TC	44967		44967					399	2949	15.25
Jkarta JMeter	AC	82062	6.18	82062					839	7306	11.23
	TC	13274		13274					111	833	15.94
JRuby	AC	163076	33.04	162814		262			1977	17637	9.25
	TC	4935		4935					132	413	11.95
Keepassx	AC	18501	3.85		18439		62		109	1295	14.29
	TC	4808			4808				26	172	27.95
lightGBM	AC	22612	16.23		19227	4	3381		122	1393	16.23
	TC	1393					1393		6	83	16.78
Mongo	AC	2356692	13.61	4969	1816201	458583	76939		11705	159337	14.79
	TC	173155			1379		171776		40	8576	20.19
MPV Player	AC	117809	760.06		7055	108951	1803		14	5216	22.59
	TC	155				155			0	24	6.46
Musescore	AC	593434	3.65		509193	77379	6862		1626	23085	25.71
	TC	162767			162767				68	963	169.02
Mypaint	AC	43993	32.64		5361		38632		378	3278	13.42
	TC	1348					1348		8	96	14.04
Netdata	AC	48438	16.58		1849	46589			0	1139	42.53
	TC	2921				2921			0	300	9.74
NMap	AC	213559	20.15	45	35826	156127	20950	611	317	6718	31.79
	TC	10599			10597				0	1095	20.07
Notepad++	AC	77622	14.83		76401	32	1189		189	3695	21.01
	TC	5235			2548		2687		57	492	10.64
Onion	AC	16870	4		1640	15216	14		23	1193	14.14
	TC	4214			319	3895			2	226	18.65
Open XML SDK	AC	230775	1.98					230775	3991	58336	3.96
	TC	116411						116411	209	1724	67.52
PDF Creator	AC	45323	1.17					45323	1272	6564	6.90
	TC	38754						38754	338	3188	12.16
Powershell	AC	405873	148.13		7253		12	398608	2900	29084	13.96
	TC	2740						2740	47	195	14.05
Rosegarden	AC	169850	135.02		169850				856	9905	17.15
	TC	1258			935	323			0	50	25.16
Shiro	AC	37723	45.84	37723					832	4267	8.84
	TC	823		823					9	26	31.65
Sqoop	AC	83607	2.03	83468			139		841	6425	13.01
	TC	41114		41114					399	3371	12.20

Application	LOC		LOC AC/TC Ratio	Java	C++	C	Python	C#	NCIASS	NOM	Method Avg size (LOC/NOM)
Squirrel SQL	AC	194865	7.02	194865					3576	16706	11.66
	TC	27762		27762					569	3102	8.95
VLC	AC	472561	95.45		142794	328572	1195		806	19472	24.27
	TC	4951			159	4792			0	194	25.52
Voldemort	AC	136769	2.69	129226	2940		4603		1330	13148	10.40
	TC	50837		50764			73		463	2638	19.27
VSCode	AC	38681	36.56	38537	29	25	74	16	10	1780	21.73
	TC	1058						1058	2	118	8.97
Worldwind	AC	329382	21.70	324935	4447				3339	26030	12.65
	TC	15179		15179					107	616	24.64

This potentially different testing effort between objects means that comparing complexity metric results between objects should be done with care, if at all; indeed an AC/TC ratio of cumulative complexity values for one objects may be lower than for another objects simply because the former one may have been more tested than the latter one. Comparing average complexity values should be less sensitive to a potentially different testing effort.

For almost half of the objects, the average size of TC methods is smaller than the average size of AC methods while, it is surprisingly the opposite for the other half. Amorok, Bitcoin, Dita, Django, Filezilla, Handbrake, Hibernate ORM, Jakarta JMeter, Mongo, Muscore, Mypaint, NMap, Onion, Open XML, PDF Creator, Powershell, Shiro, VLC, Voldemort, WorldWind Java have a higher average number of methods for AC than TC.

We also note that for pen source objects, the average AC function size is in range [3.96, 51.03] while the average TC function size is in range [6.46, 169.02] while, for Industry objects, the AC average function size is in range [113, 196] or [3, 10] and the TC average function size is in range [165, 194] or [6.75, 13.5] (we distinguish between objects Industry 1-3 on the one hand and objects Industry 4-5 on the other since they look significantly different).

5.1.2 Descriptive statistics on Cyclomatic Complexity

Table 3 shows cyclomatic (V(G)) and Halstead (V, D, E, and MI) complexity metric data for AC and TC code for each object as returned by the Understand tool. Data include the cumulative value for the entire (AC or TC) code, the mean, median, min and max values. The table also includes the ratio of AC to TC for Cyclomatic Complexity to measure the extent to which AC is larger or lesser than TC.

All case study software report a higher cumulative Cyclomatic Complexity value for AC than TC. This is partly due to the size of the objects. AC is two to hundred times cumulatively more complex than TC: see last column in Table 3. Audacity is an exception: Audacity's AC is 4920 times cumulatively more complex than its TC for V(G). Although this may be an artifact of the differences of LOC between AC and TC for these objects (see discussion in previous section), data suggests size is not the only reason: for instance, Audacity's AC is only 2917 times larger than its TC. Application code appears to be more complex than test code. The average cyclomatic complexity values of AC and TC methods

look very similar: e.g., 2.2 and 1.3 respectively for Apache Ant, 1.5 and 1.2 for Hibernate. Table 3 shows a minimum average Cyclomatic Complexity value of 1.0 (Amorok AC, Light GBM AC and MPV player TC) and a maximum of 16.5 (Handbrake TC). Almost all objects have a higher cumulative cyclomatic complexity for AC than TC with exception to 14 objects where TC is larger.

Although AC appears to be more complex than TC, this does not mean TC is simple. A critical look at the top five average cyclomatic complexity values raises an interesting observation. When ranking average cyclomatic complexity values, irrespective of the kind of code (AC or TC), the top two objects exhibit higher TC cyclomatic complexity than AC cyclomatic complexity: for instance, Notepad Plus Plus has a TC cyclomatic complexity value of 14.3 and an AC cyclomatic complexity value of 5.1; on average, a TC method is more complex than a AC method, although, cumulatively, AC is 2.7 times more complex than TC. A similar observation is made for Onion: average TC cyclomatic complexity value of 10.7 and an average AC cyclomatic complexity value of 2.9 while the cumulative AC to TC ratio is 1.45.

Although AC has a higher average cyclomatic complexity value than TC for a majority of the objects, we observe that TC is on the average more complex than AC for 14 objects, with sometimes small differences (e.g., Mypaint) and sometimes larger differences (e.g., Onion): Amorok (1.1 vs. 1.2), Foundation (3.1 vs. 4.0), Light GBM (1.0 vs. 1.6), Mongo (1.1 vs. 2.1), Mypaint (2.5 vs. 2.6), Open XML (1.4 vs. 1.8), Onion (2.9 vs. 10.7), PDF Creator (1.45 vs. 1.48), Rosegarden (0.1 vs. 3.5), Voldemort (1.9 vs. 2.6) and VSCode (2.2 vs. 2.6). This is an indication that some objects have TC methods that are more difficult to understand or maintain than their respective AC methods. With this large amount of objects, it is hard to believe in the hypothesized simplicity of TC.

This is an initial step towards verifying the stated hypothesis that TC is simple. Using typical guidance for using cyclomatic complexity values [5] (Section 3.1), test code in the analyzed systems is in general not simple, nor easy to understand because values tend to be higher than 20 and go up to 2,097. We record a number of instances with a maximum TC cyclomatic complexity larger than 50, which indicates methods that are extremely difficult to maintain. Although not a recommended practice for any kind of source code, observing AC methods with such high complexity values is not entirely surprising at the

outset; It is however rather surprising to find TC methods with such extremely high values. For example, Notepad has a TC method with a cyclomatic complexity of 2097, a value that is much larger than that of any method in its AC (the AC methods have a maximum cyclomatic complexity value of 734). We can make a similar observation for Handbrake and Onion. In other instances, though the maximum cyclomatic complexity value of AC methods is larger than that of TC methods, TC methods have reasonably high values: VLC has TC maximum cyclomatic complexity value of 156 while its AC reaches 326; Curl has TC maximum of 97 and AC maximum of 724. If test code methods are, as hypothesized, reduced to a single control flow, to be simple and easy to understand, then the numbers suggest this is not the reality in practice. We observe only a few objects with maximum TC cyclomatic complexity values lesser than 50. Of all the objects, Hibernate appears as the easiest to maintain with AC methods cyclomatic complexity not exceeding 29 and TC methods cyclomatic complexity values not exceeding 7.

With a few exceptions, when the median cyclomatic complexity value is larger than one, the code being analyzed is primarily procedural (e.g., C); otherwise, when the code is primarily object-oriented, the median cyclomatic complexity value tends to equal one. This may be due to the larger prevalence of getters and setters, and other simple methods in object-oriented code than in procedural code. The fact that the median and mean cyclomatic complexity values are very often equal to one leads us to conclude that, despite some interesting observations we made earlier, the mean and median values are not very informative as descriptive statistics: there are simply too many methods/functions with a cyclomatic complexity of one. Given the minimum cyclomatic complexity value tends to be one, the maximum cyclomatic complexity value is indicative of the range. The maximum AC cyclomatic complexity value is in range [29, 10019], and in range [29, 734] when we omit outlier Mongo, while the maximum TC cyclomatic complexity value is in range [2, 2097], and in range [2, 196] when we omit outlier Notepad++. This suggests that TC tends to be simpler than AC. Cyclomatic Complexity density, a transformation of CC, is a measure of a module's cyclomatic complexity divided by its length (size or LOC). Some authors [80] validate the usefulness of cyclomatic density which has shown to be a useful approximation and predictor of the productivity and difficulty of maintaining code. This metric shows the decision density or how many decisions there are for a given series of lines

of code. A low cyclomatic complexity density predicts a lack of logic while a high cyclomatic density suggest a code dense with decisions. The motivation for this metric is to derive a complexity metric that factors out the size component (thereby normalizing the complexity of the module to better predict difficulty and maintenance productivity) due to the perceived correlation between CC and LOC. In this analysis we observe all objects with a higher cyclomatic complexity density for AC over TC except for 15 objects (Amule, Apache Httpd, Curl, Foundation DB, Hibernate, Industry 2, Industry 5, Jfreechart, LightGBM, Mongo DB, Netdata, Notepad++, Onion, Rosegarden and VSCode).

In this section we conclude that AC tends to be more complex than TC but that does not necessarily mean TC is simple.

Now let's turn our attention to explaining our analysis with detailed Halstead values. Halstead Maintainability Index (MI) also indicates that AC and TC are relatively equally maintainable for each object. There are a few exceptions though. Once again, Audacity reports 7.76, MPV reports 5.22, Shiro reports 5.39, Apache reports 4.37, Dita reports 4.23, Foundation reports 2.95, Light GBM reports 2.26. Apache httpd appears to be an outlier: MI value of 4.3 for TC and MI value of .02 for AC. Jakarta JMeter and JRuby are also on that trend, though to a lesser extent.

5.1.3 Descriptive statistics on Using Distributions, Graphs and Average Values for Cyclomatic Complexity

Descriptive statistics such as mean and median values do tell a story, as we showed in previous section. However, as we alluded to in these sections, they should be considered with extreme care because they are heavily influenced by the distribution of methods' complexity metric values: for instance, we mentioned that with too many method cyclomatic complexity values of one, mean and median values become less useful. Taking Apache httpd as an example, the average MI value of TC is two orders of magnitude higher than the average MI value of AC. Table 2 tells us that Apache Httpd's LOC for AC is 360 times the TC LOC TC. Assuming standard coding principles are followed, whereby functions are kept simple with a majority of them having a few (to a very few) number of LOC and therefore a low (to a very low) complexity, a much larger number of AC methods may (and do, as confirmed below) artificially lower the average value.

We therefore need to look at distributions, such as the ones in Appendix A . The appendix provides a few distributions for illustration purposes: frequency distributions of AC and TC method cyclomatic complexity values for Apache httpd and Jfreechart; These two objects have representative distributions of what we obtain for the other objects, though the scales vary. We repeat below the distribution for AC method cyclomatic complexity values as an example. The appendix then includes boxplot of cyclomatic complexity values for AC and TC for all objects, using a logarithmic scale on the y-axis when warranted. (We do not report on the Halstead complexity metric values since the observations we make with cyclomatic complexity, and the conclusions we draw, are overall similar to those obtained with Halstead complexity metrics.) The core features of a box plot are the minimum value, the lower quartile, the median, the upper quartile, the maximum value and the outliers. The distributions are definitely not normal.

Figure 1. Distribution of cyclomatic complexity values for Apache Httpd AC

A clear observation we can make from the boxplots (Appendix A) is that the distributions are heavily skewed (to the left) causing the AC and TC boxplots to have the same minimum value, lower quartile, and median in the case of almost all objects.

Apache httpd AC and TC boxplots have the same minimum value and lower quartile, and similar median values (2 for AC and 2.5 for TC). Curl's AC and TC boxplots have the same minimum value, a similar lower quartile (2 for AC and 1 for TC), and similar median values (3 for AC and 2 for TC). These distributions, as expected, make descriptive statistics misleading. For instance, without counting Apache httpd Figure 3 test methods with a cyclomatic complexity of one, the mean and median values of test method cyclomatic

complexity values are 9 and 8, respectively; when counting methods with a cyclomatic complexity of one, these mean and median values are 5.6 and 2.5, respectively.

We will turn to inferential statistics to make a more convincing conclusions on the median and mean values.

Table 3. METRIC VALUES (CYCLOMATIC AND HALSTEAD) FOR SOFTWARE OBJECTS

Application		V(G)		V		D		E		MI		CC/LOC	V(G) AC/TC
Amorok	AC	cum.	13412.0	cum.	4052516	cum.	98000	cum.	84774635	cum.	136.31	0.077240712	10.93
		mean	1.0	mean	312.9	mean	7.6	mean	6545.3	mean	121.56986		
		median	1.0	median	104	median	5	median	530	median	122.32		
		min	1.0	min	4	min	1	min	4	min	12.67		
		max	47.0	max	52479	max	1005	max	3645030	max	218.05		
	TC	cum.	1227.0	cum.	444150	cum.	7707	cum.	7946986	cum.	128.86	0.07001027	
		mean	1.2	mean	446.4	mean	7.7	mean	7986.9	mean	117.84475		
		median	1.0	median	196	median	6	median	997.5	median	117.36		
		min	1.0	min	4	min	1	min	4	min	45.13		
		max	14.0	max	63373	max	461	max	1377055	max	204.02		
Amule	AC	cum.	16861.0	cum.	4256525	cum.	56893	cum.	982163092	cum.	127.55	0.161959925	17.75
		mean	2.9	mean	732.2	mean	9.8	mean	168959.8	mean	124.08626		
		median	1.0	median	116	median	6	median	688.5	median	125.02		
		min	1.0	min	4	min	1	min	4	min	-28.08		
		max	219.0	max	1728260	max	2624	max	898160036	max	209.95		
	TC	cum.	950.0	cum.	31657	cum.	1182	cum.	784988	cum.	140.83	0.253198294	
		mean	2.0	mean	67.6	mean	2.5	mean	1677.3	mean	125.59945		
		median	1.0	median	64	median	5	median	288	median	127.97		
		min	1.0	min	4	min	1	min	8	min	58.17		
		max	55.0	max	24207	max	588	max	753257	max	176.65		
Apache ant	AC	cum.	20093.0	cum.	2137071	cum.	74957	cum.	49237472	cum.	148.03	0.200063724	5.12
		mean	2.2	mean	228.8	mean	8.0	mean	5772.2	mean	146.33346		
		median	1.0	median	59	median	6	median	350	median	153.425		
		min	1.0	min	4	min	1	min	4	min	0		
		max	82.0	max	17836	max	169	max	1105832	max	203.31		
	TC	cum.	3927.0	cum.	486696	cum.	14799	cum.	6453086	cum.	154.57	0.13789592	
		mean	1.3	mean	163.1	mean	5.0	mean	2162.6	mean	133.36249		
		median	1.0	median	490.5	median	17	median	7259	median	134.34		
		min	1.0	min	20	min	2	min	40	min	0		
		max	21.0	max	11183	max	201	max	376971	max	192.34		
Apache httpd	AC	cum.	28634.0	cum.	12181606	cum.	187872	cum.	80445580	cum.	108.68	0.098290202	180.09
		mean	5.0	mean	1312.2	mean	24.46	mean	104733.21	mean	106.60536		
		median	2.0	median	345	median	12	median	3942.5	median	107.59		
		min	1.0	min	4	min	1	min	8	min	0		
		max	350.0	max	914396	max	3250	max	131298137	max	214.1		

Application		V(G)		V		D		E		MI		CC/LOC	V(G) AC/TC
	TC	cum.	159.0	cum.	49016	cum.	924	cum.	1566536	cum.	122.38	0.196296296	
		mean	5.7	mean	1289.89	mean	24.32	mean	41224.63	mean	107.32333		
		median	2.5	median	490.5	median	17	median	7259	median	108.76		
		min	1.0	min	20	min	2	min	40	min	0		
		max	25.0	max	11183	max	201	max	376971	max	162.38		
Audacity	AC	cum.	113160.0	cum.	18002336	cum.	315482	cum.	1.231E+09	cum.	119.49	0.165070807	4920.00
		mean	3.5	mean	554.1	mean	9.7	mean	37884.7	mean	115.68196		
		median	2.0	median	209	median	9	median	1818	median	115.73		
		min	1.0	min	4	min	1	min	4	min	0		
		max	299.0	max	2671128	max	6564	max	451303988	max	209.96		
	TC	cum.	23.0	cum.	7713	cum.	208	cum.	173830	cum.	124.14	0.09787234	
		mean	1.4	mean	482.1	mean	13.0	mean	10864.4	mean	114.255		
		median	1.0	median	395.5	median	12.5	median	6113.5	median	112.945		
		min	1.0	min	28	min	2	min	56	min	95.07		
		max	3.0	max	4981	max	136	max	128386	max	135.1		
Bitcoin	AC	cum.	20016.0	cum.	3841736	cum.	176000	cum.	328189021	cum.	123.5	0.172960268	4.25
		mean	2.7	mean	879.03	mean	19.22	mean	35836.32	mean	118.43407		
		median	1.0	median	173	median	9	median	1489.5	median	118.78		
		min	1.0	min	2	min	1	min	4	min	0		
		max	356.0	max	266530	max	2495	max	22947656	max	213.55		
	TC	cum.	4708.0	cum.	2980630	cum.	47902	cum.	159901565	cum.	114.99	0.113467656	
		mean	2.2	mean	1180.92	mean	18.98	mean	63352.44	mean	112.19454		
		median	1.0	median	232	median	8	median	1816	median	111.39		
		min	1.0	min	4	min	1	min	4	min	0		
		max	45.0	max	91189	max	874	max	10230777	max	176.08		
Client	AC	cum.	13596.0	cum.	3792814	cum.	68039	cum.	255832346	cum.	129.57	0.125760799	17.68
		mean	3.0	mean	825.1	mean	14.8	mean	55652.0	mean	112.9351		
		median	1.0	median	297.5	median	11	median	3069.5	median	113.49		
		min	1.0	min	4	min	1	min	4	min	0		
		max	650.0	max	2615241	max	43091	max	227401359	max	211.81		
	TC	cum.	769.0	cum.	223966	cum.	4749	cum.	4511580	cum.	127.43	0.096511044	
		mean	1.3	mean	382.8	mean	8.1	mean	7712.1	mean	123.36343		
		median	1.0	median	171	median	6	median	1065	median	122.32		
		min	1.0	min	8	min	1	min	8	min	0		
		max	15.0	max	26026	max	745	max	842105	max	186.18		
Curl	AC	cum.	12270.0	cum.	3398918	cum.	58432	cum.	177821492	cum.	116.32	0.226162609	1.89
		mean	8.5	mean	1578.69	mean	27.14	mean	82592.43	mean	105.28132		
		median	3.0	median	540	median	16	median	8741.5	median	106.66		
		min	1.0	min	18	min	2	min	36	min	0		
		max	724.0	max	181049	max	1584	max	12165665	max	163.66		

Application		V(G)	V	D	E	MI	CC/LOC	V(G) AC/TC
	TC	cum. 6482.0 mean 6.6 median 2.0 min 1.0 max 97.0	cum. 1428086 mean 957.80 median 396.5 min 13 max 141013	cum. 20797 mean 13.95 median 11 min 2 max 675	cum. 61266955 mean 41091.18 median 4544.5 min 26 max 10043470	cum. 104.24 mean 105.57034 median 107.085 min 0 max 204.97	0.226318913	
Ditaa	AC	cum. 1596.0 mean 2.7 median 1.0 min 1.0 max 98.0	cum. 213599 mean 363.9 median 7 min 1 max 1830	cum. 6047 mean 10.3 median 768 min 8 max 1888308	cum. 6598707 mean 11241.4 median 129.29 min 28.7 max 177.62	cum. 134.81 mean 126.03986 median 129.29 min 28.7 max 177.62	0.242996346	31.29
	TC	cum. 51.0 mean 1.7 median 1.0 min 1.0 max 7.0	cum. 18144 mean 604.8 median 398 min 19 max 3757	cum. 365 mean 12.2 median 11 min 2 max 35	cum. 353391 mean 11779.7 median 4465 min 38 max 131495	cum. 126.75 mean 108.54139 median 105.855 min 0 max 168.48	0.102822581	
Django	AC	cum. 24343.0 mean 2.3 median 1.0 min 1.0 max 49.0	cum. 271462676 mean 26154.99 median 186 min 8 max 408866	cum. 355331 mean 34.24 median 9 min 1 max 334	cum. 79076847902 mean 76189.27 median 1575 min 8 max 123987814	cum. 208.98 mean 148.23 median 145.32 min 0 max 210.98	0.265330369	1.27
	TC	cum. 19200.0 mean 1.2 median 1.0 min 1.0 max 21.0	cum. 5012126 mean 318.39 median 176 min 8 max 83359	cum. 99042 mean 6.29 median 5 min 1 max 236	cum. 87621551 mean 5566.10 median 885 min 8 max 12503850	cum. 200.04 mean 187.11 median 180.91 min 0 max 215.01	0.121422925	
Filezilla	AC	cum. 19714.0 mean 4.5 median 2.0 min 1.0 max 275.0	cum. 3000079 mean 682.0 median 259 min 4 max 308476	cum. 67804 mean 15.4 median 11 min 1 max 3718	cum. 139380907 mean 31684.7 median 2856 min 4 max 29590702	cum. 111.29 mean 109.34416 median 107.13 min -42.04 max 208.29	0.194971912	597.39
	TC	cum. 33.0 mean 1.2 median 1.0 min 1.0 max 3.0	cum. 80247 mean 2972.1 median 1397 min 8 max 40316	cum. 364 mean 13.5 median 15 min 1 max 129	cum. 2937672 mean 108802.7 median 28460 min 8 max 2033070	cum. 79.74 mean 101.70188 median 92.03 min 0 max 159.96	0.017925041	
FoundationDB	AC	cum. 45433.0 mean 3.1 median 1.0 min 1.0 max 610.0	cum. 14942670 mean 1219.31 median 168 min 4 max 1784413	cum. 301484 mean 24.60 median 8 min 1 max 28207	cum. 896426808 mean 73147.84 median 1320 min 4 max 189819237	cum. 132.17 mean 121.13912 median 122.59 min -165.43 max 213.55	0.21211046	158.86

Application		V(G)		V		D		E		MI		CC/LOC	V(G) AC/TC
	TC	cum.	286.0	cum.	31783	cum.	795	cum.	867712	cum.	199.23	0.29822732	
		mean	4.0	mean	441.43	mean	66.25	mean	12051.56	mean	180.89		
		median	2.0	median	254	median	9	median	2340	median	180.11		
		min	1.0	min	15	min	2	min	30	min	0		
		max	72.0	max	8476	max	58	max	491608	max	210.58		
Handbrake	AC	cum.	19030.0	cum.	2221764	cum.	41698	cum.	99013610	cum.	111.69	0.15709486	27.38
		mean	2.9	mean	337.8	mean	6.3	mean	15054.5	mean	99.50838		
		median	1.0	median	415	median	13	median	5303.5	median	99.475		
		min	1.0	min	8	min	1	min	8	min	-10.95		
		max	136.0	max	147305	max	3323	max	9447824	max	182.88		
	TC	cum.	695.0	cum.	134076	cum.	1007	cum.	7310349	cum.	66.37	0.16102873	
		mean	16.5	mean	3192.3	mean	24.0	mean	174055.9	mean	99.140424		
		median	1.0	median	64	median	4	median	248	median	99.37		
		min	1.0	min	8	min	1	min	3	min	0		
		max	196.0	max	147305	max	3323	max	9447824	max	182.86		
Hibernate	AC	cum.	21107.0	cum.	2461274	cum.	86741	cum.	412910812	cum.	145.75	0.084690201	2.55
		mean	1.5	mean	156.58	mean	5.52	mean	2626.83	mean	131.27441		
		median	1.0	median	51	median	4	median	228	median	133.29		
		min	1.0	min	4	min	1	min	4	min	0		
		max	29.0	max	14392	max	68	max	978656	max	209.95		
	TC	cum.	8277.0	cum.	1724444	cum.	42424	cum.	33204179	cum.	137.31	0.100808711	
		mean	1.2	mean	207.86	mean	5.11	mean	4002.43	mean	134.13833		
		median	1.0	median	44	median	4	median	204	median	134.22		
		min	1.0	min	4	min	1	min	4	min	0		
		max	7.0	max	20926	max	67	max	1255560	max	213.55		
Hibernate ORM	AC	cum.	3023.0	cum.	406552	cum.	12612	cum.	8116464	cum.	132.43	0.197220772	2.51
		mean	2.0	mean	263.8	mean	8.2	mean	5267.0	mean	122.57471		
		median	1.0	median	87	median	6	median	525	median	125.56		
		min	1.0	min	8	min	1	min	8	min	0		
		max	69.0	max	28134	max	663	max	601542	max	186.61		
	TC	cum.	1202.0	cum.	334615	cum.	7643	cum.	4360900	cum.	128.1	0.06913211	
		mean	1.1	mean	307.8	mean	7.0	mean	4011.9	mean	125.84878		
		median	1.0	median	83	median	6	median	518	median	130.09		
		min	1.0	min	4	min	1	min	4	min	0		
		max	20.0	max	3713	max	28	max	85399	max	208.22		
Industry 1	AC	cum.	3517.0	cum.	1227992	cum.	9821	cum.	63358007	cum.	89.6	0.042014096	0.73
		mean	8.3	mean	2875.8	mean	23	mean	148379.4	mean	86.98		
		median	3.5	median	156	median	10	median	914	median	88.56		
		min	1.0	min	4	min	1	min	4	min	0		
		max	166.0	max	16968	max	426	max	2002	max	91.51		

Application		V(G)	V	D	E	MI	CC/LOC	V(G) AC/TC
	TC	cum. 4838.0 mean 3.7 median 2.0 min 1.0 max 56.0	cum. 21456330 mean 16749.6 median 181 min 8 max 129459	cum. 45936 mean 35.8 median 17 min 1 max 820	cum. 6325641126 mean 4938049.3 median 1286 min 8 max 961878	cum. 91.8 mean 95.01 median 94.11 min 0 max 101.42	0.020756376	
Industry 2	AC	cum. 1283.0 mean 5.09 median 4.0 min 1.0 max 144.0	cum. 410441 mean 1628.73 median 88.11 min 2 max 1494	cum. 4283 mean 17.00 median 10 min 1 max 416	cum. 31220415 mean 123890.536 median 457 min 2 max 1014	cum. 156.18 mean 131.24 median 140.11 min 0 max 189.43	0.032970139	0.34
		cum. 3721 mean 6.91 median 3.0 min 1.0 max 39.0	cum. 8260221 mean 1532.57 median 109.95 min 4 max 4729.5	cum. 15412 mean 28.64 median 18 min 1 max 520	cum. 210961817 mean 39213.41 median 613 min 4 max 81339	cum. 191.20 mean 201.48 median 199.16 min 0 max 203.65	0.041905985	
		cum. 6858 mean 18.4 median 5.0 min 1.0 max 125.0	cum. 2,495695 mean 6465.53 median 104.18 min 4 max 11312	cum. 19260 mean 48.75 median 8.87 min 1 max 284	cum. 112659215 mean 285213.20 median 991.88 min 4 max 1334.6667	cum. 88.6 mean 93.56 median 90.22 min 0 max 95.49	0.153097444	
		cum. 19547.0 mean 26.3 median 2.0 min 1.0 max 25.0	cum. 42929054 mean 57778.27 median 121.19 min 8 max 86318	cum. 90688 mean 122.05 median 11.88 min 1 max 215.89	cum. 1.244e10 mean 167429.34 median 858.28 min 8 max 641252	cum. 89.9 mean 88.41 median 86.13 min 0 max 90.16	0.135479623	
Industry 3	AC	cum. 2510.0 mean 1.16 median 1.0 min 1.0 max 15.0	cum. 174563 mean 87.23 median 25 min 8 max 6477	cum. 7910 mean 3.95 median 2 min 1 max 59	cum. 2206746 mean 1102.82 median 50 min 8 max 382143	cum. 129.50 mean 120.11 median 122.32 min 0 max 123.96	0.415838304	14.59
		cum. 172.0 mean 1.19 median 1.0 min 1.0 max 4.0	cum. 20767 mean 546.50 median 156 min 19 max 1776	cum. 482 mean 15.06 median 7 min 2 max 21	cum. 234031 mean 61258.71 median 1051.5 min 38 max 37296	cum. 127.3 mean 131.34 median 130.98 min 0 max 146.71	0.335282651	
		cum. 643.0 mean 1.31 median 1.0 min 1.0 max 11.0	cum. 66779 mean 172.56 median 38 min 2 max 2502	cum. 2612 mean 6.75 median 3 min 1 max 34	cum. 932435 mean 2409.39 median 152 min 4 max 72558	cum. 120.31 mean 130.31 median 126.65 min 0 max 149.22	0.166278769	
Industry 4	AC							80.36

Application		V(G)	V	D	E	MI	CC/LOC	V(G) AC/TC
	TC	cum. 8.0 mean 2.0 median 1.0 min 1.0 max 3.0	cum. 1465 mean 366.25 median 413 min 108 max 531	cum. 33 mean 8.25 median 8 min 4 max 13	cum. 14411 mean 3602.75 median 3538 min 432 max 6903	cum. 100.91 mean 95.23 median 98.21 min 0 max 118.94	0.296296296	
Inkscape	AC	cum. 36227.0 mean 1.6 median 1.0 min 1.0 max 262.0	cum. 22704752 mean 1015.6 median 225 min 4 max 2522698	cum. 295251 mean 13.2 median 9 min 1 max 5758	cum. 1.355E+09 mean 60623.3 median 2043 min 4 max 269928686	cum. 120.22 mean 115.58191 median 115.82 min -79.98 max 220.76	0.074084148	214.36
		cum. 169.0 mean 1.5 median 1.0 min 1.0 max 5.0	cum. 89202 mean 810.9 median 370 min 18 max 27006	cum. 1182 mean 10.7 median 11 min 1 max 286	cum. 1522529 mean 13841.2 median 4004 min 18 max 433771	cum. 121.15 mean 113.52039 median 116.87 min 38.61 max 164.31	0.073638344	
		cum. 12733.0 mean 1.7 median 1.0 min 1.0 max 51.0	cum. 1575344 mean 195.16 median 59 min 4 max 7347	cum. 48344 mean 5.99 median 5 min 1 max 78	cum. 27247809 mean 3375.60 median 264 min 4 max 405405	cum. 150.02 mean 138.18718 median 135.83 min 0 max 207.54	0.116839024	
		cum. 1232.0 mean 1.5 median 1.0 min 1.0 max 15.0	cum. 405256 mean 430.21 median 272 min 8 max 6358	cum. 8450 mean 8.97 median 7 min 1 max 69	cum. 8498957 mean 9022.25 median 2133 min 8 max 419628	cum. 130.27 mean 119.32421 median 120.69 min 0 max 185.46	0.02739787	
Jfreechart	AC	cum. 21719.0 mean 2.7 median 1.0 min 1.0 max 51.0	cum. 2281014 mean 266.44 median 83 min 8 max 17088	cum. 70414 mean 8.22 median 6 min 1 max 154	cum. 58879690 mean 6877.664992 median 474 min 8 max 1602216	cum. 143.01 mean 156.01 median 130.29 min 0 max 181.87	0.264665741	5.49
		cum. 3959.0 mean 1.3 median 1.0 min 1.0 max 21.0	cum. 1348734 mean 457.4 median 303 min 8 max 14563	cum. 30706 mean 10.4 median 10 min 1 max 144	cum. 29213286 mean 9906.2 median 3294 min 8 max 1750608	cum. 138.77 mean 120.04 median 122.94 min 0 max 201.25	0.298252222	
		cum. 36397.0 mean 2.1 median 1.0 min 1.0 max 426.0	cum. 5944927 mean 302.06 median 114 min 4 max 93287	cum. 150964 mean 7.7 median 6 min 1 max 296	cum. 335833457 mean 17063.84 median 684 min 4 max 23615635	cum. 138.37 mean 127.05269 median 129.26 min 0 max 209.33	0.223190414	
JRuby	AC	cum. 36397.0 mean 2.1 median 1.0 min 1.0 max 426.0	cum. 5944927 mean 302.06 median 114 min 4 max 93287	cum. 150964 mean 7.7 median 6 min 1 max 296	cum. 335833457 mean 17063.84 median 684 min 4 max 23615635	cum. 138.37 mean 127.05269 median 129.26 min 0 max 209.33	0.223190414	75.05

Application		V(G)		V		D		E		MI		CC/LOC	V(G) AC/TC
	TC	cum.	485.0	cum.	72311	cum.	2560	cum.	895672	cum.	151.53	0.098277609	
		mean	1.2	mean	134.91	mean	6.4	mean	1671.023	mean	132.95298		
		median	1.0	median	72	median	5	median	360	median	133.535		
		min	1.0	min	8	min	1	min	8	min	0		
		max	9.0	max	2041	max	36	max	63271	max	204.41		
Keepassx	AC	cum.	3054.0	cum.	427823	cum.	11550	cum.	8565093	cum.	129.93	0.165072158	13.11
		mean	2.4	mean	330.4	mean	8.9	mean	6614.0	mean	113.69981		
		median	1.0	median	146	median	7	median	1060	median	116.335		
		min	1.0	min	10	min	2	min	22	min	31.3		
		max	48.0	max	28602	max	584	max	992609	max	208.29		
	TC	cum.	233.0	cum.	173548	cum.	2590	cum.	4460251	cum.	115.26	0.048460899	
		mean	1.4	mean	1009.0	mean	15.1	mean	25931.7	mean	99.192589		
		median	1.0	median	698	median	13	median	8620	median	100.29		
		min	1.0	min	25	min	2	min	50	min	0		
		max	11.0	max	25969	max	501	max	795401	max	147.85		
lightGBM	AC	cum.	1335.0	cum.	680152	cum.	18672	cum.	27801759	cum.	129.32	0.059039448	9.96
		mean	1.0	mean	488.3	mean	13.4	mean	19958.2	mean	116.96415		
		median	2.0	median	219	median	10	median	2273	median	114.675		
		min	1.0	min	4	min	1	min	4	min	20.52		
		max	35.0	max	48016	max	1226	max	3249235	max	205.86		
	TC	cum.	134.0	cum.	70404	cum.	868	cum.	1005732	cum.	187.98	0.096195262	
		mean	1.6	mean	848.24	mean	10.46	mean	12117.25	mean	184.32		
		median	1.0	median	682	median	9	median	6528	median	180.93		
		min	1.0	min	30	min	2	min	60	min	0		
		max	6.0	max	2962	max	26	max	70392	max	201.88		
Mongo	AC	cum.	182531.0	cum.	167907982	cum.	2517212	cum.	6450634454	cum.	135.45	0.077452208	10.02
		mean	1.1	mean	1232.84	mean	18.49	mean	47375.39993	mean	121.09176		
		median	1.0	median	155	median	7	median	994	median	121.95		
		min	1.0	min	4	min	1	min	4	min	-2374.91		
		max	10019.0	max	16497738	max	42166	max	606572002	max	213.55		
	TC	cum.	18211.0	cum.	9587395	cum.	112195	cum.	417705460	cum.	145.77	0.105171667	
		mean	2.1	mean	978.71	mean	11.45	mean	42640.41	mean	127.14983		
		median	1.0	median	191	median	7	median	1266	median	129.68		
		min	1.0	min	8	min	1	min	8	min	0		
		max	83.0	max	129459	max	320	max	39096618	max	177.39		
MPV Player	AC	cum.	23190.0	cum.	3592760	cum.	84254	cum.	113009019	cum.	116.02	0.196844044	927.60
		mean	4.4	mean	688.8	mean	16.2	mean	21665.8	mean	102.73209		
		median	2.0	median	381.5	median	14	median	5466	median	104.04		
		min	1.0	min	10	min	1	min	10	min	0		
		max	107.0	max	168981	max	4507	max	4992074	max	178.16		

Application		V(G)	V	D	E	MI	CC/LOC	V(G) AC/TC
	TC	cum. 25.0 mean 1.0 median 3.0 min 1.0 max 2.0	cum. 4400 mean 183.3 median 110 min 70 max 3062	cum. 155 mean 6.5 median 5 min 3 max 103	cum. 44198 mean 1841.6 median 675 min 280 max 33630	cum. 125.39 mean 120.40815 median 126.04 min 0 max 141.48	0.161290323	
Musescore	AC	cum. 41760.0 mean 1.8 median 1.0 min 1.0 max 243.0	cum. 13778244 mean 596.8 median 140 min 4 max 246951	cum. 273861 mean 7 median 1 min 1 max 5635	cum. 687739924 mean 938 median 4 min 4 max 30432620	cum. 123.72 mean 120.54783 median 120.55 min -48.81 max 213.02	0.070370083	39.47
		cum. 1058.0 mean 1.1 median 1.0 min 1.0 max 13.0	cum. 291451 mean 302.6 median 31 min 8 max 41006	cum. 6287 mean 11.9 median 2 min 1 max 915	cum. 7681767 mean 29791.6 median 62 min 8 max 1783268	cum. 116.44 mean 136.40204 median 152.91 min 0 max 196.13	0.006500089	
		cum. 8177.0 mean 2.5 median 1.0 min 1.0 max 54.0	cum. 82138 mean 25.1 median 261 min 11 max 20917	cum. 1831 mean 10 median 2 min 2 max 525	cum. 3475597 mean 2934 median 22 min 878846 max 878846	cum. 124.43 mean 113.11175 median 114.3 min 0 max 176.85	0.185870479	
		cum. 248.0 mean 2.6 median 1.0 min 1.0 max 21.0	cum. 31728 mean 330.5 median 125.5 min 15 max 3821	cum. 671 mean 6.99 median 4 min 2 max 33	cum. 550006 mean 5729.22 median 498 min 30 max 126093	cum. 197.5 mean 190.04 median 181.90 min 0 max 218.98	0.183976261	
Netdata	AC	cum. 8831.0 mean 7.8 median 3.0 min 1.0 max 231.0	cum. 1927370 mean 1692.2 median 565 min 13 max 97647	cum. 25188 mean 22.1 median 18 min 2 max 1705	cum. 107931209 mean 94759.6 median 9834 min 26 max 5922011	cum. 93.91 mean 88.25 median 80.17 min 0 max 135.18	0.182315537	12.54
		cum. 704.0 mean 2.3 median 1.0 min 1.0 max 41.0	cum. 64508 mean 215.0 median 203.5 min 19 max 33350	cum. 1264 mean 4.2 median 6 min 2 max 359	cum. 2606101 mean 8687.0 median 1317 min 38 max 3435050	cum. 107.37 mean 98.479077 median 93.08 min 0 max 166.14	0.241013352	
		cum. 30729.0 mean 4.7 median 1.0 min 1.0 max 54.0	cum. 4030415 mean 614.2 median 243 min 8 max 169656	cum. 80605 mean 12.3 median 10 min 1 max 2540	cum. 25292314 2 mean 38543.6 median 2329.5 min 8 max 37851011	cum. 122.93 mean 110.42934 median 113.16 min 0 max 184.96	0.143889979	
NMap	AC	cum. 30729.0 mean 4.7 median 1.0 min 1.0 max 54.0	cum. 4030415 mean 614.2 median 243 min 8 max 169656	cum. 80605 mean 12.3 median 10 min 1 max 2540	cum. 25292314 2 mean 38543.6 median 2329.5 min 8 max 37851011	cum. 122.93 mean 110.42934 median 113.16 min 0 max 184.96	0.143889979	23.57

Application		V(G)	V	D	E	MI	CC/LOC	V(G) AC/TC
	TC	cum. 1304.0 mean 1.03 median 2.0 min 1.0 max 21.0	cum. 200199 mean 158.9 median 462.5 min 38 max 19574	cum. 5118 mean 4.1 median 16.5 min 2 max 508	cum. 73192170 mean 58089.0 median 7648.5 min 76 max 891667	cum. 122.52 mean 101.9364 median 102.81 min 0 max 153.49	0.123030475	
Notepad ++	AC	cum. 18926.0 mean 5.1 median 1.0 min 1.0 max 734.0	cum. 2565949 mean 694.4 median 162 min 4 max 270039	cum. 55233 mean 14.9 median 9 min 1 max 3629	cum. 186462571 mean 50463.5 median 1452 min 4 max 22365037	cum. 111.84 mean 114.95206 median 119.13 min -180.25 max 205.45	0.243822628	2.70
		cum. 7019.0 mean 14.3 median 1.0 min 1.0 max 2097.0	cum. 71095 mean 144.5 median 128 min 4 max 12386	cum. 1357 mean 2.8 median 6 min 1 max 915	cum. 10736465 mean 21822.1 median 869 min 4 max 1213828	cum. 139.55 mean 145.58088 median 150.43 min 0 max 167.33	1.34078319	
		cum. 3499.0 mean 2.9 median 2.0 min 1.0 max 38.0	cum. 305509 mean 256.1 median 230 min 8 max 27724	cum. 8110 mean 6.8 median 9 min 1 max 747	cum. 7948880 mean 6662.9 median 2004 min 8 max 836053	cum. 137.31 mean 116.69433 median 116.58 min 52.85 max 186.37	0.207409603	
		cum. 2420.0 mean 10.7 median 6.0 min 1.0 max 69.0	cum. 132535 mean 586.4 median 471 min 22 max 17071	cum. 2255 mean 10.0 median 9 min 2 max 316	cum. 2156004 mean 9539.8 median 4400 min 44 max 343244	cum. 119.6 mean 102.55605 median 101.16 min 0 max 170.34	0.574276222	
Opn XML SDK	AC	cum. 82410.0 mean 1.4 median 1.0 min 1.0 max 245.0	cum. 3294512 mean 56.47 median 38 min 2 max 433126	cum. 144735 mean 2.48 median 3 min 1 max 224	cum. 128258645 mean 2198.62 median 114 min 4 max 97020224	cum. 219.37 mean 190.03 median 189.22 min 0 max 219.90	0.357101072	26.47
		cum. 3113.0 mean 1.8 median 1.0 min 1.0 max 23.0	cum. 9164703 mean 5315.95 median 162 min 6 max 618694	cum. 28682 mean 16.64 median 7 min 1 max 474	cum. 363954560 mean 21213.87 median 1141 min 8 max 90501768	cum. 186.25 mean 184.75 median 180.11 min 0 max 215.76	0.026741459	
		cum. 9520.0 mean 1.5 median 1.0 min 1.0 max 38.0	cum. 842457 mean 128.35 median 39 min 2 max 9984	cum. 33622 mean 5.122 median 3 min 1 max 94	cum. 10400228 mean 1584.43 median 117 min 8 max 253048	cum. 195.57 mean 199.03 median 185.86 min 0 max 214.28	0.210047879	
PDF Creator	AC	cum. 9520.0 mean 1.5 median 1.0 min 1.0 max 38.0	cum. 842457 mean 128.35 median 39 min 2 max 9984	cum. 33622 mean 5.122 median 3 min 1 max 94	cum. 10400228 mean 1584.43 median 117 min 8 max 253048	cum. 195.57 mean 199.03 median 185.86 min 0 max 214.28	0.210047879	2.01

Application		V(G)	V	D	E	MI	CC/LOC	V(G) AC/TC
	TC	cum. 4748.0 mean 1.5 median 1.0 min 1.0 max 28.0	cum. 1175551 mean 368.72 median 142 min 8 max 4764	cum. 27689 mean 8.69 median 5 min 1 max 57	cum. 13266858 mean 7298.26 median 732 min 8 max 271548	cum. 186.25 mean 189.06 median 180.51 min 0 max 200.16	0.122516385	
Powershell	AC	cum. 81489.0 mean 2.8 median 1.0 min 1.0 max 129.0	cum. 117745 mean 4.0 median 22 min 3 max 1177	cum. 2900 mean 0.1 median 180 min 4 max 32159	cum. 3539483 mean 121.7 median 7 min 1 max 512	cum. 126.99 mean 116.9978 median 117.035 min 0 max 205.47	0.200774627	270.73
		cum. 301.0 mean 1.8 median 1.0 min 1.0 max 10.0	cum. 69848 mean 358.19 median 103 min 11 max 3901	cum. 1602 mean 8.22 median 5 min 1 max 59	cum. 1805272 mean 9257.81 median 515 min 11 max 230159	cum. 187.98 mean 180.96 median 143.26 min 0 max 201.58	0.109854015	
		cum. 180.0 mean 1.0 median 1.0 min 1.0 max 41.0	cum. 4737711 mean 478.3 median 144 min 4 max 179332	cum. 96280 mean 9.7 median 6 min 1 max 2939	cum. 159747063 mean 16127.9 median 882 min 4 max 8739389	cum. 129.73 mean 123.78127 median 122.08 min -65.14 max 213.41	0.001059759	
		cum. 177.0 mean 3.5 median 1.0 min 1.0 max 35.0	cum. 54252 mean 1085.0 median 561.5 min 8 max 21126	cum. 1614 mean 27.36 median 13 min 1 max 143	cum. 3376737 mean 67534.7 median 7029 min 8 max 131298137	cum. 104.52 mean 102.48862 median 99.095 min 0 max 168.81	0.140699523	
Apache Shiro	AC	cum. 5786.0 mean 1.52 median 1.0 min 1.0 max 34.0	cum. 565003 mean 148.45 median 57 min 8 max 6107	cum. 25368 mean 6.67 median 5 min 1 max 100	cum. 8732435 mean 2294.38 median 275 min 8 max 431747	cum. 156.34 mean 129.81599 median 133.29 min 0 max 208.72	0.198069287	185.21
		cum. 545.0 mean 1.11 median 1.0 min 1.0 max 7.0	cum. 131359 mean 269.73 median 116 min 8 max 3341	cum. 3409 mean 7 median 6 min 1 max 33	cum. 1666934 mean 3422.86 median 696 min 8 max 103571	cum. 146.58 mean 180.30 median 148.74 min 0 max 192.26	0.106403749	
		cum. 12334.0 mean 1.9 median 1.0 min 1.0 max 37.0	cum. 2006332 mean 312.3 median 142 min 4 max 44730	cum. 52696 mean 8.2 median 6 min 1 max 1713	cum. 35816170 mean 5574.5 median 912 min 4 max 1079676	cum. 137.97 mean 126.42625 median 129.26 min 0 max 204.57	0.147523533	

Application		V(G)	V	D	E	MI	CC/LOC	V(G) AC/TC
	TC	cum. 5034.0 mean 1.50 median 1.0 min 1.0 max 17.0	cum. 998984 mean 296.3 median 133 min 8 max 12361	cum. 25721 mean 7.6 median 6 min 1 max 52	cum. 15276608 mean 4531.8 median 798 min 8 max 494440	cum. 137.2 mean 120.04 median 100.17 min 0 max 186.23	0.122440045	
Squirrel SQL	AC	cum. 27870.0 mean 1.7 median 1.0 min 1.0 max 176.0	cum. 3881922 mean 195.51 median 62 min 8 max 17455	cum. 113672 mean 5.73 median 4 min 1 max 112	cum. 69856735 mean 3518.34 median 264 min 8 max 1532944	cum. 143.81 mean 132.4384 median 130.805 min 0 max 208.48	0.143022092	7.42
	TC	cum. 3757.0 mean 1.2 median 1.0 min 1.0 max 15.0	cum. 528544 mean 142.73 median 82 min 4 max 7114	cum. 17843 mean 4.82 median 5 min 1 max 53	cum. 7415573 mean 2002.59 median 336 min 4 max 263218	cum. 152.2 mean 131.16212 median 126.52 min 0 max 184.96	0.135328867	
VLC	AC	cum. 83145.0 mean 4.3.0 median 1.0 min 1.0 max 326.0	cum. 13126768 mean 674.1 median 334 min 4 max 141295	cum. 268177 mean 13.8 median 12 min 1 max 3002	cum. 502490798 mean 25805.8 median 3938 min 4 max 8783253	cum. 117.63 mean 106.25235 median 106.44 min -20.85 max 208.29	0.175945539	108.40
	TC	cum. 767.0 mean 4.0.0 median 1.0 min 1.0 max 156.0	cum. 153540 mean 791.4 median 443 min 34 max 15344	cum. 3258 mean 16.8 median 14 min 3 max 390	cum. 5624244 mean 28990.9 median 5797 min 102 max 902943	cum. 112.08 mean 100.32777 median 103.27 min 0 max 160.08	0.154918198	
Voldemort	AC	cum. 24733.0 mean 1.9 median 1.0 min 1.0 max 92.0	cum. 3716241 mean 249.78 median 106 min 8 max 57976	cum. 100984 mean 6.79 median 5 min 1 max 218	cum. 73526714 mean 4941.98 median 590 min 8 max 2630968	cum. 137.84 mean 124.29038 median 128.58 min 0 max 206.74	0.180837763	4.49
	TC	cum. 5508.0 mean 2.1 median 1.0 min 1.0 max 20.0	cum. 1583546 mean 500.97 median 245 min 8 max 14033	cum. 30872 mean 9.774438469 median 9 min 1 max 124	cum. 40745773 mean 12890.1528 median 2266.5 min 8 max 1740092	cum. 119.15 mean 114.71663 median 114.85 min 0 max 198.13	0.108346283	
Vscode	AC	cum. 3992.0 mean 2.2.0 median 1.0 min 1.0 max 48.0	cum. 1505599 mean 428.95 median 180 min 4 max 198761	cum. 22997 mean 6.551851852 median 8 min 1 max 157	cum. 64239046 mean 18301.72251 median 1460 min 8 max 10203587	cum. 130.99 mean 134.33769 median 142.8 min 0 max 160.98	0.103203123	12.79

Application		V(G)	V	D	E	MI	CC/LOC	V(G) AC/TC
	TC	cum. 312.0 mean 2.6 median 1.0 min 1.0 max 11.0	cum. 204511 mean 330.9239482 median 146.5 min 4 max 13480	cum. 4698 mean 7.601941748 median 6 min 1 max 88	cum. 4559041 mean 7377.088997 median 972 min 4 max 1186240	cum. 200.04 mean 214.07 median 198.56 min 0 max 218.71	0.29489603	
WorldWind	AC	cum. 57172.0 mean 2.2 median 1.0 min 1.0 max 117.0	cum. 9188614 mean 353.0 median 125 min 4 max 260991	cum. 253434 mean 9.74 median 7 min 1 max 6021	cum. 254162257 mean 966.66 median 854 min 4 max 23108544	cum. 135.24 mean 107.14501 median 107.73 min 0 max 171.85	0.173573541	57.98
	TC	cum. 986.0 mean 1.6 median 1.0 min 1.0 max 23.0	cum. 373735 mean 606.75 median 307.50 min 11.00 max 18043.00	cum. 6450.00 mean 19.47.00 median 9.00 min 2.00 max 50.00	cum. 6397181.00 mean 10385.03.00 median 2710.00 min 22.00 max 721720.00	cum. 118.21 mean 123.60688 median 126.69 min 0 max 210.18	0.064958166	

Table 4. MAXIMUM CYCLOMATIC COMPLEXITY AND MEDIAN VALUES,
RESULTS FOR WILCOXON'S RANK SUM TEST, AND KOLMOGOROV
SMIRNOV TEST

Application	Maximum V(G) values		Median V(G) values		Wilcoxon RS	Kolmogorov Smirnov Test		T-test
	AC	TC	AC	TC	p-value	D value	p-value	p-value
Amorok	47	14	1	1	2.20E-16	0.26754	2.20e-16	2.2e-16
Amule	219	55	1	1	3.01E-15	0.18496	2.68e-13	9.323e-08
Apache Ant	82	21	1	1	< 2.2e-16	0.34917	2.20e-16	2.2e-16
Apache httpd	350	25	2	2.5	0.4903	0.18012	0.3479	0.4997
Audacity	299	3	2	1	0.01929	0.28041	0.1502	4.808e-10
Bitcoin	356	45	1	1	< 2.2e-16	0.39585	2.20e-16	2.2e-16
Client	650	15	1	1	2.20E-16	0.44689	2.20e-16	2.2e-16
Curl	724	97	3	2	< 2.2e-16	0.38092	2.20e-16	0.02849
Ditaa	98	7	1	1	0.1441	0.13571	0.6692	0.003986
Django	49	21	1	1	2.20E-16	0.3104	2.20e-16	2.2e-16
Filezilla	275	3	2	1	4.677e-06	0.44386	4.828e-05	2.2e-16
FoundationDB	610	72	1	2	0.0005206	0.24529	0.0002236	0.5082
Handbrake	136	196	1	1	0.6492	0.0032144	0.97	0.7124
Hibernate	29	7	1	1	2.20E-16	0.27825	2.20e-16	2.2e-16
Hibernate	69	20	1	1	< 2.2e-16	0.17297	2.20e-16	2.2e-16
Industry 1	166	56	3.5	2	< 2.2e-16	0.26228	2.20e-16	2.20e-16
Industry 2	144	39	4	3	0.0359	0.25845	0.01052	0.1872
Industry 3	125	25	5	2	1.52e-10	0.38449	7.46e-07	2.20e-16
Industry 4	15	4	1	1	0.07585	0.9506	0.9506	0.02329
Industry 5	11	3	1	1	0.8373	0.19513	0.955	0.9989
Inkscape	262	5	1	1	2.2e-16	0.13856	0.03036	2.2e-16
Jakarta jmeter	51	15	1	1	2.89e-16	0.27517	2.20e-16	2.331e-11
Jfreechart	51	21	1	1	< 2.2e-16	0.22655	2.20e-16	0.7991
JRuby	426	9	1	1	5.94e-09	0.1369	5.04e-06	2.2e-16
Keepassx	48	11	1	1	5.62e-15	0.26862	1.99e-10	8.553e-16
lightGBM	35	6	2	1	8.88E-08	0.27856	3.89e-06	2.2e-16
Mongo	10019	83	1	1	2.20e-16	0.10573	2.20e-16	2.2e-16
MPV Player	107	2	3	1	1.728e-09	0.67718	6.099e-10	2.2e-16
Muscore	243	13	1	1	2.20E-16	0.64631	2.20e-16	2.2e-16
Mypaint	54	21	1	1	0.1563	0.084361	0.4691	0.2201
Netdata	231	41	3	1	2.20E-16	0.5858	2.20e-16	2.2e-16
NMap	594	31	1	2	0.07921	0.98478	0.2868	0.76
Notepad ++	734	2097	1	1	2.20E-16	0.3032	2.20e-16	2.2e-16
Onion	38	69	2	6	2.20E-16	0.43752	2.20e-16	2.2e-16
Opn XML SDK	245	23	1	1	2.20E-16	0.056495	5.26e-07	2.2e-16

Application	Maximum V(G) values		Median V(G) values		Wilcoxon RS	Kolmogorov Smirnov Test		T-test
	AC	TC	AC	TC	p-value	D value	p-value	p-value
PDF Creator	38	28	1	1	2.2e-16	0.10232	2.2e-16	2.2e-16
Powershell	129	10	1	1	1.90E-07	0.13465	0.0006311	6.402e-12
Rosegarden	41	35	1	1	0.02563	0.17542	0.0936	0.6563
Apache Shiro	34	2	1	1	4.367e-12	0.075419	8.999e-09	1.196e-06
Apache Sqoop	37	17	1	1	5.91e-16	0.081698	2.41e-13	6.8e-16
Squirrel SQL	176	15	1	1	< 2.2e-16	0.29846	2.20e-16	2.2e-16
VLC	326	156	1	1	0.0005712	0.13281	0.002055	0.06574
Voldemort	92	20	1	1	5.81E-09	0.14672	2.20e-16	0.0005795
Vscode	48	11	1	1	2.2e-16	0.31511	2.2e-16	2.2e-16
WorldWind	117	23	1	1	2.2e-16	0.01596	2.20e-16	2.2e-16

5.2 Inferential Statistics

Previous sections confirm our intuition that TC tends to be simpler than AC (Introduction) but that frequency distributions of complexity values are not normal, heavily skewed and that therefore we cannot overly rely on descriptive statistics (Chapter 3), thereby calling for the use of non-parametric statistical methods.

The mean values are highly affected by the distribution as for almost all objects, there are a higher number of data point with a cyclomatic complexity of 1 which skews the distribution to the left thereby affecting the mean and median. This is very predominant in application code. The test code rather has less skewness in the distribution and less amount of data points with a cyclomatic complexity less than 5 as shown in the box plot. Also, looking at the boxplots and sample distributions in Appendix A , there are way many more AC methods with a cyclomatic complexity value higher than 10 (it goes up to 10019 Table 4), than for TC.

First, we proceeded to confirm our intuition by performing a Shapiro-Wilk Normality test on the datasets to check whether the normality assumption of the t-test is satisfied. The results in Appendix D (Table 7) reject the normality assumption for all our distributions. It is therefore, as expected, not appropriate to use parametric tests. Also, another possible reason why all objects reject the null hypothesis of the Shapiro-Wilk is that when the dataset has more than 5000 (as in the case of Shapiro-Wilk in R), the slightest deviation from normality will lead to a rejection of the null hypothesis. For a large dataset,

even big departures from normality will not easily be detected. In such a case, graphical representations like histogram, QQ plots and boxplots are enough to judge the deviations from normality. Though in such instances, graphical representation of skewness, kurtosis and outliers suffice to predict non-normality of the data, performing the test will give more accurate and valid results especially on an approximately normal data. Recall from Chapter 3 that we select non-parametric tests for non-normal data. In this analysis, we will focus on using Wilcoxon Rank Sum test as our primary test and use Kolmogorov Smirnov as a confirmatory test. We select Wilcoxon Rank Sum Test over Kolmogorov Smirnov due to its high power as explained in Chapter 3. With these tests we compare the distribution of AC method cyclomatic values and the TC method cyclomatic values for each object separately.

In recording the mean values, we encounter situations where the average values of two variables look almost similar. In such an instance, it is possible to assume that these values are almost the same. We need to verify that these values are either statistically different or almost similar. Therefore, for instances where the p-value is greater than the alpha significant level, we can reject the difference in the mean values. Table 4 show statistical test results when we use the Wilcoxon Rank Sum Test and the Kolmogorov Smirnov Test. All p-values for Wilcoxon Rank Sum test are much smaller than the 0.05α level, with the exception of Apache httpd (0.49), Dita (0.06), Handbrake (0.64), Mypaint (0.15), Shiro (0.06) and VSCode (0.54).

In Section 5.1.2, we observed instances of objects where TC shows higher average cyclomatic complexity values than AC. We will proceed to verify with Wilcoxon Rank Sum Test if, perhaps, these values are drawn from the same distribution or are statistically different by which we can either accept the values or reject them as outliers. For objects such as Apache, Mypaint and VSCode, which previously had their average TC method cyclomatic complexity value greater than AC values, results of Wilcoxon Rank Sum Test (p-values) lead us to reject the null hypothesis. At this point we consider these objects as outliers, which allow us to reject the null hypothesis of our tests for all case study systems but these: Kolmogorov Smirnov Test also reports a similar set of values that lead to the rejection of the null hypothesis: Apache httpd (p-value of 0.34), Dita (p-value of 0.67), Handbrake (p-value of 0.9), VSCode (p-value of 0.18), Mypaint (p-value of 0.46), and Shiro

(p-value of 0.45), Rosegarden (p-value of 0.09). Recall that the variation in the values between results of Kolmogorov Smirnov and Wilcoxon Rank Sum is because Wilcoxon Rank Sum uses ranks to calculate the p-value and therefore it is sensitive to a shift in the median values while Kolmogorov Smirnov calculates the p-value using a shift in the probability distribution frequency. Recall that the null and alternate hypotheses for Wilcoxon Rank Sum are:

- H_0 : There is a statistically significant difference between the median method cyclomatic complexity values of AC and TC for each objects.
- H_1 : The distributions of AC and TC method cyclomatic complexity values are drawn from different distributions.

Results, as discussed previously, allow us to reject the null hypothesis for the majority of the objects, which shows that, as similar as the cyclomatic complexity mean and median values for AC and TC methods may seem (**Table 3**), they are statistically significantly different.

As discussed earlier there are some instances for which we have higher mean values for TC than AC. We therefore regard these objects to have more complex test code methods than application code. The ratio for AC to TC are given as: Amorok (1.1:1.2), Light GBM (1.0:1.6), Mongo (1.1:2.1), Notepad ++ (5.1:14.3), Open XML (1.4:1.8), Onion (2.9:10.7), PDF Creator (1.45:1.48), Rosegarden (0.1:3.5) and Voldemort (1.9:2.6).

Though some instance have higher mean values for TC than AC contrary to what we observe for all the other case study systems, however, for some instances, the statistical test results does not allow us to reject the null hypothesis. Mean values for object like Apache Httpd (5.0:5.7), Foundation (3.1:4.0), Mypaint (2.5:2.6), VSCode (2.2:2.6) which tend to be greater than production code will be regarded as outliers. Likewise, that of Dita, Handbrake, Shiro and Rosegarden which tend to have higher average values for AC than for TC will also be regarded as outliers due to the rejection of the null hypothesis. (Boxplots in Appendix A).

To conclude, all the metrics we used show AC methods tend to have a higher complexity than TC methods: The cyclomatic complexity values of AC methods are higher than TC method complexity values; Their Halstead values are higher; the mean and median values of AC complexity are higher than TC complexity values. And for a slight difference

in the mean values, statistical tests show that the difference is very statistically significant and cannot be ignored. Test code as hypothesized by some authors is expected to be simple but the results gained so far proves otherwise.

5.3 On the Use of Non-Parametric Statistical Tests

In this study, we have privileged the use of non-parametric statistical tests over parametric statistical tests. We believe it is important that, in addition to justifying the use of non-parametric tests by the fact distributions are not normal, we go further and explain why non-parametric statistical tests are better suited in our study.

In our attempt to use statistical tests to explain the difference between AC complexity and TC complexity, one may argue that it suffices to use the student's t-test even when the normality assumption is rejected, given that the sample of method complexity values is large (recall the NOM column in **Table 2**). With such large samples, the Central Limit Theorem (CLT) suggests that the use of a t-test is legitimate [70]. Although a t-test may legitimately be used in our context, since we have large samples, we argue it is inappropriate to use it in our context on the following grounds. (1) In our results, the population size, that is the set of methods, is fixed for each object and does not allow for an increase in the sample size which would have, in some sense, warranted the use of parametric tests given it would have been possible to increase the sample size (as parametric tests are powerful in such cases). (2) Our analysis does not warrant the use of parametric tests for a non-normal distribution because it rejects one of the main assumptions of the t-test which is the normality and homogeneity of variance (homoscedasticity) assumptions as explained in Section 3.4. A test for normality rejects the normality assumption which makes it erroneous to use a t-test, leading to a potential of Type I (false positives) error when using the t-test. (3) In our context, non-parametric tests will perform better than parametric tests (including a t-test) as the former will allow us to detect smaller statistical differences than the latter. (And, indeed, descriptive statistics indicate that mean and median values of AC and TC are close to each other). One may argue that for large sample sizes, the t-test is robust against deviations from the normality and equal variance (homogeneity of variance) assumptions when using the central limit theorem and the probability of large numbers with sample averages. This is only possible for larger dataset out of which a smaller sample is drawn from. The idea is that increasing the sample size would move the distribution towards

a normal distribution; in our context, we argue, given the heavily skewed distributions we observe, that increasing the set of methods in an object, if that were at all possible from an engineering point of view, would certainly not guarantee we converge towards a normal distribution.

Moreover, CLT (the law of large numbers) does not make a large-sample non-normal distribution approximately normal to the extent a t-test can be used; rather, only the sampling averages become approximately normally distributed. Therefore, if we desire to test for the difference between the original sample groups, it is not appropriate to compare the differences between some sample averages of the original data. That being said, if it were legitimate to rely on CLT and proceed with a t-test, that would mean that given any non-normal distribution, we can make it normal by taking a larger sample of the data; this is not correct. In this case the sampling average is not relevant. The use of sample averages (through a t-test) rather than original averages will result in different data sets which is not what we would want to compare. One of the assumptions of the t-test is that each population under comparison (not the sample average) should have a normal distribution.

Our analysis favours the use of non-parametric tests due to the skewness of the distributions and the violations to the normality assumption. While we agree, to some extent, with someone who may advocate for the use of the t-test, we conclude that it is not appropriate and it is misleading (Type II error) as one is likely to accept the null hypothesis in certain instance while one will reject the null hypothesis using non-parametric tests like the Wilcoxon Rank Sum test and the Kolmogorov Smirnov test.

The values of **Table 4** show significant differences between the results obtained using the parametric t-test and non-parametric tests like Wilcoxon Rank Sum and Kolmogorov Smirnov. In the case of Curl, we observe a p-value of 0.02 (almost at the significance level) using the t-test while the non-parametric tests yield the lowest p-value possible ($2.2e-16$). Audacity, FileZilla, Handbrake, Inkscape, Keepassx, MPV Player, Open XML are examples of such high variations in values leading to (potential) error.

A similar observation is made in the cases of Voldemort, Apache Ant, Squirrel SQL, Jakarta, Apache Httpd and Hibernate leading to false positives. In situations where slight differences in values matter, the t-test would not lead to a more convincing conclusion and this, we believe, could be misleading.

We therefore advocate for the use of non-parametric tests in this study. This is because non-parametric tests perform better on non-normal distributions and can detect changes and shifts in the distributions and median values that the t-test cannot detect. One could argue that the t-test is very robust to violations to the normality and equal variance assumptions and therefore, the t-test would still give satisfactory results for data which are either non-normal or heteroscedastic or both. However, in such circumstances, non-parametric tests would yield superior performance, especially in certain cases where the p-values are close to the desired significance level.

Results for Heteroscedastic t-test are included in **Table 4**, along with the results for the Wilcoxon Rank Sum and Kolmogorov-Smirnov tests. As expected, although the t-test may still give acceptable results, it cannot detect some differences which the Wilcoxon Rank Sum and the Kolmogorov detect, and therefore using a t-test we believe can lead to misleading conclusions. This is a confirmation of our initial intuition and the reason for selecting non-parametric statistical tests.

5.4 On Correlation among Software Metric

In this section we look at how different kinds of code determine the correlation that exist between software metrics. We will use Spearman's correlation when attempting to confirm whether there is a monotonic relationship between two groups of data. In Table 5, we list the values obtained for Spearman's correlation on AC, comparing Cyclomatic Complexity and LOC. In our investigation, almost all the Spearman's rho values obtained for AC imply a high correlation ranging from 0.35 to 0.87. This results confirms empirical results obtained by a large majority of authors as explained in Chapter 2. However, this does not apply to TC as the results are the opposite, to the point that results indicate a negative correlation for a number of objects. FileZilla has the highest correlation between Cyclomatic Complexity and LOC for AC (0.89) but has one of the least correlation for its TC (0.20). The only application that appears to have highly correlated LOC and CC for both AC and TC is Curl (0.88 and 0.87, respectively) and Foundation DB (0.73 and 0.84 respectively). Except for these two, all objects have a high correlation for AC and a weak correlation for TC.

The empirical results we observed from the related works in Chapter 2 seems to be missing an element in their analysis which is a fundamental part of our study. That is, the

kind of code affects the correlation of the complexity metrics (the kind of metrics). Therefore, it is not ideal for two complexity metrics to be substituted one for another by the mere fact that some studies suggest a strong correlation between certain metrics (complexity metrics in our case). All these metrics have different objectives and in their attempt to determine the complexity of a piece of code and it is quite erroneous to discredit the explanatory power of one to exist.

For example, we record instances where there is negative correlation – that is as LOC increase, Cyclomatic Complexity decreases: VSCode (-0.22), Rosgarden (-0.17), PDF Creator (-0.22), Notepad++ (-0.11) and Muscore (-0.49). Muscore has the highest difference with a 0.84 value for AC and -0.49 for TC. The notion of a strong correlation between LOC and CC cannot be extended to every kind of code. Therefore an attempt to substitute one metric for another, without considering any of these factors (kind of code, kind of software, and kind of metric) will fail. Open XML presents the least form of monotonicity between LOC and CC with values of 0.372 for AC and 0.07 for TC. It is followed by VSCode which reports 0.55 correlation for AC and 0.22 for TC. Handbrake on the other hand has a low correlation of 0.32 for AC but has a high correlation for TC. This is contrary to what is observed for most objects (where there is a higher correlation in AC but a lower correlation for TC).

Though our analysis suggests a high correlation for AC and a very low correlation for TC, it is not right for one to merit the substitute one metric with over another without considering the kind of code, kind of metric and kind of software. And if a one of the metrics is preferred in certain situations, a very strong justifiable reason has to be given for its choice.

In all these instances, we record a p-value of $-2.2e-16$ or less for AC which is strong enough to reject the null hypothesis that there is no correlation. Test code on the other hand has objects where the values of the correlation coefficient can be rejected for p-values greater than the alpha level of significance. The exceptions are Filezilla with a rho value of 0.20 and a p-value of 0.31, MPV Player with a rho value of 0.36 and 0.07 for p-value, Keepassx with a rho value of 0.11 and a p-value of 0.12, Powershell with 0.01 and 0.78 repectively, Rosegarden with 0.17 and 0.19, and OpenXML with 0.07 and 0.67. P-values

for these are higher than the alpha significance level which leads us to accept the null for these cases.

We proceed to repeat the same correlation experiment for the test code written by these same companies and organisation. We assume the same coding principles, methodologies and paradigms are followed in the two kind of code. Our experiment focuses only on the correlation of LOC, CC and HE in test code as we believe numerous researches including our finding support the correlation that exists between the complexity metrics for application code evident in our results. We are, however, interested in finding whether the same exist for different kind of code, which is test code. In comparing what has been hypothesized to the results gained, Lines of Code and Halstead effect are not correlated at all. Table 6, we observe a sharp difference from what is usually seen in AC. We observe the predominance of low and negative correlation values running through almost all cases. The same observation is made for Halstead Effort and Cyclomatic complexity. There is a very low correlation and the idea of substituting one metric for another is not advisable for TC.

The negative values and low correlation values produced for TC predicts that Cyclomatic complexity, Halstead Effort and Lines of Code do not have any sort of relation and it will therefore be inappropriate to substitute one for the other. In other words, the metrics seem to measure different aspects of test code. While we observe a higher level of complexity for most application code (always perceived to be largely complex) we observe a very low or almost no correlation for test code (always perceived to be simple). The results suggest that the level of complexity seems to affect the level of correlation. Possible reasons (particularly for LOC and CC) include:

1. The predominance of control flow statements in application over test code. For the same amount of code (LOC) in application code and test code, application code may have many logical branches and loops that will, as observed in the results, generate a high cyclomatic complexity value. And therefore CC will proportionally increase with LOC and invariably have a strong correlation for almost every given amount of LOC. Test code on the other hand may use test frameworks (for instance `assert()` call in a JUnit test) which hide (i.e., it resides in the framework) the control flow for the evaluation of the oracle leading to a low CC for the same amount of LOC. A Java test not using JUnit would have to

embed the control flow for the oracle in the test itself which would increase control flow, thereby moderately increasing CC, leading to a higher CC for the same amount of LOC; resulting in a moderate correlation. We will likely observe a low correlation between CC and LOC in test code as the control flow for test code is always quite simple even for a large piece of code. An embedded control flow in the test code (and general control flow statements in the test code) on one hand will cause a proportional increase of CC with LOC, resulting in a higher correlation. This results in a changing correlation for test code making it difficult to predict any sort of correlation between LOC and CC, if even there is any at all.

2. The kind of tests (e.g., unit testing, integration testing and system testing) also has an impact on the level of correlation of test code. Unit tests may appear more linear (few branches, simple, and straight) than system test which may require complex set-up and therefore complex control flow. This is because the scope for unit test is smaller, while system tests may need longer, larger and more complex setup which would involve control flow. The use of unit tests alone may result in a low correlation while a system test will report a stronger correlation. This is because for the same amount of LOC, the linearity of unit tests leads to fewer control flow branches and therefore a low CC value. Correlation will be low as CC does not increase for an increase in LOC without additional control flow. A system test on the other hand, due to complex setup it may require, will have many conditions leading to a large amount of control flow statements, hence a larger CC value for the same amount of LOC (a stronger correlation). The kind of test also impacts the level of complexity and correlation. Our analysis does not differentiate different kinds of tests so we cannot confirm these intuitions.

Table 5. CORRELATION COEFFICIENT, P-VALUES AND STATISTIC FOR
COMPARING CYCLOMATIC COMPLEXITY AND LINES OF CODE

Application	Spearman's rho		Statistic (S)		p-value	
	Production Code	Test Code	Production Code	Test Code	Production Code	Test Code
Amorok	0.7484398	0.2826294	9.12E+10	119200000	< 2.2e-16	< 2.2e-16
Amule	0.8310898	0.6087374	5.567E+09	6684300	< 2.2e-16	< 2.2e-16
Apache Ant	0.8527345	0.313269	2.60E+10	9340470	< 2.2e-16	< 2.2e-16
Apache httpd	0.811654	0.498923	2.5e+15	8934731	< 2.2e-16	< 2.2e-16
Audacity	0.7731698	0.5459371	1.40E+12	308.76	< 2.2e-16	0.02869
Bitcoin	0.7745475	0.386350	1.60E+10	15716	< 2.2e-16	0.00089
Client	0.8458951	0.3737259	2.577E+09	20790000	< 2.2e-16	< 2.2e-16
Curl	0.8797098	0.8676859	60994000	21986000	2.20E-16	< 2.2e-16
Ditaa	0.8390775	0.3717422	5424700	2824	< 2.2e-16	0.0431
Django	0.5384983	0.0661646	9.91E+10	7.38E+11	< 2.2e-16	< 2.2e-16
Filezilla	0.8924248	0.2002189	1.525E+09	2620.1	< 2.2e-16	0.3167
FoundationDB	0.7314024	0.8440161	1.45E+11	10966	< 2.2e-16	< 2.2e-16
Handbrake	0.3529543	0.8485892	1.93E+10	4.642E+09	< 2.2e-16	< 2.2e-16
Hibernate	0.8390727	0.3397333	98915000	117470000	< 2.2e-16	< 2.2e-16
Hibernate	0.6790383	0.2627793	1.88E+11	6.73E+10	< 2.2e-16	< 2.2e-16
Industry 1	0.05809031	0.007931312	9601600	303950000	0.25	0.7815
Industry 2	0.9209294	0.8240325	1282.1	570860	< 2.2e-16	2.2e-16
Industry 3	0.8795279	0.3826746	4784.1	1808300	< 2.2e-16	1.709e-10
Industry 4	0.199784	-0.350367	1.558e+09	119590	< 2.2e-16	0.001343
Industry 5	0.2723476	-0.3023716	21642000	72.933	4.95e-11	0.5098
Inkscape	0.764367	0.2744665	8.34E+10	160930	< 2.2e-16	0.003712
Jakarta jmeter	0.7548558	0.4901934	1.63E+10	49467000	< 2.2e-16	< 2.2e-16
Jfreechart	0.8719291	0.574748	168360	1.838E+09	< 2.2e-16	< 2.2e-16
JSRUBY	0.7998944	0.632227	2.23E+11	4941700	< 2.2e-16	< 2.2e-16
Keepassx	0.839651	0.1165798	58040000	749180	< 2.2e-16	0.1278
lightGBM	0.8317869	0.4278641	78925000	64974	< 2.2e-16	3.21E-05
Mongo	0.6395512	0.2862239	2.80E+14	2.31E+11	< 2.2e-16	< 2.2e-16
MPV Player	0.8607678	0.3645325	3.324E+09	1461.6	< 2.2e-16	0.07989
Muscore	0.8236439	-0.4906538	3.72E+11	303500000	< 2.2e-16	< 2.2e-16
Mypaint	0.6853768	0.2129898	2.094E+09	147530	< 2.2e-16	0.02995
Netdata	0.8607678	0.3653626	3.324E+09	3151000	< 2.2e-16	3.19E-11
NMap	0.7815778	0.2179744	1.26E+10	5398800	< 2.2e-16	4.329e-05
Notepad plus plus	0.8666138	-0.1102369	1.141E+09	47379000	< 2.2e-16	0.005421
Onion	0.8001629	0.2103819	59004000	2677600	< 2.2e-16	0.0004663
Opn XML SDK	0.3729942	0.0076572	2.08E+13	4.412E+09	< 2.2e-16	0.6757
PDF Creator	0.587326	-0.2241322	2.74E+10	2.23E+10	< 2.2e-16	< 2.2e-16
Powershell	0.8023586	0.0167814	8.62E+11	2947100	< 2.2e-16	0.7869
Rosegarden	0.8020894	-0.1701537	3.21E+10	40043	< 2.2e-16	0.1976
Shiro	0.5901554	0.3046109	2706100000	13059000	< 2.2e-16	7.898e-12
Sqoop	0.7271721	0.6016462	1.25E+10	2438400000	< 2.2e-16	2.2e-16
Squirrel SQL	0.773741	0.4688885	1.83E+11	2.707E+09	< 2.2e-16	< 2.2e-16
VLC	0.8378148	0.1542142	2.02E+11	2255800	< 2.2e-16	0.01426
Voldemort	0.7740988	0.5696082	8.95E+10	1.423E+09	< 2.2e-16	< 2.2e-16
Vscode	0.5588973	-0.2241322	920400000	2.23E+10	< 2.2e-16	2.20E-16
WorldWind	0.8589899	0.1008642	4.18E+11	64493000	< 2.2e-16	0.005538

Table 6. CORRELATION OF LOC VS CC AND CC VS HALSTEAD EFFORT FOR
TEST CODE

Test Code	Spearman's rho		Test Code	Spearman's rho	
	LOC vs HE	CC vs HE		LOC vs HE	CC vs HE
Amorok	0.318546	-0.4688933	JRuby	0.2359847	0.8640336
Amule	0.1334175	0.7890728	Keepassx	0.2895168	0.3582617
Apache Ant	0.5092279	0.3068285	LightGBM	0.5526408	0.5969304
Apache HTTPD	0.9457816	0.3164342	Mongo DB	0.3298503	0.4910320
Audacity	0.5092279	0.3574877	MPV Player	0.8258287	0.4508373
Bitcoin	0.6076619	0.5554357	Muscore	0.5291308	-0.0978287
Client	0.6357196	0.3574877	Mypaint	0.4719101	0.1519379
Curl	0.6486515	0.6700446	Netdata	0.9031964	0.7323997
Ditaa	0.2785671	0.697921	NMap	0.8468941	0.4294187
Django	0.2878933	0.2784571	Notepad ++	0.870604	0.4610390
Filezilla	0.09648793	0.1635965	Onion	0.6768024	0.6990263
FoundationDB	0.5368896	0.8224289	OpenXML	0.1259020	0.2000405
Handbrake	0.5599499	0.8145304	PDF Creator	0.5644849	0.4747389
Hibernate ORM	0.2627885	0.7172306	Powershell	0.3044482	0.4629908
Hibernate	0.316615	0.7064122	Rosegarden	0.8362338	0.80
Industry 1	0.0019411	0.0311890	Apache Sqoop	0.9455115	0.5621386
Industry 2	0.8813916	0.8198210	Apache Shiro	0.9411423	0.2543022
Industry 3	-0.2166831	0.3156131	Squirrel SQL	0.2950118	0.7184319
Industry 4	0.4269099	0.5280768	VLC	0.9098565	0.029988
Industry 5	-0.2594373	0.9805807	Voldemort	0.4178033	0.7781585
Inkspace	0.5663003	0.2752109	Vscode	-0.08548622	0.301735
Jfreccahart	0.39871	0.6555923	WorldWind Java	0.3597182	0.440394
Jakarta Jmaeter	0.4809119	0.6731702			

Chapter 6 THREATS TO VALIDITY

Threats to validity in software engineering are classified into construct, external, internal, and conclusion threats [42]. Construct validity is about the relation between the theory behind the experiment and the observations that are made. Our theory, or hypothesis, following claims from prominent authors (e.g., [41]), is that test code is less complex than the application code it tests. Since tests are typically implemented as methods [10] we compared the complexity of methods in test code with the complexity of methods in application code. Even though there is a debate about what is a good complexity metric for code, we decided to use the well-known cyclomatic complexity and Halstead metrics to measure method complexity (in test and application code) in addition to the number of lines of code (LOC), though we report on results when only using cyclomatic complexity. We argue that these decisions make sense and should not adversely introduce threats to construct validity in our study.

We want to compare (test) code with (application) code and how they affect complexity metrics using open source software and Industry software. We emphasize here that the concept of open source used in this document refers to source code we collected online from repositories and that, the testing effort of open source software development presented in this document through empirical data is not a characterization of the people that contributed the (test/application) code. We acknowledge that not all test code may have been contributed to the repository by the contributors and this may very well affect the conclusions on the adequacy of testing or how well tested most open source code are. The results do not also characterizes the quality of open source software, if one uses the amount of test code as a surrogate measure of quality. What we refer to as Industry code, on the other hand is code that was provided by Industry partners. We selected metrics that have been reported to be often used to measure source code complexity, at the same, recognizing that there is an ongoing debate about whether some of these metrics correlate or not. We therefore selected LOC, cyclomatic complexity and Halsted measures.

In this study we used a set of criteria for the selection of open source projects. One criterion was the selection of an open source object with more than 10k AC LOC. The definition of what makes a program large is quite ambiguous, undefined and very subjective on an individual and organizational level (contexts) and has not been well defined in

literature. A number of arbitrary minimum threshold values have been suggested on many reputable websites [22][79] (ranging from 10k, 50k, 100k, etc). While we do agree with all these, we have not found, at the time of writing of this document, literature that discusses what may be considered large enough for a study like ours. We believe that an open source projects with more than 10k LOC is large enough to contain sufficient tests for our study, although by looking at ratio values of application code LOC to test code LOC this does not appear to be a sufficient criterion. Also, the size was considered among many factors; it was not the only selection criterion; and therefore it happened that this criterion was not necessarily satisfied (for Industry 4 and 5) as all the criteria taken together resulted in the selection (out of 500 open source software).

External validity is about whether we can generalize results outside of the scope of the study. Of course, our study should be replicated, expended, especially with case study systems from industry and with other complexity metrics. However, our selection of 40 open-source software led us to select what we believe is a representative set of systems. At least they are well-known and popular; they are not trivial. Although general conclusions should be taken with care, our observations for open source are, we believe, generalizable to some extent.

Internal validity is about the treatments and how sure we can be that they cause the outcome we observe. This relates to our selection of complexity metrics, which we already commented on above. This also relates to our measurement of code complexity. To avoid issues when measuring code, we relied on a commercial software package that is used in industry (Understand). This threat also relates to our selection of objects, which we already commented on. We should add that we selected objects that come with both application code and test code that tests that application code, and for which test code can be easily distinguished from application code (i.e., test code is in separate, identifiable software packages) as this facilitated the use of Understand. Despite our effort to select software for which we can easily distinguish test code from application code, some test code may not have been measured as such and may have contributed to application code data and vice versa; we believe that, given the amount of methods we measured, this should only have a very limited impact on the results. We also wanted systems with both application code and test code because comparing application code from one system to test code from another

system does not make sense: for instance, different developers, with possibly varying development practices/habits would likely be involved thereby introducing differences in application code and test code complexity values that are not due to the nature (test vs. application) of the code. One threat to validity related to the objects, however, is the possible impact of the effort that has been put into the testing activity for these systems. We identified for instance that twelve case study system (Apache Httpd, Audacity, Foundation, Filezilla, Inkscape, Jruby, MPV Player, Mypaint, Powershell, Rosegarden, Shiro and VLC and VSCode) seemed to have been much less tested than the other case study systems. On the topic of sufficiency of tests, it is worth noting that filtering the amount of test cases presented with the AC is vital. We do recognize that not all tests may have been committed to the repository for the subjects we analyzed and this may play down on testing effort of the developers. While the testing effort presented in this material is not a characterization of the developers for such subjects, we believe filtering the LOC ratio of AC/TC of not less than 10 may perhaps lead to more representative results, while maintaining complex AC. We therefore tried to discuss Apache Httpd, Mypaint and VSCode separately as these are the only units among the aforementioned whose average Cyclomatic Complexity rejects the null hypothesis of our statistical analysis. The reader will however note that results for Apache Httpd, Mypaint and VSCode are sometimes similar to those obtained for other case study systems. The potential impact of testing effort on the phenomenon we want to study, if there is one, is therefore unclear and should be studied. In order to draw conclusions from the data we needed to use inferential statistics because, although very informative, descriptive statistics can be misleading due to heavily skewed distributions of complexity values. We relied on standard non-parametric statistical tests; all results, except average values for three, are statistically significant.

Chapter 7 CONCLUSIONS

On non-trivial software, the large test code base needs adequate maintenance similarly to application code. It has often been argued that test code should be simple, some authors even arguing that a method implementing a test case should be reduced to a single control flow. If this is indeed the case, application code and test code may have to be considered differently from a software maintenance point of view, despite the fact that both are source code. For instance, if a Cyclomatic Complexity value threshold has been shown through empirical evaluation on application code to warrant code refactoring and such a complexity level is un-heard of in test code, the threshold is useless as a decision mechanism to refactor test code, despite the fact that test code may nevertheless need refactoring.

In this study, we tried to confirm or refute this claim about the respective complexity of application code and test code by measuring the complexity of test code and application code of a number of large, non-trivial and well-known open source software systems.

We decided to measure the Cyclomatic Complexity of test methods and application logic methods with a commercial source code analysis software package.

We observe that descriptive statistics such as average and mean values provide interesting information but that this information can be misleading if not used with care. This is due to the fact that (test and application) code contains a very large proportion of simple methods that have a Cyclomatic Complexity of 1 or 2 and that this heavily skews frequency distributions of Cyclomatic Complexity values to the left. We therefore complemented the descriptive statistical analysis with an inferential statistical analysis, using non-parametric tests.

Our results indicate that, overall, application code is indeed statistically more complex than test code. However, contrary to the claim that test methods should be as simple as possible, to the extent that they should be reduced to a single flow of control, test code appears to be very complex in some cases. While the majority of test methods have a Cyclomatic Complexity value below 50, which is particularly considered difficult to understand, it is, however, not rare to observe test methods with a Cyclomatic Complexity value above 100, 150 or even 1000. Above a cyclomatic complexity value of 50, the code is typically considered practically unmaintainable. We have identified test methods with Cyclomatic Complexity values of 83, 97, 156, 186, and as large as 2,097.

Another interesting observation we made is that there is more than one line of application code for each line of test code in open source software whereas there is more than one line of test code per line of application code in industry systems we observed. Test code relative to application code appears to be different in industry and open-source. One should therefore be careful when studying open-source and attempting to generalize to industry. In determining the complexity difference in these two kinds of code (application code and test code), the kind of software really matters.

From a code maintenance point of view, although test code is statistically less complex than application code, the two seem to be relatively similar to each other to possibly justify generalization of code maintenance research results on application code to code maintenance of test code. One may however be cognisant of the typical structure of test code (e.g., set-up, execution, tear-down), which could prevent such generalization. More work is warranted to better study test code maintenance.

In this study, we have illustrated by means of empirical results from open-source software systems the correlation between software metrics. Our observations suggest that the monotonicity that exists in software metrics is not exclusively due to the kind of metrics but largely due to factors such as kind of code, kind of software and kind of metrics. While numerous studies hypothesize the existence of some form of (strong) correlation between Lines of Code (LOC) and Cyclomatic Complexity (CC), this study reveals that this observation is only true for application code and not for test code. Contrary to what most authors have extrapolated to be the rule for all source code, test code has a weak or almost no correlation between LOC and CC. We investigated an outlier claim made by some authors who argued that the extent of correlation between the two is only strong when the software is analyzed as an aggregate unit and is rather moderate in modules, however, we find that this claim is not wholly valid. At the lowest level of granularity, which is the method level, there still exist a strong correlation between Cyclomatic Complexity and Lines of Code for application code.

In other studies, some authors present a verifiable evidence of a stable relationship between Cyclomatic Complexity and Lines of Code and attempt to nullify the strength and relevance of Cyclomatic Complexity by giving merit to Lines of Code but fail to present an explanation for other kind of code (test code to be specific) and a quintessential lucid

justification for the use of Lines of Code over Cyclomatic Complexity. We find their study open to both sides as one could as well use their results to advocate the use of CC over LOC. In our study, we have outlined reasons why CC should be preferred over LOC. Given the weak monotonicity between Cyclomatic Complexity and Lines of Code, Cyclomatic Complexity and Halstead Effort, Lines of Code and Halstead Effort for test code, we disagree that Cyclomatic Complexity and Halstead metrics are redundant as some studies suggest. Rather, we advocate for the use of Cyclomatic Complexity over Lines of Code (or both or Cyclomatic density) due to reasons such as cognitive complexity, numerical complexity, adequacy of testing, interdependency and code refactoring that cannot be accounted for by Lines of Code. To have a better analysis, the two (cyclomatic Complexity and Lines of Code) and Cyclomatic density suffice as all these metrics have different objectives and algorithms for measurement. In addition, the amount of test cases on open source software and the adequacy they attain suggest most open source software do not come with enough test code, with a Production Code to Test code LOC ratio of 129:1 and a structural coverage of 40%.

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APPENDICES

Appendix A Distributions of cyclomatic complexity values for objects.

A.1 Sample representative distributions

Figure 2. Distribution of cyclomatic complexity values for Apache Httpd AC

Figure 3. Distribution of Cyclomatic complexity values for Apache Httpd TC
(logarithmic scale)

Figure 4. Distribution of cyclomatic complexity values for JFreechart AC
(logarithmic scale)

Figure 5. Distribution of cyclomatic complexity values for JFreechart TC
(logarithmic scale)

A.2 Boxplots for all objects

Figure 6. Box Plot of CC for objects with method CC values in range [1, 100].

Figure 7. Box Plot of CC for objects with method CC values in range [1, 500].

Figure 8. Box Plot of CC for objects with method CC values in range [1, 1000].

Figure 9. Box Plot of CC for objects with method CC values in range [1, 10000].

Appendix B : LINEAR SCALE ZOOMED IN ON THE LEFT QUADRANT

B.1 LINEAR SCALE LINEAR SCALE ZOOMED IN ON THE LEFT QUADRANT (PRODUCTION CODE)

Figure 10. Scatter Plot of LOC (x) vs CC (y) for Amorok, zoomed into the bottom left quadrant.

Figure 11. Scatter Plot of LOC (x) vs CC (y) for Curl, zoomed into the bottom left quadrant.

Figure 12. Scatter Plot of LOC (x) vs CC (y) for Dita, zoomed into the bottom left quadrant.

Figure 13. Scatter Plot of LOC (x) vs CC (y) for Handbrake, zoomed into the bottom left quadrant.

Figure 14. Scatter Plot of LOC (x) vs CC (y) for Hibernate, zoomed into the bottom left quadrant.

Figure 15. Scatter Plot of LOC (x) vs CC (y) for Hibernate ORM, zoomed into the bottom left quadrant.

Figure 16. Scatter Plot of LOC (x) vs CC (y) for Notepad++, zoomed into the bottom left quadrant.

Figure 17. Scatter Plot of LOC (x) vs CC (y) for Onion, zoomed into the bottom left quadrant.

Figure 18. Scatter Plot of LOC (x) vs CC (y) for VLC, zoomed into the bottom left quadrant.

Figure 19. Scatter Plot of LOC (x) vs CC (y) for Open XML (PC), zoomed into the bottom left quadrant.

B.2 LINEAR SCALE ZOOMED IN ON THE LEFT QUADRANT (PRODUCTION CODE)

Figure 20. Scatter Plot of LOC (x) vs CC (y) for Amorok (TC), zoomed into the bottom left quadrant.

Figure 21. Scatter Plot of LOC (x) vs CC (y) for Curl (TC), zoomed into the bottom left quadrant.

Figure 22. Scatter Plot of LOC (x) vs CC (y) for Curl (TC), zoomed into the bottom left quadrant.

Figure 23. Scatter Plot of LOC (x) vs CC (y) for Handbrake (TC), zoomed into the bottom left quadrant.

Figure 24. Scatter Plot of LOC (x) vs CC (y) for Hibernate ORM (TC), zoomed into the bottom left quadrant.

Figure 25. Scatter Plot of LOC (x) vs CC (y) for Hibernate (TC), zoomed into the bottom left quadrant.

Figure 26. Scatter Plot of LOC (x) vs CC (y) for Notepad ++ (TC), zoomed into the bottom left quadrant.

Figure 27. Scatter Plot of LOC (x) vs CC (y) for Onion (TC), zoomed into the bottom left quadrant.

Figure 28. Scatter Plot of LOC (x) vs CC (y) for Open XML (TC), zoomed into the bottom left quadrant.

Figure 29. Scatter Plot of LOC (x) vs CC (y) for VLC, zoomed into the bottom left quadrant.

Appendix C : EXPORTING METRIC VALUES USING SCITOLS VERSION 4.0

C.1 Analyze Files or Directories Using SciTools Understand.

Open *Understand*, and go to *File -> New -> Project*.

Figure 30. Naming a new Project in Understand

We name the Project with a name such as *ProjectXXX_AC* or *ProjectXXX_TC* depending on whether the code we intend to measure is *Application Code* (AC) or *Test Code* (TC). Click on *Next*.

To maintain privacy and avoid releasing proprietary information, we replace *XXX* with a name that is meaningful, though not attributable to an organization and record the mapping between the chosen string *XXX* and the actual details of the product (e.g., product/system/package name and version information) separately. This is to enhance data privacy.

We select all Languages to ensure adequate coverage. We do not select VHDL since it is no longer supported by Understand. Tick *Fuzzy* instead of *Strict*. Click *Next*.

Figure 31. Selecting Source Code Languages Understand should Export
Tick Add source files manually. Click *Next*.

Figure 32. Choosing How to Import Files and Settings

The next window allows us to select a single (source code) file or an entire directory. To select an entire directory, we click on the “*Add a Directory*”. We use the “*Add a file*” for selecting single files. After selection, we click ok.

Figure 33. Add Project Directory for Analysis in Understand

Understand will display the file path. We Click *Next*

Figure 34. Complete the Project Configuration and Settings for Analysis.

Understand will automatically select *begin analyzing project sources*. We Click *Finish*.

Understand will start analyzing the code. A progress bar will be shown at the bottom left corner, displaying the percentage of code analyzed.

Figure 35. Analysing and Extracting Source Code Information in Understand.

C.2 Exporting Metric Summaries

In this session, we extract other (simple) metrics, some of which are programming language specific.

C.3 Collecting General Metric Values about Code

To collect general metric values, such as number of Lines of Code, number of comment lines, we click on Metrics from the Menu Bar, select “*Metrics Summary*”, click on “*Copy All*” and paste this data into the text editor (Notepad, Word, Pages, etc.) and save the file with a name consistent with the naming convention discussed in Section C.1: for instance ProjectXXX_AC_Summary and ProjectXXX_TC_Summary.

Figure 36. Exporting Metrics Summary for Source Code

C.4 Collecting more detailed Metric values for Different Programming Languages

To collect more detailed metrics, such as the number of Java classes and methods, we click on “Metrics” from the Menu Bar and select *Browse Metrics*. A pane with two sections appears at the bottom right corner with two sections: we name the left section S1 and the right S2 for clarity. The left section (S1) contains a Directory Structure and the right section (S2) lists a metric summary for the files and folders selected in section S1. Drag or enlarge the pane for proper visibility.

Figure 37. Browse Detailed Metric Summary for Source Code

The tool displays the Directory Structure and a list of the programming languages used. We unfold the list of programming languages and chose a language. After that we right click the programming language, select “*Metric Summary*”, copy-paste the data in a text editor and save according to the previously used naming convention: for instance ProjectXXX_AC_JavaSummary and ProjectXXX_TC_JavaSummary if you selected Java. Ignore languages like HTML, CSS, JavaScript.

Figure 38. Extracting Detailed Metrics for Specific Programming Languages

C.5 Ancillary Metrics

For collecting all detailed metrics in a csv file format, we right click on the *Directory Structure* on the left section S1 (as described previously) and select *Metric Summary*. Once it has completed generating the values for the metrics, we select all, copy and paste in a text editor (notepad, word, pages etc.) and save according to the previously used naming convention: for instance *ProjectXXX_AC_AncillaryMetrics* for application code and *ProjectXXX_TC_AncillaryMetrics* for test code.

Figure 39. Extract Ancillary Metrics from Understand.

Appendix D NORMALITY TEST USING SHAPIRO-WILK

Table 7. Normality Test for Shapiro-Wilk

Application	p-value		Application	p-value	
	Production Code	Test Code		Production Code	Test Code
Amorok	2.2e-16	2.2e-16	JRuby	2.2e-16	2.2e-16
Amule	2.2e-16	2.2e-16	Keepassx	2.2e-16	2.2e-16
Apache Ant	2.2e-16	2.2e-16	Light GBM	2.2e-16	8.443e-15
Apache Httpd	2.2e-16	3.539e-05	Mongo	2.2e-16	2.2e-16
Audacity	2.2e-16	4.304e-05	MPV Player	2.2e-16	2.186e-10
Bitcoin	2.2e-16	2.2e-16	Muscore	2.2e-16	2.2e-16
Client	2.2e-16	2.2e-16	Mypaint	2.2e-16	2.379e-16
Curl	2.2e-16	2.2e-16	NetData	2.2e-16	2.2e-16
Ditaa	2.2e-16	3.12e-08	NMap	2.2e-16	2.2e-16
Django	2.2e-16	2.2e-16	Notepad ++	2.2e-16	2.2e-16
FileZilla	2.2e-16	4.02e-09	Onion	2.2e-16	2.2e-16
Foundation DB	2.2e-16	2.2e-16	OpenXML	2.2e-16	2.2e-16
Handbrake	2.2e-16	2.2e-16	PDF Creator	2.2e-16	2.2e-16
Hibernate ORM	2.2e-16	2.2e-16	Powershell	2.2e-16	1.21e-11
Hibernate	2.2e-16	2.2e-16	Rosegarden	2.2e-16	2.2e-16
Industry 1	2.2e-16	2.2e-16	Apache Shiro	2.2e-16	2.2e-16
Industry 2	1.13e-12	2.2e-16	Apache Sqoop	2.2e-16	2.2e-16
Industry 3	7.52e-12	2.2e-16	Squirrel SQL	2.2e-16	2.2e-16
Industry 4	2.2e-16	2.2e-16	VLC	2.2e-16	2.2e-16
Industry 5	2.2e-16	0.02906	Voldemort	2.2e-16	2.2e-16
Inkscape	2.2e-16	6.232e-15	VSCode	2.2e-16	2.2e-16
Jfreechart	2.2e-16	2.2e-16	WorldWind Java	2.2e-16	2.2e-16
Jakarta JMeter	2.2e-16	2.2e-16			

Appendix E Collecting data from Understand.

E.1 Export Metrics Using SciTools Understand Version 4.0

Here, we describe the process of extracting and anonymizing data from SciTools Understand for the purpose of replication. A detailed description with diagrams is done in Appendix C . One way to simplify the analysis is to separate application code from test code in separate folders and then select either one of the folders or the other (but not both).

The analysis of Application Code was performed separately from the analysis of Test Code. So essentially, the instructions we provide here was executed on Application Code once and on Test Code once. We summarize the extraction process in the next sections with the detailed description in Appendix C .

Analyze Files or Directories Using SciTools Understand.

- Open *Understand*, and Go to *File -> New -> Project*.
- We name the Project with a name such as *ProjectXXX_AC* or *ProjectXXX_TC* depending on whether the code we intend to measure is *Application Code* (AC) or *Test Code* (TC). Click on *Next*.
- We select all Languages to ensure adequate coverage. We do not select VHDL since it is no longer supported by Understand. Tick *Fuzzy* instead of *Strict*. Click *Next*.
- The next window allows us to select a single (source code) file or an entire directory. To select an entire directory, we click on the “*Add a Directory*”. We use the “*Add a file*” for selecting single files. After selection, we click ok. Understand will display the file path. We Click *Next*
- Understand will automatically select *begin analyzing project sources*. We Click *Finish*.
- Understand will start analyzing the code. A progress bar will be shown at the bottom left corner, displaying the percentage of code analyzed.

E.2 Basic Metrics with Methods Calls and Halstead using A Script

Exporting Metrics Data using Understand

In our study we wrote scripts using the Application Programming Interfaces (APIs) of Understand to extract the preferred metrics suitable for our study rather than the generic ones provided through the interface of the application (Understand). Now that Understand has been instructed to process code and generate its own representations of code data, we ask Understand to process that data to produce metrics data. On the *Menu bar* Click on *Tools*. We select *Run*. A pop-up Window will appear.

Figure 40. Specifying file paths to Run a Script Using Command in Understand

Understand requires *two inputs* in order to proceed:

In the Command field, we browse into the location folder to where the script file “_calls_with_halstead 2.3.pl” is saved.

In the parameter field, we specify the where Understand saves the analysis results (the metrics values). We use the same naming convention as in Appendix C Section C.2. Here, a careful attention needs to be given the format of this input parameter. The parameter must start with “-f “, followed by the fully specified path to the location on disk where Understand is to save the results. An example input is: “-f C:\users\...\ProjectXXX.csv”.

The third (optional) input Working Directory field is kept empty since Understand automatically recognizes it by default.

We click *Run*. The run will grey out the UI of Understand, meaning it is extracting data in the background.

For our purpose we will use two scripts, one written in Perl and the other written in Visual Basic:

- `calls_with_halstead 2.3.pl` for exporting all metrics.
- Anonymizing Script 1.3 for anonymizing exported data.

The `call_with_halstead 2.3` code is written in Pearl using Understand APIs to write a custom script for exporting preferred metrics values with a generic code structural template (or base) from SciTools Understand.

```
# Synopsis: Export all metrics to a csv file, same as Projects|Export Metrics
in the GUI with Halstead metrics
#
# Language: C/C++, Java, C#, Python
#
# Usage:
sub usage ($)
{
    return << "END_USAGE";
}
${ \(\shift @_ ) }
Usage: cjs_metric_export_with_halstead.pl -db database -f name
      -db database          Specify Understand database (required for
                           uperl, inherited from Understand)
      -f|file name          name of the file to export (*.csv)
END_USAGE
}

use Understand;
use Getopt::Long;
use strict;

my $dbPath;
my $help;
my %metrics;
my %metricList;
my %file_metric;
my $exportFile;
GetOptions(
    "db=s" => \$dbPath,
    "help" => \$help,
    "f|file=s" => \$exportFile,
);

# help message
die usage("") if ($help);

# export file
die usage("Please specify the file to export metrics to\n") if (! $exportFile);

# open the database
my $db=openDatabase($dbPath);

# check language
if ( $db->language() !~ "C|Java|c#" ) {
    die "This script is designed for C and Java only\n";
}

my $functions = "Function ~unknown ~unresolved,method ~unknown ~unresolved";
```

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my $classes = "Class ~unknown ~unresolved ,Struct ~unknown ~unresolved,Union
~unknown ~unresolved";
my $codefiles = "Code File ~unknown ~unresolved";
my $headerFiles = "Header File ~unknown ~unresolved";

my $validReferences = "ada call ~dispatch,"
    ."c call ~virtual, c use ptr,"
    ."basic call,"
    ."cobol call,"
    ."csharp call ~virtual, csharp use ptr,"
    ."fortran call,"
    ."java call,"
    ."jovial call, jovial asm use,"
    ."pascal call ~virtual,"
    ."vhdl call,"
    ."php call";

my @ents = $db->ents($functions.", ".$classes.", ".$codefiles.", ".$headerFiles);

    foreach my $ent (@ents){
        next if $ent->library;
        foreach my $metric($ent->metrics()){
            $metrics{$ent->id()}{$metric}=$ent->metric($metric);
            $metricList{$metric} = 1;
        }
    }

printMetrics($exportFile);
print "Metrics exported to $exportFile\n";

closeDatabase($db);

# subroutines
# print the metrics to the specified file
sub printMetrics()
{
    my $filename = shift;
    open (FILEHANDLE, ">".$filename) || die "Can't create $filename: $! \n";

    #print metric header
    print FILEHANDLE
"Kind,Name,Signature,Calls,Cyclomatic,CountLine,CountDeclClassMethod,CountDeclC
lass,AvgCyclomatic,MaxCyclomatic";
    print FILEHANDLE ",n1,n2,N1,N2,Len,Voc,Vol,Dif,Eff";
    print FILEHANDLE "\n";

    #Print Functions
    foreach my $ent (sort {lc($a->longname()) cmp lc($b->longname());} $db-
>ents($functions)){
        next if $ent->library;

        my @projCalls;
        my @calls = $ent->refs($validReferences, $functions, 1);
        foreach my $callRef(sort {lc($a->ent->longname()) cmp lc($b->ent-
>longname());} @calls) {
            next if ($callRef->ent->library);
            push (@projCalls, $callRef);
        }

        print FILEHANDLE "Function,\"".$ent->longname()."\",";
    }
}

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    my $parameters = $ent->parameters(0);
    $parameters =~ tr// /;
    print FILEHANDLE $ent->longname. "(" . $parameters. ")", ".@projCalls;
    print FILEHANDLE printStoredMetrics($ent);
    print FILEHANDLE halsteadFunc($ent);
    print FILEHANDLE "\n";
}

#Print Classes
foreach my $ent (sort {lc($a->longname()) cmp lc($b->longname());} $db->ents($classes)){

    next if $ent->library;

    my @projCalls;
    my @calls = $ent->refs($validReferences, $functions, 1);
    foreach my $callRef(sort {lc($a->ent->longname()) cmp lc($b->ent->longname());} @calls) {
        next if ($callRef->ent->library);
        push (@projCalls, $callRef);
    }

    my $kindname = "Class";
    $kindname = "Struct" if $ent->kind->check("Struct");
    $kindname = "Union" if $ent->kind->check("Union");
    print FILEHANDLE "$kindname, \"\". $ent->longname(). "\", ";
    print FILEHANDLE $ent->longname. ", ".@projCalls;
    print FILEHANDLE printStoredMetrics($ent);
    print FILEHANDLE ",0,0,0,0,0,0,0,0,0,0";
    print FILEHANDLE "\n";
}

#Print code files
foreach my $ent (sort {lc($a->name()) cmp lc($b->name());} $db->ents($codefiles)){

    next if $ent->library;

    my @projCalls;
    my @calls = $ent->refs($validReferences, $functions, 1);
    foreach my $callRef(sort {lc($a->ent->longname()) cmp lc($b->ent->longname());} @calls) {
        next if ($callRef->ent->library);
        push (@projCalls, $callRef);
    }

    print FILEHANDLE "CodeFile", "\". $ent->name(). "\", ";
    print FILEHANDLE $ent->longname. ", ".@projCalls;
    print FILEHANDLE printStoredMetrics($ent);
    print FILEHANDLE halsteadFile($ent);
    print FILEHANDLE "\n";
}

#Print Header Files
foreach my $ent (sort {lc($a->name()) cmp lc($b->name());} $db->ents($headerFiles)){

    next if $ent->library;

    my @projCalls;
    my @calls = $ent->refs($validReferences, $functions, 1);
    foreach my $callRef(sort {lc($a->ent->longname()) cmp lc($b->ent->longname());} @calls) {

```

```

        next if ($callRef->ent->library);
        push (@projCalls, $callRef);
    }

    print FILEHANDLE "HeaderFile".",\"".$Sent->name()."\",";
    print FILEHANDLE $Sent->longname. ", ".$projCalls;
    print FILEHANDLE printStoredMetrics($Sent);
    print FILEHANDLE halsteadFile($Sent);
    print FILEHANDLE "\n";
}
close (FILEHANDLE);
}

sub printStoredMetrics {

    my $Sent = shift;
    my $line = "";
    $line .= $Sent->metric('Cyclomatic')?", ".$Sent->metric('Cyclomatic'):",0";
    $line .= $Sent->metric('CountLine')?", ".$Sent->metric('CountLine'):",0";
    $line .= $Sent->metric('CountDeclClassMethod')?", ".$Sent->
>metric('CountDeclClassMethod'):",0";
    $line .= $Sent->metric('CountDeclClass')?", ".$Sent->
>metric('CountDeclClass'):",0";
    $line .= $Sent->metric('AvgCyclomatic')?", ".$Sent->
>metric('AvgCyclomatic'):",0";
    $line .= $Sent->metric('MaxCyclomatic')?", ".$Sent->
>metric('MaxCyclomatic'):",0";
    return $line;
}

sub halsteadFunc {
    my $func = shift;
    my $startref = getDeclRef($func);
    my ($endref) = $func->refs("end", "", 1);

    unless ($startref and $endref) {
        #print "warning: no end reference in ".$func->longname."\n";
        return "0,0,0,0,0,0,0,0,0,0";
    }
    my $file = $startref->file;
    my $fileid = $file->id;
    my $lexer = $file->lexer();
    my ($n1, $n2, $N1, $N2) = scanEntity ($lexer, $startref->line(), $endref->
>line());

    # do the calcs
    my ($n, $N) = ($n1 + $n2, $N1 + $N2);

    my $V = $n ? int ($N * ((log $n)/(log 2))) : 0;
    my $D = $n2 ? int (($n1 / 2) * ($N2 / $n2)) : 0;
    my $E = $D * $V;

    # add them to the file-based metrics
    $file_metric{$fileid}{n1} += $n1;
    $file_metric{$fileid}{n2} += $n2;
    $file_metric{$fileid}{N1} += $N1;
    $file_metric{$fileid}{N2} += $N2;
    $file_metric{$fileid}{N} += $N;

```



```

    $file_metric{$fileid}{n} += $n;
    $file_metric{$fileid}{V} += $V;
    $file_metric{$fileid}{D} += $D;
    $file_metric{$fileid}{E} += $E;

    # print the metrics for this function
    return "$n1, $n2, $N1, $N2, $N, $n, $V, $D, $E";
}

sub halsteadFile($)
{
    my $file = shift;
    my $fileid = $file->id();
    my $rstring = "";
    my @array = ("$file_metric{$fileid}{n1}", "$file_metric{$fileid}{n2}",
"$file_metric{$fileid}{N1}"
        , "$file_metric{$fileid}{N2}", "$file_metric{$fileid}{N}",
"$file_metric{$fileid}{n}"
        , "$file_metric{$fileid}{V}", "$file_metric{$fileid}{D}",
"$file_metric{$fileid}{E}");
    foreach (@array){ $rstring .= $_?"$_":"0";}
    return $rstring;
}

# return declaration ref (based on language) or 0 if unknown
sub getDeclRef
{
    my ($ent) = @_;
    my $decl;
    return $decl unless defined ($ent);

    ($decl) = $ent->refs("definein", "", 1);
    ($decl) = $ent->refs("declarein", "", 1) unless ($decl);
    return $decl;
}

# scan the code in the specified range of lines
# and return the 4 basic operator/operand metrics
sub scanEntity
{
    my ($lexer, $startline, $endline) = @_;
    my $n1=0;
    my $n2=0;
    my $N1=0;
    my $N2=0;

    my %n1 = ();
    my %n2 = ();

    foreach my $lexeme ($lexer->lexemes($startline,$endline))
    {
        if (($lexeme->token eq "Operator") || ($lexeme->token eq "Keyword") ||
($lexeme->token eq "Punctuation"))
        {
            if ($lexeme->text() !~ /[(){}\[\]\]/)
            {
                $n1{$lexeme->text()} = 1;
                $N1++;
            }
        }
        elsif (($lexeme->token eq "Identifier") || ($lexeme->token eq "Literal")
|| ($lexeme->token eq "String"))
    }

```

```

        {
            $n2{$lexeme->text()} = 1;
            $N2++;
        }
    }

    $n1 = scalar( keys(%n1));
    $n2 = scalar( keys(%n2));

    return ($n1,$n2,$N1,$N2);
}

sub callby_tree {
    my ($level,$entity,$used,$maxlevels,$parents) = @_;

    foreach my $ref ($entity->refs("callby ~inactive","",1)) {
        my $ent = $ref->ent();
        next if exists $$used{$ent->id()};
        $$used{$ent->id()} = 1;
        if (!$maxlevels || $level < $maxlevels) {
            my $found=0;
            foreach my $parent (@$parents) {
                $found = 1 if $parent == $ent;
            }
            if (!$found) {
                push @$parents,$ent;
                callby_tree($level+1,$ent,$used,$maxlevels,$parents);
                pop @$parents;
            }
        }
    }
}

sub openDatabase($)
{
    my ($dbPath) = @_;

    my $db = Understand::Gui::db();

    # path not allowed if opened by understand
    if ($db&&$dbPath) {
        die "database already opened by GUI, don't use -db option\n";
    }

    # open database if not already open
    if (!$db) {
        my $status;
        die usage("Error, database not specified\n\n") unless ($dbPath);
        ($db,$status)=Understand::open($dbPath);
        die "Error opening database: ", $status, "\n" if $status;
    }
    return ($db);
}

sub closeDatabase($)
{
    my ($db)=@_;

    # close database only if we opened it
    $db->close() if (!Understand::Gui::active());
}

```

Anonymizing Data in an Excel File

Understand exports explicit details about the code including file names, source directories, paths, and source code information revealing sensitive information about the code and the company we are extracting from. When exporting data from our Industry partners, our aim was to write a script that anonymizes all these information to avoid any ability to map a particular extract to an organization. The anonymizing process goes as follows: we Open the csv files in *Microsoft Excel* and anonymize the data using the *Anonymizing Script 1.3*. This is done either importing it into *Macros* or copying and pasting the code into the *Macros Editor*. We *Save* the files after the anonymization is complete. To use Marcos in Excel this is one of the many procedures we used.

- Open File. Go to Options. select Customize Ribbon. On the right section, Under the Customize the Ribbon, select Main Tabs, and check Developer in the checkbox. Click OK.
- Once developer appears on the Main Tab, select Developer and click on Visual Basic. Under VBA Project, double click on the name of the project as shown in the left pane to open the text editor. Copy and paste the code in Anonymizing Script 1.3 and Run (Play icon).
- Once this is complete, Save the new anonymized data using the preset naming convention

The anonymizing script 1.3 follows as:

```
Sub sbNewMarcos()  
  
Dim pname As String  
pname = Application.InputBox("Enter the Title", "Project Title")  
  
Dim spa As String  
spa = Space(1)  
  
Dim str As String  
str = "."  
  
Dim str1 As String  
str1 = "new"  
  
Dim hash As String  
hash = "-"  
  
Dim celltxt As String  
Dim placeholder As String
```

```

Dim N As Long, i As Long, j As Long
N = Cells(Rows.Count, "A").End(xlUp).Row
j = 2
For i = 2 To N
    celltxt = Cells(i, "B").Value
    If InStr(1, celltxt, ".") Then
        placeholder = "nothing new"
    Else

        'If Cells(i, "B").Value = "Yes" Then
        Cells(i, "B").Value = Cells(i, "G").Value
        'Cells(i, "B").ClearContents
        j = j + 1

    End If
Next i

Range("A:B").EntireColumn.Insert

'Genaerate a Name
Columns("A").Formula = "=Concatenate(""" & pname & """, """" & spa & """, """" &
hash & """, C1 ,RandBetween(1000,10000) ,"""" & str & """,
Trim(Right(Substitute((D1), """" & str & """, Rept(""" & spa &
""", Len(D1))), Len(D1)))"
'Columns("A").Formula = "=Substitute((I1), """" & str & """, """" & str1 & """)"

'Copy and paste the Column A into B as Values to remove formula References
Range("A1").EntireColumn.Select
Selection.Copy
Columns("B").PasteSpecial xlPasteValues

'Delete the placeholder with the formula
Range("A:A").Delete

'Delete the names of the Functions and Classes
Range("C:C").Delete

'Delete the names of the File Names// Currently being held at C
Range("C:C").Delete

Range("A1").Value = "Name"

Columns("A").ColumnWidth = 50
Columns("B").ColumnWidth = 50
'ActiveWorkbook.Save

End Sub

```