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

Francielly Grigorio[1],

Daniel Miranda de Brito[2],

Eudisley Anjos[3],

Mario Zenha-Rela[4]

[1]Centre for Informatics, Federal University of Paraíba, João Pessoa – PB, Brazil
[1]franciellygrigorio@gmail.com

[2]Centre for Informatics, Federal University of Paraíba, João Pessoa – PB, Brazil
[2]britmb@gmail.com

[3]CISUC, University of Coimbra, Coimbra, Portugal
[3]eudisley@ci.ufpb.br

[4]CISUC, University of Coimbra, Coimbra, Portugal
[4] mzrela@dei.uc.pt

***Abstract:*** Understanding how systems evolves can reveal important pieces of information that can help open source stakeholders to identify what can be improved in the software system's internal organization. Once software complexity is one of the most important attributes to determine software maintainability, controlling its level in the system evolution process makes the software easier to maintain, reducing the maintainability costs. Otherwise, uncontrolled complexity makes the maintenance and enhancement process lengthy, more costly and sometimes it can contribute to the system abandonment. This work investigates the evolution of complexity in discontinued FLOSS projects, through statistical analysis with data obtained from analisis of SonarQube Software. SonarQube is an open-source software quality tool that analyzes the project's source code and give the developers a feedback about the internal status of what is being developed. After several analyses, the outcome showed interesting results. A substantial portion of inactive FLOSS projects do not seem to be able to keep up with the extra work required to control the systems complexity, presenting a different behaviour of the successful active FLOSS projects. Though, some inactive FLOSS projects do have a complexity evolution that resembles with the curves belonging to active projects.

***Keywords:*** Software Complexity, FLOSS, software inactivity, open source success.

## I. Introduction

Although Free/Libre Open Source Software (FLOSS) projects has increasingly gained visibility among programmers in these past years, it is still a challenge for these kind of projects to manage to reach success and high quality systems

(Michlmayr, Hunt, & Probert, 2005). The lack of a rigid structure more present in proprietary software, sometimes may prejudice the prosecution of the system. The amount of discontinued projects is undoubtedly higher compared to the number of active projects. To illustrate this scenario, consider the data extracted in November, 2012, from SourceForge.net, one of the most popular Free Software repositories. Out of over 174,000 hosted projects, 65% of them were classified as "dormant", (no development within the last two years) while 28% were classified as "active", and the 7% remainder were classified as "inactive" (its development was allegedly ceased by the lead developer) (Khondhu, Capiluppi, & Stol, 2013).

Predict model projects in order to correctly foresee success or failure is still a significant challenge in software engineering (Beaver, Cui, Charles, & Potok, 2009). The evolution of these projects may occurs very quickly depending on programming effort from collaborators.

According to Lehman's second law of software evolution, system's complexity increases unless work is done to maintain or reduce it. So, as the FLOSS systems grow in size and, consequently, features and capabilities, they will also grow in complexity if the level of required work is not reached (Capiluppi & Beecher, 2009). The deterioration of the integrity of the software, result of its continuous evolution, may manifest itself as growing complexity (Lehman, 1978). This phenomenon, called code decay in the literature, is likely to make it progressively more difficult to understand the inner workings of the software and, hence, to implement functional additions and changes (Eick, Graves, Karr, Marron, & Mockus, 2001). Thereby, it will be required increasing levels of work done to control complexity, in order to avoid system regression and to maintain their evolution (Capiluppi & Beecher, 2009).

Given the great commitment necessary to keep a working and evolving FLOSS project, it is not unusual to find projects in which the lead developer(s) lost the interest on it. This was proven by the numbers of "discontinued" and "dormant" projects hosted by SourceForge.net repository shown previously. Occasionally, there are contributors willing to continue the development, but its complexity makes it more practical for them to start a new project as a replacement to the original (Terceiro & Chavez, 2009). Sometimes even the lead developer(s) realize that the code became so complex that it is more cost-effective to rewrite large parts of the software, or even to rewrite it entirely from scratch, than investing time in enhancing existing code (Terceiro & Chavez, 2009).

During the initial research on the theme, we notice that some discontinued projects hosted by web-based repositories, even when declared inactive by its developers (The inactive tag of SourceForge.net only can be setted by the development team) still hold a high download rate per week. That means that projects that no longer have updates in their systems and no maintenance whatsoever still manage to be successful. For instance, we can mention the ffdshow project (Ivanov et al., n.d.), that currently counts with about eighteen thousands of weekly downloads. Below in Table 1, you can see some discontinued projects hosted by SourceForge.net repository that have a high download rate per week. If these projects continue being that popular, what is reason why they are discontinued then? To better understand this question, it is important to consider not only the interest of the public that utilizes the software, but also the internal operation of the system. If the system reaches a point where it is difficult to make necessary changes that contribute to the system's evolution, this can lead to its inactivation. In this case, the software development is ceased, but it is not necessarily discontinued. discontinued. The difference is that though the system cannot suffer further modifications, it is still running correctly so it can have a large number of page visits and high weekly downloads rate, as well as a wide range of users. Therefore, regardless external discriminators of success, what determines whether a project will continue to evolve or cease its development can be also related to the state of its internal structure. It is in the light of these questions, we propose to explore the source code complexity in order to acquire an overview about the internal behaviour of the system.

TABLE I: DISCONTINUED PROJECTS HOSTED ON SOURCEFORGE.NET WITH A HIGH WEEKLY DOWNLOAD RATE'

| **Project** | **Weekly Downloads** |
|---|---|
| ffdshow | 18,881 |
| VirtualDubMod | 8,461 |
| Guliverkli2 | 4,763 |
| butt (broadcast using this tool) | 1,088 |
| Python/XML | 1,240 |

In this paper, we approach the relation between discontinued FLOSS and complexity metrics. We think that complexity is one of the most important attributes to be evaluated attributes to be evaluated in way to ensure an acceptable level of system maintenance. A project with an uncontrolled complexity can become difficult to maintain, and it can contribute to its abandonment. We think that understanding the complexity evolution for these software and the relation with its failure, it can guide us on how to avoid similar failures in software that are still under development. This paper is organised as follows: in Section II we show significant related work about FLOSS projects in order to situate the reader in the subject and relevance of this work. In Section III we state the research strategy containing the methodology we adopted to guide our work. In Section IV we presented the theoretical grounding to our statistical analysis. The results are presented in Section V, in Section VI we discuss future work, and we finalize the paper with the conclusions in Section VI.

## II. Related Work

The categorization of OSS projects has been the target of an extensive number of studies, such in (Capiluppi, Lago, & Morisio, 2003), (English & Schweik, 2007), where is established that a considerable number of OSS projects tend to be discontinued, suffering the “abandonment tragedy” (English & Schweik, 2007).

A study conducted by (Beecher et al., n.d.), investigates whether the inclusion of a specific project in the same forge and distribution of a successful FLOSS project has an influence on its evolutionary characteristics. For the analysis, they sampled 50 projects from both forges: Debian and Source-Forge, and studied their evolution. They concluded that Debian projects do indeed show different characteristics than projects from SourceForge. Debian projects were shown to have a longer period of evolution, were larger in size, attracted more developers and experienced greater activity than SourceForge projects. Their second research question was based on the Debian sample only and assessed the presence of two phases of evolution, i.e. before and after the inclusion into the Debian forge. However, their results were ineficient to conclude that there was a statistically significant difference before and after the inclusion.

Using a sample set of 83 projects hosted on Source-Forge.net that had at least 7 developers that have ever contributed code and had at least 100 bugs reported, (Wang, 2005) concluded that the success of an OSS project can be predicted by just considering its first 9 month development data with his K-Means clustering predictor at relatively high confidence. k-means clustering is a machine learning algorithm used to cluster observations into groups of related observations without any prior knowledge of those relationships.

Contrary to the idea of most existing studies on the maintainability of OSS projects, which shows that evolving software tends to decrease its quality and maintainability (Bakota et al., 2012), through our research of related work we found that this is not necessarily true, as stated in (Khondhu et al., 2013).

In their paper, (Stamelos, Angelis, Oikonomou, & Bleris, 2002) show empirical results on the relationship between the size of application components and the delivered quality measured through user satisfaction. Quality characteristics of 100 applications written in C for GNU/Linux were compared to industrial standards. They limited their analysis to the component level – a component is any C function in the program. They have determined that, up to a certain extent, the average component size of an application is negatively related to the user satisfaction for this application. Their findings relating structural quality to user satisfaction reflects the connection between internal structure and the application acceptability by the user, what may contribute to determine whether an OSS project will become successful or not. In (Schweik, English, Paienjton, & Haire, 2010), the authors investigated what factors lead to success or abandonment of open source software (OSS) projects. As mentioned in their paper, the most important external discriminators of success and abandonment in the growth stage of development process are the quantity of page visits and the download rate. However, it is not clear which factors in the source code structure affects these number.

## III. Research Design

### *A. Research Strategy*

Our research strategy is based on the Goal-Question- Metric (GQM) approach (Basili, Caldiera, & Rombach, 1994). According to this strategy, we must first specify our goals, then we must delineate those goals to the data that are designated to define those goals operationally, and finally provide a underlying structure for interpreting the data with respect to the stated goals. The GQM approach is a mechanism for defining and interpreting operational and measurable software. It can be used in isolation or, better, within a context of a more general approach to software quality improvement. The following are the objectives and questions that make up the strategy in this paper.

– **Goal**. The overall goal of this paper consists in study the relation between source code complexity metrics and the success of FLOSS projects, as well as investigate how further this relation can affect the system’s survival. Once it is clear that we cannot directly point out the cause of the software’s abandonment, we propose to explore the internal factors that may contribute to the project failure.

– **Questions**. This paper addresses the following research question:

1) How the internal properties of the software influence the abandonment of a project?

2) In which point of development process discontinued FLOSS projects tend to fail?

– **Metrics and Definitions**. In order to analyse the OSS, we used the following metrics and definitions:

– **Lines of Code (LoC)**: Number of physical lines that contain at least one character which is neither a whitespace or a tabulation or part of a comment.

– **Complexity:** It is the cyclomatic complexity, also known as McCabe's complexity metric. Whenever the control flow of a function splits, the complexity counter gets incremented by one. Each function has a minimum complexity of 1.

– **Complexity/class**: Average complexity by class.

– **Complexity/file:** Average complexity by file.

– **Complexity/function:** Average complexity by function.

– **Normalized Complexity:** Outcome value of dividing the total complexity of each system version by its size (source code number of lines) of that same version.

*B. Data Collection and Analysis*

In this subsection we specify how the data collection and the analysis of the data obtained was performed. *SonarQube Software*: Firstly, aiming to pick a source code quality measurement tool that matched with our needs to fulfil the goals proposed at the beginning of this study, we have chosen to use the SonarQube software. SonarQube is an open source software that aims to be the source code's quality management platform, allowing control over a large number of software metrics by the development team. The software main goal is to identify how the code is evolving, as well the behaviour of the multiple quality measures, while pointing possible software bugs.

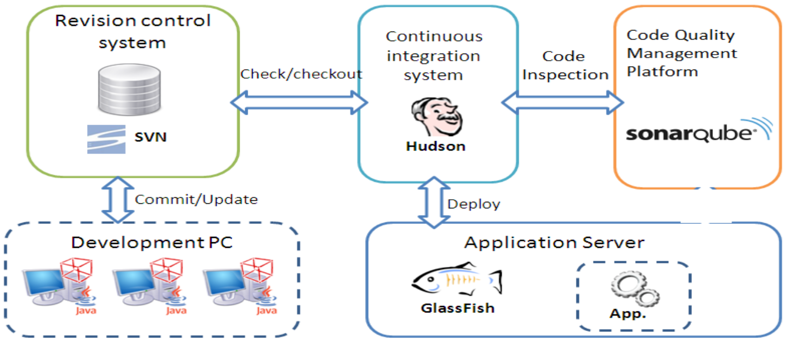


Figure. 1: Integration of SonarQube: How the software works.

When a SonarQube analysis is performed, the outcome is generated automatically through a complete inspection on the code base, after which the results are displayed through the web interface displayed in graphics and dashboards.

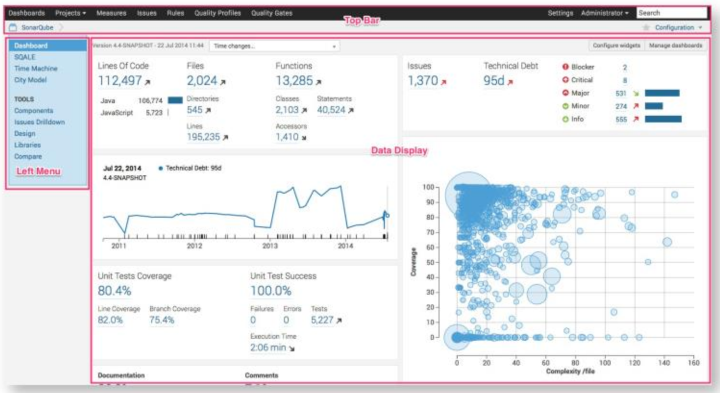


Figure. 2: SonarQube Web Interface.

Bellow, we detail the steps taken to perform this empirical study.

**1) Sampling of projects**. In way to find the software to fit in our strategy, we performed a research through the SourceForge.net repository. The results were filtered to show projects only written in Java, so they were ordered using two tags: inactive and rating. We chose the Java language because it is a widely used object-oriented programming language. Moreover, the rating was important to check how relevant the software among the discontinued ones was. Once that projects had a high value of rating, most of them had a high download rate per week. Then, we manually selected ten projects with more than five released versions to proceed with analysis. We checked the last update date to include only projects that were inactive for more than two years. Afterwards, we selected three successful and active FLOSS projects. They were used to compare with the unsuccessful ones. Two out of them, are well-known systems (Tomcat and Hibernate), and the third one, JabRef, is a smaller software, but still very popular. We chose them based on the availability and good organization of the source code (what simplifies the analysis).

**2) Extracting data**. The source code of the selected projects was manually extracted from the respective projects' web-pages on SourceForge.net repository. All released versions available were downloaded.

**3) Analysing the source code**. As stated before, we used the SonarQube tool to execute the analysis. A Python script was written to automatize the analysis via terminal. Once the analysis is performed, the results are available in the web interface, and count with the extraction of almost twenty metrics analysed. Within the range of metrics generated by the analysis, we adopted six metrics to proceed with our research. The metrics we chose to proceed within this work are presented in the previous subsection.

**4) Evaluating the results**. The final step is the evaluation process. The results are obtained through the execution of SonarQube and data analysis.

The following table (Table 2) shows information from the ten discontinued FLOSS projects analysed. As we can observe, all of the samples has at least two years of inactivity, what assures that the projects are discontinued in fact. They also present a significant number of downloads per project, which shows on the other hand that all of them had some relevance in the Open Source Software scenario.

TABLE II: DATA OF SELECTED DISCONTINUED PROJECTS.

| **Project ID** | **First Version** *(dd-mm-yyyy)* | **Last Version** *(dd-mm-yyy)* | **Released versions** | **Number of downloads** |
|---|---|---|---|---|
| Saxpath | 24-01-2001 | 26-04-2002 | 7 | 21,759 |
| Jaxen | 25-07-2001 | 26-04-2002 | 10 | 43,682 |
| Jo1 | 18-03-2002 | 07-07-2005 | 9 | 23,502 |
| IdeaVIM | 17-04-2003 | 30-03-2010 | 53 | 9,568 |
| RemoteTea | 14-08-2003 | 02-01-2008 | 5 | 15,474 |
| JRFD | 20-12-2003 | 09-02-2011 | 26 | 18,172 |
| G4J | 16-09-2004 | 19-09-2005 | 11 | 45,158 |
| Gilead | 10-11-2008 | 22-05-2010 | 7 | 28,791 |
| LslPlus | 28-07-2008 | 06-03-2009 | 14 | 20,220 |
| MorarChat | 21-12-2009 | 14-01-2012 | 15 | 19,535 |

## IV. Statistical Analysis

### *A. Correlation*

In order to determine how the complexity metrics are correlated, we started to seek for some correlation coefficient that could measure this connexion. Correlation coefficient is a measure of association between two variables, and it ranges between 1 and 1. If the two variables are in perfect linear relationship, the correlation coefficient will be either 1 (total positive correlation) or 1 (total negative correlation). The correlation coefficient is 0 if there is no linear relationship between the variables. Two different types of correlation coefficients are in use. One is called the Pearson product-moment correlation coefficient, and the other is called the Spearman rank correlation coefficient, which is based on the rank relationship between variables (“Encyclopaedia of Measurement and Statistics”, 2007).

The Pearson product-moment correlation coefficient (sometimes referred to as the **PPMCC** or **PCC** or **Pearson’s r**) is more widely used in measuring the association between two variables. Given paired measurements ($X_1$; $Y_1$); ($X_2$; $Y_2$); ($X_n$; $Y_n$), the Pearson product-moment correlation coefficient is a measure of association given by

$$r_P = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2 \sum_{i=1}^{n}(Y_i - \overline{Y})^2}}$$

Where $\overline{X}$ and $\overline{Y}$ are the simple mean of $X_1$; $X_2$; ... $X_n$ and $Y_1$; $Y_2$; ... $Y_n$, respectively.

Bellow you can find examples of scatter diagrams with different values of Pearson’s correlation coefficient.

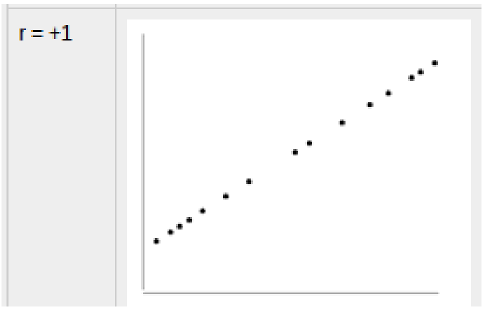


Fig. 3: Data lie on a perfect straight line with a negative slope

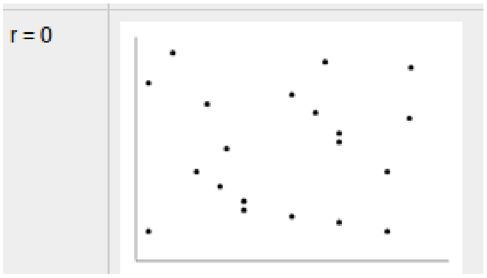


Fig. 4: No linear relationship between the variables.

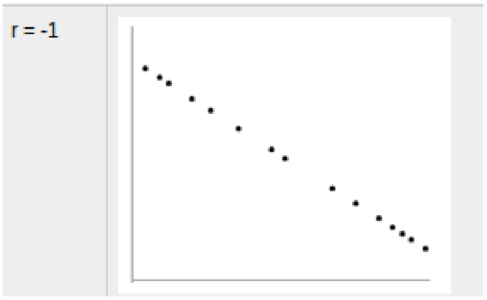


Fig. 5: Data lie on a perfect straight line with a positive slope.

## *B. R Programming To Calculate Correlation*

R is an open-source (GPL) statistical environment, started by Robert Gentleman and Ross Ihaka (hence the name, R) of the Statistics Department of the University of Auckland in 1995. R is a powerful statistical program but it is first and foremost a programming language. R provides a wide variety of statistical and graphical techniques, including linear and nonlinear modelling, classical statistical tests, time-series analysis, classification, clustering, and others. R is easily extensible through functions and extensions, and, besides, routines have been written for R by people all over the world and mad freely available from the R project website as "packages".

R can perform correlation with the cor() function. Built-in to the base distribution of the program are three routines: for Pearson, Kendal and Spearman Rank correlations. The detailed steps undertaken are the following:

1) The first step is to arrange your data in a .CSV file. Use a column for each variable and give it a meaningful name. Don't forget that variable names in R can contain letters and numbers but the only punctuation allowed is a period. In our case, we arranged the data in a readable formatation, so we could copy the data into a .CSV file.

2) The second step is to read your data file into memory and give it a sensible name.

3) The next step is to attach your data set so that the individual variables are read into memory.

4) Finally, to get the correlation coefficient you type: cor( var1, var2, method = "method")

The default method is "pearson" so you may omit this if that is what you want. If you type "kendall" or "spearman" then you will get the appropriate correlation coefficient.

## V. Results

Subsection IV.A shows the evaluation of the outcome obtained by performed analyse detailed in Subsection III.B. As described in Section III, we defined our goal that is addressed by the research questions. Subsections IV.B discuss questions 1 and 2. Subsection IV.C explain the exception in the results pattern.

### *A. Evaluating analysis outcome*

Given the results of the analysis made with SonarQube, we began to interpret some of the data obtained. The data collected allows us to affirm that the projects are consistently growing since their first release. Delimiting the number of released versions served to not select small projects that are locally developed for a certain public. Thus, the selected projects were being actively developed and receiving new features as an effect of new user requirements.

In order to make a more complete analysis of the systems' metrics and compare them to each other, we made some normalizations. Thereby, we calculated the complexity ratio by dividing the total complexity of each system version by its size (source code number of lines) of that same version. We called it *"normalized complexity"*.

As we can observe through the statistics, shown by Fig. 1, 3, 5, 6, 7 and 9, six out of ten projects analysed have a resembling behaviour. These six projects (Jaxen, IdeaVIM, JRFD, G4J, Gilead and MorarChat), show a gradual (Fig. 1, 3, 6 and 7) or uncontrolled (Fig. 5 and 9) rise in their normalized complexity, which tends to remain for the upcoming versions. Comparing them with the graphics that shows the normalized complexity of active applications (Fig. 11), we can point out the differences. While the active projects has a more controlled complexity, presenting almost a constant normalized complexity, with small decreases on its value, the discontinued projects do not seem to be able to control the system's complexity, since its complexity is gradually increasing or sometimes it is even widely varying. In the other hand, Fig. 2, 4, 8 and 10 shows that the normalized complexity metric is kept almost constant for these projects. This demonstrate that these inactive projects (Jo!, RemoteTea, Saxpath and LslPlus) have a very similar behaviour to the active ones.

*B. Addressing paper questions*

**Question 1**.*"How the internal properties of the software influence the abandonment of a project?"*

The complexity data reveals interesting issues. As verified in the previous subsection, on six out of ten inactive projects analysed the complexity grows as the time passes, according as the discontinued projects evolve. Also, the curve drawn by the complexity sometimes may shows a lot of variations. Therefore, the increasing complexity of these projects enables us to assert that these projects can not completely control the complexity as faster as it grows. The level of work needed to keep the control over the complexity seems not to be reached by the developers, and this could also contribute to the abandonment of these projects.

In order to further investigate the relationship between the complexity of a project and its abandonment, we calculate de standard deviation of the complexity metrics. The standard deviation measures how close the set of data is to the mean value of the data set. If the data set have a high standard deviation then the values are spread out very much. If the data set have a small standard deviation then the data points are very close to the mean. The following graphs (figure 12 and 13) shows that discontinued projects have a larger standard deviation than the active ones, when it comes to its normalized complexity, indicating that active projects could possibly have a more effective control over its complexity. However, it is mandatory to notice that not all of the inactive projects presents the same behaviour. Fig. 12 ratifies what we observed previously about similarities etween inactive and active projects. According to Fig. 12, Jo!, RemoteTea, Saxpath and LslPlus projects, shows indeed a low standard deviation, indicating that these projects kept the normalized complexity under control.

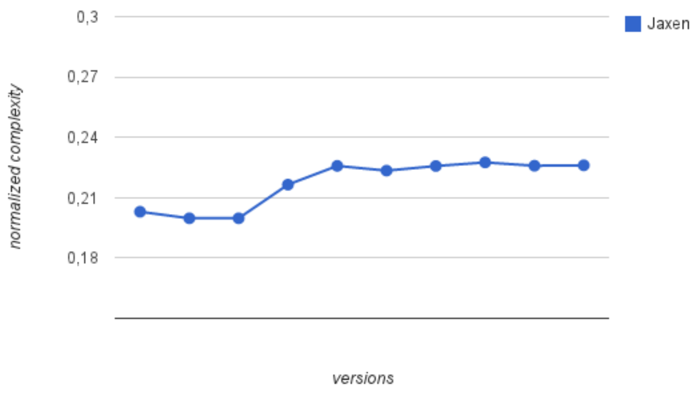


Fig. 6: Normalized Complexity of each version of Jaxen Application.

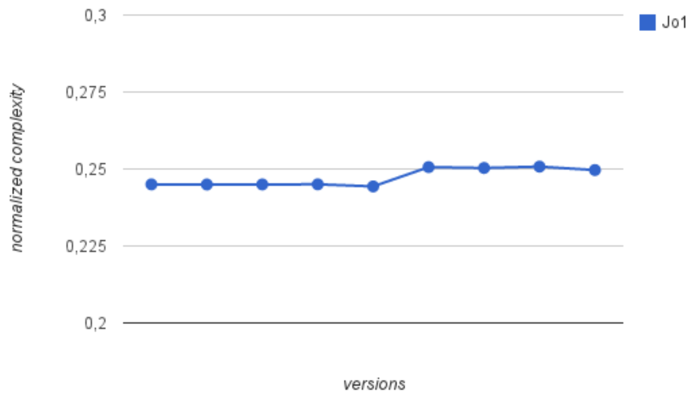


Fig. 7: Normalized Complexity of each version of Jo! Application

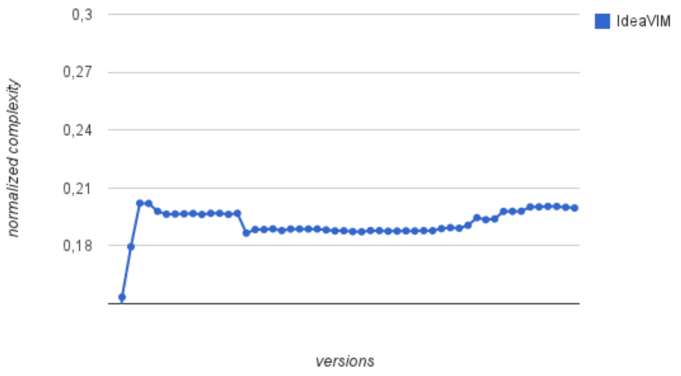


Fig. 8: Normalized Complexity of each version of Jaxen Application.

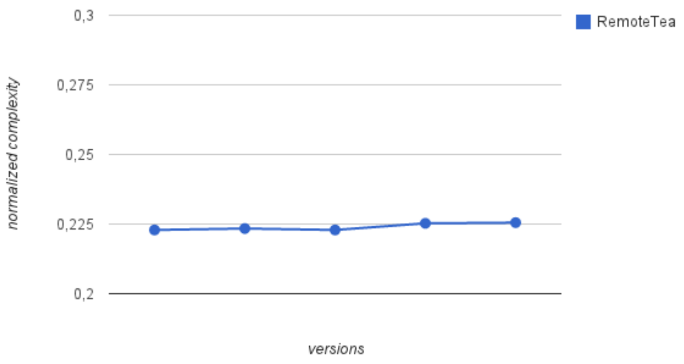


Fig. 9: Normalized Complexity of each version of Jaxen Application.

Moreover, observing the graphs we also identified that the complexity/function metric has a higher impact in the systems' evolution among the other complexity related metrics also analysed. We calculate the standard deviation as well as the variance of this metric. The variance measures how far a set of numbers is spread out. A variance of zero indicates that all the values are identical. Therefore, a small variance means that the variable has its numbers not so spread out, thus the similar values indicates constancy in the metric. We found out that both standard deviation and variance is larger for discontinued projects as well (Fig. 14, 15, 16 and 17), what lead us to conclude that in some projects the complexity may have a connection with its failure, especially when we focus in its complexity by function.

**Question 2.** *"In which point of development process discontinued FLOSS projects tend to fail?"*

As seen in Section I, there are a lot of projects hosted by web-based repositories that became so complex that it is more cost-effective to rewrite large parts of its source code. When an application reaches this apex of complexity, we can declare it a failed project. Therefore, this "failure point" – considering only the structural motivations – it is when the complexity makes the system no longer maintainable and then the project becomes discontinued.

However, as we can notice from the charts, the structural elements of software do not determine precisely when a project must be discontinued. Taking in account Fig. 5, which shows the behaviour of the normalized complexity of JRFD project, we can see that in the sixth released version of the software occurs a peak on the value of its normalized complexity, but this factor is clearly not sufficient to immediately cease its development. That lead us to conclude that, though the complexity may have a contribution on the discontinuation of a project, the point of development process that a project tend to fail is a complex question that involves way more external aspects rather than a limited subset of factors dictated by internal properties.

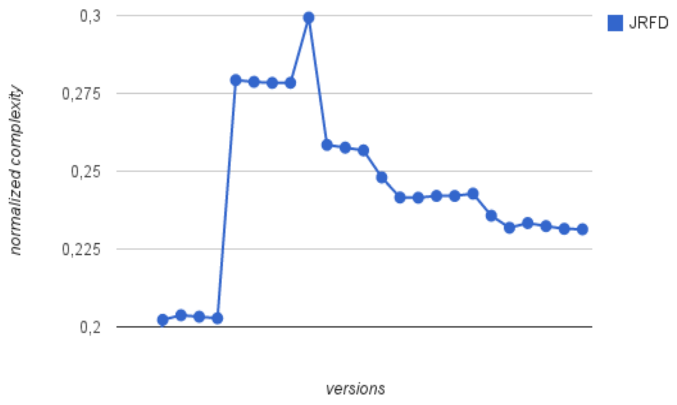


Fig. 10: Normalized Complexity of each version of Jaxen Application.

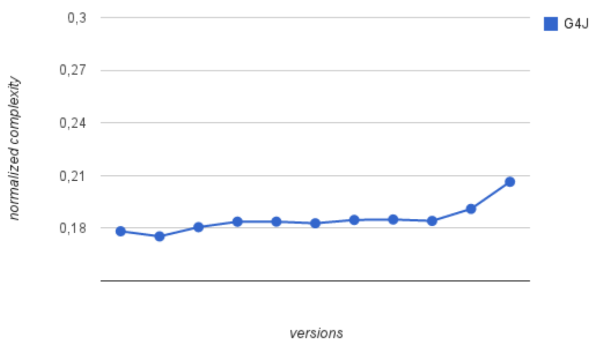


Fig. 11: Normalized Complexity of each version of G4J Application

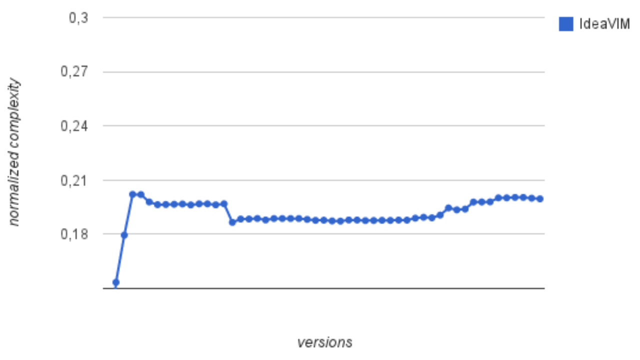


Fig. 12: Normalized Complexity of each version of IdeaVIM Application.

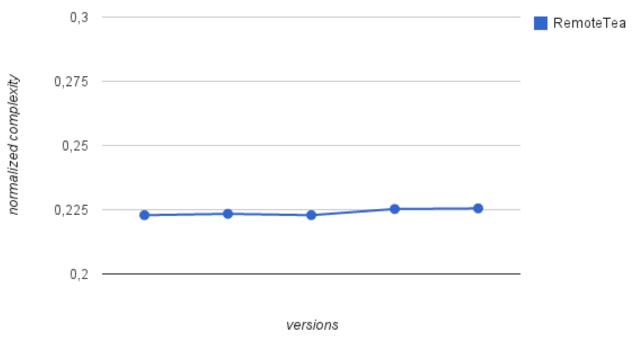


Fig. 13: Normalized Complexity of each version of RemoteTea Application

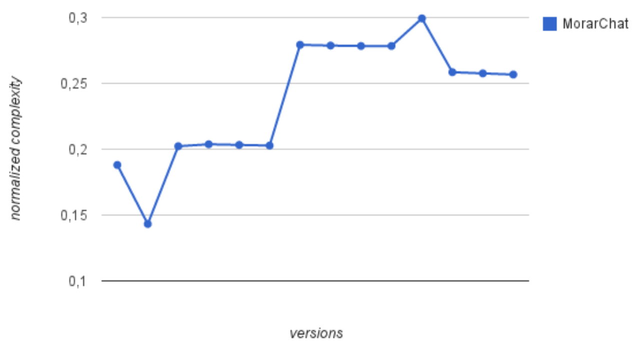


Fig. 14: Normalized Complexity of each version of MorarChat Application.

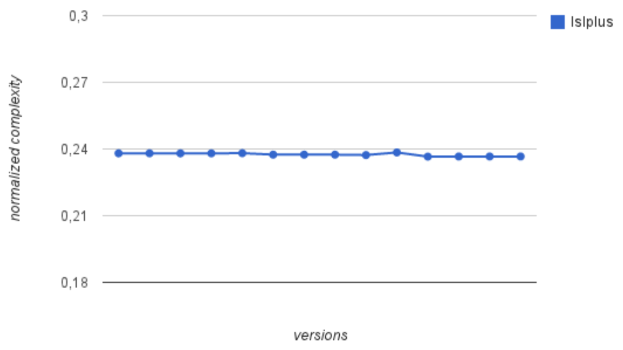


Fig. 15: Normalized Complexity of each version of LslPlus Application

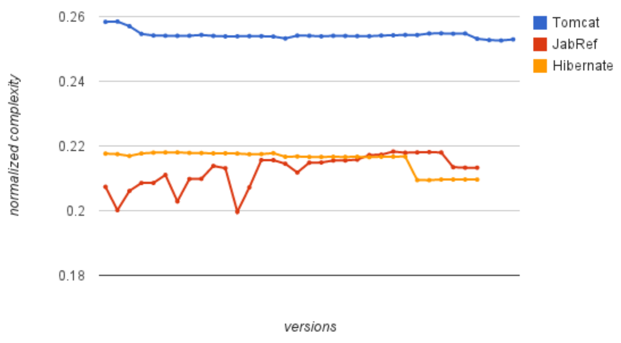


Fig. 16: Released versions Normalized Complexity of Actives FLOSS projects: Tomcat, JabRef and Hibernate Applications.

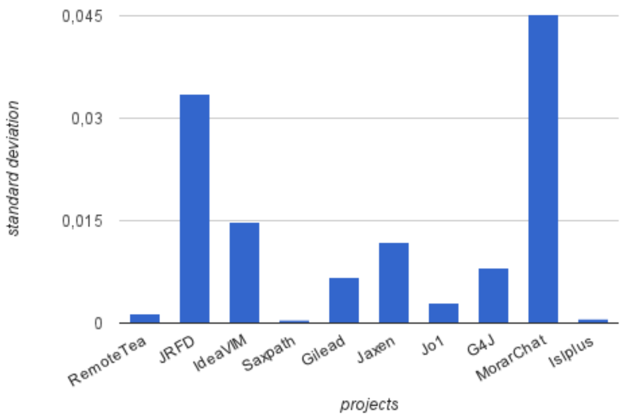


Fig. 17: Normalized Complexity standard deviation of discontinued FLOSS projects.

*C. Correlation between complexity metrics*

As we can see from the figures bellow, which show the Pearson's coefficient of the complexity metrics from the projects analysed, we can notice that the projects present different correlations for the same pairs of metrics analysed. For instance, the correlation between the LoC x Complexity by function metric is strongly positive for Jaxen application, but it is strongly negative for RemoteTea application and even non existent for Jo! application. Therefore, for each project, its class, function or file characteristics, has a stronger correlation with the other metrics, indicating that this particular metric has a greater impact over the characteristics of the project as a whole. What could determine which of them – the class, the function or the file – exerts this role, is the definition of its architecture and its definition of module. Once there is not a formal definition of a module, and what a module is in the context of a project, it largely depends on the nature and design of the project. So, this distribution of correlation may has to do of how the development team see the set of modules that compose the source code, and how they implement the additions and modifications in this software.

In order to have a clearer view of what metrics have deeper relation with the Complexity metric, we construct the table below. Take x for positive correlation with th Complexity metric and □x for negative correlation.

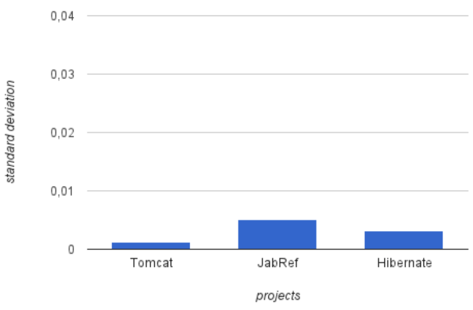
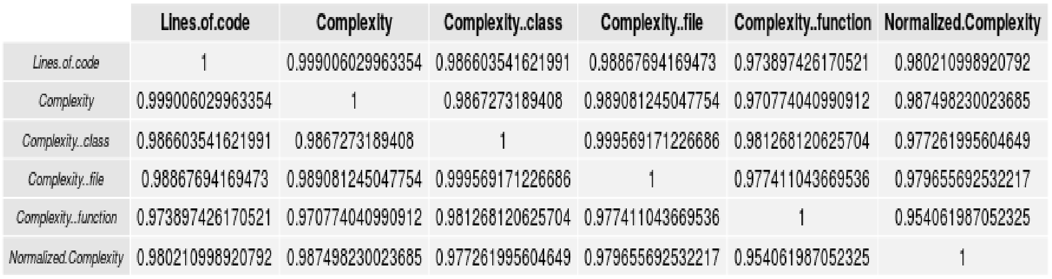
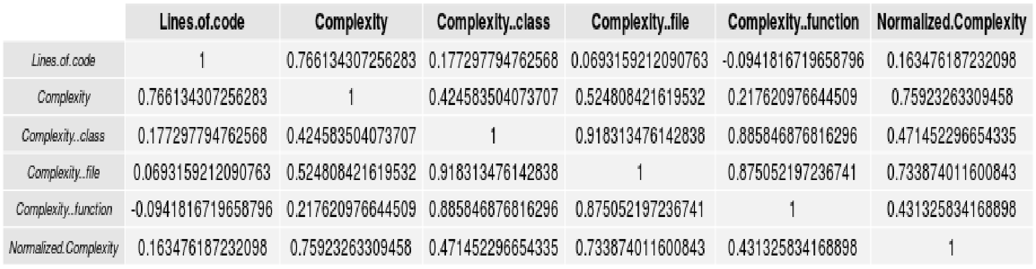


Fig. 18: Normalized Complexity standard deviation of actives FLOSS projects.



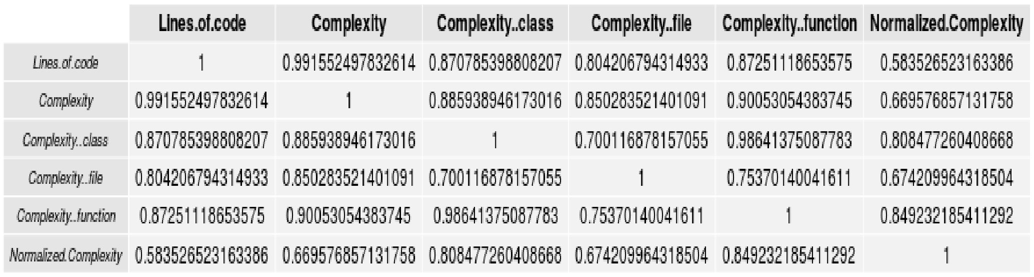
| | Lines.of.code | Complexity | Complexity..class | Complexity..file | Complexity..function | Normalized.Complexity |
|---|---|---|---|---|---|---|
| *Lines.of.code* | 1 | 0.999006029963354 | 0.986603541621991 | 0.98867694169473 | 0.973897426170521 | 0.980210998920792 |
| *Complexity* | 0.999006029963354 | 1 | 0.9867273189408 | 0.989081245047754 | 0.970774040990912 | 0.987498230023685 |
| *Complexity..class* | 0.986603541621991 | 0.9867273189408 | 1 | 0.999569171226686 | 0.981268120625704 | 0.977261995604649 |
| *Complexity..file* | 0.98867694169473 | 0.989081245047754 | 0.999569171226686 | 1 | 0.977411043669536 | 0.979655692532217 |
| *Complexity..function* | 0.973897426170521 | 0.970774040990912 | 0.981268120625704 | 0.977411043669536 | 1 | 0.954061987052325 |
| *Normalized.Complexity* | 0.980210998920792 | 0.987498230023685 | 0.977261995604649 | 0.979655692532217 | 0.954061987052325 | 1 |

Fig. 19: Pearson's correlation coefficient of Jaxen Application.



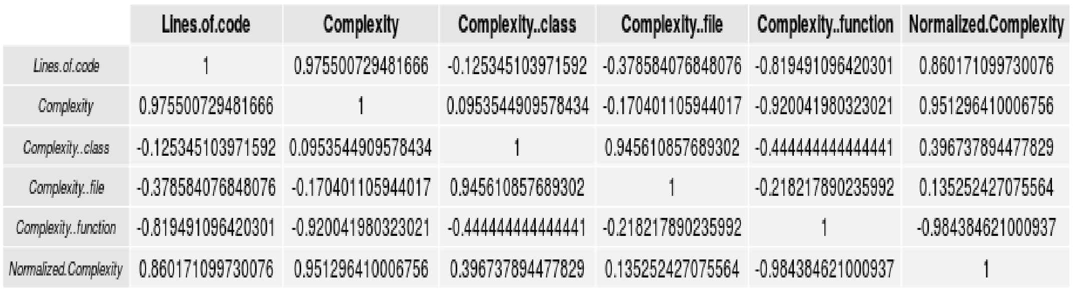
| | Lines.of.code | Complexity | Complexity..class | Complexity..file | Complexity..function | Normalized.Complexity |
|---|---|---|---|---|---|---|
| *Lines.of.code* | 1 | 0.766134307256283 | 0.177297794762568 | 0.0693159212090763 | -0.0941816719658796 | 0.163476187232098 |
| *Complexity* | 0.766134307256283 | 1 | 0.424583504073707 | 0.524808421619532 | 0.217620976644509 | 0.75923263309458 |
| *Complexity..class* | 0.177297794762568 | 0.424583504073707 | 1 | 0.918313476142838 | 0.885846876816296 | 0.471452296654335 |
| *Complexity..file* | 0.0693159212090763 | 0.524808421619532 | 0.918313476142838 | 1 | 0.875052197236741 | 0.733874011600843 |
| *Complexity..function* | -0.0941816719658796 | 0.217620976644509 | 0.885846876816296 | 0.875052197236741 | 1 | 0.431325834168898 |
| *Normalized.Complexity* | 0.163476187232098 | 0.75923263309458 | 0.471452296654335 | 0.733874011600843 | 0.431325834168898 | 1 |

Fig. 20: Pearson's correlation coefficient of Jaxen Application.



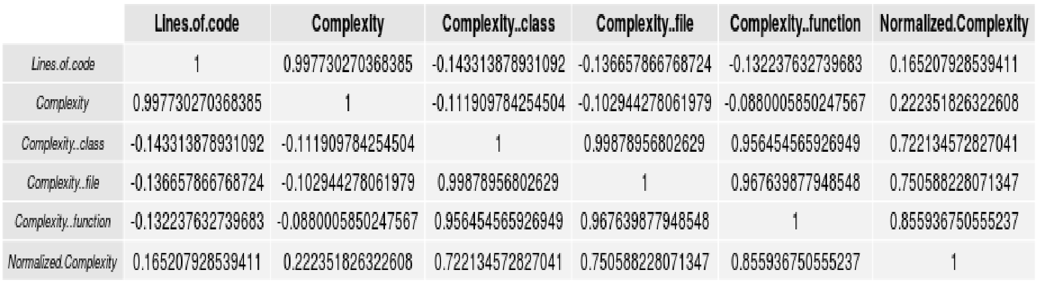
| | Lines.of.code | Complexity | Complexity..class | Complexity..file | Complexity..function | Normalized.Complexity |
|---|---|---|---|---|---|---|
| *Lines.of.code* | 1 | 0.991552497832614 | 0.870785398808207 | 0.804206794314933 | 0.87251118653575 | 0.583526523163386 |
| *Complexity* | 0.991552497832614 | 1 | 0.885938946173016 | 0.850283521401091 | 0.90053054383745 | 0.669576857131758 |
| *Complexity..class* | 0.870785398808207 | 0.885938946173016 | 1 | 0.700116878157055 | 0.98641375087783 | 0.808477260408668 |
| *Complexity..file* | 0.804206794314933 | 0.850283521401091 | 0.700116878157055 | 1 | 0.75370140041611 | 0.674209964318504 |
| *Complexity..function* | 0.87251118653575 | 0.90053054383745 | 0.98641375087783 | 0.75370140041611 | 1 | 0.849232185411292 |
| *Normalized.Complexity* | 0.583526523163386 | 0.669576857131758 | 0.808477260408668 | 0.674209964318504 | 0.849232185411292 | 1 |

Fig. 21: Pearson's correlation coefficient of Jaxen Application.



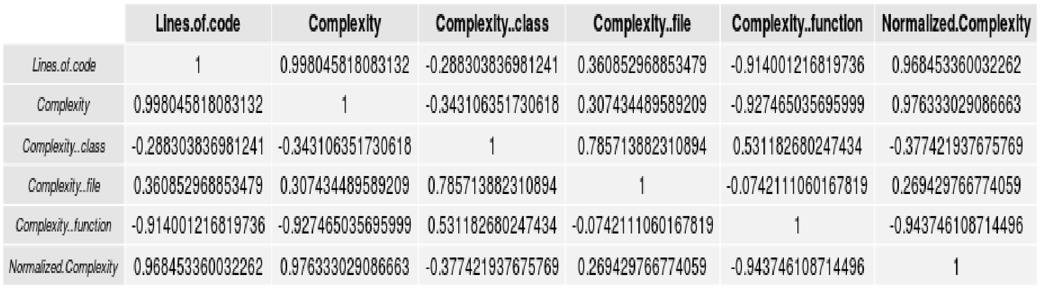
| | Lines.of.code | Complexity | Complexity..class | Complexity..file | Complexity..function | Normalized.Complexity |
|---|---|---|---|---|---|---|
| Lines.of.code | 1 | 0.975500729481666 | -0.125345103971592 | -0.378584076848076 | -0.819491096420301 | 0.860171099730076 |
| Complexity | 0.975500729481666 | 1 | 0.0953544909578434 | -0.170401105944017 | -0.920041980323021 | 0.951296410006756 |
| Complexity..class | -0.125345103971592 | 0.0953544909578434 | 1 | 0.945610857689302 | -0.444444444444441 | 0.396737894477829 |
| Complexity..file | -0.378584076848076 | -0.170401105944017 | 0.945610857689302 | 1 | -0.218217890235992 | 0.135252427075564 |
| Complexity..function | -0.819491096420301 | -0.920041980323021 | -0.444444444444441 | -0.218217890235992 | 1 | -0.984384621000937 |
| Normalized.Complexity | 0.860171099730076 | 0.951296410006756 | 0.396737894477829 | 0.135252427075564 | -0.984384621000937 | 1 |

Fig. 22: Pearson’s correlation coefficient of Jaxen Application



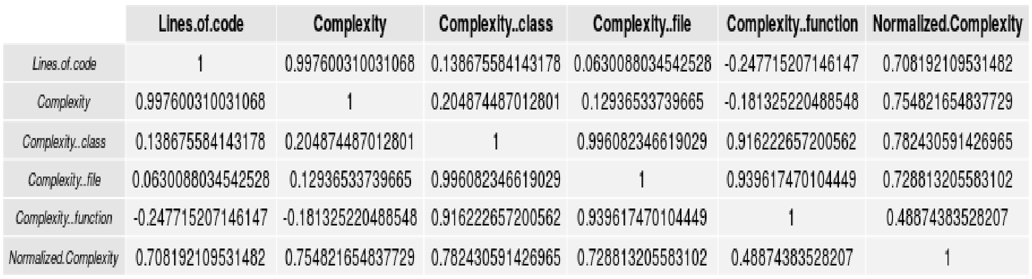
| | Lines.of.code | Complexity | Complexity..class | Complexity..file | Complexity..function | Normalized.Complexity |
|---|---|---|---|---|---|---|
| Lines.of.code | 1 | 0.997730270368385 | -0.143313878931092 | -0.136657866768724 | -0.132237632739683 | 0.165207928539411 |
| Complexity | 0.997730270368385 | 1 | -0.111909784254504 | -0.102944278061979 | -0.0880005850247567 | 0.222351826322608 |
| Complexity..class | -0.143313878931092 | -0.111909784254504 | 1 | 0.99878956802629 | 0.956454565926949 | 0.722134572827041 |
| Complexity..file | -0.136657866768724 | -0.102944278061979 | 0.99878956802629 | 1 | 0.967639877948548 | 0.750588228071347 |
| Complexity..function | -0.132237632739683 | -0.0880005850247567 | 0.956454565926949 | 0.967639877948548 | 1 | 0.855936750555237 |
| Normalized.Complexity | 0.165207928539411 | 0.222351826322608 | 0.722134572827041 | 0.750588228071347 | 0.855936750555237 | 1 |

Fig. 23 Pearson’s correlation coefficient of Jaxen Application



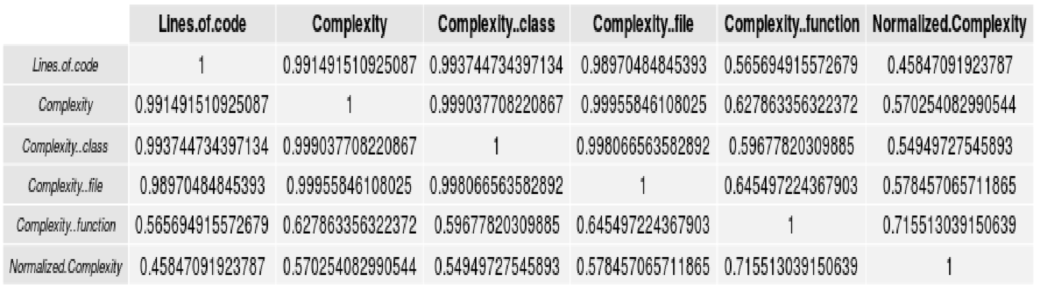
| | Lines.of.code | Complexity | Complexity..class | Complexity..file | Complexity..function | Normalized.Complexity |
|---|---|---|---|---|---|---|
| Lines.of.code | 1 | 0.998045818083132 | -0.288303836981241 | 0.360852968853479 | -0.914001216819736 | 0.968453360032262 |
| Complexity | 0.998045818083132 | 1 | -0.343106351730618 | 0.307434489589209 | -0.927465035695999 | 0.976333029086663 |
| Complexity..class | -0.288303836981241 | -0.343106351730618 | 1 | 0.785713882310894 | 0.531182680247434 | -0.377421937675769 |
| Complexity..file | 0.360852968853479 | 0.307434489589209 | 0.785713882310894 | 1 | -0.0742111060167819 | 0.269429766774059 |
| Complexity..function | -0.914001216819736 | -0.927465035695999 | 0.531182680247434 | -0.0742111060167819 | 1 | -0.943746108714496 |
| Normalized.Complexity | 0.968453360032262 | 0.976333029086663 | -0.377421937675769 | 0.269429766774059 | -0.943746108714496 | 1 |

Fig. 24 Pearson’s correlation coefficient of Jaxen Application



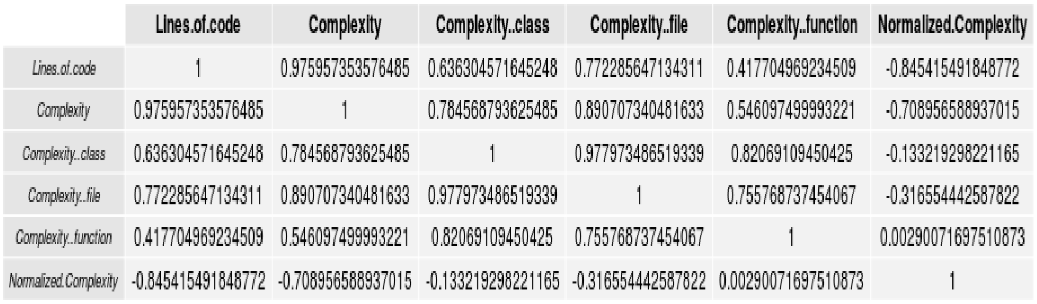
| | Lines.of.code | Complexity | Complexity..class | Complexity..file | Complexity..function | Normalized.Complexity |
|---|---|---|---|---|---|---|
| Lines.of.code | 1 | 0.997600310031068 | 0.138675584143178 | 0.0630088034542528 | -0.247715207146147 | 0.708192109531482 |
| Complexity | 0.997600310031068 | 1 | 0.204874487012801 | 0.12936533739665 | -0.181325220488548 | 0.754821654837729 |
| Complexity..class | 0.138675584143178 | 0.204874487012801 | 1 | 0.996082346619029 | 0.916222657200562 | 0.782430591426965 |
| Complexity..file | 0.0630088034542528 | 0.12936533739665 | 0.996082346619029 | 1 | 0.939617470104449 | 0.728813205583102 |
| Complexity..function | -0.247715207146147 | -0.181325220488548 | 0.916222657200562 | 0.939617470104449 | 1 | 0.48874383528207 |
| Normalized.Complexity | 0.708192109531482 | 0.754821654837729 | 0.782430591426965 | 0.728813205583102 | 0.48874383528207 | 1 |

Fig. 25 Pearson’s correlation coefficient of Jaxen Application



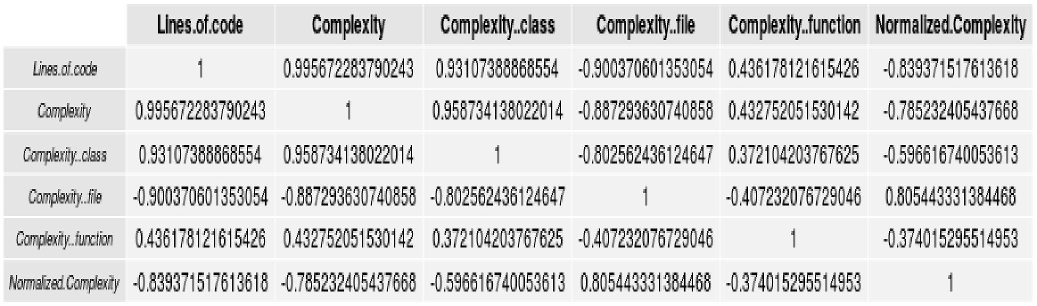
| | Lines.of.code | Complexity | Complexity..class | Complexity..file | Complexity..function | Normalized.Complexity |
|---|---|---|---|---|---|---|
| Lines.of.code | 1 | 0.991491510925087 | 0.993744734397134 | 0.98970484845393 | 0.565694915572679 | 0.45847091923787 |
| Complexity | 0.991491510925087 | 1 | 0.999037708220867 | 0.99955846108025 | 0.627863356322372 | 0.570254082990544 |
| Complexity..class | 0.993744734397134 | 0.999037708220867 | 1 | 0.998066563582892 | 0.59677820309885 | 0.54949727545893 |
| Complexity..file | 0.98970484845393 | 0.99955846108025 | 0.998066563582892 | 1 | 0.645497224367903 | 0.578457065711865 |
| Complexity..function | 0.565694915572679 | 0.627863356322372 | 0.59677820309885 | 0.645497224367903 | 1 | 0.715513039150639 |
| Normalized.Complexity | 0.45847091923787 | 0.570254082990544 | 0.54949727545893 | 0.578457065711865 | 0.715513039150639 | 1 |

Fig. 26 Pearson's correlation coefficient of Jaxen Application



| | Lines.of.code | Complexity | Complexity..class | Complexity..file | Complexity..function | Normalized.Complexity |
|---|---|---|---|---|---|---|
| Lines.of.code | 1 | 0.975957353576485 | 0.636304571645248 | 0.772285647134311 | 0.417704969234509 | -0.845415491848772 |
| Complexity | 0.975957353576485 | 1 | 0.784568793625485 | 0.890707340481633 | 0.546097499993221 | -0.708956588937015 |
| Complexity..class | 0.636304571645248 | 0.784568793625485 | 1 | 0.977973486519339 | 0.82069109450425 | -0.133219298221165 |
| Complexity..file | 0.772285647134311 | 0.890707340481633 | 0.977973486519339 | 1 | 0.755768737454067 | -0.316554442587822 |
| Complexity..function | 0.417704969234509 | 0.546097499993221 | 0.82069109450425 | 0.755768737454067 | 1 | 0.00290071697510873 |
| Normalized.Complexity | -0.845415491848772 | -0.708956588937015 | -0.133219298221165 | -0.316554442587822 | 0.00290071697510873 | 1 |

Fig. 27: Pearson's correlation coefficient of MorarChat Application.



| | Lines.of.code | Complexity | Complexity..class | Complexity..file | Complexity..function | Normalized.Complexity |
|---|---|---|---|---|---|---|
| Lines.of.code | 1 | 0.995672283790243 | 0.93107388868554 | -0.900370601353054 | 0.436178121615426 | -0.839371517613618 |
| Complexity | 0.995672283790243 | 1 | 0.958734138022014 | -0.887293630740858 | 0.432752051530142 | -0.785232405437668 |
| Complexity..class | 0.93107388868554 | 0.958734138022014 | 1 | -0.802562436124647 | 0.372104203767625 | -0.596616740053613 |
| Complexity..file | -0.900370601353054 | -0.887293630740858 | -0.802562436124647 | 1 | -0.407232076729046 | 0.805443331384468 |
| Complexity..function | 0.436178121615426 | 0.432752051530142 | 0.372104203767625 | -0.407232076729046 | 1 | -0.374015295514953 |
| Normalized.Complexity | -0.839371517613618 | -0.785232405437668 | -0.596616740053613 | 0.805443331384468 | -0.374015295514953 | 1 |

Fig. 28: Pearson's correlation coefficient of LslPlus Application.

## *D. Detailed Analysis of Behaviours*

Though we collected a small sample of projects, the outcome provided was very diversified, once the projects presented a very divergent behaviour from each other. The main difference is that the output of four out of the ten projects analysed (Jo!, RemoteTea, Saxpath and LslPlus projects) hold constant values for the studied complexity metrics. Thereby, we decided to further investigate these detached projects in order to verify what could have lead them to this result. Our aim was to answer the question: If the project has a controlled complexity why did it become discontinued?

Accessing Saxpath webpage on SourceForge.net we found out that the project was not discontinued. In fact, it had the inactive tag because it had been incorporated into another software. In other words, the project did not show any signs of uncontrolled complexity and it was active indeed. Also, when accesing RemoteTea webpage on SourceForge.net we noticed that the inactive tag was gone, indicating that the project could be reactivated any time by its development team. That is, the project was not totally abandoned (even it did not receive any released version in the last six years). However, in the case of Jo! and LslPlus projects when accessing the respective webpages on SourceForge.net, we did not find any sign of activation by their development team. Posteriorly, we investigate the current state of the remaining six projects that had increasingly complexity. Through an inspection in their website, we found out that all of them, with the exception of IdeaVim project, remained inactive.

TABLE III: DISCONTINUED PROJECTS HOSTED ON SOURCEFORGE.NET HIGH WEEKLY DOWNLOAD RATE

| **Project ID** | **First Version** *(dd-mm-yyyy)* | **Last Version** *(dd-mm-yyy)* | **Released versions** | **Number of downloads** |
|---|---|---|---|---|
| Saxpath | 24-01-2001 | 26-04-2002 | 7 | 21,759 |
| Jaxen | 25-07-2001 | 26-04-2002 | 10 | 43,682 |
| Jo1 | 18-03-2002 | 07-07-2005 | 9 | 23,502 |
| IdeaVIM | 17-04-2003 | 30-03-2010 | 53 | 9,568 |
| RemoteTea | 14-08-2003 | 02-01-2008 | 5 | 15,474 |
| JRFD | 20-12-2003 | 09-02-2011 | 26 | 18,172 |
| G4J | 16-09-2004 | 19-09-2005 | 11 | 45,158 |
| Gilead | 10-11-2008 | 22-05-2010 | 7 | 28,791 |
| LslPlus | 28-07-2008 | 06-03-2009 | 14 | 20,220 |
| MorarChat | 21-12-2009 | 14-01-2012 | 15 | 19,535 |

IdeaVim project is the only one that presents growth on its complexity only until the 4th version, and then have the metric under control, with small variations. Apart from that peak, its behaviour is more similar to an active project, once its complexity is very controlled as the application evolves. Thus, excluding the first 4 released versions, the remaining 39 versions had its complexity controlled, what shows that development team keep up with the work at the level required by the software growth. Accessing their webpage on SourceForge.net, we found out that they left a note to users, informing that the project was discontinued because Jetbrains Fig. 17: Normalized Complexity standard deviation of discontinued FLOSS projects. took over the IdeamVIM plugin several years ago, and that any support should be directed to the company. Jetbrains is a software development company whose tools are targeted towards software developers and project managers (Hunger, 2010). The company lists 75,000 customers worldwide, among them Apple, LinkedIn, Siemens, and Bank of America.

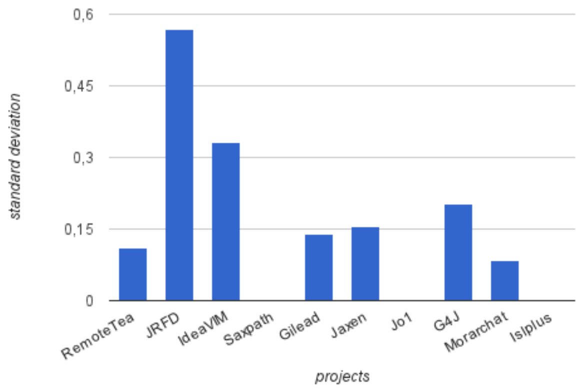


Fig. 29: Complexity by function standard deviation of discontinued s FLOSS projects.

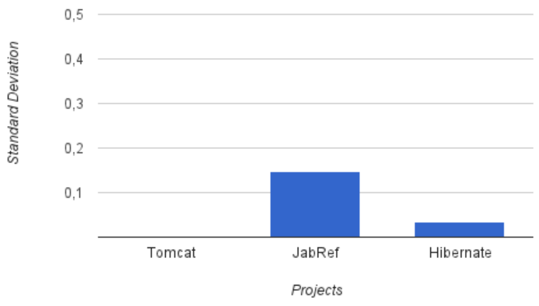


Fig. 30: Complexity by function standard deviation of actives FLOSS projects.

Therefore, it is suitable state that internal properties of the software can not be used to precisely determine whether a project will be abandoned or not, but it can provide an understanding about what could have contributed to software failure. In the case of complexity, we could notice that there is a relation between uncontrolled complexity and software abandonment. Thus, it is important that an analysis over external factors of the software be performed to explore another reasons that could influence the software abandonment. For instance, a study about social impact on software architecture, as we did in a previous work (Siebra, Anjos, & Rolim, 2014), also helps the developers to identify elements that commits the software evolution.

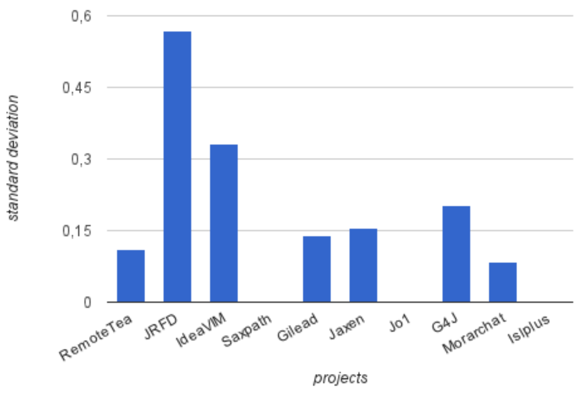


Fig. 29: Complexity by function standard deviation of discontinued s FLOSS projects.

## VI. Future Work

This work has limitations that motivates future works. Firstly, the study should be replicated with a larger number of projects samples. The samples used in our work were restricted only to projects written in Java and hosted by SourceForge.net repository. The study would become more complete if it include projects written in other languages, such as C language, once a considerable number of FLOSS projects are written in this language. Also, future works could have projects hosted by other repositories, such as GitHub and Google Code. Moreover, we recognize that there are a lot of other metrics besides the ones we used in this study, that could help in exploring the FLOSS abandonment phenomenon. Additional investigation is necessary, in order to discover others variables that may influence the software failure.

Also, a more detailed analysis needs to be performed, in order to find correlation between another complexity metrics in order to confirm the relation of complexity and software inactivity. In future works, it could be used complex maintainability models instead of only simple complexity metrics, utilizing practical tools for measuring maintainability like SQALE, SIG, ColumbusQM and Quamoco.

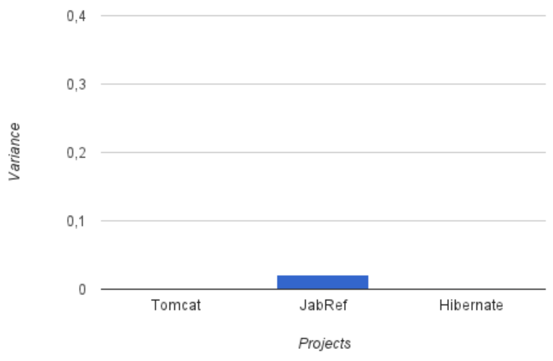


Fig. 32: Complexity by function variance of actives FLOSS projects.

Furthermore, it is import to point out that the results of our work could be also valid for every kind of project, once private systems are even more complex and cohesive than FLOSS (Maccormack et al., 2008). In order to confirm this assumption, future work in this theme is required. Moreover, a further investigation whether the projects analyzed could have evolved to other versions and given origin to successful projects, it would be also a worth future work as well.

Finally, this work has shown another direction for future work. We believe that one work that seems to be relevant is to understand if there is a way to classify if a project is doomed to failure. The failure could be based on known projects that would be used to train a classification mechanism, like a Neural Network. Studies have shown that we can learn with successful projects, but we always forget to learn with projects that have failed.

## VII. Conclusion

This paper presents a study of discontinued FLOSS projects complexity. By sampling projects hosted at SourceForge.net, tagged as “inactive”, it was investigated whether there is a relation between the metrics used to analyse FLOSS projects complexity, and the abandonment of them. Though several tests performed in this work, we found interesting results that confirmed some of this relationships. The majority of the discontinued FLOSS projects we have analysed (60%), showed a substantial complexity grow since its first release compared to its last one. While the active projects revealed a more controlled complexity, presenting almost a constant normalized complexity, some discontinued FLOSS do not seem to be able to control the system complexity. The inability to handle the extra work needed to control the system complexity seems to contribute to the failure of the system, as predicted by Lehman's law of software evolution mentioned earlier. One possible explanation of these failures is the use of anti-patterns, that are responses to recurrent problems that should not be done, because they can jeopardise the projects' evolution and control. We also observed that the complexity by function metric seems to have a stronger relationship with the abandonment of the projects, since it is the metric that shows a larger standard deviation for discontinued projects than the active ones.

Besides, we found some projects (40%) that exhibited a different behaviour, having its complexity's curve more similar to the curve of active projects. A detailed search showed that two out of these four projects was actually still under development.

Through a statistical analysis of the data extracted with SonarQube, we calculated the Pearson's coefficient of correlation between the complexity metrics and we found that the projects have variants behaviours. Some projects, as Jaxen Project and IdeaVim project present strong correlation between all the diverse complexities (class, file and function) and the total complexity. Some of them, as Jo! and Gilead, present a really weak correlation between all of the three variations and the total complexity. Based on this fact, we decided to investigate it further, and then started to investigate what have happened to each project separately.

Despite the fact that the IdeaVim project presents an increasingly growth on its complexity until its 4th released version, later its development team managed to keep the complexity under control. Accessing its website we found out that it was incorporated into another software.

These results lead us to conclude that although the complexity may contribute to the software abandonment, once an uncontrolled complexity demands a higher level of work from contributors, it requires more extra information about the project to guide improvement decisions related to its activity. Therefore, it is mandatory to also evaluate external elements that may interfere in the software evolution.

We believe that the results of this study can be helpful for FLOSS projects practitioners, since they can find an explanation of abandonment of collaborators. We also believe that this work can be considered as a base for future works in the area of FLOSS projects, specifically in the area of discontinued projects, which still needs further investigation

**References**

Bakota, T., Hegedus, P., Ladanyi, G., Kortvelyesi, P., Ferenc, R., & Gyimothy, T. (2012). A cost model based on software maintainability. In *Icsm* (p. 316-325). IEEE Computer Society. Retrieved from http://dblp.uni-trier.de/db/conf/icsm/icsm2012.htmlBakotaHKFG12

Basili, V. R., Caldiera, G., & Rombach, H. D. (1994). The goal question metric approach. In *Encyclopedia of software engineering*. Wiley.

Beaver, J. M., Cui, X., Charles, J. S., & Potok, T. E. (2009). Modeling success in floss project groups. In T. J. Ostrand (Ed.), *Promise* (p. 16). ACM. Retrieved from http://dblp.uni-trier.de/db/conf/promise/promise2009.htmlBeaverCCP09

Beecher, K., Boldyreff, C., Rank, S., Beecher, K., Boldyreff, C., & Rank, S. (n.d.). Evolutionary success of open source software: An investigation into exogenous drivers. *Electronic Communications of the EASST*, 2008.

Capiluppi, A., & Beecher, K. (2009). Structural complexity and decay in floss systems: An inter-repository study. In A. Winter, R. Ferenc, & J. Knodel (Eds.), *Csmr* (p. 169-178). IEEE. Retrieved from http://dblp.uni-trier.de/db/conf/csmr/csmr2009.htmlCapiluppiB09

Capiluppi, A., Lago, P., & Morisio, M. (2003). Characteristics of open source projects. In *European conference on software maintenance and reengineering*.

Eick, S. G., Graves, T. L., Karr, A. F., Marron, J. S., & Mockus, A. (2001, January). Does code decay? assessing the evidence from change management data. *IEEE Trans. Softw. Eng.*, 27(1), 1–12. Retrieved from http://dx.doi.org/10.1109/32.895984 doi: 10.1109/32.895984

Encyclopedia of measurement and statistics. (2007). In N. J. Salkind (Ed.), *Encyclopedia of measurement and statistics* (??th ed.). SAGE Publications, Inc. Retrieved from http://dx.doi.org/10.4135/9781412952644 doi: http://dx.doi.org/10.4135/9781412952644

English, R., & Schweik, C. M. (2007). Identifying success and tragedy of floss commons: A preliminary classification of sourceforge.net projects. In *Proceedings of the 29th international conference on software engineering workshops*. ICSEW '07.

Hunger, M. (2010). Jetbrains developer tools. In *infoq*.

Ivanov, A., Andy2222, Bergholm, D., Rosbach, H. K.,

Krakow, K., & Barry, T. (n.d.). *Ffdshow*. http://sourceforge.net/p/ffdshow.

Khondhu, J., Capiluppi, A., & Stol, K. (2013). Is it all lost? A study of inactive open source projects. In *Proceedings of the 9th international conference on open source systems*.

Lehman, M. M. (1978). Programs cities, students, limits to growth? *Programming Methodology*, 42-62.

Maccormack, A., Rusnak, J., Baldwin, C. Y., Maccormack, C. A., Rusnak, J., & Baldwin, C. Y. (2008). *Exploring the duality between product and organizational architectures: A test of the mirroring hypothesis, working paper* 08-039.

Michlmayr, M., Hunt, F., & Probert, D. (2005). Quality practices and problems in free software projects. In M. Scotto & G. Succi (Eds.), *Proceedings of the first international conference on open source systems* (p. 24-28). Genova, Italy.

Schweik, C. M., English, R., Paienjton, Q., & Haire, S. (2010,05/2010). Success and abandonment in open source commons: Selected findings from an empirical study of sourceforge.net projects. In *Second international workshop on building sustainable open source communities (oscomm 2010).*

Siebra, B., Anjos, E., & Rolim, G. (2014). Study on the social impact on software architecture through metrics of modularity. *ICCSA* (5), 618-632.

Stamelos, I., Angelis, L., Oikonomou, A., & Bleris, G. L. (2002). Code quality analysis in open source software development. In *Information systems journal* (Vol. 12, pp. 43–60).

Terceiro, A., & Chavez, C. (2009). Structural complexity evolution in free software projects: A case study. In M. Ali Babar, B. Lundell, & F. van der Linden

(Eds.), *Qacos-osspl 2009: Proceedings of the joint workshop on quality and architectural concerns in open source software (qacos) and open source software and product lines (osspl).*

Wang, Y. (2005). Prediction of success in open source software development. *University of California, Davis.*