

Assessing the Representativeness of Open Source Projects in Empirical Software Engineering Studies

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Abstract—BACKGROUND: Software engineering researchers have carried out many empirical studies on open source software (OSS) projects to understand the OSS phenomenon, and to develop better software engineering techniques. Many of these studies typically use only a few successful projects as study subjects. Recently, these studies have received criticisms and challenges on their representativeness on OSS projects.

AIM: First, we aim to examine whether successful OSS projects are representative to the whole population of OSS. If successful projects are the minority of OSS population, conclusions from existing studies may only partially reflect the OSS phenomenon. Second, we aim to examine to what extent data extracted from successful projects are different from data extracted from the majority. If data extracted from successful projects are different from data extracted from the majority, approaches from existing studies may be ineffective on unsuccessful projects.

METHODOLOGY: We selected 11,684 OSS projects on SourceForge, and classified these projects into four categories based their attractiveness to users and developers. We use the K-means clustering technique to produce combined result. Furthermore, we selected eight indicators that are used in many existing studies (e.g., team sizes), and compared indicators that are extracted from different categories to investigate their differences.

RESULT: For the first research aim, the result shows that 66.1% projects are under developing; 14.7% projects are user preference; 14.2% projects are developer preference; and only 5.0% projects are considered successful. For the second research aim, the result shows that all the eight analyzed indicators are highly imbalanced with the gamma distribution, and the result reveals that users and developers of SourceForge have different perceptions on the development status defined by SourceForge.

CONCLUSION: We conclude that successful projects are not representative to the whole population of OSS, and data extracted from successful projects are quite different from data extracted from the majority. The result implies that conclusions drawn from only a few successful projects may be inadequate. This work is important to allow researchers to refine conclusions of existing studies, and to better understand, and to carefully select OSS project subjects for their future empirical experiments.

I. INTRODUCTION

Open source software (OSS) is a software development phenomenon that attracts much attention from stakeholders with diverse backgrounds. Ever since its inception, many advocated developers and commercial organizations have put forward tremendous efforts to the OSS development, and benefit from knowledge exchange and be able to rapidly drive innovations [36]. With their contributions, open source portals

such as SourceForge now host millions of OSS projects. Among these projects, especially those successful ones such as Linux have attracted many users and developers.

The OSS phenomenon also attracts much attention from academic research. To present, researchers have conducted many studies on OSS projects to understand the OSS phenomenon, or to evaluate software engineering approaches. Scacchi [30] surveyed existing studies, and point out that these studies cover various perspectives of OSS (see Section II for detailed descriptions of some such studies). Nevertheless, some researchers criticize that conclusions drawn in many existing studies may not be fully representative, since these studies select only few successful projects for analysis. In particular, Crowston *et al.* [11] reviewed more than one hundred published empirical studies on OSS projects. Their result shows that most studies selected fewer than ten successful projects for analysis (see Section II-D for the subject selection in some existing studies on OSS). Considering this undesirable trend, Crowston *et al.* [11] challenge the representativeness of existing empirical studies on OSS, and suspect that conclusions drawn from those successful OSS projects such as Linux might be significantly different from conclusions drawn from the majority of OSS projects (see the third paragraph of Section 3.3 in their paper [11] for details). Crowston *et al.*'s challenge shocked the foundation of existing studies on OSS, and needs to be responded with a more systematic empirical analysis. In particular, various researchers attempted empirical studies on the OSS projects to understand software engineering theories and practices (see Section II-A for details). For these studies, if data extracted from their selected subjects are quite different from data extracted from the majorities of projects, the reliability of their conclusions could be further challenged, and their proposed theories or practices may not be truly reflected in general. Researchers also conducted various empirical studies on the OSS projects to understand the OSS phenomenon (see Section II-B for details). For these studies, if selected subjects are not the majority of the OSS projects, their drawn conclusions on OSS may not be representative, and may only partially reflect the reality of OSS.

In respond to Crowston *et al.*'s challenge, we attempted to answer some of many related questions. Are successful OSS projects the majority of the whole population of OSS projects?

Are data extracted from successful OSS projects significantly different from data extracted from other projects? These questions are still open, and to answer these questions, there is a strong need for a quantitative study on the representativeness of OSS projects with regard to their success. However, such a quantitative study on the representativeness of OSS projects is challenging, since it requires a carefully designed analysis methodology and tremendous effort to analyze statistics from a large number of OSS projects.

In this paper, we propose a methodology that extracts statistics from OSS projects and analyzes extracted data to answer the preceding research questions. Literature shows existing studies tend to select successful projects that are attractive to both users and developers. As a result, we define the success of an OSS project as its attractions to users and developers. Based on the definition, we conduct the first empirical study on individual indicators and the representativeness of OSS projects related to their project success. The result of this study allows researchers to refine their conclusions, and to select better subjects in their future studies. To the best of our knowledge, this work is first of its kinds to quantitatively analyze OSS projects.

This study makes the following contributions:

- A methodology that analyzes the representativeness of OSS projects concerning to their project success. As researchers typically select projects that are attractive to both users and developers, we classify projects into four categories: under developing projects, user preference projects, developer preference projects, and successful projects based on their attractions to users and developers.
- The first empirical analysis on the representativeness of OSS projects concerning to their success. Our results show that successful projects are the minority of OSS projects. To present a full overview of OSS, we suggest that researchers should analyze more user preference projects, developer preference projects, and under developing projects.
- An analysis on eight indicators used in our empirical study. We find that indicators of successful projects are typically thousand times larger than indicators of the majority of projects, therefore conclusions drawn from successful projects can be significantly different from conclusions drawn from the majority. If researchers need to claim that their conclusions are general to all OSS projects, they should select subject projects from all the four categories.
- More analyzed results on OSS. For example, we find that existing channels fails to attract users for participating OSS development. As user feedbacks are important for OSS developers to improve their projects, we suggest that researchers should provide better channels to collect user feedbacks. As another example, we find that users and developers have different perceptions of some development status. We suggest that development status should be more clearly defined to eliminate the difference in perceptions.

The rest of our paper is as follows. Section II presents related work. Section III presents our analysis methodology. Section IV presents our empirical study. Section V discusses issues of our findings. Section VI concludes the paper.

II. RELATED WORK

A. Empirical studies to understand software engineering theories or practices

Researchers conducted various empirical studies on OSS projects to understand software engineering theories or practices. Capra *et al.* [8] conclude that when a project comes to an end, its governance becomes less formal, and its development effort increases. Gyimothy *et al.* [19] validate that some object-oriented metrics (*e.g.*, couplings between object classes) can be used to predict the fault-proneness of classes. Kim *et al.* [24] conclude that refactoring clones may not always improve software qualities. Kim *et al.* [23] also conclude that refactoring may introduce more defects, and the benefits of refactoring should be reconsidered. Shi *et al.* [31] enumerate various findings on the documentation evolution of five open source API libraries. Bachmann *et al.* [3] conclude that most committed bug reports are not related to bug fix or feature request. Bird *et al.* [4] conclude that biases exist in defect datasets, and such biases have negative impacts on defect prediction techniques. Aversano *et al.* [2] conclude that design patterns are suitable to support software that tends to change more frequently. Gabel and Su [14] conclude that there is a general lack of uniqueness in software. Ko *et al.* [25] conclude that word frequencies in bug reports generally follow Zipf's law. Harman and McMin [20] enumerate various findings on search based testing. Grechanik *et al.* [17] enumerate various findings on code structures of Java programs. Zhong *et al.* [38] conclude that some simple test-suite-reduction approaches are as effective as some complicated ones. Most of the preceding studies analyze only few successful projects. If data extracted from those selected projects are quite different from data extracted from the majority, there can be a threat to validity to their conclusions.

B. Empirical studies to understand the OSS development

Researchers conducted various empirical studies on OSS projects to understand the OSS phenomenon. Mockus *et al.* [27] conclude that OSS projects overall can have lower defect densities and higher productivity than commercial software. Paulson *et al.* [29] conclude that OSS project does not have higher productivity, but defects in OSS projects are more rapidly found and fixed than commercial software. Ajila and Wu [1] conclude that software companies can achieve higher productivity and quality if they reuse OSS projects in a systematic way. Penta and German [15] conclude that explicit contributors and copyright owners are not necessarily the most frequent committers. Gurbani *et al.* [18] enumerate various lessons and open questions on the OSS development. Jensen and Scacchi [22] conclude that OSS projects have different ways to migrate their participants from peripheral

TABLE I
SUBJECT SELECTIONS AND USED DATA SOURCES IN SOME EXISTING STUDIES ON OSS

Author [Ref]	Subject	Data source
Mockus <i>et al.</i> [27]	Mozilla and Apache	email lists, cvs archives, and bug reports
Ye and Kishida [36]	GIMP	email lists and cvs archives
Paulson <i>et al.</i> [29]	Linux, Apache, and Gcc	code metrics (<i>e.g.</i> , growing rates)
Huntley [21]	Apache and Mozilla	cvs archives
Dinh-Trong <i>et al.</i> [13]	FreeBSD	email lists, cvs archives, and bug reports
Kim <i>et al.</i> [24]	Carol and DNSJava	cvs archives
Gyimothy <i>et al.</i> [19]	Mozilla	code metrics (<i>e.g.</i> , methods per class)
Gurbani <i>et al.</i> [18]	a telephony server	team sizes, lines of code, numbers of downloads, and <i>etc.</i>
Bird <i>et al.</i> [5]	Apache, Ant, Python, Perl, and PostgreSQL	email lists
Sowe <i>et al.</i> [32]	Debian	email lists
Capra <i>et al.</i> [8]	75 projects	team sizes, lines of code, numbers of downloads, and <i>etc.</i>
Olbrich <i>et al.</i> [28]	Lucene and Xerces 2	cvs archives
Koch [26]	about 100 projects	numbers of downloads, web hits, team sizes, and <i>etc.</i>
Boulanger [6]	Linux, Apache, and MySQL	defect densities and <i>etc.</i>

roles to core leadership positions. Godfrey and Tu [16] conclude that Linux is growing faster than they expected. Bird *et al.* [5] conclude that OSS projects can have latent social networks. Sowe *et al.* [32] conclude that OSS developers communicate frequently, and their communication follows the fractal cubic distribution. Yamauchi *et al.* [35] conclude that the communication of OSS developers heavily relies on electronic media. Ye and Kishida [36] conclude that learning is one of the major driving forces that attract OSS developers. Dagenais and Robillard [12] conclude that the documentation development of OSS follows three production models: initial effort, incremental changes, and bursts. Again, the preceding studies typically select only few successful OSS projects to analyze. If selected successful projects are not representative, findings in these studies may not be generalizable to the whole population of OSS.

C. Characteristics of OSS projects

Capiluppi *et al.* [7] analyzed 406 projects hosted on Freshmeat for characteristics of OSS projects. As they analyzed data manually, only about four hundred projects were analyzed, and their data were extracted eight years ago. On the contrary, as we analyze statistics automatically, our empirical study analyzes much more up-to-date projects. Furthermore, our study focuses on the representativeness of OSS projects with regard to their success, instead of presenting general characteristics.

D. Subject Selection in Literature

Table I shows selected OSS projects and used data sources of some existing studies on OSS. Column “Author [Ref]” lists authors and references of these studies. In this table, we focus on studies that were published in the past ten years. Column “Subject” lists selected subjects of these studies. We find that except the two studies (*i.e.*, Capra *et al.* [8] and Koch [26]), all the other studies in Table I select only few successful OSS projects as subjects. Column “Data source” lists major data sources used in these studies.

We find that many data sources are relevant to the indicators that are analyzed in our methodology. For example, Gurbani *et al.* [18], Capra *et al.* [8], and Koch [26] all use team sizes as data sources, and our empirical study shows that the indicator

of team sizes is highly imbalanced. Besides direct usages, we find that some data sources used in existing studies rely on our indicators indirectly. For example, Mockus *et al.* [27], Ye and Kishida [36], Dinh-Trong *et al.* [13], Bird *et al.* [5], and Sowe *et al.* [32] all use email lists as data sources. Email lists indirectly rely on team sizes, and small teams typically have quite different email communications with large teams.

III. METHODOLOGY

To assess and classify the successfulness of the OSS projects, our methodology implements the following three major steps:

Step 1: Selecting OSS projects as subjects. The statistics from a single project can be random or even false. For example, a programmer may build tools to download released files from a project automatically to increase download numbers, since download numbers have an impact on user’s choices. To reduce the negative impacts from such a false statistic, we choose as many OSS project as possible, since most projects do not produce false statistics to deceive users. We define the success of an OSS project as its attractions to users and developers. For users and developers, different development status would have different attractions. In particular, SourceForge defines the seven development status: *inactive*, *mature*, *production/stable* (referred to as *production* for short), *beta*, *alpha*, *pre-alpha*, and *planning*. To ensure the representativeness of our study, we retrieve projects of all the seven development status for analysis.

Step 2: Extracting statistics of subjects. Through the website of a project, SourceForge provides various statistics of the project. For example, Figure 1 shows an HTML file returned from SourceForge, and the file lists numbers of read transactions, numbers of write transactions, and numbers of total updated files on the two days (*i.e.*, 3rd and 4th, November, 2010). We implemented a tool to parse all these HTML files for extracting statistics. A value of a single day can be random, and sums within a duration can better reflect the natures of a project. The duration should not be too short or too long, since sums within a too short duration cannot fully reflect the natures of a development status, and sums within a too long duration may reflect natures of multiple development

Date (UTC)	Read Transactions	Write Transactions	Total Files Updated
04 Nov 2010 -	0	0	0
03 Nov 2010	0	0	0

Fig. 1. Some statistics on SourceForge

status. Capiluppi *et al.* [7] state that 90% OSS projects do not change their development status over six months. For the preceding considerations, we choose to calculate sums within two months. Among extracted statistics, we choose four user-related indicators to analyze user preference, and four developer-related indicators to analyze developer preference as follows:

Sum_web_hits. SourceForge provides web servers for its hosted projects. On these server, developers can release websites of their projects, and users can browse their contents for projects of their interests. We use `sum_web_hits` to denote the total number of web hits for each project. This indicator reflects the attraction of a project to users for browsing its contents.

Sum_downloads. SourceForge provides file servers for its hosted projects. On these server, developers can release executable files of their projects, and users can download these files for a try. We use `sum_downloads` to denote the total number of downloaded files for each project. If a user feels that a project is indeed useful, the user may download its released files for a trial, and the indicator reflects the attraction of a project to users for trying it.

Sum_forum_posts. SourceForge provides forums for its hosted projects. In these forums, developers and users can discuss various issues about their projects. We use `sum_forum_posts` to denote the total number of all posts for each project. The indicator reflects the attraction of a project to users for participating.

Sum_opened_bugs. SourceForge provides bug-report servers to its hosted projects. On these servers, users can report bugs, and developers can fix reported bugs. We use `sum_opened_bugs` to denote the total number of opened bugs for each project. For example, the bug report server of Notepad++¹ lists all its bug reports, and most of them are from users. If a user finds a bug of a project, the user can report the bug to the project, so the indicator reflects the attraction of a project to users for improving its quality.

To present developer preferences, we analyze the four developer-related indicators as follows:

Team_sizes. In SourceForge, the website of a project lists names of all its developers, and we use `team_sizes` to denote the total member of developers for each project. If a developer makes contribution continuously to a project, the developer may require to be added to the developer list of the project. The indicator reflects the attraction of a project to developers for the identification of its team.

Sum_read_transactions. For the ease of the collaboration among developers, SourceForge provides a concurrent versions system for its hosted projects. Developers can check out source

files of their projects. We use `sum_read_transactions` to denote the total number of read transactions for each project. If a developer is interested in a project, the developer can check out its source files for code review. The indicator reflects the attraction of a project to developers for reading its code.

Sum_write_transactions. In SourceForge, some developers of a project have the right to check-in source files of the project, and we use `sum_write_transactions` to denote the total number of write transactions for each project. As developers need to write files after development, the indicator reflects the attraction of an OSS project to developers for putting programming efforts on the project.

Sum_updated_files. When developers check in source files to a project repository, some files of the project may be updated, and we use `sum_updated_files` to denote the total number of updated files for each project. As each write transaction can update only one file or many files, the indicator reflects the attraction of an OSS project to developers for putting real programming efforts on the project.

Step 3: Analyzing extracted statistics. Our first aim is to examine whether successful OSS projects are representative to the whole population of OSS. To achieve this research objective, we need to answer the following research question:

(1) To what extent are indicators extracted from successful projects different from indicators extracted from other projects?

Our second objective is to examine to what extent data extracted from successful projects are different from data extracted from the majority. To achieve the research objective, we need to answer the following research question:

(2) To what extent are successful projects representative to the whole population of OSS projects.

To answer the first research question, we present cumulative percentages and various quantile-quantile plots (Q-Q plots) of all the indicators, since cumulative percents and Q-Q plots are both widely used to compare distributions of samples [34]. From the result, we are able to see the differences between data sources in successful projects and data sources in other projects, and estimate whether conclusions drawn from successful projects can be significantly different from conclusions drawn from the majority of OSS projects or not.

To answer the second research question, we classify all the OSS projects into the following four categories:

(1) **User preference projects:** These projects are attractive to users, but are not attractive to developers.

(2) **Developer preference projects:** These projects are attractive to developers, but are not attractive to users.

(3) **Successful projects:** These projects are attractive to both users and developers, and are considered successful.

(4) **Under developing projects:** These projects are not attractive to either users or developers.

Values of different indicators cannot be compared directly, and thus cannot be used for classification. We first normalize all the extracted indicators to make them comparable. After normalization, for each project, we use the sum of user-related indicators to present its user preference, and use the

¹http://sourceforge.net/tracker/?group_id=95717&atid=612382

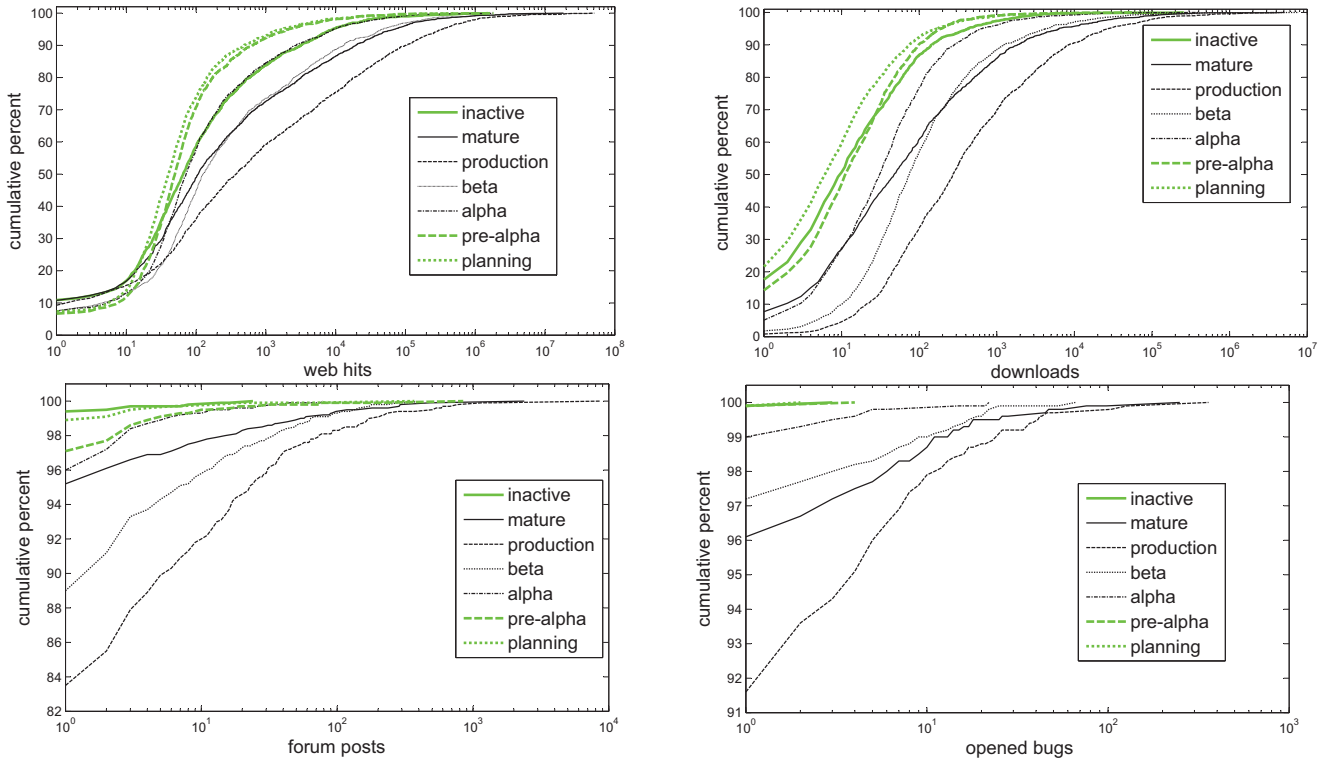


Fig. 2. Cumulative percents of user-related indicators

sum of developer-related indicators to present its developer preference. Based on the preceding two sums, we use a clustering technique described in [33] to classify projects into categories, and calculate percents of all the categories to present the representativeness of each category.

IV. EMPIRICAL ASSESSMENT

Based on our methodology, we conducted an assessment to address the research questions as follows:

- RQ1: To what extent are indicators that are extracted from successful projects different from indicators that are extracted from others?
- RQ2: To what extent do successful projects represent the whole population of OSS projects?

Our first research objective leads to the first research question. To answer the research question, we present cumulative percents and Q-Q plots of all the indicators (RQ1). Our second research aim leads to the second research question. To answer the research question, we cluster collected OSS projects into four categories, and analyze clustering result to present the representativeness of OSS projects with regard to their success (RQ2).

From SourceForge, our extraction tool extracted statistics for two months, and the extraction was completed within one week. For each development status, we randomly extracted statistic from 2,000 projects. During the extraction, we find that only few projects changed their development status during the week, and some projects do not have specific statistic. For example, some projects do not release any files, thus they do not have download numbers. We filter out the two types of

Web hit	Frequency	Percent	Cumulative percent
0	161	10.4%	10.4%
1	8	0.5%	10.9%
...	...	...	...
1,327,487	1	0.1%	99.9%
1,523,322	1	0.1%	100.0%

projects to eliminate the impacts from changed development status and missing statistics. The remaining 11,684 projects include 1,554 inactive projects, 1,672 mature projects, 1,556 production/stable projects, 1,631 beta projects, 1,672 alpha projects, 1,750 pre-alpha projects, and 1,849 planning projects. More details of our work can be found on our project site².

A. RQ1: To what extent are indicators that are extracted from successful projects different from indicators that are extracted from others?

1) *The cumulative percents of indicators:* Figure 2 presents cumulative percents of user-related indicators. We build the figure based on distributions of these indicators, and we next use the inactive curve of web hits in this figure as an example to illustrate the building process. We organize sums of web hits by their frequencies. Table II shows distributions of sum_web_hits for inactive projects partially. Column “Web hit” lists sums of web hits for inactive projects. Column “Frequency” lists frequencies of inactive projects with corresponding sums. Column “Percent” lists percents of corresponding frequencies. Column “Cumulative percent” lists cumulative percents of corresponding frequencies. For example, from the

²<http://itechs.iscas.ac.cn/cn/membersHomepage/zhonghao/oss.html>

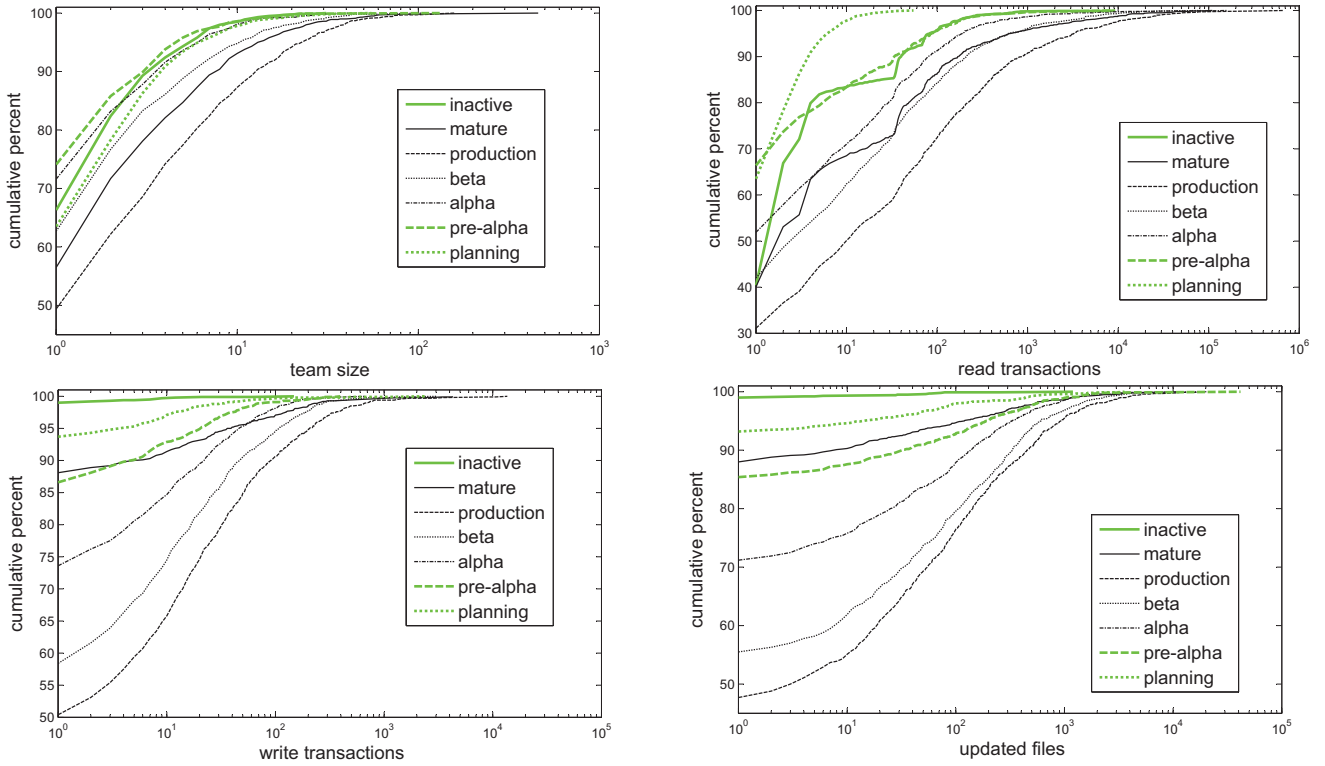


Fig. 3. Cumulative percents of developer-related indicators

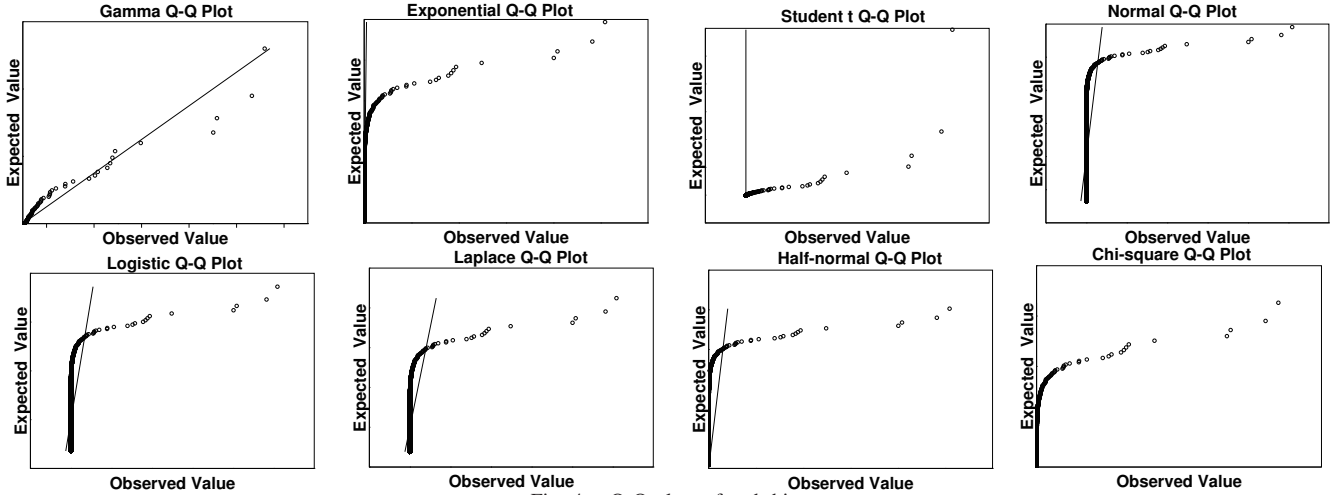


Fig. 4. Q-Q plots of web hits

last row of Table II, only 1 inactive project has 1,523,322 web hits; the corresponding frequency is approximately 0.1% (1/1554); and the cumulative percent is 100% (*i.e.*, no inactive project has more than 1,523,322 web hits in the two months). To build the inactive curve shown in Figure 2, we use Column “Web hit” in Table II to fill in the horizontal axis, and Column “Cumulative percent” in Table II to fill in the vertical axis. As several elite projects have much more web hits than the majorities have, we choose the logarithmic scale instead of the linear scale for the horizontal axis of Figure 2 to better present web hits. Based on the results shown in Figure 2, we derive the following findings:

Finding and implication 1: From Figure 2, we find that all the four indicators are highly unbalanced. Indicators of

several elite projects are hundreds or even thousands larger than indicators of the majorities. If researchers plan to draw conclusions from user-related indicators, they should be aware of this huge difference.

Finding and implication 2: We find that many users are willing to browse contents or download files for a trial run, but far fewer users will post on forums or open bug reports. The existing communication channels between users and developers may be too complicated for users to participate, and developers should consider providing a more user friendly and attractive environment.

Finding and implication 3: We find that different development status have different attractions to users, and the attraction order to users is as follows: production, mature, beta,

alpha, inactive, pre-alpha, and planning. However, some development status are not of the same meanings as users would normally expect. For example, in contrary to expectations from many users, we find that some mature projects still have many bugs to be fixed.

Figure 3 shows cumulative percents of developer-related indicators. Comparing with the results as shown in Figure 2, we come to the following findings:

Finding and implication 4: We find that all the four developer-related indicators are also quite unbalanced. Several elite projects are hundreds or even thousand times more attractive to developers than the majority projects. Our results are consistent with existing empirical studies. For example, Capiluppi *et al.* [7] reported that 49% projects have only one developer. Our results show that about 50% projects have only 1 developer, and 90% projects have fewer than 10 developers. Capiluppi *et al.* [7] consider that a team forms a community only when it has more than 10 developers. Following their definition, we find that only 10% projects can have communities, since only these projects have more than 10 developers. Thus, we conclude existing approaches on social networks of OSS projects (*e.g.*, the one proposed by Bird *et al.* [5]) are applicable for only 10% elite projects.

Finding and implication 5: We find that different development status also have different attractions to developers, and the attraction order to users is as follows: production, beta, alpha, mature/pre-alpha, planning, and inactive. Comparing with Finding 3, we find that users and developers can have different perceptions on some development status, since the two orders are different.

2) *The QQ plots of indicators.*: In statistics analysis, Q-Q plots are commonly used to compare shapes of two distributions. In Q-Q plots, the horizontal axis and the vertical axis list quantiles of theoretical distributions and observed distributions, respectively. If two compared distributions are identical, the Q-Q plot follows 45-degree line. If two compared distributions agree after linearly transforming, the Q-Q plot follows some lines, but not necessarily 45 degrees.

To reveal which distributions all the indicators follow, we draw various Q-Q plots for the eight common distributions (*i.e.*, gamma, exponential, student t, normal, logistic, laplace, half-normal, and chi-square distributions). Figure 4 shows the drawn Q-Q plots of web hits. For the sub-graph of each distribution, the horizontal axis lists quantiles of the corresponding theoretical distribution, and the vertical axis lists quantiles of observed web hits. Due to space limit, we do not present Q-Q plots of other indicators. The Q-Q plots of these indicators are all similar with the Q-Q plots of web hits. From the Q-Q plots shown in Figure 4, we come to the sixth finding as follows:

Finding and implication 6: We find that all the indicators follow the gamma distribution, since only the Q-Q plots of the gamma distribution are linear. In particular, web hits and downloads are identical with the gamma distribution, and other indicators agree with the gamma distribution after linearly transforming. Here, the lower parts and the higher parts of

some indicator may follow different distributions. We further discuss this issue in Section IV-D.

B. RQ2: To what extent do successful projects represent the whole population of OSS?

To combine all the indicators, we define the normalization function as follows:

$$norm(x_i) = \frac{\log(x_i + 1) - \log(\min(x) + 1)}{\log(\max(x) + 1) - \log(\min(x) + 1)} \quad (1)$$

Based on the preceding two sums, we use the K-means clustering technique [33] to cluster all projects. Figure 5 shows the results. In Figure 5, horizontal axes list attractions to users, and vertical axes list attractions to developers. For each figure, we use a legend to show percents of categories: “×” denotes percents of developer preference projects; “○” denotes percents of successful projects; “+” denotes percents of user preference projects; and “.” denotes percents of under developing projects. From the legend of Figure 5, we come to our seventh finding as follows:

Finding and implication 7: We find that in total, 66.1% projects are under developing; 14.7% projects are user preference; 14.2% projects are developer preference; and only 5.0% projects are successful. Given the small percentage of successful projects, the sample size is not large enough to be representable to the whole population of OSS projects.

Based on the clustering result of Equation 1, in Figure 5, we further illustrate the clustering result of each development status. From these figures, we derive our eighth and ninth findings as follows:

Finding and implication 8: We find that users may have incorrect perception on some development status. For example, as shown in Figure 5, 23.6% mature projects are user preference. However, at the same time, 63.2% mature projects are under developing. We further investigate under developing projects, and find that some projects have no developers at all. These projects are already abandoned by their developers. In most of the cases, developers may refer a project as mature, simply because they do not want to maintain the project any more.

Finding and implication 9: We find that in general, a project is often not attractive to users or developers during its early development status such as planning, pre-alpha, and alpha. Gradually, some projects can become more attractive to developers and users in the follow-up development status, but the increase of user attractions are much slower than the increase of developer attractions. For example, 5.9% planning projects are developer preference, and 6.5% planning projects are user preference. At the same time, 11.6% pre-alpha projects are developer preference, but only 6.9% are user preference. The trend shows that users are slower to change than developers are. As another example, inactive projects also show similar trends, since 13.2% inactive projects are still user preference even after they become inactive.

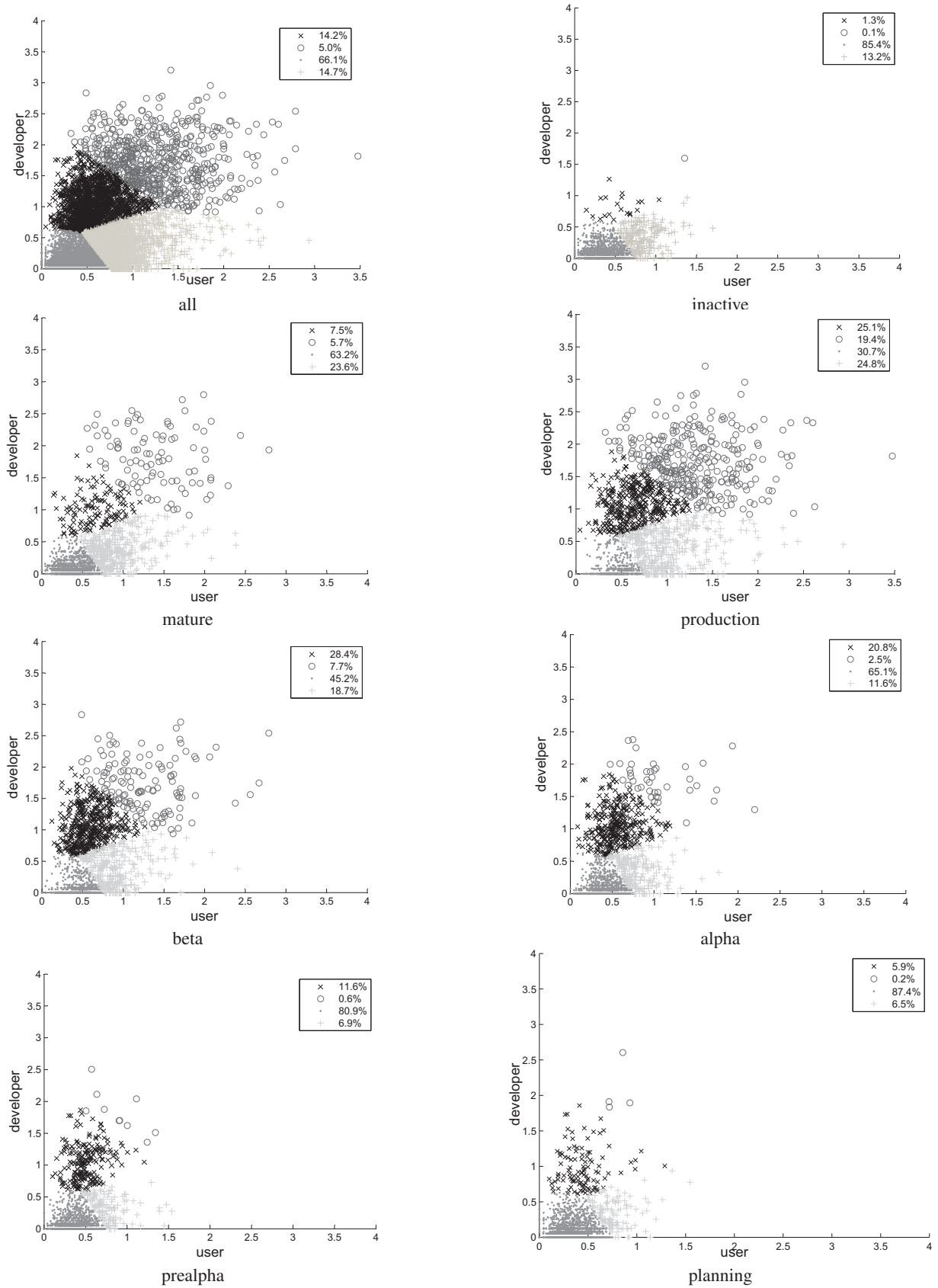


Fig. 5. Clustering results

C. Summary

We summarize our findings into the following results.

Result 1. Based on Finding 7, we conclude that successful OSS projects are not representative to the whole population of OSS, since successful projects are in the minority.

Result 2. Based on Findings 1, 4, and 6, we conclude that all the eight indicators follow the gamma distribution, and indicators of few successful OSS projects are much larger than the majorities. The highly unbalanced distributions of analyzed indicators imply that conclusions drawn from successful projects can be quite different from conclusions drawn from the majority.

Result 3. Based on Findings 3, 5, 8, and 9, we conclude that different development status have different attractions to users and developers. In addition, we find that users and developers have different perceptions on development status in SourceForge. As the different perceptions mislead users, we suggest that these status should be clearly defined to eliminate differences.

Result 4. Based on Finding 2, we conclude that existing channels fail to attract users for participating OSS development. As user feedback is quite important for OSS development, we suggest that researchers and practitioners should provide better channels to collect user feedbacks.

D. Threats to validity

In this section, we discuss the briefly threats to validity that can affect our findings and results under a well-known guidance for case studies [37].

The threats to internal validity include that we choose limited indicators, and these indicators may not well reflect the success of OSS projects. However, our selected indicators are consistent with existing literature. For example, when Crowston *et al.* [10] define the success of OSS projects, they also take both users and developers into account as the two major audiences. The threats should be reduced if we introduce more indicators into analysis in future work. The threats to internal validity also include the setting of our study. For example, we set the duration for calculating sums as two months, and the impacts of other durations are not evaluated in our study. As another example, we analyze indicators as a whole for their distributions. Although all the indicators are best described by the gamma distribution, some indicators are not perfectly described by the gamma distribution, and different ranges of a single indicator may follow different distributions. The threat could be reduced by revisiting our study with different settings. We released all our data on our project website, so other researchers can also try different settings, and propose their theories to explain their findings.

The threats to external validity include that we do not consider selected data and normalization techniques used in specific empirical studies. Our findings support that conclusions drawn from existing empirical studies may not be representative. However, a specific empirical study may use data other than our analyzed indicators, and may have techniques to reduce the huge differences of collected data. As a result,

the impacts of our findings to existing empirical studies may vary and could not be fully determined. The threat should be reduced by revisiting existing empirical studies with data extracted from both successful projects and other projects. Like any other empirical studies, the threats to external validity include the time issue. All results reflect the state of the art, and can become inapplicable years later with the rapid progress of the OSS development. The threat could be reduced by replicating the empirical study years later with update-to-date data and our proposed methodology.

V. DISCUSSIONS AND FUTURE WORK

Open source vs closed source. Our study provides no evidences that open source software is inferior to closed source software, or on the contrary. Instead of providing such a comparison, our study provides insights on the subject selection of future studies to ensure the representativeness of their conclusions. We agree that a convincing comparison between open source software and closed source software may be achieved, if replicating our study with comparable numbers of closed source projects (e.g., with ISBSG data³). In future work, we plan to work towards this research direction.

Studies on unsuccessful projects. Our study reveals that most OSS projects are unsuccessful, but existing studies typically focus on only successful projects. With our findings, researchers can improve their work in two following directions. First, researchers can conduct studies on more unsuccessful projects to provide comprehensive understanding on the OSS phenomenon. Second, researchers can propose approaches that are effective for the predominate unsuccessful projects to achieve success. In future work, we plan to work towards both the two directions, so that we can provide more comprehensive empirical results and more effective approaches.

Life cycles of OSS projects. Chillarege [9] presents the product life cycle of commercial software. In future work, we plan to investigate whether OSS projects follow similar life cycles, and to propose approaches that can predicate the development status changes of a given OSS project. In addition, our empirical study analyzes only one period of statistics from SourceForge. In future work, we plan to extract more statistics from different time period and compare these statistics to reveal the evolution of OSS projects in relation to their project success.

VI. CONCLUSION

There are many existing empirical studies that are conducted on several quite successful projects (e.g., Linux, Mozilla, and Apache), and their conclusions heavily rely on representativeness of their selected subjects. As an attempt to investigate the true representativeness of these selected subjects, we conducted an empirical study based on an extensive collection of 11,684 projects hosted on SourceForge, allowing us to understand to what degree successful projects can be used to represent the entire OSS community.

³<http://www.isbsg.org>

An assessment methodology has been devised and employed in the study, the result shows only 5% projects are considered truly successful, and the indicators extracted from successful projects are quite different from indicators extracted from the majority. As a result, we can reasonably indicate that the conclusions produced by many of the empirical studies may be incorrectly representing the reality in the entire OSS community, techniques and methods derived from these studies may only be relevant to the selected successful projects. The successful projects are in fact the minority cases according to our assessment.

The statistics produced from the study are also important to reflect the current status of theories and conclusions drawn from many OSS empirical studies, and can be used as a reference for researchers to determine the correct sample size and the limitations of selected project subjects.

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