Empirical Studies on Reducing Developers' Effort Spent on Resolving Software Issues

by

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Abstract

Software issue resolving process is one of the most frequent maintenance activities during the software development process. An issue tracking system (ITS) is often used to better manage the software issues. However, previous research work has shown that the issue resolving process needs development teams to put a large amount of effort to address the reported issues. When developers raise questions to clarify the description of issue reports during the issue resolving process, it takes time for developers to receive the response for the questions. Hence, the raised questions may negatively affect the efficiency of the issue resolving process. Moreover, a large proportion (e.g., 80% in Firefox) of the reported issues are rejected (e.g., the issue is not reproducible). The issue reports might exist in the ITS for a long time before they are rejected (e.g., over 50% of rejected issue reports are rejected after 6.73 days in Firefox). Even though these reports are rejected eventually, developers must have wasted valuable resources on triaging, inspecting and rejecting such reports.

In this thesis, we conduct two empirical studies to reduce the effort spent on the software issue resolving process. In the first study, we investigate how the process of resolving issues is impacted by the questions raised from the issue reports in the resolving process and apply machine learning techniques to predict if developers will raise questions from a new issue report. Our prediction result can give developers

an early warning whether questions will be raised when the issue report is created. Developers can take proper actions to handle the issue reports that are likely to have questions raised, in order to improve the effectiveness of the issue resolving process. In the second study, we investigate the characteristics of issue reports that can be rejected by developers in the resolving process. We propose to prioritize the valid issue reports at higher positions and the predicted rejected issue reports at lower positions, so that developers can put more effort on the valid issue reports.

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Chapter 1

Introduction

1.1 Background

Software issues can be errors of code snippets (called *bugs*), enhancements, and new feature requests [1]. For example, software issues can arise from mistakes made in either source code or software requirement, which lead software products to present an incorrect behavior. To allow developers to better manage the reported issues of a software project, *Issue Tracking Systems* (ITSs), like JIRA and Bugzilla are widely used by software development teams to report, process and track reported issues. Moreover, ITSs provide a platform for developers to comment on issue reports, so they can cooperate and resolve these issues [2].

Figure 1.1 shows the typical life cycle of an issue report [3]. Note that the life cycle shown in Figure 1.1 may vary slightly depending on the project and the used ITS. When an issue is newly reported by a developer or user, the report gets the NEW status. The issue report remains in the NEW status, until a triager either assigns the issue report to himself or another developer, or rejects the issue report immediately.

The assignee resolves, i.e., fixes or rejects the issue report, and labels it with a

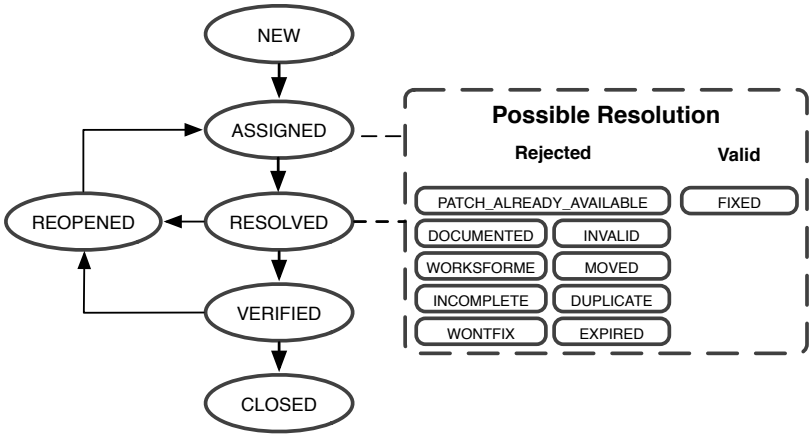


Figure 1.1: The typical life cycle of an issue report within an ITS.

resolution value. After the issue report is resolved, the issue report changes to the state RESOLVED with a resolution type.

After the issue report is resolved, the resolution type and the solution are to be verified by other developers. If the other developers are satisfied with the resolution, the issue report is closed. Otherwise, the issue report is reopened and (re)assigned.

Different projects might use different labels for the same reason of resolving an issue report. For example, fixed issue reports are labeled as FIXED in Firefox and Eclipse, while Linux uses the CODE_FIX label. The MOVED label is only used in the Linux and the Eclipse projects. The detailed descriptions of different types of resolution are explained in the Table 3.1.

1.2 Research Problems

Fixing issues that are reported in ITSs is an important activity in the software development, because software issues may negatively affect the quality of software products. However, resolving issues is expensive [4, 5]. A survey by the National Institute of Standards and Technology estimated that the annual cost of software issues is

about $59.5 billion [5]. Moreover, the ITS of a popular project usually receives a large number of issue reports. For example, there were more than 157,000 issue reports in the Firefox ITS by the end of 2015 (according to our studies in Chapter 3 and Chapter 4). Once receiving issue reports, developers need to investigate the reported issues and assign issue reports to appropriate developers who will be able to fix it, which is known as *triaging*. Developers can become overwhelmed with a large number of issue reports if each report is manually triaged [2, 6, 7]. If an issue report is triaged and determined as a valid problem, the assignee of the issue report needs to handle the issue. A development team usually has limited resources and tight schedules to fix a large amount of issue reports. Hence, it is desirable to investigate the existing threats to the efficiency of software issue resolving process and propose approaches to reduce the effort that is spent on the issue resolving process.

Numerous approaches have been proposed to improve the effectiveness of issue resolving process [2, 6, 7]. Murphy et al. [2] apply the text categorization based on the description of issue reports to predict which developer should work on an issue report. Jeong et al. [7] propose a graph model to reduce the reassignments of issue reports by using Markov chains based on an issue tossing history. Ahsan et al. [6] use Latent Semantic Indexing and Support Vector Machine to obtain an automatic issue triage system. All these studies try to improve the effectiveness of the triaging process. However, even the issue reports can be accurately assigned to appropriate developers, the resources can be wasted on rejecting invalid issue reports after the triaging process (e.g., developers spent the effort to determine whether an issue is duplicated with existing issue reports).

To help development teams better estimate software maintenance efforts and better manage software projects, empirical studies about the issue-fixing time (i.e., [8, 9, 10]) are conducted. In order to accelerate the issue resolving process, the study by Arcuri and Yao [11] propose an evolutionary approach to automating the task of fixing issues based on the *Automatic Programming* techniques [12]. Nevertheless, to our best of knowledge, the limited empirical evidence is provided to show how to help developers handle reported issues to improve the efficiency of the issue resolving process.

1.3 Research Statement

There exist limitations of the efficiency of the issue resolving process. Zhang et al. [9] report that the threats to the efficiency of resolving issues can happen in any phase of the issue resolving process (e.g., reporting an issue, triaging the issue and verifying the resolution of issue reports).

An important factor that affects the efficiency of the resolving process is the interaction among developers to discuss how to address a reported issue during the issue resolving process [13, 14]. Questions can be raised by developers from the issue reports during the discussion for addressing the issues. We observe that there is a considerable proportion (24.89% to 47.04%) of issue reports in the subject systems (i.e., Linux, Firefox and Eclipse) that have questions raised by developers during the issue resolving process. Dealing with the raised questions in such a lot of issue reports does have a serious threat to the efficiency of the issue resolving process.

Another threat to the efficiency of the issue resolving process is the rejected issue reports. It is very normal that developers decide to reject an issue report due to

many reasons (i.e., invalid description, unreproducible for developers and duplicate with previous issues). Our study shows that there is a large proportion of issue reports rejected by developers, such as 64% in Linux, 80% in Firefox, and 49% in Eclipse. Developers should focus more resources on the issue reports that are more likely to describe real problems and need to be fixed.

To help improve the efficiency of the issue resolving process, we believe that in-depth empirical studies on the limitations of resolving process are highly demanded. In this thesis, we aim to give developers an early warning whether questions can be raised from an issue report when the issue report is created, so that developers can take proper actions (e.g., adding detailed hardware or software configurations for Linux issues) to handle the issue reports that are likely to have questions raised. Then, we strive for helping developers reduce the amount of the effort wasted on the rejected issue reports during the issue resolving process. We apply machine learning techniques (i.e., random forest and learning-to-rank) to predict the rejected issue reports. As a consequence, developers can focus the limited resources on the valid issue reports and improve the effectiveness of the issue resolving process.

1.4 Thesis Objectives

The objectives of the thesis are as follows:

- **Studying on the questions raised in the issue resolving process (Chapter 3).**

  When resolving issues, developers might raise questions in order to clarify the described issue [13, 15, 16]. Once a question is raised, developers need to wait for the response before taking further actions. The extra waiting period can delay

the issue being resolved. We first investigate the frequently concerned topics in the questions raised from issue reports by developers, and then we inspect how the raised questions impact on the efficiency of issue resolving process. We also apply prediction models to predict if questions are likely to be raised by a developer from an issue report during the issue resolving process. The target of this study aims to give the developers an instant warning whether questions can be raised from an issue report by developers when the issue report is created. Therefore, developers can take proper actions to handle such issue reports that are likely to have questions raised, in order to reduce unnecessary questions.

- **Reducing the effort spent on the rejected issue reports during the fixing process (Chapter 4).**

  Not all of the assigned issue reports will be addressed in the end [17]. A triager or developer may choose to reject an issue report. As long as an invalid or useless issue report is not rejected, developers could be wasting valuable resources (e.g., time) on the report. In this study, we examine the risks of wasting effort on rejecting issue reports during the resolving process, and build the random forest model to predict whether a new issue report will be rejected. As the prediction results might miss important valid issue reports, we further apply the learning-to-rank technique to rank the valid issue reports at higher positions, and the triager can give a higher priority to the issue reports that are more likely to describe a valid problem. The development teams can apply our approach to reduce the effort spent on rejecting issue reports.

1.5 Organization of Thesis

The remaining chapters of this thesis are organized as follows:

- Chapter 2: We give an overview of the existing studies on the issue triaging and the resolving process, the factors that impact on the issue resolving process, the rejected issue reports and the application of machine learning to the software engineering.
- Chapter 3: We examine the issue reports that contain the raised questions by developers during the resolving process and propose an approach to predict whether questions can be raised from an issue report when the issue report is created.
- Chapter 4: We propose an approach to automatically detect the rejected issue reports. Therefore, developers could reduce effort spent on the rejected issue reports during the resolving process.
- Chapter 5: We conclude our contribution of the thesis and outlines the future work.

Chapter 2

Background and Related Work

In this chapter, we discuss the existing work on the issue triaging process, the resolving process, the factors that can impact the efficiency of the issue resolving process, the studies of rejected issue reports, and machine learning techniques.

2.1 Studies on the Issue Triaging Process

The issue resolving process begins with the issue triaging. To improve the effectiveness of the triaging process, previous studies proposed a plenty of approaches to reduce the effort spent on the triaging process [2, 6, 7]. For instance, Murphy et al. [2] apply the text categorization based on the description of issue reports to predict the developer who should work on the issue report. Jeong et al. [7] notice the overhead generated by the reassignment of issue reports during the issue resolving process and propose a graph model using Markov chains based on the tossing history of issue reports to reduce the tossing events of issue reports. Ahsan et al. [6] develop an automatic issue triaging system using Latent Semantic Indexing and Support Vector Machine techniques.

Different from their work, we observe that developers waste limited resources

on the rejected issue reports after the issue triaging. We apply the Learning-to-rank model to automatically prioritize the issue reports by the likelihood of validity of issue reports. The triager can assign issue reports that are more likely valid to developers to reduce the waste of resources on rejected issue reports during the issue resolving process.

2.2 Studies on the Issue Resolving Process

After an issue is discovered, the issue resolving process starts until the issue is resolved. Many studies have attempted to empirically study the issue resolving process. Kim and Whitehead Jr [18] report the statistics of the issue resolving time, such as the time that developers take to fix reported issues. Weiss et al. [19] have proposed an automatic technique to predict the time needed to fix a particular bug. Their proposed approach could be applied to new bug reports. Zhang et al. [9] investigate the delays in each step of the bug fixing process, such as the delay in assigning a bug report to the right developer, the delay for developers to start the fix after the assignment, and the delay for testers to start the verification after the bug is fixed.

Hosseini et al. [20] propose an auction-based multi-agent mechanism for assigning software issues to developers in order to minimize backlogs and the overall issue report lifetime. Pan et al. [21] study various bug fixing patterns in a number of open source software systems. Khomh et al. [22] conduct research on the effect of the release cycle on bugs. Their results show that the amount of crashes is similar to the traditional release model, and bugs are fixed faster under the rapid release models, but proportionally fewer bugs are fixed compared to the traditional release model.

In this thesis, we aim to improve the efficiency of the issue resolving process

from two perspectives. For instance, the negative impact of raising questions (i.e., in Chapter 3) during the issue resolving process and the resource wasted on the rejected issue reports (i.e., in Chapter 4).

2.3 Studies on Factors that Impact on the Issue Resolving Process

The factors that impact the efficiency of the issue resolving process have attracted both academia and industry [8, 23, 24, 25, 26].

2.3.1 Studies on the Quality of Issue Reports

The quality of issue reports can affect the efficiency of the issue resolving process [27, 28, 29, 30, 31]. Hence, Hoomieijer et al. [27] propose a linear regression model to predict the quality of issue reports. They determine the quality of issue reports by measuring whether the report is addressed within a given amount of time. Different from their work, the raised questions in Chapter 3 is considered as another indicator of issue report quality in our thesis.

Zimmermann et al. [28] point out that the issue reports widely differ in the quality, and BettenBurg et al. [32] conduct a survey among developers to figure out what factors make a good issue report, and provide a tool to measure the quality of a new issue report. BettenBurg et al. [29] also deliver a survey to Eclipse developers to figure out what kind of information is widely needed by developers. Insufficient information in an issue report is considered as a bad quality of issue reports. Moreover, the results show that steps to reproduce and the testing case can determine the quality of the issue reports and inaccurate reproduce guide in the issue reports can make an issue report with bad quality. The insufficient and incorrect information can be

confusing to the developers, and then developers might raise questions. Different from previous work, in Chapter 3 of this thesis, we conduct a further empirical study on how the raised questions influence the efficiency of handling an issue report, and apply machine learning techniques to predict the occurrence of the raised questions from an issue report.

Philip et al. [30] point out that the bad quality of an issue report is one of the reasons of the tosses of issue reports during the software development. Poor issue report quality can result in multiple assignments in the development process, which prove our result in RQ3.2 of Chapter 3 (i.e., the issue report with raised questions has a higher rate to experience the reassignment during the addressing process).

Schugerl et al. [31] reveal that the quality of the description in the issue report can determine the time consumed in the evaluation and fixing issues. A bad quality of description in an issue report can take a longer time to be addressed. Hence, we considered the elapsed time as one of the factors to measure the effort spent on an issue report in Chapter 3 and Chapter 4.

2.3.2 Studies on the Cooperation between Developers during the Issue Resolving Process

Another important factor that affects the efficiency of resolving process is the interaction among developers to discuss how to address a reported issue during the issue resolving process [13, 14]. Breu et al. [13] study the raised questions by developers during the issue resolving process, and if a reporter is not active in the discussion of the software issue, the efficiency of the resolving process can be affected. Hence, Breu et al. [13] provide techniques to elicit the right information and facilitate the

communication between developers and users. Breu et al. [13] focus on enhancing the ITS at the system level, but our work in Chapter 3 aims to improve the quality of issue reports at the file level.

Moreover, Breu et al. [33] highlight the concerns on the frequently raised questions from the issue reports and categorize these raised questions. They find out that the constant involvement of developers is important for handling the reported issues. Different from our work in Chapter 3, they focus more on the interaction between developers but ignore the impact of these raised questions on the whole resolving process.

2.4 Studies on the Rejected Issue Reports

The effort spent on the rejected issue reports (i.e., duplicated issue reports) is considered as a waste of resources on the development team [34, 35, 36, 37, 38, 39, 40]. Most of the previous work on rejected issue reports focuses on duplicated issue reports. Anvik et al. [41] find that around 20%-30% of the issue reports of Eclipse and Firefox are duplicated reports. Cavalcanti et al. [34] report that there are 32%, 43% and 8% duplicated issue reports in Epiphany, Evolution and Tomcat respectively. Bettenburg et al. [32, 35] find that merging the information that is available across duplicated reports produces additional useful information. Davidson et al. [36] and Cavalcanti et al. [42, 34] study the effort spent on closing duplicated issues. Rakha et al. [37] investigate the needed effort for identifying duplicated issues.

Several approaches address the challenges of automatically detecting duplicated issue reports. These approaches use the textual [38, 39, 40] (e.g., the description), categorical [43, 44, 45] (e.g., the component field) and topical [46, 47, 48, 49] (e.g.,

using LDA) information available in issue reports to decide if a new issue report is duplicated with existing reports in the ITS.

Joorabchi et al. [14] notice the harm on the issue resolving process from the reports that can not be reproduced. Hence, they conduct an empirical study on those bug reports that developers are not able to reproduce. Their results highlight that the non-reproducible bugs remain active in a longer time, which means there are a lot of effort can be consumed on such bugs.

However, duplicated and non-reproducible issue reports are a subset of our studied subjects of rejected issue reports. An issue report that is rejected by developers may be due to the invalid description and even the expiration of issue reports. The effort spent on determining to reject an issue report wastes the resources of development teams and negatively influence the efficiency of issue resolving process. Hence, our work in Chapter 4 extends the existing work on the rejected issue reports by focusing on all types of rejected issue reports, rather than only duplicated reports.

2.5 Machine Learning Techniques

There are several approaches that apply machine learning (ML) techniques to the empirical studies of software engineering. To minimize the cost and improve the effectiveness of the software testing process, Gondra et al. [50] apply the Artificial Neural Network (ANN) model to predict the fault-proneness (i.e., a module can either contain errors or be error-free) and use Support Vector Machines (SVM) as a state-of-the-art classification method. The results show that SVM performs better than ANN in the fault-proneness prediction. Hall et al.[51] apply Naive Bayes, logistic regression and SVM to predict defects in the source code, as the accurate prediction of where

faults are likely to occur in code can help direct test effort, reduce costs and improve the quality of software. Different from their works, our proposed prediction model aims to improve the effectiveness of the issue resolving process. In particular, we apply the random forest models both in Chapter 3 and Chapter 4. Random forest is an ensemble learning method. It constructs multitude of decision trees at the training time but correct for decision trees' habit of overfitting to their training set. We choose to use a random forest model because it is robust to data noise and generally achieves good performance in software engineering studies [37, 52, 53, 54, 55, 56].

Learning-to-rank is known as a machine learning ranking approach. It is widely applied in the application of information retrieval. The training data consists of lists of items with some partial order specified between items in each list. This order is typically induced by giving a numerical or ordinal score or a binary judgment (e.g."relevant" or "not relevant") for each item. Ye et al. [50] apply learning-to-rank techniques to locate a bug by leveraging domain knowledge (i.e., functional decompositions of source code files into methods, API descriptions of library components used in the code, the bug-fixing history, and the code change history). Zhou et al. [57] propose an approach to automatically retrieve duplicated bug reports using learning-to-rank techniques based on textual and statistical features of bug reports and propose a similarity function for bug reports based on the features. In our thesis, we apply the learning-to-rank techniques to automatically retrieve the valid issue reports, which can avoid wasting effort on the invalid issue reports.

2.6 Latent Dirichlet Allocation (LDA)

Latent Dirichlet Allocation (LDA) is an example of a topic model for topic discovery in natural language processing. LDA is a statistical technique that expresses documents as probability distribution of topics, where each topic is a probability distribution of words referred to as a topic model. In LDA, each document may be viewed as a mixture of various topics where each document is considered to have a set of topics that are assigned to it via LDA. Hindle et al. [58] report that the topics generalized from LDA match the perception of developers and managers. Zhao et al. [59] apply LDA to find out what is the reason for bug reworking in Linux, Firefox, PDE, Ant and HTTP. Venkatesh et al. [60] conduct a research on what concerns do developers have when they use the Web APIs. Different with their goals, we use LDA to extract the concerned topics of the raised questions by developers during the resolving process to figure out what kind of questions are more frequently asked by developers when they address a reported issue.

2.7 Summary

In this chapter, we introduce the existing studies on improving the efficiency of issue triaging and handling process, the relevant studies on the possible threats to the efficiency of handling issue reports, the existing research on the rejected issue reports and the applications of machine learning techniques in empirical studies of the software engineering.

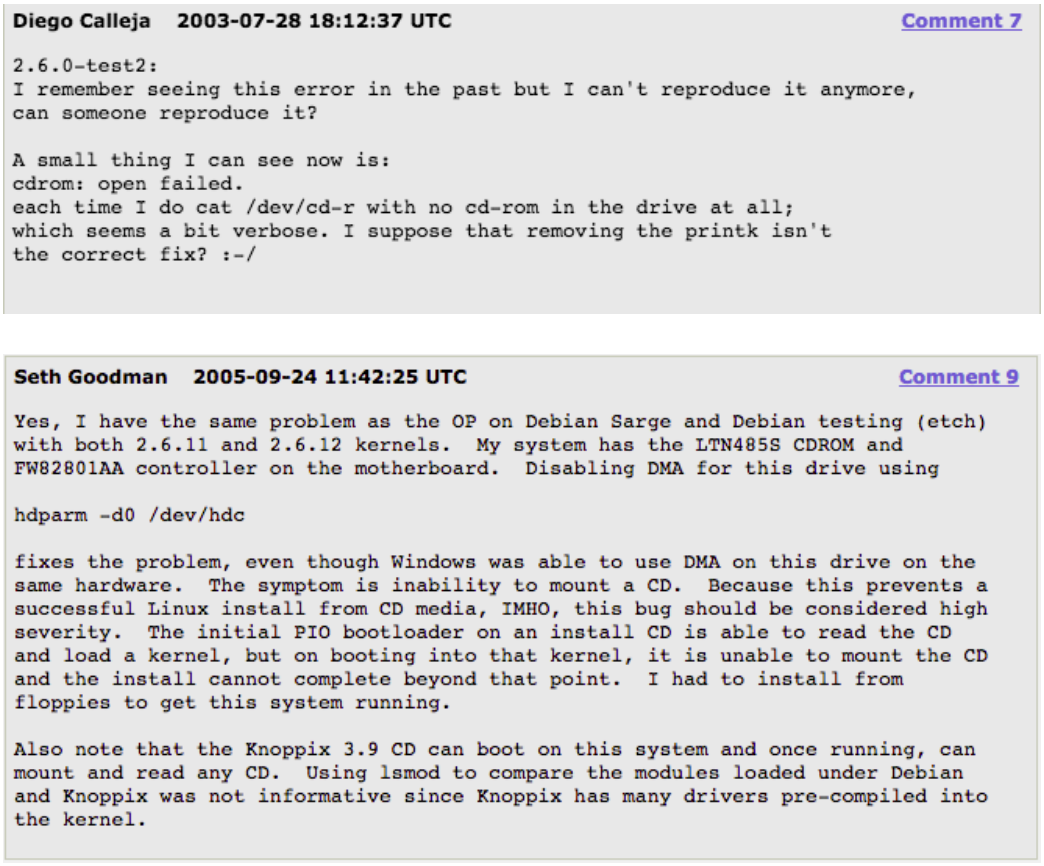
Chapter 3

An Empirical Study on the Questions Raised in the Issue Resolving Process

In this chapter, we perform an empirical study on the questions raised from issue reports during the issue resolving process, and aim to reduce the negative impact of the raised questions on the issue resolving process. We examine the raised questions from 174,233 issue reports in three large-scale systems (i.e., Linux, Firefox and Eclipse). First, we apply the Latent Dirichlet Allocation (LDA) technique to explore the frequent topics of the raised questions. Then we investigate how the process of resolving issues is impacted by the questions raised from the issue reports. Finally, we build prediction models (i.e., random forest, logistic regression and naive bayes) to predict if questions are likely to be raised by a developer from an issue report.

3.1 Introduction

The delay in resolving issues can affect the satisfaction of users [33]. Investigating the factors that impact the efficiency of the issue resolving process has attracted both academia and industry [8, 23, 24, 25, 26]. An important factor that affects the



Diego Calleja 2003-07-28 18:12:37 UTC Comment 7

```
2.6.0-test2:
I remember seeing this error in the past but I can't reproduce it anymore,
can someone reproduce it?

A small thing I can see now is:
cdrom: open failed.
each time I do cat /dev/cd-r with no cd-rom in the drive at all;
which seems a bit verbose. I suppose that removing the printk isn't
the correct fix? :-/
```

Seth Goodman 2005-09-24 11:42:25 UTC Comment 9

```
Yes, I have the same problem as the OP on Debian Sarge and Debian testing (etch)
with both 2.6.11 and 2.6.12 kernels.  My system has the LTN485S CDROM and
FW82801AA controller on the motherboard.  Disabling DMA for this drive using

hdparm -d0 /dev/hdc

fixes the problem, even though Windows was able to use DMA on this drive on the
same hardware.  The symptom is inability to mount a CD.  Because this prevents a
successful Linux install from CD media, IMHO, this bug should be considered high
severity.  The initial PIO bootloader on an install CD is able to read the CD
and load a kernel, but on booting into that kernel, it is unable to mount the CD
and the install cannot complete beyond that point.  I had to install from
floppies to get this system running.

Also note that the Knoppix 3.9 CD can boot on this system and once running, can
mount and read any CD.  Using lsmod to compare the modules loaded under Debian
and Knoppix was not informative since Knoppix has many drivers pre-compiled into
the kernel.
```

Figure 3.1: An example from Linux-53

efficiency of resolving process is the interaction among developers to discuss how to address a reported issue during the issue resolving process. For example, Breu et al. [13] find that the active and ongoing participation of developers in the discussion of an issue report can affect the efficiency of resolving issue reports. When resolving issues, developers might raise questions in order to clarify the described issue [13, 15, 16] or the requested feature [15]. Once a question is raised, developers need to wait for the response before taking further actions. The extra waiting period can delay the issue being resolved. If developers raise unnecessary questions on issue reports,

the efficiency of resolving process could be affected. For example, in the issue report *Linux-53*[1] (shown in Figure 3.1), a developer raises questions due to missing steps to reproduce, and he can not reproduce the issue anymore in Comment-7. Hence, he asks if there is an explicit way to reproduce the reported issue in a raised question. In the Comment-9 (after more than two years), another developer figures out how to reproduce the issue in a specific hardware and software environment, under a particular configuration. If the issue reporter could provide the detailed steps to reproduce the issue when creating the issue report, such questions would be avoided and the issue report would be addressed sooner.

Sillito et al. [61] investigate what information developers generally need and how developers usually obtain such information. However, it is unclear how raising questions impacts the issue resolving process. We investigate 174,233 issue reports of three well known and long-lived systems (i.e., Linux, Firefox and Eclipse). We observe that there is a considerable proportion (24.89% to 47.04%) of issue reports in each system that have questions raised by developers during the issue resolving process. Dealing with the raised questions in such a large amount of issue reports does have a serious threat to the efficiency of the issue resolving process. Hence, we are interested in understanding what questions are raised and how the raised questions impact the issue resolving process, and further identify the possibilities to reduce the negative impact of the raised questions.

In this chapter, we conduct an in-depth analysis on the questions raised during the entire issue resolving process. First, we investigate what questions are asked, in order to understand the reason why developers raise questions and what information is sought by developers to answer the questions. Second, we investigate the impact

[1]https://bugzilla.kernel.org/show_bug.cgi?id=53

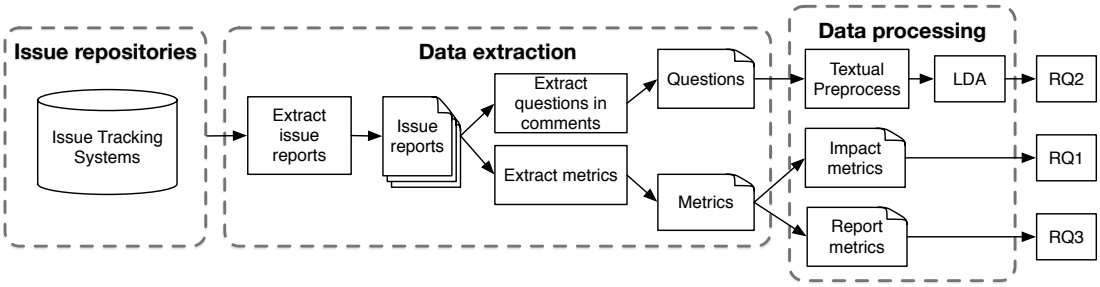


Figure 3.2: Overview of our approach

that raising questions has on the issue resolving process. Finally, we examine the feasibility of predicting if questions will be raised from a given issue report at the time when the report is created.

3.2 Experimental Setup

In this section, we present the dataset, and the steps to extract and process questions from issue reports. Figure 3.2 depicts the overview of our experiment.

3.2.1 Datasets

We choose to study issue reports from three popular ultra-large-scale and open-source systems, i.e., Linux[2], Firefox[3] and Eclipse[4]. Linux is known as a popular operating system. Firefox is a well-known web-browser. Eclipse has over 250 different open source projects, like the widely used integrated development environment (IDE) for software development, modeling tools, reporting tools, and much more. As the three systems are representative open source systems, studying issue reports in the three systems can reflect the practice in the open source community.

[2]https://bugzilla.kernel.org (accessed in Feb. 2016 and viable in Jul. 2016)
[3]https://bugzilla.mozilla.org (accessed in Feb. 2016 and viable in Jul. 2016)
[4]https://bugs.eclipse.org/bugs (accessed in Feb. 2016 and viable in Jul. 2016)

Table 3.1: Description of resolution types, and the numbers and percentages of the number of issue reports of a resolution type in the studied projects.

A "-" denotes that the project does not use this resolution type.

Type	Description	Linux[6]		Firefox		Eclipse	
(T0)	FIXED[1] The reported issue is fixed by the assignee.	8,409	36.35%	27,085	19.52%	41,449	50.77%
(T1)	PATCH_ALREADY_AVAILABLE A patch already exists for the reported issue.	2,182	9.43%	-		-	
(T2)	INVALID The issue report cannot be addressed.	3,468	15.00%	19,635	14.15%	6,734	8.25%
(T3)	WONTFIX[2] The issue will not be addressed.	976	4.22%	6,224	4.49%	8,175	10.01%
(T4)	DUPLICATE The report is a duplicate of another report.	1,555	6.72%	40,733	29.35%	16,132	19.76%
(T5)	WORKSFORME[3] The issue cannot be reproduced.	1,378	5.96%	23,472	16.91%	8,312	10.18%
(T6)	DOCUMENTED The reported issue describes intended behaviour.	623	2.69%	-		-	
(T7)	INCOMPLETE[4] The report is incomplete.	2,238	9.67%	19,467	14.03%	-	
(T8)	MOVED The issue report was moved to a different ITS.	73	0.32%	-		5	0.01%
(T9)	EXPIRED[5] The issue no longer exists in the latest version.	2,232	9.65%	2,151	1.55%	-	
(T10)	NOT ECLIPSE The reported issue is not related to Eclipse.	-		-		870	1.03%
Total number of resolved issue reports		23,134	100%	138,767	100%	81,647	100%

[1]CODE_FIX, [2]WILL_NOT_FIX, [3]UNREPRODUCIBLE, [4]INSUFFICIENT_DATA and [5]OBSOLETE in Linux.
[6]The percentage given is the percentage of all resolved issue reports.

For each system, we collect all its issue reports from the first issue report until February 2016. For each issue report, we download all the properties and comments, as well as the changes made to the attributes (e.g., severity, priority, #CC) in the entire history. As we aim to predict if questions can be raised from a newly created issue report (RQ 3.3), we retrieve the initial value of the attributes of issue reports and issue reporters (details are discussed in Section 3.3.3) that are provided at the creation time of the issue reports.

To examine the impact of raising questions on the issue addressing process, we exclude the issue reports that are not resolved (i.e., issue reports still with the status of NEW, ASSIGNED and REOPENED). As the life cycle of issue reports is described

Table 3.2: The number of issue reports in each studied ITS

ITS	Collection period	# of reports	# of resolved reports	# of reports with questions	# of reports without questions
Linux	2002 to 2016	27,100	23,134	10,882(47.04%)	12,252(52.96%)
Firefox	1999 to 2016	157,340	138,767	54,644(39.38%)	84,123(60.62%)
Eclipse	2001 to 2016	406,303	357,744	88,967(24.87%)	268,777(75.13%)
Total		590,743	519,645	154,493(29.73%)	365,152(70.27%)

```
Check :
http://www.alsa-project.org/alsa-doc/doc-php/template.php3?company=Creative+Labs&
card=Soundblaster+16&chip=sb16&module=sb16
```

Figure 3.3: An illustrative example of a url link containing "?"

in Section 1.1, after the issue report is resolved, the issue report changes to the state RESOLVED with a resolution type as shown in Table 3.1. There are eleven resolution types in our studied projects, as listed as "T0-T1"" in Table 3.1. Different projects might use different labels for the same reason of rejecting an issue report. For example, fixed issue reports are labeled as FIXED in Firefox and Eclipse, but Linux uses the CODE_FIX label. The MOVED label is only used in the Linux and the Eclipse projects.

Table 3.2 shows the descriptive statistics of the issue reports that we collected from the issue tracking systems (ITSs) of the three subject systems.

To investigate all raised questions occurred across the issue resolving process, we go through all the comments of issue reports and extract the raised questions from the comments using regular expressions. Specifically, we consider a sentence ending with the question symbol "?" as a question. We only extract questions from comments which is posted by developers before the issue report is resolved However, our extracted questions might contain noises.

In summary, there might be three kinds of noise in our extracted questions:

```
May 10 12:11:54 jtb [ 9215.990028]  [<ffffffff81058215>] ?
try_to_wake_up+0x1d1/0x1f6
May 10 12:11:54 jtb [ 9215.990034]  [<ffffffff8146b1a3>] ? printk+0x79/0x92
May 10 12:11:54 jtb [ 9215.990054]  [<ffffffffa004c46e>] ?
iwl_tx_agg_stop+0xda/0x212 [iwlcore]
May 10 12:11:54 jtb [ 9215.990059]  [<ffffffff8105f0c1>]
warn_slowpath_null+0x23/0x39
May 10 12:11:54 jtb [ 9215.990077]  [<ffffffffa0022763>]
___ieee80211_stop_tx_ba_session+0x69/0x94 [mac80211]
May 10 12:11:54 jtb [ 9215.990082]  [<ffffffff8146de8b>] ? _spin_lock_bh+0x20/0x4f
May 10 12:11:54 jtb [ 9215.990097]  [<ffffffffa00228e0>]
```

Figure 3.4: An illustrative example of call trace message containing "?"

```
Here is a snippet:
public static void main(String[] args) {
        Display display = new Display();
        final Shell shell = new Shell (display);
        Button button = new Button(shell, SWT.PUSH);
        button.setText("button.");
        button.pack();
        button.setLocation(20, 20);
//      shell.setLayout(new GridLayout());
        display.addFilter(SWT.KeyDown, new Listener() {
                public void handleEvent(Event e) {
                        shell.setOrientation(shell.getOrientation() ==
SWT.RIGHT_TO_LEFT ? SWT.LEFT_TO_RIGHT : SWT.RIGHT_TO_LEFT);
                }
        });
        shell.open();
        while (!shell.isDisposed()) {
                if (!display.readAndDispatch()) display.sleep();
        }
        display.dispose();
}
```

Figure 3.5: An illustrative example of a code snippet containing "?"

1) URL links (e.g., https://www.***./?). It is common that developers use a URL link in a comment to refer other issue reports or external pages to help address the issues. It is possible that a URL link contains the symbol of "?". For example, Figure 3.3 shows a URL link appears in the comments of the report Linux-135. In this example, there exists the symbol of "?" in the URL link, and it is identified as

a question. To exclude such kind of noise, we use a regular expression to identify all URL links (i.e., strings that start with "http://" or "ftp://") and exclude them.

2) Execution logs. It is common that developers paste execution logs in the comments to help discuss and investigate the reported issues. Figure 3.4 shows an example of a call trace embedded in a comment (i.e., in Comment-5 Linux-12595). We use a regular expression to identify the embedded call trace from the comments. The format of the call traces usually starts with a date and contains "address format" (e.g., [<ffffffffa002789f>]) before the symbol of "?".

3) Code snippet. Code snippet embedded in a comment allows developers to discuss and investigate the potential reason for generating the corresponding issue in the code snippet. However, the code snippets can contain noises that are identified as questions. For example, Figure 3.5 displays an example of noise that is identified as a question in the code snippet embedded in Eclipse-29779 Comment-103. The symbol of "? :" is an operator in programming languages (i.e., C, C++, Java and so forth), and the symbol of "?" can exist in a code snippet. In this case, "?" is followed by an identifier and a symbol of ":" (e.g., return num>max?num:max). Hence, we exclude such noise using the regular expression to identify code snippets.

3.2.2 Question Extraction

An issue reporter may submit additional comments that provide extra information to enrich the description of the issue report. As shown in Figure 3.6, the reporter posts a new comment (i.e., in Comment1) to enrich the content of the description. Therefore, we start the questions extraction from the first comments which is not posted by the issue reporter.

Eclipse-Bug 250:
Jean-Michel Lemieux [2001-10-10 21:38:55 EDT]:
Destription
We need to support 'ext' connection method for CVS. This will allow any external transport clients for handling authentication and connection with any tool the user want's to use. ...
Jean-Michel Lemieux [2001-10-23 12:58:11 EDT]:
Comment1
EXT connection method is supported, however configuration is done via the plugin.xml. ...
DJ Houghton [2001-10-23 23:48:51 EDT]:
Comment2
PRODUCT VERSION: 0.135
James Moody [2001-10-25 10:49:36 EDT]:
Comment3
Fixed in v206

Figure 3.6: An example of the enriched comment

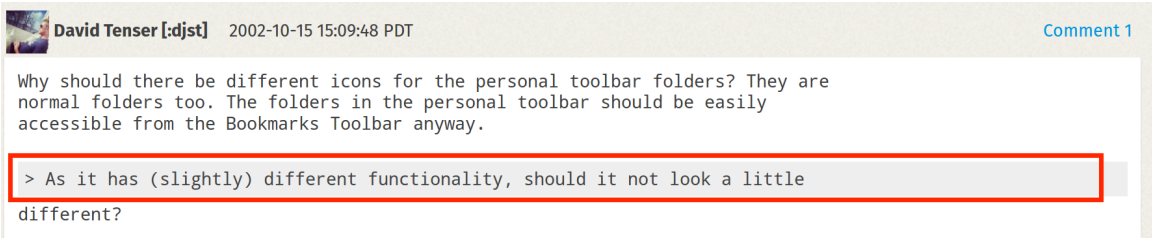


Figure 3.7: An illustrative example of a replying comment

During the resolving process, developers might raise questions from the previous comments instead of the description of issue reports. To ensure the extracted questions are more related to the issue reports, we choose to use a conservative approach to filter out questions raised from the replying comments. The subject issue tracking systems support the feature of replying comments (i.e., start with the symbol of ">"), so we can identify the replying comments by the feature. As illustrated in Fig 3.7, a question (i.e., *Why should there be different icons for the personal toolbar folders?*) is raised in a comment due to an early comment (i.e., *As it has (slightly) different functionality, should it not look a little different?*). Hence, we exclude the extracted

questions from the replying comment.

3.2.3 Question Processing

After collecting the raised questions from the comments, we apply general textual preprocessing steps, such as tokenizing text, removing stop words and stemming words. Tokenizing text is to obtain a sequence of strings that do not contain delimiters (e.g., white space and punctuation symbols). Stop words are the non-descriptive words like "a", "is", "was", and "the" [60]. The stemming step aims to normalize the words to their ground forms [62]. For instance, the stemmed version of "working" and "worked" is the same with "work". We apply the Porter stemming algorithm as previous studies [60, 62, 63].

3.3 Experimental Results

3.3.1 RQ3.1: What questions are asked by developers?

Motivation. Developers may raise questions when they encounter issue reports with insufficient information. Finding out what questions are frequently asked can help us better understand the information that developers need when resolving issues. Moreover, if we obtain the information frequently asked by developers during the issue resolving process, issue reporters can provide such details at the creation time of issue reports. As a result, we can help developers avoid raising question during the issue resolving process. In this research question, we aim to investigate the concerned topics in the raised questions by developers during the issue resolving process.

Table 3.3: The distribution of topics in the issue reports for three subject systems

Linux			Firefox			Eclipse		
Index	**Labeled Topics**	**Frequency**	**Index**	**Labeled Topics**	**Frequency**	**Index**	**Labeled Topics**	**Frequency**
1	Configuration	2,452(20.58%)	1	Safe mode	8,776(14.41%)	1	**Current status**	**4,750(4.68%)**
2	Driver	2,443(20.51%)	2	**Current status**	**4,005(6.58%)**	2	Component	3,299(3.25%)
3	Commits	1,867(15.67%)	3	**Reproduce steps**	**2,652(4.36%)**	3	**Reproduce steps**	**3,109(3.07%)**
4	**Current status**	**800(6.72%)**	4	Crash	1,457(2.39%)	4	**Final resolution**	**2,727(2.69%)**
5	**Final resolution**	**266(2.23%)**	5	Extension	1,246(2.05%)	5	Plugin	2,648(2.61%)
6	Sound & Speaker	159(1.33%)	6	Image feature	1,087(1.79%)	6	Package dependencies	1,783(1.76%)
7	Expired report	156(1.31%)	7	**Final resolution**	**1,055(1.73%)**	7	**Operating system**	**1,699(1.68%)**
8	**Operating system**	**123(1.03%)**	8	Cookies data	1,038(1.70%)	8	Version control	1,698(1.67%)
9	Concurrency	101(0.85%)	9	Browser	985(1.62%)	9	Jar dependencies	1,636(1.61%)
10	Email	96(0.81%)	10	Bookmark/History folder	922(1.51%)	10	Development environment	1,585(1.56%)
11	Suggestion	96(0.81%)	11	Page loading	871(1.43%)	11	Log information	1,582(1.56%)
12	Cache	89(0.75%)	12	User interface	869(1.43%)	12	Encoding	1,508(1.49%)
13	Closing report	72(0.60%)	13	Plugin	861(1.41%)	13	Requirement	1,364(1.35%)
14	Version Control	70(0.59%)	14	Tab groups	792(1.30%)	14	EMF	1,246(1.23%)
15	Memory	69(0.58%)	15	**Operating system**	**781(1.28%)**	15	Zip files	1,194(1.18%)
16	Frequency	65(0.55%)	16	Additional information	677(1.11%)	16	Suggestion	1,173(1.16%)
17	Level	65(0.55%)	17	Configuration	667(1.10%)	17	Workspace	1,158(1.14%)
18	Log information	62(0.52%)	18	Human oriented	630(1.03%)	18	Concurrency	1,128(1.11%)
19	**Reproduce steps**	**61(0.51%)**	19	Issue relation	610(1.00%)	19	JDT	1,094(1.08%)
20	Patch	59(0.50%)	20	Blocking issues	595(0.98%)	20	Solution	1,036(1.02%)
Topic [1]		9,171(76.99%)			30,576(50.21%)			37,417(36.90%)

[1] The total number of the issue reports that contain the questions associated with the 20 most frequent topics.

Approach. To answer this question, we first present our approach to extract topics from questions and then discuss the extracted topics. Details are described in the subsections.

Topic Extraction

To summarize the topics in raised questions, we apply the Latent Dirichlet Allocation (LDA) [64] that is widely used for topic extraction in the literature of software engineering. LDA is a statistical model. The input for LDA is a list of documents, and the output of LDA is the distribution probability of each extracted topic in each document.

In our experiment, we treat the raised questions from the same issue report as one document, so that we can know the distribution of topics in the raised questions for each issue report. We follow the standard natural language processing steps (see Section 3.2.3) to preprocess each document. Specifically, we remove stop words from each document and do the stemming to normalize the document.

LDA Parameter Setting We run with 1,000 Gibbs sampling iterations by following the guideline from previous work [65], and set the number of keywords for each topic to be 20. The number of topics (we denote it by K) impacts the quality of the topics extracted by LDA [65, 66, 67, 68, 69]. To find the optimal number of topics (we denote by K), we compute the following three metrics:

- *Arun*2010 [66] that is computed based on two matrices (i.e., Topic-Word and Document-Topics), which are generated from LDA. The lower value, the better.
- *CaoJuan*2009 [67] that calculates the cosine distance of topics. The minimum

value of $CaoJuan2009$ indicates that the corresponding K is the optimal number of topics.

- $Griffiths2004$ [65, 69] that is computed based on an estimate multinomial distribution of K topics to words in the corpus. The maximum value of $Griffiths2004$ indicates that the corresponding K is the optimal number of topics.

We apply the *FindTopicsNumber* function from R package *ldatuning* by varying K from 2 to 500. As the *FindTopicsNumber* function takes a very long time to finish for a large dataset, we apply it on a statistically representative sample of 2,368 issue reports. The sample issue reports are randomly selected from 174,233 issue reports with the confidence level at 95% and the confidence interval at 2%. The sample is statistically representative. In the other words, the distribution of topics in the 2,368 issue reports can represent the distribution of topics in the 174,233 issue reports. Therefore, the number of topics obtained from a statistically representative sample can represent the number of topics obtained from the 174,233 issue reports. The optimal number of topics suggested by the three metrics $Arun2010$, $CaoJuan2009$, and $Griffths2004$ are 107, 162, and 182, respectively. Accordingly, we set the number of topics as 150 in our experiment that is close to the three suggested Ks.

LDA Topic Labelling Each LDA topic is represented by a vector of 20 words. To better understand the meaning of each topic, we asked four graduate students to manually label each topic based on its keywords [70]. The four graduate students all study in computer science one of them is the 3rd year Ph.D student, the rest of them are master students. The four students independently assign labels. The four graduate students all study in computer science. One of them is a 3rd year Ph.D.

student, and the rest of them are master students. When different labels are assigned to the same topic, a discussion is conducted until a consensus is reached.

We present the 20 most frequent topics for each system in Table 3.3, as over 76%, 50% and 36% of issue reports are related to the top 20 most freqently asked questions in Linux, Firefox and Eclipse respectively. For each topic, the frequency is computed as the number of issue reports that contain questions associated with the topic. We consider that an issue report (i.e., a document) is associated with topics, if the corresponding topics are assigned the highest score by LDA in the document.

Results. In Linux, three topics, i.e., *Configuration*, *Driver* and *Commits*, appear in more than a half (i.e., 56.76%) of all issue reports. The topic, *Configuration*, refers to questions raised by developers to clarify the hardware and/or software configuration of the machine of issue reporters. For instance, questions related to *Driver* are raised to clarify the detailed information of drivers for the reported issue. Questions associated with *Commits* are asked to find out which commit introduces the issue. We think that at least two types of questions (i.e., *Configuration* and *Driver*) can be reduced or even avoided by developing a tool to automatically collect the configuration and driver information for issue reporters.

In Firefox, the most frequently occurring topic is the *Safe mode*, which appears in 14.41% of all issue reports. Firefox has a large number of add-ons. In the safe mode of Firefox, all add-ons are disabled. When an issue is reported to Firefox, developers need to ensure that the issue is caused by bugs of Firefox not by bugs of add-ons. Therefore, developers usually ask issue reporters if Firefox is in the safe mode. To avoid such types of questions, we suggest issue reporters to reproduce the issue in the safe mode and explicitly mentions the usage of the safe mode in the

description.

In Eclipse, there is no topic clearly occurring more frequently than others. As shown in Table 3.3, the 20 most frequent topics only cover 36.90% of the population. One reason may be that Eclipse project is embedded with multiple plug-in components. The reported issues can be caused by various reasons from different plug-in components and developers of different plug-in components have different focuses of the needed information in the issue resolving process. It may be difficult to provide a universal solution to reduce or avoid questions raised in the Eclipse issue reports.

As a summary, the majority of the 20 most popular topics vary across systems. The list of the 20 most frequent topics in each system is shown in Table 3.3. The coverage of the 20 most frequent topics also varies across systems. For instance, the 20 topics appear in 76.99%, 50.21%, and 36.90% of issue reports in Linux, Firefox, and Eclipse, respectively. The difference may be due to the characteristics of the three systems. In Linux, developers deal with the kernel of an operating system to support different hardware/drivers) and various configurations. In Firefox, developers maintain a widely used browser that is enhanced by many add-ons, and issue reports can be created against bugs of Firefox or its add-ons. In Eclipse, there are many subprojects that do not overlap too much with each other.

Among the 20 topics, there are only four common topics across systems. The four common topics are *Current status*, *Final resolution*, *Operating system*, and *Reproduce steps*. The topic *Current status* refers to questions that are raised by developers to check the current status of an issue report. The resolution of an issue report may be delayed for a long period [71], then developers lose track of the issue

report. The topic *Final resolution* refers to questions that clarify the final decision made on issue reports, and it happens when developers cannot reach a consensus. This type of question is likely to be reduced or avoided if all involved developers decide to solve the issue only after the issue is fully discussed. Questions related to topics *Reproduce steps* and *Operating system* are generally essential to clarify the detailed steps and the environment to reproduce an issue. Issue reporters should try their best to provide as many details as possible on the reproduce steps and the environment.

> *From LDA model, the common topics of the questions raised from the issue reports are Current status, Final resolution, Operating system, and Reproduce steps among the three subject systems. However, the majority of raised questions are specific to each system.*

3.3.2 RQ3.2: What is the impact of raising questions?

Motivation. There are a considerable amount of issue reports having questions raised during the issue resolving process. As shown in Table 3.2, questions are raised in 47.04%, 39.38%, and 24.87% of issue reports in Linux, Firefox, and Eclipse, respectively. But it is unclear how having questions impacts the issue resolving process. Hence, in this research question, we study how raising questions to hanlde an issue affect the efficiency of the issue resolving process.

Approach. To answer this question, we first describe our measurements of the impact and the null hypothesis. Then we discuss our findings on the impact of raising questions. Details are described in the following subsections.

Measurement of the Impact

In our experiment, we measure the impact of raising questions on the issue resolving process from four perspectives. Specifically, we use the following four metrics.

- *Time elapsed* measures the duration between the time when an issue report is responded by the developers (e.g., posting comments or modifying some fields of an issue report) and the time when the issue is resolved.
- *The number of developers* is the count of developers that are involved in the issue resolving process.
- *The number of comments* is the count of comments that are posted by the issue reporter or developers during the issue resolving process.
- *The number of assignments* counts the times that an issue report is assigned/reassigned to developers.

The smaller value of the aforementioned four metrics, the more efficient the issue resolving process is. The smaller values indicate that an issue is resolved quicker, involves fewer developers, derives fewer comments, and is assigned to the appropriate developer with fewer iterations.

Null Hypothesis

To study the impact of raising questions, we divide the issue reports into two groups for each system. The first group (as a control group) contains all issue reports that do not have questions raised during the issue resolving process. The second group (as

an experimental group) contains all remaining issue reports that have questions. For each of the four aforementioned metrics, we test the following null hypothesis:

H_1^0: *There is no difference in the distribution of the values of the metric between the issue reports without and with raised questions.*

To test the null hypothesis, we apply the Mann-Whitney U test [72] with the 95% confidence level(i.e., p-value < 0.05). The Mann-Whitney U test is also known as the Wilcoxon rank sum test, which is a statistical method having no assumption on the distribution of two assessed variables, i.e., the values of the assessed metric. If there is a statistically significant difference, i.e., p-value <0.05, we reject the null hypothesis and conclude that the distribution of the values of the corresponding metric is significantly different between the issue reports with and without questions.

Moreover, the control group and the experimental group are drawn from the same population. Our hypothesis is that the distribution of the values of metrics should be identical between the two groups. If we control one variable (i.e., one metric), the distribution of the corresponding metric will become statistically significantly different between the control and experimental group. Therefore, we could establish the causation between the controlled variable(i.e., issue reports with questions or not) and the assessed metrics[5].

Results. Raising questions could be one of the risks of delaying the issue resolving process in terms of the elapsed time. Figure 3.9 shows the distribution of each metric in two groups, i.e., issue reports with questions (WQ) and issue reports without questions (NQ). The result of Mann-Whitney U test shows that there exists a statistically significant difference between the issue reports with

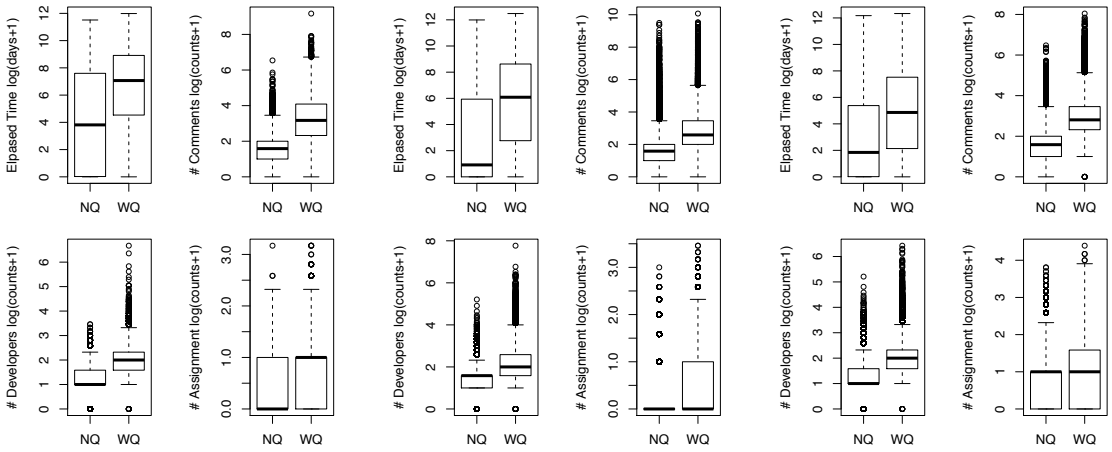
[5]http://www.abs.gov.au/websitedbs/a3121120.nsf/home/statistical+language+-+correlation+and+causation (accessed in Feb. 2016 and viable in Jul. 2016)

Linux-Bug 915:
Greg Kroah-Hartman [2003-07-12 20:32:55 UTC]:
Can you attach your .config?
Roger Luethi [2003-07-14 11:50:20 UTC]:
Created *attachment-527*
Greg Kroah-Hartman [2003-07-15 12:42:23 UTC]:
Ok, I've duplicated this now, I'll work on it...

Linux-Bug 9147:
Erik Boritsch [2007-12-01 16:44:03 UTC]:
The bug is still there with CONFIG_ACPI_EC is not set. Any other ideas?
Sebastien Caille [2007-12-05 15:16:34 UTC]:
I tried to dump /proc/interrupts every 5 seconds. ... Something is definitely triggering the irq1 when acpi=on...
Daniele C. [2007-12-05 15:44:15 UTC]:
... maybe i8042 multiplexer is triggering a wrong IRQ.

Figure 3.8: Examples of raised questions

questions and that without questions (i.e., p-value<0.05) in the elapsed time. Hence, we can reject the null hypothesis H_1^0 for this metric. Additionally, we observe that the group with questions has a longer elapsed time by comparing with the other group (i.e., control group). The result shows that raising questions could introduce a non-negligible waiting period and the extra time on re-investigate the issue with new information provided in the answers. For instance, an issue report of Linux (i.e., *Linux-Bug 915* in Figure 3.8) shows that the assignee of the issue report named Greg requested the configuration file from the reporter, and the reporter provided the requested file after about two days, then the assignee reproduced the issue with the newly attached configuration file after another day. If the configuration file is provided



(a) Linux (b) Firefox (c) Eclipse

Figure 3.9: The distribution of the impact metrics for issue reports without and with questions

(NQ: Issues reports that have no questions; WQ: Issue reports With Questions). We show the value of metrics by log scale based on 2.

at the creation time, three days could be saved in resolving this issue report.

Raising questions involves more developers and incurs more comments to address the reported issues. The results of the Mann-Whitney U test show that the issue reports with questions involve significantly more developers and comments (i.e., p-value < 0.05) during the issue resolving process in the three subject projects. If a developer can not address the issue report by herself or himself, she or he may ask questions that involve other developers to answer. For instance, in *Linux-bug 9147* (Figure 3.8), a developer encountered an unexpected issue that the bug still exists with a specific configuration, therefore he or she asked help from other developers who may be in charge of the particular module. The answer from the second developer further triggers the discussion with the third developer.

Issue reports with raised questions have a higher rate of reassignment. The results of the Mann-Whitney U test show that the issue reports with raised questions have significantly more reassignments by comparing with the control group without raised questions (i.e., p-value < 0.05). The previous study [30] shows that an issue report that experiences multiple reassignments takes a longer time to be resolved. However, our results show that the raising of questions could be one of the reasons of reassignment. An assignee may raise questions if she or he does not have time to fix the issue or can not fix the issue (an example happened in Eclipse-bug 10025: *would you be able to fix this up?*), or another developer could be involved to make a decision on the issue report (an example happened in Eclipse-bug 123976: *Shouldn't this be resolved as invalid instead of fixed?*). In such cases, issue reports could be reassigned.

> *In terms of the elapsed time, the number of developers and comments and the number of the assignments, the raised questions by developers could be one of the reasons that reduce the efficiency of the issue resolving process.*

3.3.3 RQ3.3: Is the occurrence of questions predictable?

Motivation. The results of RQ3.2 shows that raising questions can reduce the efficiency of the issue resolving process. To give developers an early warning if a newly report issue will trigger questions, we investigate the feasibility of predicting the occurrence of questions using only the information that is available at the creation time of the issue reports. The early warning can notice developers to take proper

actions at the creation time of issue reports to avoid raising questions during the issue resolving process.

Approach. To answer this question, we first describe our metrics used to build the prediction model. Then we present our modeling techniques, performance measures and comparison. Finally, we discuss the predictive power and influential metrics.

Metrics Extracted from Issue Reports

In this subsection, we describe the definition, the collection, and the selection of metrics. Details are described as follows.

1) Metric definitions. To better describe the features and the attributes of an issue report, we extract metrics from issue reports by four perspectives: the textual factors, the characteristic factors, the supportive factors and the historical factors. In total, we extract 13 metrics from issue reports.

a. Textual factors that are extracted directly from the textual data (e.g., the description and title of an issue report). We collect the following three metrics.

- *Length of the Title* is defined as the number of words contained in the title of an issue report. A longer title is more likely to provide sufficient information about the issue, and thus developers may raise fewer questions.
- *Length of the Description* is the number of words in the description field of the issue report. Similar to the title, a longer description is likely to provide more elaborate information about the issue.
- *Readability* is the Coleman-Liau index(CLI) [73] of the issue description, which has been applied in the evaluation of issue reports [27]. The CLI reveals how

difficult to understand the text, and it is calculated as $CLI = 0.0588 * L - 0.296 * S - 15.8$, where L is the average number of the characters per 100 words, and S is the average number of sentences per 100 words. A lower readability is more likely to make developers confused and ask questions.

b. Characteristic factors that are extracted from the meta-data of an issue report (e.g., the importance and the complexity of a reported issue). We compute the following five metrics.

- *Is Regressive* is a boolean variable that indicates whether the issue report was reported and fixed before and reoccurs. Developers are more likely to raise more questions on the issues that have the regressive property.
- *Severity* describes the severity of an issue report, and ranges from 1 to 5 (i.e., "enhancement" to "blocking") in Linux, and from 1 to 7 (i.e., "enhancement" to "blocker") in both Firefox and Eclipse.
- *Priority* captures the priority of an issue report, and ranges from 1 (low priority) to 5 (high priority).
- *Is Blocking* is a boolean variable that indicates whether the issue must be addressed before addressing the issues that are listed in the "Blocks" field.
- *Is Dependent* is a boolean variable that indicates whether another issue must be addressed before addressing the reported issue.

c. Supportive factors that are extracted from the information used to assist developers to reproduce and resolve the reported issue. We calculate the following three metrics.

- *Has steps to reproduce* is a boolean variable that indicates whether an issue report describes the steps to reproduce the reported issue. Developers are more likely to ask questions about how to reproduce the issue, if details of the reproduce steps are missing in the issue report.

- *The number of attachments* counts the attachments that include the patches and the testing case for the issue report.

- *The number of CCs* is the number of unique developers contained in the carbon-copy(CC) list of the issue report. A developer listed in the CC field will get informed if there is a change in the issue report. More developers included in the CC list indicates a higher chance of interactions among developers.

d. Historical factors that are computed based on the history of the reporter that happened before the creation time. We compute the following two metrics.

- *Reputation of the reporter* is a float value to describe the reputation of the issue reporter. We compute the reputation of a reporter as the proportion of issue reports that are previously filed by the reporter and get fixed in the end [74, 27]: $reputation = \frac{|opened \cap fixed|}{|opened|+1}$. Note that 1 is added to the denominator in case a reporter did not report any issues in the past.

- *The rate of rejected issues previously reported.* Issue reports can be rejected as different resolutions, e.g., Worksforme, Duplicate, Invalid and so on. There are nine, seven and six types of resolutions for rejecting issue reports in Linux[6],

[6]https://bugzilla.kernel.org/query.cgi?format=advanced (accessed in Feb. 2016)

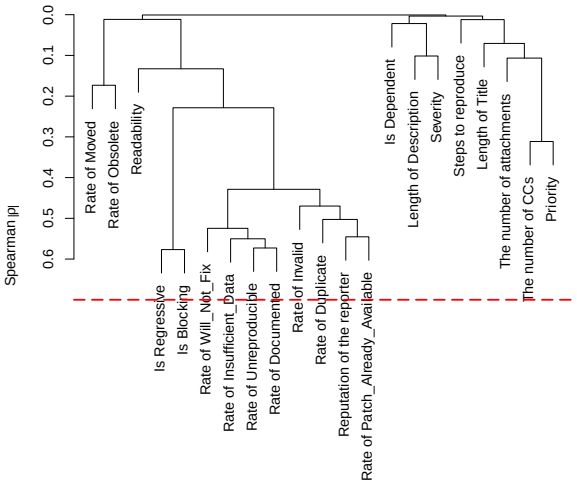


Figure 3.10: The Spearman correlation analysis for Linux.
The dotted red line indicates the threshold value of 0.7.

Firefox[7] and Eclipse[8] respectively. To better describe the experience of developers, we use a list of float values to indicate the rate of different types of rejected issue reports previous reported by the reporter. We use T_i to denote the i_{th} type of rejected resolution (i.e., i = 1 to 9 in Linux, 1 to 7 in Firefox and 1 to 6 in Eclipse), and calculate $rate^{T_i}_{reporter}$ as $rate^{T_i}_{reporter} = \frac{|opened \cap T_i|}{|opened|+1}$.

2) Metric computation. The values of all aforementioned metrics are collected using only the information that is available at the creation time of issue reports. Therefore, we can apply these metrics to predict the chance of having questions raised at the creation time of an issue report. For the fields (e.g., severity, the number of CC) whose values may be changed during the issue resolving process, we trace back to the initial value that is filled in the creation time of an issue report.

[7]https://bugzilla.mozilla.org/query.cgi?query_format=advanced (accessed in Feb. 2016 and viable in Jul. 2016)

[8]https://bugs.eclipse.org/bugs/query.cgi?format=advanced (accessed in Feb. 2016 and viable in Jul. 2016)

3) Metric selection. The existing highly correlated factors can lead to overfitting of a model [75]. To analyze correlation, we calculate the Spearman rank correlation for our metrics to test whether there is any highly correlated pair of metrics. We apply the variable clustering technique (i.e., R function *varclus*) to see the correlation coefficient ρ. If the correlation coefficient of a pair of metrics is higher or equal to 0.7, we consider the pair of metrics is highly correlated and pick only one of them. The value of 0.7 has been applied in previous studies [37, 76, 77]. Figure 3.10 depicts the Spearman rank correlation of the metrics in Linux. As there is no any pair of metrics that has the correlation coefficient value greater or equal than 0.7, we do not exclude any metrics in Linux, Firefox, and Eclipse.

Prediction Model

To build a better prediction model, we experiment with three different prediction models [78], i.e., random forest, logistic regression and naive Bayes. Logistic regression is a generalized linear model which is a pretty well-behaved classification algorithm that can be trained as long as the features are expected to be roughly linear [79, 80]. Unlike logistic regression, the random forest is an ensemble learning model and do not expect linear features or even features that interact linearly [81, 52]. NaiveBayes is a simple probabilistic classifier, which applies Bayes' theorem with the assumption of independence between every pair of features [82, 83].

Model Performance

To evaluate the performance of the prediction model, we use precision, recall, accuracy, F-measure, which are explained below.

- Precision (*precision*) is defined as the proportion of the issue reports that are predicted as having questions and truly have questions [84, 85]: $precision = \frac{TP}{TP+FP}$.
- Recall (*recall*) measure the completeness of a prediction model. A model is considered as more complete if more issue reports with questions could be captured [84, 85]: $recall = \frac{TP}{TP+FN}$.
- F-Measure (*F-measure*) is used to balance the precision and recall. It is a combining way to describe a model [78]: $F\text{-}measure = 2 \times \frac{precision \times recall}{precision+recall}$.
- Accuracy (*accuracy*) calculates the percentages of the correct prediction [78]: $accuracy = \frac{TP+TN}{TP+FP+TN+FN}$.
- Area Under Curve (AUC) gives us an overview of the ability of the prediction model. AUC is the area under the curve plotting the true positive rate against the false positive rate. The AUC value could be ranged from 0.5 (worst, i.e., random guessing) to 1 (best, i.e., all targets could be captured by the prediction model).

Model Comparison

To obtain a reliable performance measure, we apply ten times of 10-fold cross-validation. In the 10-fold cross-validation, the data is equally divided into 10 parts.

In each fold, the 9 parts are used to train the model and the remaining part is used to test the model. To compare the performance of our selected prediction models, we apply the Scott-Knott effect size clustering (SK-ESD) [86] on the results of the ten times cross-validation. The Scott-Knott effect size clustering ranks the performance based on the effect size of their differences. We use the R package *ScottKnottESD* for the comparison.

Results. It is feasible to predict the occurrence of questions solely based on the information that is available at the creation time of the issue reports. Table 3.5 shows the precision, recall, F-Measure, accuracy, and AUC of our prediction models. For instance, the random forest model achieves the AUC values at 0.78 in Linux, 0.65 in Firefox, and 0.70 in Eclipse, significantly outperforming the random guessing with a large margin (i.e., **from 0.15 to 0.28**). The random forest model generally performs the best in our selected models in terms of F-measure and the AUC value. The result of the SK-ESD shows that the AUC value achieved by the random forest model is statistically significantly higher than the logistic regression model and naive bayes model, except in Firefox where the logistic regression model achieves the similar performance as the random forest model (i.e., both with a median AUC of 0.65).

During the issue resolving process, additional information (e.g., discussions among developers) can be collected as developers progress. The additional information that can be collected at a later stage of the issue resolving process is likely to improve the performance of the model in predicting the raising questions. However, since our goal is to give developers an early warning when a new issue report is created, it is worth mentioning that our model is purposely built under a difficult setting (i.e., all metrics

Table 3.4: The five important metrics in the random forest models.

The metrics are clustered and ranked using Scott-Knott effect size clustering.

ITS	Rank	Metric	Importance
Linux	1	Number of CCs	0.1048
	2	Priority	0.0151
	3	Readability	0.0114
	4	Number of attachments	0.0108
	5	Description length	0.0076
Firefox	1	Number of CCs	0.0419
	2	Severity	0.0076
	3	Reputation	0.0069
	4	Rate of DUPLICATE	0.0059
	5	Description length	0.0058
Eclipse	1	Number of CCs	0.0255
	1	Reputation	0.0255
	2	Description length	0.0173
	3	Rate of DUPLICATE	0.0151
	4	Rate of WORKSFORME	0.0114

Table 3.5: The median value of performance measures of our models in three studied systems

(**bold** font highlights the performance of the best model in each system)

Model	System	Precision	Recall	F-Measure	Accuracy	AUC
Random forest	Linux	0.70	**0.70**	**0.70**	**0.72**	**0.78**
	Firefox	0.52	**0.57**	**0.54**	0.62	**0.65**
	Eclipse	**0.37**	**0.66**	**0.47**	0.63	**0.70**
Logistic regression	Linux	**0.71**	0.62	0.66	0.70	0.76
	Firefox	**0.53**	0.52	0.53	**0.63**	**0.65**
	Eclipse	**0.37**	0.55	0.44	0.65	0.66
Naive Bayes	Linux	0.68	0.49	0.57	0.65	0.70
	Firefox	0.50	0.38	0.42	0.60	0.60
	Eclipse	0.36	0.39	0.38	**0.68**	0.63
Random guessing	Linux	0.47	0.50	0.48	0.50	0.50
	Firefox	0.39	0.50	0.44	0.50	0.50
	Eclipse	0.25	0.50	0.33	0.50	0.50

are collected using only the information available at the creation time, and any other information that can be collected at a later stage of the issue resolving process is not used). As a summary, we conclude that it is feasible to predict the occurrence of questions for newly created issue reports, especially in Linux and Eclipse.

Influential Factors

To figure out the influential factors, we apply the permutation test technique [77]. Specifically, there is one metric randomly permuted for each time and the model is built with the permuted set of metrics. We use R function *importance* in the package *RandomForest* to conduct the permutation test. Moreover, we apply the Scott-Knott effect size clustering (SK-ESD) [86] to group the importance of the metrics. If there is no significant difference in the importance scores between metrics, those metrics are considered as having the same rank.

The number of carbon-copy(CC) is the most influential factor in all three subject systems. A long CC list indicates that the issue reporter intentionally involves more developers into the issue report. The involvement of more developers i more likely to trigger questions. When filling a long CC list, the issue reporter should try her or his best to provide every detail of the issue in the description. This may not prevent all questions raised during the discussion, but at least can avoid questions raised against the issue description.

Table 3.4 shows the average importance value of all the top five influential metrics based on the results of Scott-Knott effect size clustering. Another common influential metric is the description length. The remaining influential metrics vary across systems. For instance, the priority, readability, and the number of attachments are the three influential metrics in Linux. When reporting an issue in Linux, we suggest the issue reporter improve the readability of the description and attach necessary files, such as configurations. In the other two systems Firefox and Eclipse, the experience of the reporter (such as the reputation of reporters, and the rate of duplicate/worksforme issues reported by reporters) play more important roles in predicting the occurrences

of questions. We conjecture that, in the two systems, the issue reporters with less experience may not have a clear checklist on the description and attribute fields when creating issue reports. It is beneficial to design a tool to automatically check if the appropriate information is provided by the issue reporter at the creation time.

It is feasible to predict if future questions will be raised by the developers from the issue report at the creation time of an issue report. The number of CCs is the most influential metric to all three subject systems.

3.4 Threats to validity

In this section, we discuss the threats to the validity to our study, by following Yin's guidelines [87] of case study research.

External Validity concerns the threats to generalize our findings. Our three subject systems are representative open source systems that have a long history. As a result, our findings can reflect the current practice in open source community. Although our findings may not directly applicable to proprietary systems, our approach can be applied to any system with an issue tracking system to find the common types of questions, the impact of raising questions and the feasibility of predicting the occurrence of questions.

Internal Validity concerns the threats coming from the analysis methods and the selection of subject systems. The threat to our internal validity comes from the extraction of questions. Issue reports are free-form text, thus there exist different kinds of noise (i.e., link information, log information that contain question mark). To mitigate the noise, we manually examine the patterns from a sample set of issue

reports. Another internal threat is that the extracted questions can be raised against a previously posted comment other than the description. We excluded the comments that are posted to explicitly reply a previous comment. However, it is worth adding more criteria to improve the accuracy of extracting questions.

Conclusion validity concerns the relationship between the treatment and the outcome. In our study, the elapsed time may be over-estimated, as the assignee might be working on other issues at the same time or is taking vacations for many days. Therefore, we also report three other metrics (i.e., the involved developers, the number of comments and the number of assignment) to measure the impact of raising questions on the issue resolving process. Our findings remain consistent across the four metrics. Nonetheless, it is helpful to obtain the ground truth by directly interviewing developers.

The raised questions may have positive effects. For example, the raised questions can make the issues resolved in a correct way, and cause fewer regressions or reopens. However, from a statistical comparison of our effort metrics between the control group (i.e., the issue reports do not have questions) and the experimental group (i.e., the issue reports contain questions), the raised questions from issue reports generally have a negative impact on the resolving process.

3.5 Summary

In this chapter, we conduct an empirical study to understand the impact that raising questions has on the efficiency of the issue resolving process. First, we apply the LDA to extract the concerned topics in the raised questions. We find that there are four common topics of questions, including *Current Status*, *Final resolution*, *Operating*

system and *Reproduce steps* in the three subject systems. In the three subject systems, the majority questions vary across systems. Second, we examine how the raising questions impact on the issue resolving process. We measure the impact in terms of four measures that are the time elapsed in resolving an issue, the number of involved developers, the number of comments, and the number of assignments. We observe that raising questions statistically significantly results in greater values in all the four metrics. Therefore, raising questions negatively impacts the efficiency of the issue resolving process. Finally, we investigate the feasibility of predicting the occurrence of questions at the creation time of an issue report. We collect 13 metrics that are available at the creation time and experiment with three prediction modeling techniques (i.e., logistic regression, naive bayes and random forest). We find that the random forest model achieves the best performance in terms of F-measure and the AUC values. In particular, our model achieves the AUC value of 0.78, 0.65, and 0.70 in Linux, Firefox, and Eclipse, respectively. Therefore, we conclude that it is feasible to give developers an early warning of the issue reports that are likely to raise questions.

Chapter 4

Towards Reducing the Effort Spent on Rejected Issue Reports

In this chapter, we empirically study the issue reports rejected by developers during the issue resolving process. In our work, we strive for helping developers to automatically assign a lower priority to the reports that should be rejected at the time of triaging. We first examine how the issue reports that should be rejected threat the efficiency of handling issue reports. Then, we build a random forest model to predict if a newly created issue report will be rejected in the future. To avoid rejecting a valid issue report, we further propose a ranking model. Specifically, we apply the Learning-to-rank technique to prioritize the predicted valid issue reports at higher positions and the predicted rejected issue reports at lower positions.

4.1 Introduction

Once an issue report is filed into the ITS, the report is assigned by a so-called *triager* to a specific developer who will address the report further. Triaging is a time-consuming step in the process of handling issue reports [7, 88, 89, 90].

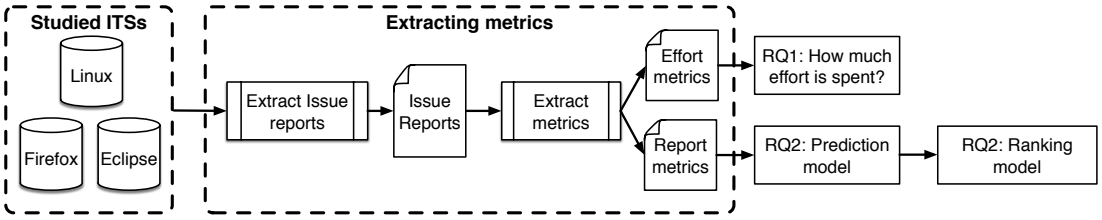


Figure 4.1: Overview of our approach

The ITS of a popular project often receives a large number of issue reports. For example, there were more than 157,000 issue reports in the Firefox ITS by the end of 2015. However, not all of the assigned issue reports will be addressed in the end [17]. A triager or developer may choose to reject an issue report. In particular, prior work [43, 91, 92, 93] reveals several common reasons to reject issue reports, such as that the reporter filed an invalid issue, the reporter misunderstood a feature of the software, or the reporter failed to provide the reproduce steps or test cases.

As long as an invalid or useless issue report is not rejected, developers could be wasting valuable resources (e.g., time) on the report. In this chapter, we show that rejected issue reports are numerous (49%-80%) in the issue tracking data of Linux, Firefox and the Eclipse IDE. Hence, issue reports that should be rejected seriously threat the efficiency of the process of handling issue reports. It is of significant interest to find how we can help developers by automatically assigning a lower priority to the reports that should be rejected at the time of triaging.

4.2 Experimental Setup

In this section, we present the ITSs that we studied and our process for collecting data for our experiments. Figure 4.1 gives an overview of our approach.

Table 4.1: The number of issue reports in each studied ITS.

ITS	# of Collected Reports	# of Resolved Reports[1]	# of Rejected Reports (%)[2]	Collection Period
Linux	27,100	23,134	14,725 (63.65%)	2002-2016
Firefox	157,340	138,767	111,682 (80.48%)	1999-2016
Eclipse	94,397	81,647	40,198 (49.23%)	2001-2016
Total	278,837	243,548	166,605 (68.41%)	

[1]The resolved reports only refer to the verified and closed reports in the entire set of collected issue reports.
[2]The percentage is computed as the proportion of the rejected reports relative to all the resolved issue reports.

4.2.1 Studied ITSs

We choose to study the dataset of ITS of three popular ultra-large-scale and open-source projects, i.e., Linux[1], Firefox[2] and the Eclipse[3] that are introduced and studied in Chapter 3. Table 4.1 shows the descriptive statistics of the issue reports that we collected from the three studied ITSs.

4.2.2 Extracting Effort Risk Metrics

To describe the risk of wasting the effort spent on rejecting an issue report, we extract the following three metrics as a proxy of the effort:

- *Time elapsed.* When a developer posts a comment or alters any field on an issue report for the first time, we consider that the developer starts to work on the report. We compute the time elapsed until the report is finally rejected. The time elapsed does not necessarily mean the actual working time by developers. Therefore, we do not interpret the time elapsed as the wasted time on the rejected issue report. Instead, we use this metric as a relative measure to assess the risk of wasting developers' effort.

[1]https://bugzilla.kernel.org (accessed in Feb. 2016)
[2]https://bugzilla.mozilla.org (accessed in Feb. 2016)
[3]https://bugs.eclipse.org/bugs (accessed in Feb. 2016)

- *The number of developers.* This metric is the number of developers that are involved in the process of rejecting an issue report. A large number of developers involved indicates that more human resources are spent on rejecting the report.

- *The number of comments.* This metric is counted as the number of comments in the discussion regarding an issue report. The larger value of this metric, the more discussion performed.

We extract these metrics from the issue reports and their change history.

4.2.3 Extracting Issue Report Metrics

We collect only the metrics that are available at the time of reporting, since the goal of our study is to predict whether a newly filed issue report will be rejected. We use the change history of an issue report to recover its initial field values that are filled at the time of reporting.

We characterize issue reports from three perspectives: issue property, issue importance and developer's experience. The details of these metrics are described as follows.

Issue property metrics

Issue property metric describe general properties of an issue report, and they can be extracted directly from an issue report. In total, we collect ten issue property metrics.

- *Title length.* The number of words in the title of an issue report. A longer title can provide more useful information about the issue, helping the developer to address the issue faster.

- *Description length.* The number of words in the description of an issue report. A longer description can provide more useful information about the issue, which might make addressing the report easier.

- *The number of CCs.* The number of unique developers that are in the carbon-copy (CC) list of the issue report. A higher number of developers in the CC list might indicate a higher awareness of an issue report across the development team.

- *Is blocking.* A boolean variable that indicates whether the report describes a blocking issue, i.e., it must be addressed before the issues listed in the *Blocks* field. A blocking issue might be more important to address because it is stopping other issue reports from being addressed.

- *Is regressive.* A boolean variable that indicates whether the report describes a regressive issue, i.e., the reported issue was fixed before but reoccurs in a newer version. A regressive issue might be more important to address because it is stopping other issue reports from being addressed.

- *Is dependent.* A boolean variable that indicates whether the report describes a dependent issue, i.e., another issue report must be addressed before the reported issue. A dependent issue report might be more difficult to address due to its dependencies on other issue reports.

- *Steps to reproduce.* A boolean variable that indicates whether the issue report contains steps to reproduce the issue. An issue report that contains steps to reproduce the issue might be more likely to be addressed quickly. We decide on the steps to reproduce metric by checking whether the description contains

one of the following keywords: steps to reproduce, steps, reproducible and reproduce [32, 37].

- *The number of attachments.* The number of attachments in the issue report. Previous work [27, 37] shows that issue reports with attachments are addressed faster.

- *Readability.* The Coleman-Liau index [73] (CLI) of the description field. The CLI approximates the grade level required to comprehend a text, ranging from 1 (easy) to 12 (hard). The CLI is calculated as follows:

$$CLI = 0.0588 * L - 0.296 * S - 15.8 \tag{4.1}$$

where L is the average number of characters per 100 words and S is the average number of sentences per 100 words.

- *Is weekend.* A boolean variable that indicates whether an issue report is opened in the weekend. An issue report that is opened in the weekend might take a longer time to be addressed since developers may wait until Monday to address it.

Importance metrics

Importance metrics can be extracted directly from an issue report and describe how important an issue report is. We select two importance metrics.

- *Severity.* A number describing the severity of an issue report, ranging from 1 to 5 (i.e., 'enhancement' to 'blocking') in Linux and from 1 to 7 (i.e., 'enhancement'

to 'blocker') in Firefox and Eclipse. An issue report that has a high severity should be addressed faster.

- *Priority.* A number describing the priority of an issue report, ranging from 1 (low priority) to 5 (high priority). An issue report that has a high priority should be addressed faster.

Developer's experience metrics

Developer's experience metrics describe the experience of the developer who opened the issue report. We choose to use the following two metrics.

- *Reputation of the reporter.* A float number describing the issue reporter's reputation. Previous work [74, 27] shows that an issue report that is opened by someone who has successfully had his reported issues addressed in the past (i.e., has a better reputation) is more likely to be addressed. We define the reputation of a reporter as the proportion of issues previously reported by that reporter that are fixed eventually [74, 27]:

$$reputation = \frac{|opened \cap fixed|}{|opened| + 1} \tag{4.2}$$

  Note that 1 is added to the denominator in case a reporter did not previously report any issues.

- *The rate of T_i issues previously reported.* A list of float numbers that indicate the rate of each type T_i (see Table 3.1, $i = \{1, .., 10\}$) of rejected issue reports which were previously reported by the reporter. If a reporter has a history of

having his reported issue rejected because of reason T_i, new issue reports may be more likely to be rejected for the same reason. We calculate $rate^{T_i}_{reporter}$ as follows:

$$rate^{T_i}_{reporter} = \frac{|opened \cap T_i|}{|opened| + 1} \tag{4.3}$$

4.3 Experimental Results

In this section, we present the results of our experiments. For every research question, we discuss the motivation, approach and results.

4.3.1 RQ4.1: How much effort is spent on rejecting issue reports?

Motivation. Table 4.1 shows that a large part of the resolved issue reports in the studied ITSs are rejected (i.e., 63.65% in Linux, 80.48% in Firefox and 49.23% in Eclipse). Typically, any effort that is spent on rejecting an issue report is a waste of valuable resources of a developer. In this question, we aim to understand the impact of rejected issue reports from the resource perspective.

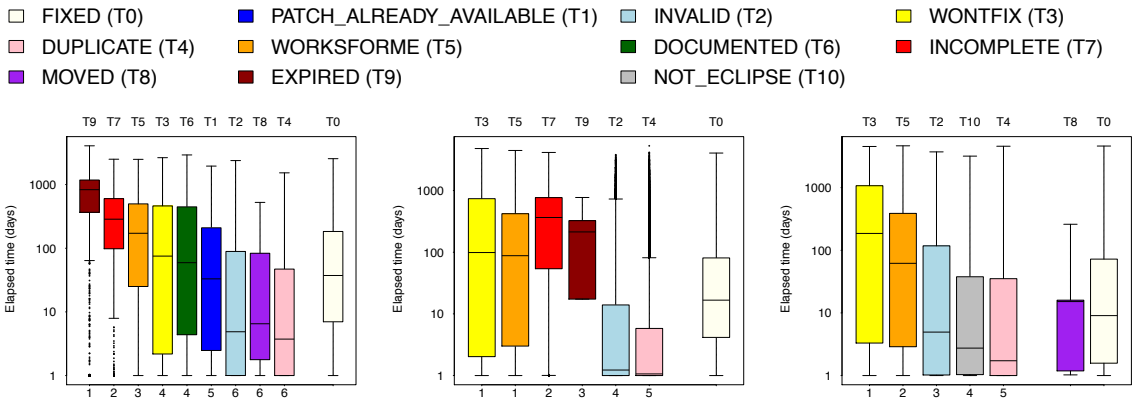
Approach. It is difficult to accurately measure effort. Therefore, we use three metrics (see Section 4.2.2) to approximate the risk of wasting effort on rejecting an issue report.

To better understand the impact of the type of rejected issue report on the effort, we extract the effort metrics for each individual resolution type of bug report. For each effort metric, we conduct a Kruskal-Wallis [94] test to decide whether the distributions are significantly different across the resolution types. The Kruskal-Wallis test is a statistical test that can determine whether two or more distributions are significantly different. When the p-value of the Kruskal-Wallis test is smaller than 0.05, at least

one of the distributions is significantly different from the other distributions. In that case, we use the post-hoc Nemenyi test [95], which conducts a pairwise statistical test on the distributions, to find which of the distributions are different. We use the results of the Nemenyi test to create groups of distributions that are not significantly different and we rank these groups using the highest mean of the distributions in that group. We use the *PMCMR* package [96] in `R` to conduct the Kruskal-Wallis and Nemenyi tests.

Results. Rejected issue reports remain unresolved in the ITS for a considerable amount of days. The longer that the rejected issue reports stay on the backlog of issue reports, the higher risk of wasting effort on them. Table 4.2 shows the five number summary of the distribution of the three effort metrics of the rejected issue reports in each studied ITS. We observe that the median number of days elapsed between the first touch of an issue report and the rejection of the report range from 6.73 (Firefox) to 72.66 (Linux) in the three studied ITSs. There exists a large difference in the number of days before an issue report gets rejected between Linux and the other two ITSs. One possible reason is that the issues reported in the Linux ITS are related to kernel and driver problems, which require longer time to debug (e.g., a very specific hardware setup is needed to reproduce the issue) and make a decision than the issues that are reported against Firefox and Eclipse.

WORKSFORME, WONTFIX, INCOMPLETE and EXPIRED issue reports take the largest number of days to get rejected. Figure 4.2 shows the distribution of the elapsed time metric for each type of rejected issue report. Figure 4.2 also shows the ranks of the types, i.e., types of which the distribution is not significantly different share the same rank. The display order of the types is based on the mean metric value.



(a) Linux (b) Firefox (c) Eclipse

Figure 4.2: The distribution of the elapsed time metric for all types of resolved issue reports in the studied ITSs.

The x-axis shows the ranks that are the result of the Kruskal-Wallis and post-hoc Nemenyi test. The ranks are ordered by the highest mean of the distributions in the rank. The y-axis shows the effort metric values (note that the y-axis is in logarithmic scale). The MOVED reports are not included in the ranking for Eclipse because there were only 5 reports with that status.

The elapsed time for FIXED issue reports is showed on the right for reference. There exists a clear difference between the elapsed time metric for the different types, with WORKSFORME, WONTFIX, INCOMPLETE and EXPIRED taking the longest to reject in Linux and Firefox.

DUPLICATE issue reports are the fastest to reject in the three studied ITSs. The short rejection time for DUPLICATE issue reports might be a direct consequence of the advanced methods for detecting duplicate issue reports [38, 39, 40, 43, 44, 45, 46, 47, 48, 49] that exist. These methods allow fast detection of duplicate issue reports, often at the triaging time.

The median number of developers that is needed to determine whether an issue should be rejected is 2. Table 4.2 shows that in all ITSs, more than half

Table 4.2: Summary of the effort metrics of the rejected issue reports in the studied ITSs.

ITS	Effort metric	Minmum	1st Quantile	Median	3rd Quantile	Maximum
Linux	Time (days)	0.00	1.17	72.66	473.90	4059.00
	# of developers	0.00	1.00	2.00	3.00	41.00
	# of comments	0.00	1.00	3.00	8.00	203.00
Firefox	Time (days)	0.00	0.01	6.73	249.60	5315.00
	# of developers	0.00	1.00	2.00	3.00	217.00
	# of comments	0.00	1.00	2.00	4.00	595.00
Eclipse	Time (days)	0.00	0.04	7.18	232.00	4649.00
	# of developers	0.00	1.00	2.00	3.00	58.00
	# of comments	0.00	1.00	2.00	4.00	213.00

of the rejected issue reports involve two or more developers. In extreme cases, the number of developers goes up to 41 (Linux), 58 (Eclipse) or even 217 (Firefox). The Firefox issue report in which 217 developers are involved describes a bug in the pop-up blocker of the Firefox browser. The majority of developers involved in resolving this issue report post examples of websites that "exploit" the bug, as requested by the reporter. At the end of the discussion, the issue report is considered as INVALID without a clear reason: *"This bug is no longer useful to me or to anyone working on our pop-up blocker (that I know of)."* This issue report is a clear example showing how the effort of developers is wasted: the reported issue was rejected after having 217 developers involved.

The median number of comments needed to reject an issue report is 2 or 3. Table 4.2 shows that in Firefox and Eclipse, the median number of comments made in the discussion regarding a rejected issue report is 2, while in Linux it is 3. In exceptional cases, the number of comments made goes into the hundreds (203 in Linux, 595 in Firefox and 213 in Eclipse).

The number of developers and comments needed to reject issue reports does not differ considerably per type. While there are some variations, there are no large

differences between different types of issue reports for the number of developers and the number of comments metrics. Hence, we do not display the distributions per type of these metrics.

> *Rejected issue reports threat the efficiency of a development team. Valuable resources are at a risk of being wasted to investigate the issue reports that are eventually rejected.*

4.3.2 RQ4.2: Is it feasible to predict whether an issue report will be rejected?

Motivation. In the previous section, we confirmed that rejected issue reports have a considerable impact on the development team in terms of effort. An accurate prediction model can help developers to focus their effort on the issue reports that are likely to describe a valid problem. Therefore, we investigate how accurately we can predict whether a new issue report will be finally rejected, by solely using the information that is available at the creation time.

Approach. We build a prediction model for each ITS using the issue report metrics that are described in Section 4.2.3. We choose to use a random forest model because it is robust to data noise and generally achieves good performance in software engineering studies [37, 52, 53, 54, 55, 56].

1) Correlation and redundancy analysis: To remove highly correlated and redundant variables, we conduct correlation and redundancy analysis on the metrics for each ITS. We calculate the Spearman rank correlation [97] for our metrics to test whether there exist highly correlated pairs of metrics as the Spearman rank correlation is resilient to non-normally distributed data. We use a variable clustering technique (i.e.,

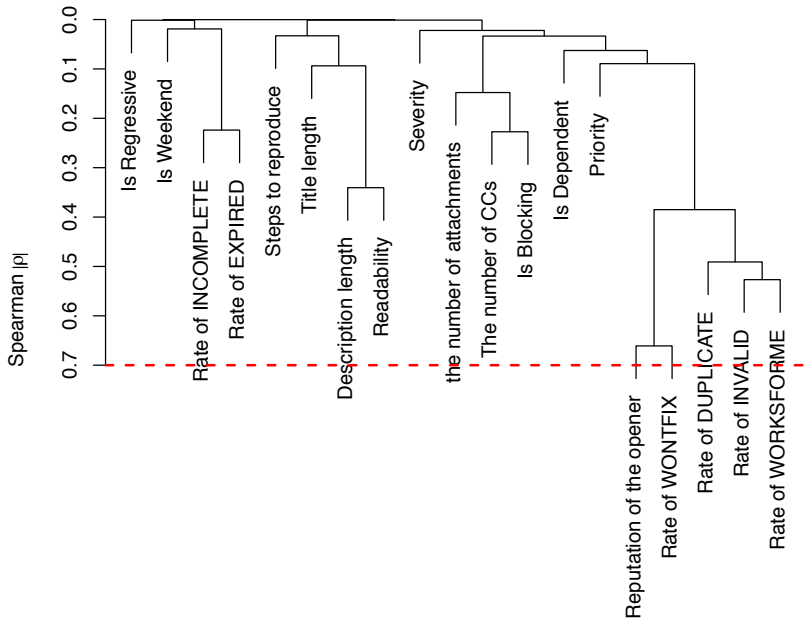


Figure 4.3: The Spearman correlation analysis for Firefox. The dotted red line indicates the threshold value of 0.7.

`varclus()`[4] in `R`) to construct a hierarchical overview of the correlation coefficient ρ.

If the correlation coefficient of two metrics is equal to or larger than 0.7, we consider this pair of metrics to be highly correlated and select one of them. The value of 0.7 has been applied as the threshold of the Spearman correlation analysis by previous studies [37, 76, 77]. Figure 4.3 shows the Spearman rank correlation of the metrics in Firefox. The horizontal lines in the forks of each pair of metrics correspond to the absolute correlation coefficient value. All metrics have a correlation coefficient value that is smaller than 0.7, which means that none of the metrics are strongly correlated. We observe that there are no correlated metrics for Linux and Eclipse neither.

In addition, we conduct redundancy analysis on the metrics using the `redun()`

[4]http://svitsrv25.epfl.ch/R-doc/library/Hmisc/html/varclus.html

function in R. Redundant metrics are metrics that can be explained by other metrics in the data, therefore they are not necessary to be included in the model. We observe that there are no redundant metrics in our data.

2) Performance evaluation: To validate the performance of our prediction models, we use four measures (i.e., precision, recall, F-measure, and accuracy) that rely on the cut-off value and an additional measure (i.e., AUC) that is free of the cut-off value. The first four measures are computed based on the confusion matrix that consists of TP (true positives), TN (true negatives), FP (false positives) and FN (false negatives). The terms positive and negative represent the prediction, and the terms true and false refer to whether the prediction matches the observation value. The values of TP, FP, TN and FN are obtained by using a cut-off value for the predicted value (from 0 to 1), which is usually 0.5. Changing the cut-off value can alter the values of the measure of precision, recall, F-measure, and accuracy.

- Precision (P) measures the correctness of our model in predicting whether an issue report will be rejected in the future. Precision is defined as the proportion of the issue reports that are predicted to be rejected that are truly rejected: $P = TP/(TP + FP)$ [84, 85].

- Recall (R) measures the completeness of our model. A model is said to be complete if it can predict all issue reports that will be rejected: $R = TP/(TP + FN)$ [84, 85].

- F-Measure (F) is the harmonic mean of the precision and recall, combining the single descriptive metrics into one metric: $F = 2 \times P \times R/(P + R)$ [85].

- Accuracy (A) calculates the percentages of the correct prediction:

$A = (TP + TN)/(TP + FP + TN + FN)$ [85].

In addition to the four measures, Area Under Curve (AUC) is used to measure the overall ability of the classifier to predict whether an issue report will be rejected. AUC is the area below the curve plotting the true positive rate against the false positive rate. The AUC value ranges from 0.5 (worst, i.e., random guessing) to 1 (best, i.e., all predictions for all issue reports are correct).

3) Model validation: We apply 10-fold cross-validation for ten times during the construction of our prediction model to prevent overfitting. During n-fold cross-validation, the data is divided into n equal-sized parts. During each fold, $n-1$ parts are used to train the model and the remaining part is used to test the model. After n folds, the standard deviation of the performance of the model is calculated to estimate the effect of overfitting. We repeat the cross-validation ten times to get an even better estimation.

4) Baseline model comparison: We use a baseline model to evaluate our random forest model. In this baseline model, we consider all issue reports that are straightforward to reject (as our random forest will allow straightforward rejection of issue reports as well). We conservatively assume that the rejected issue reports with zero or one comments were straightforwardly rejected by developers (straightforward rejection). Without a model to automatically predict whether an issue report will be rejected, developers usually investigate an issue report and conduct discussions with others then determine to reject it or not. However, developers might post one comment to explain the final resolution when an issue report was rejected or fixed (e.g.,

Linux-91[5], Fireox-1253322[6], Eclipse-15[7]).

The precision of the baseline model is considered 1, because all the straightforward rejected issue reports are truly rejected. The recall is the proportion of issue reports which are rejected by no more than one comment, compared to number of all rejected issue reports are precisely and straightforwardly rejected. The threat of our assumption is discussed in the Section 4.4

5) Important metrics: To identify the most important metrics in our random forest model, we use a permutation test [77]. In a permutation test, the values of the metric of which we want to find importance are randomly permuted in the test dataset during the cross-validation. The precision of the model on the permuted dataset and the original dataset is compared and is used as a measure to describe the importance of that metric in the model. We use the `importance()` function in the `RandomForest`[8] package in `R` during the cross-validation to obtain 100 importance scores for each metric in our dataset.

We use Scott-Knott effect size clustering (SK-ESD) [98] to group the metrics based on the effect size of their differences in importance scores. SK-ESD groups together metrics that have no significant or a negligible difference. We use the `ScottKnottESD` package in `R` with a confidence level of 95% (which is applied in previous research [37, 99] in software engineering) to cluster the metrics into groups.

Results. Our prediction model outperforms the baseline model. Table 4.3 shows the performance of our random forest and baseline model. We observe that

[5]https://bugzilla.kernel.org/show_bug.cgi?id=91 (accessed in Feb. 2016 and viable in Jul. 2016)

[6]https://bugzilla.mozilla.org/show_bug.cgi?id=1253322 (accessed in Feb. 2016 and viable in Jul. 2016)

[7]https://bugs.eclipse.org/bugs/show_bug.cgi?id=15 (accessed in Feb. 2016 and viable in Jul. 2016)

[8]https://cran.r-project.org/web/packages/randomForest/randomForest.pdf (accessed in Feb. 2016 and viable in Jul. 2016)

Table 4.3: The average performance measures and the standard deviation of our model and the baseline model in the three studied ITSs.

	Precision	Recall	F-Measure	Accuracy	AUC
Linux	0.69±0.016	0.90±0.013	0.78±0.012	0.68±0.011	0.66±0.014
Firefox	0.96±0.002	0.84±0.003	0.90±0.002	0.85±0.002	0.91±0.003
Eclipse	0.68±0.004	0.68±0.008	0.68±0.005	0.68±0.004	0.74±0.004
Baseline Model:					
Linux	1.00±0.000	0.25±0.000	0.40±0.000	0.52±0.000	0.62±0.000
Firefox	1.00±0.000	0.30±0.000	0.46±0.000	0.44±0.000	0.65±0.000
Eclipse	1.00±0.000	0.32±0.000	0.48±0.000	0.66±0.000	0.65±0.000

Table 4.4: The five important metrics in the random forest models.

The metrics are clustered and ranked using Scott-Knott effect size clustering.

ITS	Rank	Metric	Importance
Linux	1	Reputation	0.0172
	2	Is blocking	0.0111
	3	Is regressive	0.0107
	4	Readability	0.0094
	5	Number of CCs	0.0089
Firefox	1	Reputation	0.0676
	2	Rate of WONTFIX	0.0179
	3	Priority	0.0176
	4	Rate of DUPLICATE	0.0166
	5	Number of CCs	0.0143
Eclipse	1	Reputation	0.0514
	2	Rate of WONTFIX	0.0289
	3	Rate of INVALID	0.0248
	4	Rate of DUPLICATE	0.0233
	5	Rate of WORKSFORME	0.0275

our random forest models outperform the baseline model according to the F-Measure and AUC. The recall of our models is high, especially for Linux and Firefox. High recall is important in our models because it allows us to prevent developers from wasting effort on issue reports that will be rejected. We observe that the proportion of rejected issue reports in the ITS might affect the performance of the prediction model. For example, there are 49.23% rejected issue reports in Eclipse, which is the smallest number of the three studied systems, which could be the reason for the low recall of the Eclipse model.

Reputation is the most important metric for deciding whether a report

will be rejected in all three studied ITSs. Table 4.4 shows the top 5 most important metrics after clustering and ranking them with Scott-Knott effect size clustering. The importance of the reputation of the developer confirms that issue reports that are opened by a developer who has successfully had his reports addressed in the past, are more likely to be addressed [27, 74]. A possible explanation is that a large number of the rejected issue reports are reported by one-time reporters, who do not enclose sufficient information in a report to address an issue.

An observation that is related to the importance of reputation of the reporter, is that the rate of certain types of rejected issue reports ranks high in the list of important metrics. A similar reasoning for a possible explanation could be given as for the reputation metric.

Another interesting observation is that importance metrics that reporters assign to their report (e.g., severity, priority) are no guarantee for getting an issue report addressed. Only priority is an important metric in the Firefox ITS.

Our random forest model outperforms the baseline model. The reputation of a reporter is the most important metric in the model for all three ITSs.

4.3.3 RQ4.3: How accurately can we rank issue reports based on their validity likelihood?

Motivation. When there are more new issue reports filed into an ITS than the triagers can handle, a *backlog* of issue reports that need to be assigned emerges. Having a large backlog of unassigned issue reports can be a threat to the quality of a software project, as severe issues may be left unaddressed. In addition, the larger

Table 4.5: The average number of issue reports that are opened, fixed and assigned each day in the studied ITSs.

ITS	# of Daily Opened Reports	# of Daily Fixed Reports	# of Daily Assigned Reports	Total # of Backlog
Linux	5.8	2.8	4.9	3,966
Firefox	31.7	6.5	23.0	18,573
Eclipse	76.9	45.5	16.0	12,750

[1]The number of backlog refers to the total number of unassigned issue reports on February 2, 2016.

the size of the backlog, the more difficult it becomes for a triager to identify the valid issue reports.

Table 4.5 shows that there are 5.8 (Linux), 31.7 (Firefox) and 76.9 (Eclipse) new issue reports filed each day in the studied ITSs. However, the triagers are able to assign only respectively 4.88, 23.04, and 16.02 of the new issue reports to a developer every day. Hence, the backlog of unassigned issue reports grows steadily in all three studied ITSs.

Ideally, a model can be used to assist the triager in handling the backlog of unassigned issue reports. However, as shown in the previous section, our model is unable to achieve a 100% precision and recall. Therefore, our model may either mistake issue reports that should be rejected for valid reports, or the model may disregard valid issue reports.

In this question, we investigate whether we can provide the triager with a ranking of issue reports that are likely to be valid. Such a ranking allows the triager to focus the limited available time on assigning issue reports that are most likely to be valid and disregard the issue reports that are likely to be rejected.

Approach. To rank the backlog of issue reports that need to be assigned, we use a learning-to-rank (L2R) model to rank the remaining issue reports based on their validity likelihood. L2R has been widely adopted in the area of information retrieval

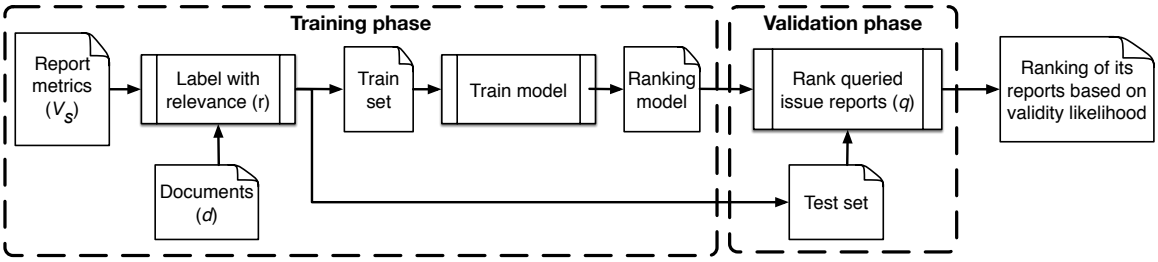


Figure 4.4: An overview of our ranking approach.

over the past years [100, 101], e.g., in search engines. A L2R model ranks a set of documents (e.g., web pages) based on their relevance to a query. For example, the query 'Bugzilla' will return a set of web pages that talk about Bugzilla, with the most relevant page on the highest rank. Figure 4.4 shows our approach for ranking issue reports.

1) Training phase: A L2R model must be trained using a set of queries and documents that are labeled with their relevance to that query. The model generates a ranking schema, which uses the feature vector V_s of an unlabeled document d to compute its relevance r to a query q. In our study, we define d, r, q and V_s as follows:

d: An issue report.

r: The likelihood of d being a valid issue report.

q: The query to retrieve the documents with the highest likelihood of being valid issue reports.

V_s: The set of features (i.e., the metrics that are described in Section 4.2.3) of d.

To train the ranking model, we label all documents in the training data as valid or rejected (according to the resolution of the issue reports). We use the the `RankLib`[9]

[9]https://sourceforge.net/p/lemur/wiki/RankLib/

software to train a random forest ranking model. We choose the random forest ranking model as it is reported to achieve high accuracy and perform faster than other ranking algorithms [102].

2) Validation phase: To validate our ranking model, we conduct ten times 10-fold cross-validation. During 10-fold cross-validation, the data is divided into ten equally-sized chunks. During each fold, nine chunks are used to train the model and one chunk is used to test the model.

We use the precision at position k ($P@k$) and the normalized discounted cumulative gain ($NDCG@k$) to evaluate the performance of the ranking model. $P@k$ corresponds to the number of relevant documents in the first k positions of the rankings. Note that generally, recall is not used to evaluate ranking models, as there are potentially thousands of documents that are relevant to a query. Because it is not possible to read all those documents for a human, we focus on precision at a position k instead. $P@k$ is defined as follows [102]:

$$P@k(\pi, l) = \frac{\sum_{t=1}^{t \leq k} I_{(l_{\pi^{-1}(j)}=1)}}{k} \tag{4.4}$$

where π is the ranked list of issue reports with their relevance labels l, $I_{\{.\}}$ is the indicator function, and $\pi^{-1}(j)$ the issue report that is ranked at position j of π.

The indicator function returns 1 for documents that are relevant and 0 for documents that are not relevant. Table 4.6 shows an example ranking of three issue reports. In this table, $P@1 = 1$, $P@2 = 0.5$ and $P@3 = 0.67$.

Precision at position k does not take the actual position in the ranking into account. Hence, in the example in Table 4.6, $P@2$ would still be 0.5 if the first and second ranks were switched, even though the actual ranking would be worse because

Table 4.6: Example ranking result of three Firefox issue reports for q = *valid issue reports.*

Rank	Report	Relevance
1	#383380: Spell Check Not giving correct spelling	Valid
2	#335348: "Save Image As ..." should include path	Rejected
3	#763312: Menus often get lost on Linux	Valid
...	...	...

a rejected issue reported was ranked the highest.

The discounted cumulative gain at position k ($DCG@k$) [102] metric takes the position of an issue report into account, as it has an explicit position discount factor in its definition. Therefore, issue reports with a high validity likelihood but a low ranking negatively affect the DCG. $DCG@k$ is defined as follows:

$$DCG@k = \sum_{j=1}^{k} \frac{2^{r_j} - 1}{log_2(1+j)} \tag{4.5}$$

where r_j is the relevance label (1 for valid reports, 0 for rejected reports) of the issue report in the j_{th} position in the ranking list.

In the example in Table 4.6, $DCG@1 = 1$, $DCG@2 = 1$ and $DCG@3 = 1.5$. The $DCG@k$ is normalized to get the $NDCG@k$ which ranges from 0 to 1:

$$NDCG@k = \frac{DCG@k}{IDCG@k} \tag{4.6}$$

where $IDCG@k$ is the ideal $DCG@K$ value, which can be obtained by reordering the list with all valid issues in the highest ranks and computing the $DCG@k$ for the list. Hence, for our example in Table 4.6, $IDCG@k = 1.63$ and $NDCG@k = 0.92$.

We compute the $P@k$ and $NDCG@k$ metrics for $k = 1, .., 20$ for all three studied ITSs. In addition, we compute $k = 30$ and $k = 40$ for Firefox as the average number

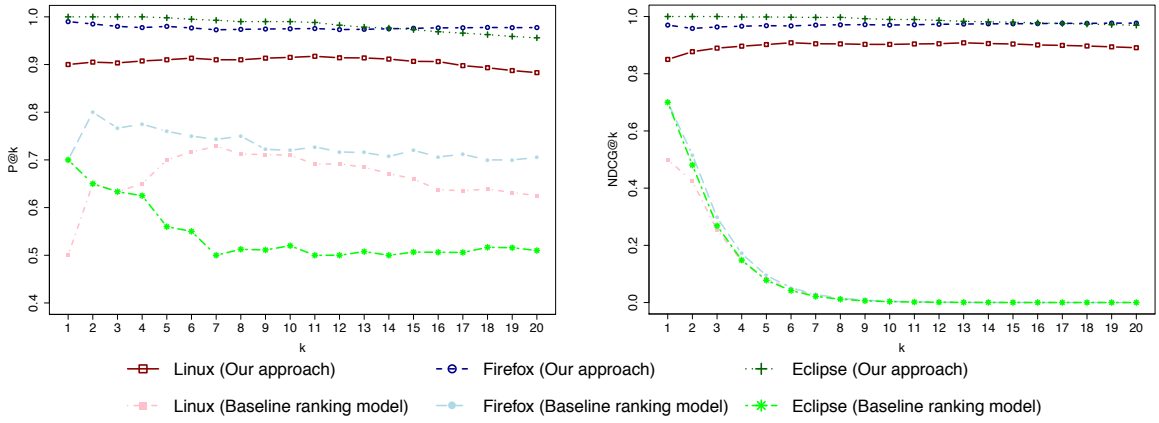


Figure 4.5: The mean values of $P@k$ and $NDCG@k$ that are achieved by our approach and the baseline ranking model.

of assigned reports per day is higher for Firefox. Hence, there is a need for high performance in a larger ranking than in Linux and Eclipse.

3) Baseline ranking model: In the current practice, the developers are likely to first handle older issue reports with a higher severity value. To measure the contribution of our ranking model, we setup the baseline ranking model based on the age and severity of issue reports. In the baseline ranking model, we first rank our testing issue reports by the reporting time (i.e., an issue report would be ranked higher if it were opened earlier) and then by severity, if issue reports are opened at the same day (i.e., an issue report would be ranked higher if it has a higher severity than other issue reports which are opened at the same day).

Results. Our ranking model achieves a high precision (i.e., 0.85 to 1.00) in the top k returned reports. The performance is better than the baseline ranking model that achieves an average $P@k$ (i.e., k from 1 to 20) around 0.69 in Linux, 0.73 in Firefox and 0.50 in Eclipse. Figure 4.5 shows the mean values of $P@k$ and $NDCG@k$ at various positions (i.e., k from 1 to 20). In the three studied ITSs, both

$P@k$ and $NDCG@k$ range from 0.85 to 1.00 for the studied values of k.

The number of daily triaged issue reports further demonstrates the practical usefulness of our approach. For instance, the average number of daily triaged issue reports in Firefox is 23, and our approach achieves a $P@23$ of 0.98 on the top 23 returned reports. By inspecting the top 23 reports, triagers who use our approach can identify about 22.5 ($\approx 23 \times 98\%$) valid reports; while triagers who pick up 23 reports by the baseline ranking model can identify only 15.64 ($\approx 23 \times 68\%$) valid reports. Although the size of the backlog of all reports may be the same as before (if the amount of daily triaged reports remain unchanged), there will be much less valid reports waiting in the backlog. As such, the issue reports that describe valid problems can be inspected and resolved at an earlier stage than before. Similar improvements of the triaging efficiency are also observed in the other two ITSs.

Our ranking model still outperforms the baseline ranking model when k increases. For instance, our model achieves an average precision (previous 20 positions) of 0.85 in Linux; while the baseline ranking model yields an average precision of 0.69. Therefore, our approach provides a good set of candidate reports that are likely to report valid issues. Enlarging the set of candidate reports is necessary, if triagers need to inspect a particular type of issues (e.g., issues with high reported priority or issues concerning security).

Our ranking model achieves high precision for the top ranked reports. Therefore, the triaging process can benefit from using a ranking model to prioritize issue reports that are likely to be valid.

4.4 Threats to validity

In this section, we discuss the threats to the validity of our study.

External Validity. One of the external threats to our results is generalization. In this chapter, we study the ITSs of three popular open source software projects. Even though these projects are well-developed, the process of rejecting issue reports may be different in industrial or other open source projects. In addition, all three studied projects make use of the Bugzilla ITS. Our findings might not hold true for projects that use other types of ITSs (e.g., JIRA). For example, we can not determine whether an issue is blocking in projects that use the JIRA ITS because JIRA does not support a field to indicate whether an issue is blocking. In order to address this threat, additional research is necessary to better understand the generalization of our results.

Internal Validity. One of the internal threats to our results is that we assume that the behaviour of development teams regarding rejected issue reports does not change over time. It is possible that at different stages in the studied period, projects enforced different policies or developers changed their habits regarding rejected issue reports. For example, as the number of new issue reports per day increases, projects may become more strict in selecting the issues that will be addressed.

Another internal threat is that our baseline model in the RQ4.2 might contain noise, as there may exist non-straightforwardly rejected issue reports among the issue reports which are rejected with one comment (e.g., in Linux-78[10], the only-one comment further analyzes the issues and discuss with the reporter how to resolve the issue). However, inclusion of such non-straightforwardly rejected issue reports only

[10]https://bugzilla.kernel.org/show_bug.cgi?id=78

improves the performance of the baseline model. Hence, our results and conclusion are not affected by this threat.

Construct Validity. In our study on the effort spent on rejecting issue reports we use metrics that can be extracted from the issue report or ITS. However, these metrics are a rough estimation of the actual effort spent by developers on rejecting the report. The usage of these metrics does not affect the evaluation of our approach in RQ4.2 and RQ4.3. In future work, this threat needs to be addressed by, e.g., interviewing developers about the effort required to reject an issue report.

4.5 Summary

In this chapter, we study the risk of wasting effort on rejected issue reports from three perspectives, i.e., the time elapsed for handling a rejected issue report, the number of developers involved and the number of comments in a rejected report. We find that rejected issue reports are indeed a threat to the efficiency of a development team. For instance, the time elapsed in dealing with rejected issue reports are 6.73 (Firefox), 7.18 (Eclipse) and 72.66 (Linux) days respectively and the median number of involved developers in rejected issue reports is two. Hence, we build a random forest model to predict whether an issue report will be rejected in the end. The results show that our prediction model outperforms the baseline model. In particular, the average precision of our model ranges from 0.68 to 0.90 in the three studied projects. However, our model cannot achieve a 100% precision. Therefore, we further propose a ranking model that prioritizes untriaged issue reports by their validity likelihood. Our ranking model achieves a higher mean precision than the baseline ranking model (i.e., 0.85 vs. 0.69 in Linux, 0.98 vs. 0.73 in Firefox, and 0.96 vs. 0.51 in Eclipse at the top 20

positions).

Chapter 5

Conclusions

In this chapter, we describe the contribution and findings of the thesis. Then, we explore the directions of the future work.

5.1 Contributions and Findings

The overall goal of this thesis is to improve the effectiveness of the issue resolving process. As raising questions by developers from issue reports is one of the threats towards the efficiency of the issue resolving process, we first examine if it is feasible to predict an issue report will be raised questions when it is created. Then, we focus the negative impact of the rejected issue reports on the efficiency of the issue resolving process and apply machine learning techniques to predict the rejected issue reports. We summarize the major contributions and findings of the thesis as follows.

- We perform an in-depth analysis on the raised questions by developers from issue reports during the issue resolving process. We observe that raising questions negatively impacts the efficiency of the issue resolving process. For example, issue reports with raised questions require more effort to fix the issues (e.g., in

terms of the elapsed time, the number of involved developers and comments and the number of assignments). Therefore, we propose an approach to predict if questions are likely to be raised by developers from an issue report when the issue report is created. The values of AUC of the prediction model in our subject systems are ranged from 0.65 to 0.78. The results of the prediction model show that it is feasible to give developers an early warning of the issue reports that are likely to raise questions by developers. The issue reporters and developers should pay more attention to the issue reports with a high chance of having questions raised.

- We conduct an empirical investigation of all types of rejected issue reports in three large projects. We find that rejected issue reports could have wasted the effort of a development team. We also propose the identification of a set of important metrics for predicting if an issue report will be rejected. Then, we propose a ranking approach that can accurately highlight valid issue reports for the issue resolving task. The results show that our approach achieves an average precision of 0.88, 0.98 and 0.96 for the top-20 ranked list of issue reports in Linux, Firefox and Eclipse, respectively. The evaluation results show that the proposed approach can reduce the effort spent on the rejected issue reports during issue resolving process. With our approach, developers can focus more resources on the issue reports that are more likely to describe real problems and need to be fixed.

5.2 Future Work

5.2.1 Combining with Texual Metrics

In this thesis, we propose metrics to characterize issue reports. All these metrics are identified from the issue reports. For instance, *The size of the title* calculates the number of words of the title from an issue report. Adding the textual metrics as independent variables to prediction models can be beneficial to the effectiveness of our models. We plan to investigate the textual metrics from the description of issue reports, and add the textual metrics to build prediction models.

5.2.2 Generalization of Our Approaches in Othe Projects

The applied issue tracking systems may be various in different projects. Our subject systems use Bugzilla to track the reported issues. However, some projects (e.g., CXF, Derby, Hadoop) utilize JIRA to track and fix the reported issues. Such differences might affect the performance of our approaches. We will pay more attention to the evaluation of the generalization of our approaches in more projects in the future.

5.2.3 Exploring the Generalization of Other Techniques

There are different kinds of machine learning models. For instance, supervised classification models (e.g., random forest, logistic regression which are applied in Chapter 3 and Chapter 4) and unsupervised classification models (e.g., k-means clustering, partition around medoids and so forth), linear models (e.g., linear regression model) and non-linear models (e.g., naive bayes). In the future work, we can apply other machine learning techniques to build prediction models.

5.2.4 Integrating Our Approaches in the Practices

In the future, we plan to apply our approaches to develop a tool to reduce the developers' effort spent on the issue resolving process.

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