An Analysis of Bug Distribution in Object Oriented Systems

Alessandro Murgia*, Giulio Concas†, Michele Marchesi‡, Roberto Tonelli§ and Ivana Turnu¶.

Department of Electrical and Electronic Engineering, University of Cagliari, piazza d’Armi, 09123 Cagliari, Italy.

SUMMARY

We introduced a new approach to describe Java software as graph, where nodes represent a Java file - called compilation unit (CU) - and an edges represent a relations between them. The software system is characterized by the degree distribution of the graph properties, like in-or-out links, as well as by the distribution of Chidamber and Kemerer metrics computed on its CUs. Every CU can be related to one or more bugs during its life. We find a relationship among the software system and the bugs hitting its nodes. We found that the distribution of some metrics, and the number of bugs per CU, exhibit a power-law behavior in their tails, as well as the number of CUs influenced by a specific bug. We examine the evolution of software metrics across different releases to understand how relationships among CUs metrics and CUs faultness change with time.

KEY WORDS: Software graphs, object-oriented programming, statistical methods, complexity measures, software metrics, bug distribution.

1. INTRODUCTION

Large software systems can be analysed as graphs so huge and intricate that can be studied using complex network theory.

In the case of object oriented (OO) software systems nodes are the classes or the interfaces, and
oriented edges are the various kinds of relationships between them, inheritance, composition, dependence. For OO systems there exist also some consolidated software metrics, also associated to the graph, usually computed at class level, the most used being the Chidamber and Kemerer (CK) suite of metrics [1]. The relationship between metrics and software quality is fuzzy, and is still the subject of ongoing research.

Related to software quality are software bugs. Several researchers analysed software evolution in order to understand the relationship between software management and bug issues. Purushothaman et al. [2] analyzed software development process to identify what are the relationships between small changes to the code and bug growth. Kim et al. [3] analyzed micro-pattern evolution in Java classes to identify which of them is more bug-prone. Śliwerski et al. [4] analyzed the fix-inducing changes, i.e. software updates that trigger the appearance of bugs. In their work, the revision history associated to compilation units (CUs) was examined to understand where bugs issues are introduced during CU evolution. Compilation units, the basic blocks examined in this paper, are files containing one or more classes, for which it is possible to compute software metrics similar to those used for classes.

A complete analysis of the relationships between graph properties of large software systems, statistic of software metrics, and the introduction and distribution of bugs in such graphs is, to our knowledge, completely missing. Zimmerman et al. considered a network analysis on dependences graphs, built on binary files [5], and how dependencies correlate with, and predict, defects. Andersson et al. [6] discussed the Pareto distribution of bugs in classes, without entering into the details of the statistical properties of software which determine such distribution. Zhang found that the bug distribution across compilation packages in Eclipse Java system seems to follow a Weibull distribution [7].

The aim of this paper is study OO systems using complex network theory, to improve the knowledge of bugs causes and to statistically determine their distribution into the system. We extend the definitions of CK software metrics to CUs to understand the evolution of faultness, i.e. how a metric variation affects the number of bugs hitting a CU. A deeper understanding of the dynamics of software development could be useful for software engineers to identify which system components will be more prone to bugs, thus focusing testing and code reviews on these components.

We also study the time evolution of software systems and of the related graphs and metrics, analysing both the source code and the bugs of various releases of two large Java systems, Eclipse [8] and Netbeans [9]. For each release we computed the associated software graph and the CK metrics for each class. Furthermore, we study the number of defects associated to CUs, as found in the bug-tracking system used for development.

We computed the correlation between OO metrics and bugs and analyzed the evolution of these metrics between one release and the next, correlating metrics changes with the number of defects. We present a scheme of classification of CUs into categories which allows us to identify which parts of the software are the most fault-prone, and how these are correlated to CK software metrics. We support our findings with significance tests.
2. Method

We analyze the source code of object-oriented systems written in Java. Both use CVS as version control system. Eclipse uses Bugzilla as issue tracker system, while Netbeans uses Issuezilla. The CVS keeps track of the source code history, Bugzilla and Issuezilla keep track of the bugs history.

2.1. Software graph and OO metrics

An oriented graph is associated to OO software systems, where the nodes are the classes and the interfaces, and the edges are the relationships between classes, namely inheritance, composition and dependence. The number and orientation of edges allow to study the coupling between nodes. In this graph the in-degree of a class is the number of edges directed toward the class, and measures how much this class is used by other classes of the system. The out-degree of a class is the number of edges leaving the class, and represents the level of usage the class makes of other classes in the system. In this context CK suite is a common metrics employed in classes analysis. We calculated for each node the values of the four most relevant CK metrics of the associated class:

- Weighted Methods per Class (WMC). A weighted sum of all the methods defined in a class. We set the weighting factor to one to simplify our analysis.
- Coupling Between Objects (CBO). The counting of the number of classes which a given class is coupled to.
- Response For a Class (RFC). The sum of the number of methods defined in the class, and the cardinality of the set of methods called by them and belonging to external classes.
- Lack of Cohesion of Methods (LCOM). The difference between the number of non cohesive method pairs and the number of cohesive pairs.

We also computed the lines of code of the class (LOC), excluding blanks and comment lines. This is useful to keep track of CU dimension because it is known that a ”long” class is more difficult to manage than a short class.

Every system class resides inside a Java file, called CU. While most files include just one class, there are files including more than one class. In Eclipse 10% of CUs host more than one class, whereas in Netbeans this percentage is 30%. In commit messages issues and issue fixing always refer to CUs. To make consistent issue tracking with source code, we decided to extend CK metrics from classes to CUs. CUs represent therefore the main element of our study. So, we defined a CU graph whose nodes are the CUs of the system. Two nodes are connected with a directed edge if at least one class inside the CU associated with the first node has a dependency relationship with one class inside the CU associated with the second node. We refer to this graph for computing in-links and out-links of a CU-node. We reinterpreted CK metrics onto this CU-graph:

- CU LOCS is the sum of the LOCS of classes contained in the CU;
• CU CBO is the number of out-links of each node, excluding those representing inheritance. This definition is consistent with that of CBO metrics for classes;
• CU LCOM and CU WMC are the sum of LCOM and WMC metrics of the classes contained in the CU, respectively;
• CU RFC is the sum of weighted out-links of each node, each out-link being multiplied by the number of specific distinct relationships between classes belonging to the CUs connected to the related edge.

For each CU we have thus a set of 6 metrics: In-links, Out-links, CU-LOCS, CU-LCOM, CU-WMC, CU-RFC and CU-CBO. This was made for all versions of Eclipse and Netbeans.

2.2. Bug extraction and metric

Onto the CU graph we look for nodes hit by Issues. To obtain this information it is necessary to check the CVS log file, and the data contained in the ITS.

We consider a CU as affected by an Issue when it is modified for issue fixing. Developers record on the CVS log all fixing activities. All commit operations are tracked in the CVS log as single entries. Each entry contains various data, among which the date, the developer who made the changes, an annotation referring to the reasons of the commit, and the list of CUs interested by the commit. In case of commits associated to an issue fixing activity, this is written in the annotation, though not in a standardized way. It is not simple to obtain a correct mapping between issue(s) and the related CU(s) [4] [10].

In our approach, we first analyzed the CVS log, to locate commit messages associated to fixing activities. Then, the extracted data are matched with information found in the ITS. Each issue is identified by a whole positive number (ID). In commit messages it can appear a string such as "Fixed 141181" or "bug #141181", but sometimes only the ID is reported. Every positive integer number is a potential issue. To discern among issues and simple numbers we applied the following strategies:

1. we considered only positive integer numbers present in the issue tracker as valid issue IDs related to the same release;
2. we did not consider some numeric intervals particularly prone to be a false positive issue ID.

The latter condition is not particularly restrictive in our study, because we do not consider the first releases of the studied projects, where issues with "low" ID appear.

All IDs not filtered out are considered issues and associated to the addition or modification of one or more CUs, as reported in the commit logs. The total number of issues hitting a CU in each release constitutes the issue metric we consider in this study. Note that an issue reported in an issue management system has a broad sense. It may denote an error in the code, but also an enhancement of the system, or a features request, or fixing a requirement error. Moreover, when many CUs are affected by a single bug, it is possible that some of them are modified not because they have the issue, but as a side-effect of modifications made in other CUs.

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### Table I: Number of CUs of Eclipse for each main release

| Release | 2.1 | 3.0 | 3.1 | 3.2 | 3.3 |
|---------|-----|-----|-----|-----|-----|
| Number of CU | 7885 | 10584 | 12174 | 13221 | 14564 |

### 3. Results

The subjects of our study were Eclipse and Netbeans projects, both open source, object oriented, Java based systems. Table I and II show the number of CUs involved in the main releases of Eclipse and Netbeans, respectively.

### Table II: Number of CUs of Netbeans for each main release

| Release | 3.2 | 3.3 | 3.5 | 3.6 | 4.0 | 5.0 | 6.0 |
|---------|-----|-----|-----|-----|-----|-----|-----|
| Number of CU | 3350 | 4421 | 7391 | 8350 | 9365 | 12137 | 37145 |

A software system usually evolves through subsequent releases. Main releases entail substantial enhancements of the system, and are usually characterized by significant changes in software sizes, as demonstrated by the data reported in Tables I and II. Between two main releases there may be different “patching releases”, intended to fix bugs and to provide minor enhancements. Even if we analyzed all the releases, we report results for the main releases and the patching release immediately preceding the next main release. In fact most of bugs are introduced in upgrading from the last patching release to the next main release.

### 3.1. Statistical analysis

We computed the statistical distributions of software metrics underlying the software graph. We compared the metrics for software graphs built using classes as basic units, already observed in literature, with the ones obtained in this work for software graphs built considering CUs. The latter distributions substantially keep the ”fat-tail” behavior of the corresponding class metrics in all cases. Fig. 1 reports the log-log plot of the complementary cumulative distribution functions (CCDF) of CBO metric of Eclipse 3.2 for classes and for CUs.

Fig. 2 reports the CCDF of CBO metrics, this time referred to Netbeans 4.0. All these distributions exhibit a power-law behavior in their tail.

We recall that a quantity $x$ obeys a power law if it is drawn from a probability distribution proportional to a negative power of $x$:

$$p(x) \propto x^{-\gamma} \text{ where } \gamma > 0. \quad (1)$$

$\gamma$ is the power-law coefficient, known also as the exponent or scaling parameter. The corresponding complementary cumulative distribution function (CCDF), i.e. the probability
that the random variable is greater than a given value $x$, is:

$$P(X \geq x) \propto x^{-(\gamma-1)}$$

A power-law, or Pareto, distribution cannot hold for $x = 0$, so eligible values of $x$ must be greater than a positive number $x_{\text{min}}$. This characteristic allows to consider distributions that are power-laws only in their right "tail", that is for $x$ greater than a given value $x_{\text{min}}$, and not for lower values of $x$. All the distributions shown in Figs. 1, 3 and 4 show a straight line behavior in their right tail. Note that the CCDF has the same analytical expression of the distribution function, with a negative exponent offset by one. Plotting $p(x)$ or $P(x)$ in log-log scale one obtains a straight line, as shown in Figs. 1 and 2.

Fig. 3 and 4 show the CCDF of WMC metric in Eclipse 3.2 and in Netbeans 4.0, respectively. These distributions are also quite similar, and present again in their tail a power-law behavior, both for classes and for CUs. We found this behavior also for all other releases, and for all metrics. The finding that the distributions of CU metrics largely coincide with those of the corresponding metrics of classes suggests that the same considerations that are valid for CUs may be extended also to classes, even in the cases where data for the classes are not directly accessible, like in our case for bugs. One goal of this paper is, in fact, to find, by means of the software graph framework, existing correlations among bugs and metrics. Thus, since bug information for classes is not directly detectable from the repository, we analyzed the bugs metric only for CUs, and use this information to obtain clues about classes.

Fig. 5 shows the CCDF of the number of bugs per CU in Eclipse 3.2. Fig. 6 shows the same distribution in Netbeans 3.4. The meaning of these power-law tail distributions is unequivocal. While most CUs present only very few bugs, there is a non-negligible number of CUs with very many bugs. We also found similar shapes (patterns) in all other main releases.
Figure 3: The CCDF of WMC metrics for classes (crosses) and CUs (stars) in Eclipse 3.2.

Figure 4: The CCDF of WMC metrics for classes (crosses) and CUs (stars) in Netbeans 4.0.

Figure 5: The CCDF of the number of bugs per CU in Eclipse 3.2.

Figure 6: The CCDF of the number of bugs per CU in Netbeans 3.4.
On the basis of these similarities, the hypothesis that the power-laws existing for bug distribution among CUs may be extended to classes, as well as to other units, like modules or packages, and that it is a property of the graph structure of the system looks sensible.

In fact similar results were obtained by Andersson et Runeson [6], and by Zhang [7]. Andersson et Runeson suggest a Pareto law governing the distribution of bugs across basic units of a software system only partially OO, showing that few modules contain most of the bugs (the 20-80 rule [12]). Zhang re-examined their results for the Eclipse software system, finding that a Weibull distribution fits data better than a power-law, studying packages instead of modules. Since the tail of a Weibull distribution is often not distinguishable from a power-law tail, their results support our hypothesis.

Let us point out what we consider our most relevant finding. We verified that a power-law distribution may be appropriate to describe the fat-tail distribution of different quantities. Note that the fat-tail contains the software units to which most of the information belongs. When a metric is distributed according to a power-law, even only in its tail, with a scaling exponent small enough, there are relatively few units with highest values of the metrics, where criticality resides, while most other units are much less critical. The 80-20 Pareto principle is a consequence of that: about 80% of the criticality is held in 20% of all units.

Our analysis is finer than those performed in [6] or in [7], in the sense that we analyzed the software structure and relationships at the level of compilation units, one level deeper than the module or the package level presented in the above works. This allowed us to recover finer information on the distributions of metrics, especially in their tail. Our results confirm those of Andersson and Runeson, and of Zhang, showing that the same framework holds at different scales, exhibiting a scale-free structure [13]. This finding qualitatively supports the use of power-laws. Finally, also Louridas et al. [14], show a large variety of cases in which power-laws well account for the distribution of different software properties.

Regarding the value of the exponent $\gamma$ and the corresponding behavior of the number of bugs per CU, this value tends to be between 2.5 and 3.5 in the various releases examined for both Eclipse and Netbeans.

According to ref. [14], a mathematical description of the fat-tail may have relevant consequences on software engineering, for example in helping to carefully select which parts of the software project are worth of more care and effort, also from an economical point of view. For instance, given $n$ modules characterized by a metric distributed according to a power-law with exponent $\gamma$, the average maximum expected value for this metric in the module with highest metric value, $<x_{\text{max}}>$, is given by the formula [15]

$$
<x_{\text{max}}>=n^{1/(\gamma-1)}
$$

This formula provides a definite expectation of the maximum value taken by the metric, and hence allows to flag specific modules with metric value of this order of magnitude.

We studied also the distributions of the number of CUs hit by a single bug, the dual of the distribution of bugs across CUs. Also in this case, we find a power-law, as shown in Figs. 7 and 8 for Eclipse and Netbeans, respectively. This means that, while most bugs affect just one or a few CUs, there are bugs that affect tens, or ever hundreds of CUs.
The value of the exponent $\gamma$ of the distributions of the number of CUs affected by a bug is consistently between 2.2 and 2.9 in all considered releases, for both Eclipse and Netbeans, meaning an ever “fatter” tail of this distribution with respect to the previously studied distribution of bugs per CU.

The finding that the distribution of bugs across CUs satisfies a power-law, may suggest a model for the introduction and the spread of bugs in the software system. We already specified that, in our investigation, we name “bug” each numerical identifier found in the repository associated to software “fixing”. Thus, generally speaking, a bug reported in a CU means that such a CU needed to be partially modified owing to this bug. Now, let us consider the graph structure of the software system. We, and many other authors in literature, verified an organized structure of such graphs, exhibiting power-law distributions for many properties of the system. In particular, there are nodes linked with many other nodes, playing the role of “hubs” of the system. For example, there are few CUs with a large number of in-links, meaning that they are extensively used by other CUs. If a bug hits such CUs, namely, the CU code need modifications, it is very likely that also the code of CUs linked to that node need to be modified. Such mechanism may generate a sort of defect propagation in the software graph, very similar to the spread of a contagious disease. The system gets infected by bugs, and a single bug may affect many different CUs, if it propagates from a hub node. On the contrary, bugs in CUs with very few links will likely remain confined to a small number of CUs.

Our heuristic conclusion is that the power-laws observed for the bug distribution is probably due to the scale-free structure of the software graph. Bugs propagate inside a constraining framework, which determines their diffusion across the software system.

From the software engineering point of view, the usefulness of finding power-laws in the tail of the bugs distribution, may be illustrated following the reasoning of Louridas et al. [14]. Once
it is shown that bugs distribution across CUs is in the form of a power-law, CUs in the tail may be identified as the most fault-prone. Thus, after the issue of a new release, the inspection of CUs for bug detection may take advantage of this information. For instance, an inspection of the highest 5% ranked CUs would imply the inspection of a high percentage of bugs, were the exact percentages is related to the power-law exponent.

3.2. Correlation

We analyzed, for each version of the system, the correlations between the considered software metrics and the number of bugs. This information may be used to understand, from the measure of the metric, which parts of the software are most affected by faults, and to devise the possible strategies to apply during software development in order to control metrics values, with the goal of reducing bug introduction.

Our analysis started computing, for various releases $R_i$ of the system, the linear correlation between a particular CK metric and the number of bugs of the same CUs. This is only a preliminary analysis in order to identify which CU metrics are more related to fault proneness. We recall that developers distinguish between "main" and "patching" releases, and that changes from a main release to the next are usually relevant also regarding metrics.

In the first part of our study we referred to the main releases. In the Eclipse project main releases are identified by two-digit numbers, that is: Eclipse 2.1, Eclipse 3.0, Eclipse 3.1, Eclipse 3.2, and Eclipse 3.3. We analyzed what can be deduced about bugs from the analysis of the software metrics for this kind of releases.

Table III shows the correlations between metrics and bugs for the main releases of Eclipse. The metrics showing the highest correlation with bugs are those taking into account the number of dependencies with other CUs, namely CBO and RFC. This fact highlights the importance of an analysis of a software system as a graph. The out-links metric is less correlated with bugs than CBO and RFC. Out-links metric includes not only dependency relationships, but also inheritance and implements relationships. A lower correlation of this metric with bugs may be interpreted with a higher ability of dependency relationships of propagating bugs with respect to the other relationships.

Table III: Pearson correlations between metrics and bugs for some releases of Eclipse:

|          | 2.1 | 3.0 | 3.1 | 3.2 | 3.3 |
|----------|-----|-----|-----|-----|-----|
| bugs-LOC | 0.49| 0.57| 0.54| 0.58| 0.48|
| bugs-CBO | 0.55| 0.53| 0.55| 0.55| 0.42|
| bugs-RFC | 0.59| 0.48| 0.44| 0.56| 0.45|
| bugs-WMC | 0.48| 0.45| 0.38| 0.48| 0.40|
| bugs-LCOM| 0.30| 0.21| 0.15| 0.34| 0.24|
| bugs-inlinks| 0.1| 0.17| 0.25| 0.28| 0.24|
| bugs-outlinks| 0.47| 0.38| 0.40| 0.55| 0.42|
The low correlation of the in-links metric with bugs indicates that it is important to take into account not only the number of links but also their direction. An out-link directed from a compilation unit A to a compilation unit B may be considered like a channel easing the propagation of defects from B to A, but not vice-versa.

Another metric that is well correlated with bugs is LOCS metric. This result can be clearly understood considering that LOCS metric is well correlated with CBO, RFC and out-links metrics. Moreover, the larger the CU, the higher the probability of being hit by some bugs. The LCOM metric is calculated taking into account the internal structure of a compilation unit, and not the relationships with other CUs. The low correlation between LCOM and bugs suggests that the fault proneness of a CU is not overly influenced by the lack of cohesion of the classes contained in the CU. This confirms once again the relevance of the information provided by an analysis of the software system viewed as a graph. The data show that, while there are metrics more or less correlated with the number of bugs, the correlations are never very strong. This is sensible, since a perfectly linear correlation would imply, for example, a doubling of the introduced bugs with the doubling of the metric, and this never occurs in reality.

### Table IV: Pearson correlations between metrics and bugs for all releases of Netbeans

|          | 3.2 | 3.3 | 3.5 | 3.6 | 4.0 | 5.0 | 6.0 |
|----------|-----|-----|-----|-----|-----|-----|-----|
| bugs-LOCS| 0.34| 0.55| 0.42| 0.4 | 0.36| 0.34| 0.35|
| bugs-CBO | 0.25| 0.44| 0.37| 0.36| 0.27| 0.28| 0.25|
| bugs-RFC | 0.38| 0.57| 0.44| 0.39| 0.33| 0.31| 0.28|
| bugs-WMC | 0.38| 0.53| 0.38| 0.35| 0.31| 0.27| 0.23|
| bugs-LCOM| 0.32| 0.44| 0.23| 0.13| 0.10| 0.08| 0.04|
| bugs-inlinks| 0.10| 0.16| 0.19| 0.12| 0.05| 0.07| 0.07|
| bugs-outlinks| 0.24| 0.40| 0.35| 0.33| 0.24| 0.25| 0.23|

In Table IV we report the correlation between a metric and the number of bugs of the CUs for various releases $R_i$ of the Netbeans system. In Netbeans the distinction between main and patching releases is fuzzier than in Eclipse; moreover there are various MR which are not followed by classic PR.

A comparison of Tables III and IV shows that Netbeans correlation values among metrics and bugs number are usually lower than in Eclipse. However, in both systems, LOCS and RFC are the two most correlated metrics to the CU faultness, while LCOM shows, in both cases, a weak correlation to CU faultness.

These results show that:

- Given a release, there exist metrics that are more correlated to CU faultness than others;
- Considering all releases, there is not one CK metric which is the most correlated for each release;
- Given a metric, its correlation with the number of bug changes release by release.
Note, however, that all correlation coefficients shown in Table III and IV are positive, so all the considered metrics are, more or less, positively correlated with bugs. This is consistent with the observation that all CK metrics and the size of the code are a measure of complexity, and therefore should in general be kept low.

3.3. Analysis of software evolution

We also analyzed the evolution of the metrics between two consecutive releases. To this purpose we define different types of CUs, distinguishing among updated, unmodified, newly introduced, and defining all these types with respect to all the different metrics.

In particular, given a release $R_i$, the next release $R_{i+1}$, and a metric $M$, we classified the compilation units in four categories:

- CU.X is the set of compilation units where metric $M$ doesn’t change between $R_i$ and $R_{i+1};$
- CU.U is the set of compilation units where metric $M$ changes (Updated);
- CU.A is the set of compilation units that exist in $R_{i+1}$ but not in $R_i$ (Added);

It must be pointed out that U and X categories are defined relative to a specific metric. A CU might exhibit a change in metric $M$ but not in metric $M'$ between the releases $R_i$ and $R_{i+1}$. Thus, it will belong to class CU.U for $M$, and to class CU.X for $M'$. This case is not common, but it is definitely possible. CU.A is defined regardless to any metric $M$, since it refers to CUs just introduced in the new release. There are also CUs existing in release $R_i$ but not in release $R_{i+1}$. These deleted CUs are not considered in our study.

Given the set of compilation units belonging to the three categories CU.U, CU.X, and CU.A, we compute:

- the fraction of compilation unit affected by bugs, which provides an infection probability;
- the average number of bugs of the infected compilation units.

In Table V we show the probability for CUs belonging to one of the families U, X and A, of being infected, in various changes of releases.

The probability that a CU belonging to family CU.U is infected is between 0.6 - 0.7 in Eclipse. This means that there is a high probability that changing the LOCS, CBO, or LCOM metrics of a CU from one release to the next results in injecting at least one error into the compilation unit. This result confirms Purushothaman’s study [2], which highlighted that code correction for defects often introduces new defects. Also the CUs added to the system, in the transition from $R_i$ to $R_{i+1}$, show a high probability to be infected, clearly larger than for the case of CUs not modified (set CU.X), and slightly smaller than for the set CU.U. Similar results were obtained also for all other metrics.

On the contrary, if the metric does not change there is a low probability that a CU is affected by bugs. These bugs clearly refer to bugs already present in $R_i$ but that were found only when checking $R_{i+1}$ release.

In order to support our findings about the deep differences among CU.U, CU.X and CU.A families, we performed chi-square significance tests. We formulate the following null hypothesis: “the subdivision of CU in U, X and A does not significantly influence the number of infected
Table V: Percentage of bug-affected CUs between two consecutive releases (shown in the top row), for different families, relative to different metrics in Eclipse

| Metric | Set     | 2.1.3-3.0 | 3.0.2-3.1 | 3.2.2-3.3 |
|--------|---------|-----------|-----------|-----------|
| LOC    | CU.U    | 0.66      | 0.61      | 0.62      |
|        | CU.X    | 0.15      | 0.17      | 0.1       |
| CBO    | CU.U    | 0.6       | 0.7       | 0.68      |
|        | CU.X    | 0.2       | 0.27      | 0.18      |
| LCOM   | CU.U    | 0.7       | 0.69      | 0.66      |
|        | CU.X    | 0.22      | 0.23      | 0.16      |
|        | CU.A    | 0.51      | 0.55      | 0.58      |

We verified that all $\chi^2$ values have a confidence level larger than 99.9 percent (the confidence level is actually much larger). Therefore we can reject the null hypothesis with a probability greater than 99.9%, and confirm that our classification of CUs into families provides significant correlations with the presence of bugs.

In Table VI we report the average number of bugs of the infected CUs. These data confirm that the CUs infected of type U and A have an average number of bugs larger than the compilation units of type X. Note also that, on average, more than one bug is found during a release lifespan even in the CUs that are not changed in the release. Thus, in general, irrespectively of the metric, we have:

- CU.U infection probability is around 60-70%;
- CU.A infection probability is around 50-60%;
- CU.X infection probability is around 10-30%;
CU.U are the most fault-prone, followed by CU.A. The mean number of bugs is in agreement with these results, and varies between:

- 2.5 and 4 for CU.U;
- 2.5 and 3.5 for CU.A;
- 1.6 and 2.5 for CU.X.

In Table VII we show the results for Netbeans. In Netbeans there are less PRs, thus we consider jumps of releases between couples of MRs. As in Eclipse, also in Netbeans LOC, CBO or LCOM variations determine a major introduction of bugs into the system, whereas the addition of new CUs determines a slightly lower rate of bug injection. Similar results were obtained also for the other metrics.

Table VII: Percentage of infected CUs between two consecutive releases (shown in the top row), for different families relative to different metrics in Netbeans.

| Metric | Set  | 3.1-3.2 | 3.2-3.3 | 3.6-4.0 | 4.1-5.0 |
|--------|------|---------|---------|---------|---------|
| LOC    | CU.U | 0.68    | 0.67    | 0.62    | 0.61    |
|        | CU.X | 0.19    | 0.15    | 0.07    | 0.06    |
| CBO    | CU.U | 0.51    | 0.57    | 0.59    | 0.67    |
|        | CU.X | 0.27    | 0.31    | 0.18    | 0.15    |
| LCOM   | CU.U | 0.53    | 0.58    | 0.67    | 0.6     |
|        | CU.X | 0.23    | 0.21    | 0.12    | 0.11    |
|        | CU.A | 0.47    | 0.28    | 0.36    | 0.39    |

The chi-square significativity test, about the classification in families for the Netbeans projects, performed using the same null hypothesis used for Eclipse yielded again confidence levels higher than 99.9 percent.

Table VIII shows bug mean values for different CUs families. Again, updated and added CUs show higher mean values than unchanged CUs. In this case, CU.U and CU.A show values closer than in Eclipse. Also in Netbeans, on average, more than one bug is found during a release lifespan even in the CUs that are not changed.

Summarizing these results, we found that:

- the most infected CUs, in both projects, are updated CUs; infection probabilities values are almost 70% in both systems;
- CUs belonging to CU.A set exhibits in general a slightly smaller infection probability than CU.U set;
- CUs belonging to CU.X set are much less infected than CUs belonging to CU.A, and never exceed 30% probability to be hit by a bug;
- usually, updated CUs have more bugs than others; this is always true in Eclipse, whereas it is almost always true in Netbeans;
Table VIII: Average number of bugs of the infected CUs relative to different metrics in Netbeans.

| Metric | Set | 3.1-3.2 | 3.2.1-3.3 | 3.6-4.0 | 4.1-5.0 |
|--------|-----|---------|-----------|---------|---------|
| LOC    | CU.U| 3.52    | 3.66      | 2.69    | 2.62    |
|        | CU.X| 1.51    | 1.44      | 1.29    | 1.24    |
| CBO    | CU.U| 3.36    | 3.75      | 3.65    | 3.87    |
|        | CU.X| 2.14    | 2.15      | 1.89    | 1.85    |
| LCOM   | CU.U| 3.28    | 3.53      | 3.01    | 3.14    |
|        | CU.X| 1.92    | 1.64      | 1.58    | 1.53    |
| CU.A   |     | 2.62    | 3.08      | 3.92    | 3.35    |

- In Eclipse, the mean number of bugs of CU.U sets is often higher than in Netbeans, whereas the opposite holds for CU.A set.

One of the main differences between Eclipse and Netbeans projects is the clear subdivision between patching release and main release. In Eclipse it is simple to verify that each main release X.0 is always followed by patching releases, of type X.0.1, X.0.2, and so on. This distinction is weaker in Netbeans, and this seems to affect the variation of its statistics.

For the family of compilation units U (CU.U), we calculated the correlation between the fractional change of some metrics, passing from \( R_i \) to \( R_{i+1} \) releases, and the number of bugs in \( R_{i+1} \). We were interested in determining if and how the growth of a metric is possibly associated to an increase in the number of bugs.

In Tables IX and X we report this correlation for Eclipse and Netbeans projects.

Table IX: Pearson correlation between metric changes and number of defect in the subsequent release in Eclipse.

| Metric variation | Subsequent releases |
|------------------|---------------------|
|                  | 2.1.3-3.0 | 3.0.2-3.1 | 3.2.2-3.3 | 3.2.2-3.3 |
| ΔCBO-bugs        | 0.37      | 0.58      | 0.49      |
| ΔLOCs-bugs       | 0.29      | 0.64      | 0.53      |
| ΔRFC-bugs        | 0.39      | 0.56      | 0.51      |
| ΔLCOM-bugs       | 0.33      | 0.32      | 0.49      |

All data in Tables IX and X show positive correlations. Correlation values are quite similar for the same pair of subsequent releases, whereas they show larger fluctuations for different metrics. A comparison of Tables IX and X shows that correlation values in Netbeans are often lower than in Eclipse. This result can be partially due to the less clear subdivision between main and patching releases in Netbeans project.
Table X: Pearson correlation between metric changes and number of defect in the subsequent release in Netbeans

| Metric variation | 3.1-3.2 | 3.2.1-3.3 | 3.6-4.0 | 4.1-5.0 |
|------------------|---------|-----------|---------|---------|
| ∆CBO-bugs        | 0.18    | 0.39      | 0.19    | 0.55    |
| ∆LOCS-bugs       | 0.30    | 0.61      | 0.55    | 0.59    |
| ∆RFC-bugs        | 0.37    | 0.60      | 0.56    | 0.59    |
| ∆LCOM-bugs       | 0.28    | 0.68      | 0.45    | 0.33    |

According to tables V, VII, IX and X, bug introduction is mainly due to updating and adding CUs. This is valid for each metric considered.

4. Conclusion

A statistical description of large software systems as directed graphs can provide much additional information on the system features with respect to more traditional approaches, from the software engineering perspective. Adopting a graph as a model for the software system, we used the compilation units as the basic software module in order to build a software graph, and redefined the CK suite of metrics to cope with CUs. These metrics were then used to investigate, with a statistical analysis, how and where bugs were introduced into two big, OO software projects like Eclipse and Netbeans. We wrote two different parsers to analyze the CVS log file and the issue tracker repositories in order to automatically associate bugs and CUs. In this paper, we introduced the concept of compilation unit graph, and of OO metrics related to compilation units, with the purpose of analyzing software projects managed using a configuration management system and a corresponding bug tracking system.

The picture of the software system as a graph allowed us to detect fat-tail distributions, well described by power-laws, for different features of the system, suggesting the same general underlying framework of many other complex networks. In particular, we found that bugs distribution among CUs, number of CUs affected by bugs, metrics distributions (namely LOCs, number of in-links and out-links of the class graph, CK metrics WMC, CBO, RFC and LCOM), all exhibit power-laws fat-tails.

Inside this framework it is possible to identify strong correlations among bugs and those metrics related to the number of external dependencies which, in the graph representation, are easily described as directed links. All these findings together indicate a possible strategy to optimize resources and efforts in software engineering for finding, forecasting, and fixing software defects.

Once the software graph reveals the fat-tail in the relationships between bug and CUs, one may identify which parts of the software are the most fault-prone and focus fixing efforts on them. Following [14], if one ranks CUs according to these power-laws, the review of a small fraction among the highest ranked may have an exponential impact on the overall amount of software defects detectable and fixable.
Our analysis goes one step further, examining software evolution across many releases. This study identifies how metric evolution is related to bug introduction. The change of some particular metrics may result in a higher probability of introducing a bug. In particular, we identify different families of CUs, related to CK metrics, showing different robustness with respect to bug affection. Our categorization into families is related to the software evolution and it is useful to investigate correlations among bugs and software metrics changes. This classification may be particularly useful to software engineers in order to decide onto which parts of a big software project it is better to concentrate efforts and resources.

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