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Extracting Actionable Information From Bug Reports

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Computer Science

by

Bo Zhou

December 2016

Dissertation Committee:

Dr. Rajiv Gupta, Chairperson
Dr. Iulian Neamtiu
Dr. Zhiyun Qian
Dr. Zhijia Zhao

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The Dissertation of Bo Zhou is approved:

Committee Chairperson

University of California, Riverside

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To my parents and my love for all the support.

ABSTRACT OF THE DISSERTATION

Extracting Actionable Information From Bug Reports

by

Bo Zhou

Doctor of Philosophy, Graduate Program in Computer Science
University of California, Riverside, December 2016
Dr. Rajiv Gupta, Chairperson

Finding and fixing bugs is a major but time- and effort-consuming task for software quality assurance in software development process. When a bug is filed, valuable multi-dimensional information is captured by the bug report and stored in the bug tracking system. However, developers and researchers have so far used only part of this information (e.g., a detailed description of a failure and occasionally hint at the location of the fault in the code), and for limited purposes, e.g., finding and fixing bugs, detecting duplicate bug reports, or improving bug triagging accuracy. We contend that this information is useful not only for software testing and debugging but also for product understanding, software evolution, and software management. This dissertation makes several advances in extracting actionable information from bug reports using data mining and nature language processing techniques. Both software developers and researchers can benefit from our approach.

We first focus on differences in bugs and bug-fixing processes between desktop and smartphone applications. Specifically, our investigation has two main thrusts: a quantitative analysis to discover similarities and differences between desktop and smartphone bug reports/processes, and a qualitative analysis where we extract topics from bug reports to understand bugs' nature, categories, as well as differences between platforms.

Next, we present an approach whose focus is understanding the differences between concurrency and non-concurrency bugs, the differences among various concurrency bug classes, and predicting bug quantity, type, and location, from patches, bug reports and bug-fix metrics.

In addition, we found that bugs of different severities have so far been "lumped together" even though their characteristics differ significantly. Moreover, we found that the nature of issues with the same severity, (e.g., high-severity), differs markedly between desktops and smartphones. To understand these differences, we perform an empirical study on 72 Android and desktop projects. We study how severity changes, quantify the differences between classes in terms of bug-fixing attributes and analyze how the topics differ across classes on each platform over time.

Finally, we aid bug reproduction and fixing: we propose a novel delta debugging technique to reduce the length of event traces by using a record&replay scheme. When we capture the event sequence while executing the application, an event dependency graph (EDG) will be generated. Then we use the EDG to guide the delta debugging algorithm by eliminating irrelevant events. Therefore, the debugging process can be improved significantly if events that are irrelevant to the crash are filtered out.

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Chapter 1

Introduction

1.1 Motivation

In less than a century the software market has grown from being non-existent, into an almost trillion-dollar industry. The total software and software services revenue for the Top-500 Software companies alone totalled \$748.7 billion in 2015, up 4.3 percent from 2014's \$717.7 billion [132]. Today, software powers almost all devices, from pacemakers to personal computers, smartphones and tablets, that we have come to rely on so heavily in our daily lives. In the future even more devices and appliances, such as household appliances, watches, cars, and even glasses, will become "smart" devices powered by software, hence the software market will only continue to expand and evolve.

Software companies are very keen on maintaining the quality of their software products since these products are key. Due to the fallibility of developers and the complexity of maintaining software, bugs invariably creep into these products. Software *bug* is the common term used to describe an error, flaw, failure or fault in a computer program or system that causes it to produce an incorrect or unexpected result, or to behave in unintended ways. Finding and fixing bugs is a major but time- and effort-consuming task for software quality assurance in software development process.

A key collaborative hub for many software projects is a database of reports describing both bugs that need to be fixed and new features to be added [35]. This database is often called a *bug tracking system* or *bug repository*. The use of a bug tracking system can improve the development process by allowing users to inform developers of the problems encountered while using that software.

Bug reports usually contain valuable information that could be used to improve the quality of the product (e.g., a detailed description of a failure and occasionally hint at the location of the fault in the code). One of the challenges is that most of the work that uses bug reports is focused on improving bug report quality (e.g., finding duplicate bug reports) and use bug reports to guide maintenance process (e.g., improve bug triaging accuracy). But there has been only limited use of bug reports in software evolution, software management and software debugging.

1.2 Dissertation Overview

This dissertation presents a study of several applications of software bug reports in many new aspects in software engineering which include using bug reports to facilitate bug understanding, software management, and software debugging process. Figure 1.1 gives the framework overview of this dissertation – we elaborate on the framework in later chapters.

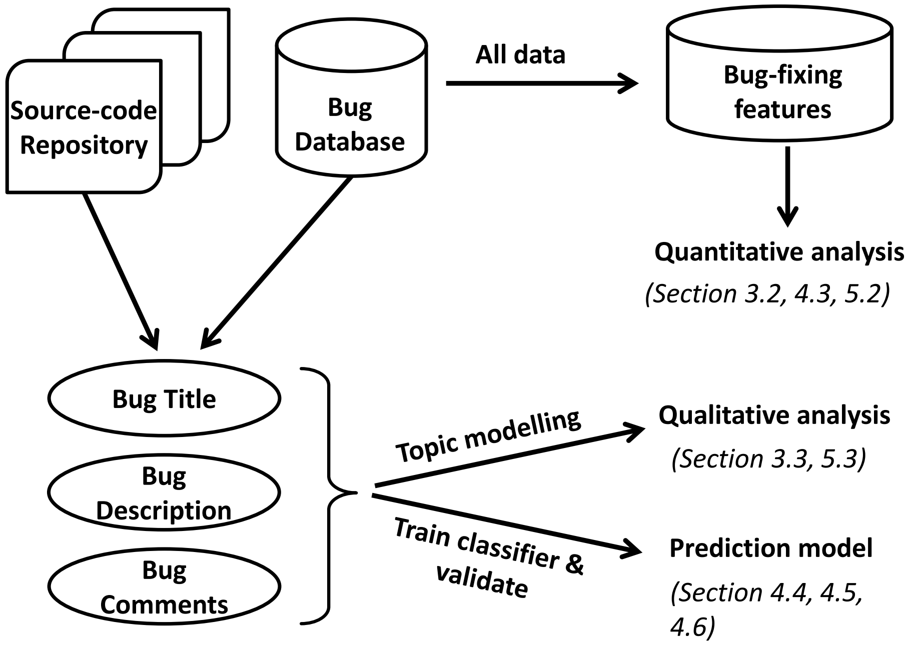


Figure 1.1: Framework overview.

1.2.1 Cross-platform Analysis

Smartphones and the applications ("apps") running on them continue to grow in popularity [126] and revenue [81]. This increase is shifting client-side software development and use, away from traditional desktop programs and towards smartphone apps [65, 74].

Smartphone apps are different from desktop programs on a number of levels: novelty of the platform (the leading platforms, Android and iOS, have become available in 2007), construction (sensor-, gesture-, and event-driven [50]), concerns (security and privacy due to access to sensitive data), and constraints (low memory and power consumption).

Empirical bugs and bug-fixing studies so far have mostly focused on traditional software; few efforts [21, 99] have investigated the differences between desktop and smartphone software. Therefore, in this dissertation we analyzed the similarities and differences in bug reports and bug-fixing processes between desktop and smartphone platforms. Our study covers 88 projects (34 on desktop, 38 on Android, 16 on iOS) encompassing 444,129 bug reports. We analyzed bugs in a time span beginning in 1998 for desktop and 2007 for Android/iOS, and ending at the end of December 2013.

In particular, we studied the bug-fix process features, bug nature and the reporter/fixer relationship to understand how bugs, as well as bug-fixing processes, differ between desktop and smartphone. We shed light on how bug characteristics vary across platforms and then use this information to help developers to improve product quality.

1.2.2 Empirical Study on Concurrency Bugs

Concurrent programming is challenging, and concurrency bugs are particularly hard to diagnose and fix for several reasons, e.g., thread interleavings and shared data complicate reasoning about program state [95], and bugs are difficult to reproduce due to non-determinism and platform-specific behavior. As a result, we show that fixing concurrency bugs takes longer, requires more developers, and involves more patches, compared to fixing non-concurrency bugs.

Many recent efforts have focused on concurrency bugs, with various goals. On one side, there are empirical studies about the characteristics and effects of concurrency bugs [46, 93, 138], but they do not offer a way to predict bug quantity, type and location. On the other side, static [39] or dynamic analyses [94] aim to detect particular types of concurrency bugs. Such analyses help with precise identification of bugs in the current source code version, but their focus is different—finding specific types of bugs in the current version, rather than using evolution data to predict the future number, kind, and location of bugs;

in addition, program analysis is subject to scalability constraints which are particularly acute in large projects. While other prior efforts have introduced models for predicting bug quantity [78, 116] and bug location [107, 122] without regard to a specific bug category, we are specifically interested in isolating concurrency bugs and reporting prediction strategies that work well for them. Hence in this dissertation we study the nature of concurrency bugs, how they differ from non-concurrency bugs, and how to effectively predict them; we use statistics and machine learning as our main tools.

Our study analyzes the source code evolution and bug repositories of three large, popular open-source projects: Mozilla, KDE and Apache. Each project has had a history of more than 10 years, and their size has varied from 110 KLOC to 14,330 KLOC. Such projects benefit from our approach for several reasons: (1) large code bases pose scalability, coverage and reproducibility problems to static and dynamic analyses; (2) large collaborative projects where bug reporters differ from bug fixers benefit from predictors that help fixers narrow down the likely cause and location of a bug reported by someone else; (3) a quantitative predictor for estimating the incidence of concurrency bugs in next releases can help with release planning and resource allocation.

1.2.3 Bug Analysis on Severity Classes

Bug tracking systems such as Bugzilla, Trac, or Jira are widely popular in large-scale collaborative software development. Such systems are instrumental as they provide a structured platform for interaction between bug reporters and bug fixers, and permit reporting, tracking the progress, collaborating on, and ultimately fixing or addressing the reported bugs (issues).

A key attribute of each bug report on these systems is *bug severity*—an indicator of the bug's potential impact on users. While different bug tracking systems use different severity scales, we found that bugs can be assigned into one of three severity classes: *high severity bugs* represent issues that are genuine show-stoppers, e.g., crashes, data corruption, privacy leaks; *medium severity bugs* refer to issues such as application logic issues or occasional crashes; and *low severity bugs* usually refer to nuisances or requests for improvement.

Severity is important for effort planning and resource allocation during the bug-fixing process; we illustrate this with several examples. First, while our intuition says that bugs with different severity levels need to be treated differently, for planning purposes we need to know how bug severity influences bug characteristics, e.g., fix time or developer workload. Second, assigning the wrong severity to a bug will lead to resource mis-allocation and wasting time and effort; a project where bugs are routinely assigned the wrong severity level might have a flawed bug triaging process. Third, if high-severity bugs tend to have a common cause, e.g., concurrency, that suggests more time and effort needs to be allocated to preventing those specific issues (in this case concurrency). Hence understanding bug severity can make development and maintenance more efficient.

To this end, we have performed a thorough study of severity in a large corpus of bugs on two platforms, desktop and Android. Most of the prior work on bug severity has focused on severity prediction [83, 84, 105, 141]; there has been no research on how severity is assigned and how it changes, on how bugs of different severities differ in terms of characteristics (e.g., in fix time, developer activity, and developer profiles), and on the topics associated with different classes of severity. Therefore, to the best of our knowledge, we are the first to investigate differences in bug characteristics based on different severity classes across multiple platforms.

1.2.4 Delta Debugging on Android

When a new bug report is filed into the bug tracking system, a developer must debug it in order to fix the problem. Debugging usually consists of two steps. The first step is reproducing the failure. Reproducing is important because without reproducing the bug, the developer will have trouble diagnosing and verifying the problem to figure out the correct fixing strategy. The second step is finding the root cause of the bug. For this purpose, the developer must track the cause-back chain which leads to the failure location and identifies the root cause.

To reproduce a particular bug, developers need information about reproduction steps, i.e., the sequence of program statement, system events or user steps to trigger the bug, and information about the failure environment, i.e., the setting in which the bug occurs [156]. Developers can obtain reproduction steps and failure environment information mainly in two ways: bug report and collection of field data. Bug reports submitted by users often do not contain reproduction steps or the information provided by users are wrong or incomplete [85, 167]. Alternatively, developers can execute the application and collect field data, i.e., data about the runtime behavior and runtime environment of deployed programs [115]. Such approaches usually generate enormous amounts of tracing data which not only makes debugging process difficulty but also risky, as the developer cannot predict when a particular bug will be found. Therefore, simplification of the bug-revealing trace is an important and essential step towards the debugging.

Minimizing Delta Debugging (DD) has been introduced as an effective and efficient procedure for simplification of the failing test-case by performing at most polynomial (of the second order) number of tests [157, 159]. DD is an extremely useful algorithm and widely used in practice. Unfortunately, we cannot directly apply the traditional DD algorithm on Android platform applications since Android applications are event-based. We cannot reduce the size of input event sequence without considering the dependency between events.

We present an approach to collect field data automatically and extract reproduction steps from captured data by using a record & replay scheme. We capture the event sequence while executing the application and generate an event dependency graph (EDG). Then we use the EDG to guide the DD algorithm by eliminating irrelevant events.

1.3 Thesis Organization

The remainder of the dissertation is organized as follows. Chapter 2 describes the framework and general process. In Chapter 3, we present the results of a cross-platform study between desktop, Android and iOS bugs. In Chapter 4, we analyze concurrency bugs and introduce three prediction models on bug number, bug type, and bug location, respectively. In Chapter 5, we compare bug characteristics between different bug severity classes. Chapter 6 presents the event-based delta debugging algorithm on Android to reduce the reproduction steps. Chapter 7 describes related work. Finally, Chapter 8 summarizes the contributions of this dissertation and identifies directions for future work.

Chapter 2

Framework Overview

In this chapter we describe the data extraction process and our empirical study framework. Figure 1.1 shows the process of our study. We first collect a large number of bug reports from multiple platforms and extract useful features. Then we use these features to build quantitative analyses, qualitative analyses, and prediction models.

2.1 Applications

We chose 88 open source projects for our study, spread across three platforms: 34 desktop projects, 38 Android projects, and 16 iOS projects. We used several criteria for choosing these projects and reducing confounding factors. First, the projects we selected had large user bases, e.g., on desktop we chose[1] Firefox, Eclipse, Apache, KDE, Linux kernel, WordPress, etc.; on Android, we chose Firefox for Android, Chrome for Android, Android platform, K-9 Mail, WordPress for Android; on iOS we chose Chrome for iOS, VLC for iOS, WordPress for iOS,

[1]Many of the desktop projects we chose have previously been used in empirical studies [17, 48, 59, 82, 153, 167].

etc. Second, we chose projects that are popular, as indicated by the number of downloads and ratings on app marketplaces. For the Android projects, the mean number of downloads, per Google Play, was 1 million, while the mean number of user ratings was 7,807. For the iOS projects, the mean number of ratings on Apple's App Store was 3,596; the store does not provide the number of downloads. Third, we chose projects that have had a relatively long evolution history ("relatively long" because the Android and iOS platforms emerged in 2007). Fourth, to reduce selection bias, we choose projects from a wide range of categories—browsers, media players, utilities, infrastructure.

Tables 2.1–2.3 show all the projects we use for our study. For each platform, we show the project's name, the number of fixed bugs, the lifespan of the project (counted in years) and the chapter number of the project used in the dissertation.

All the projects in our study offer public access to their bug tracking systems. The projects used various bug trackers: desktop projects tend to use Bugzilla, Trac, or JIRA, while smartphone projects use mostly Google Code, though some use Bugzilla or Trac. We used Scrapy,[2] an open source web scraping tool, to crawl and extract bug report features from bug reports located in each bug tracking system.

For bug repositories based on Bugzilla, Trac, and JIRA, we only considered bugs with resolution `RESOLVED` or `FIXED`, and status `CLOSED`, as these are confirmed bugs; we did not consider bugs with other statuses, e.g., `UNCONFIRMED` and other resolutions, e.g., `WONTFIX`, `INVALID`. For Google Code repositories, we selected bug reports with type `defect` and status `fixed`, `done`, `released`, or `verified`.

[2]http://scrapy.org

Desktop				
Project	Bugs		Time span	Used Chapter
	Reported	Fixed		
Mozilla Core	247,376	101,647	2/98-12/13	3, 4, 5
OpenOffice	124,373	48,067	10/00-12/13	3, 5
Gnome Core	160,825	42,867	10/01-12/13	3, 5
Eclipse platform	100,559	42,401	2/99-12/13	3, 5
Eclipse JDT	50,370	22,775	10/01-12/13	3, 5
Firefox	132,917	19,312	4/98-12/13	3, 4, 5
SeaMonkey	91,656	18,831	4/01-12/13	3, 5
Konqueror	38,156	15,990	4/00-12/13	3, 4, 5
Eclipse CDT	17,646	10,168	1/02-12/13	3, 5
WordPress	26,632	9,995	6/04-12/13	3, 5
KMail	21,636	8,324	11/02-12/13	3, 4, 5
Linux Kernel	22,671	7,535	3/99-12/13	3, 5
Thunder-bird	39,323	5,684	4/00-12/13	3, 5
Amarok	18,212	5,400	11/03-12/13	3, 4, 5
Plasma Desktop	22,187	5,294	7/02-12/13	3, 4, 5
Mylyn	8,461	5,050	10/05-12/13	3, 5
Spring	15,300	4,937	8/00-12/13	3, 5
Tomcat	11,332	4,826	11/03-12/13	3, 5
MantisBT	11,484	4,141	2/01-12/13	3, 5
Hadoop	11,444	4,077	10/05-12/13	3, 5
VLC	9,674	3,892	5/05-12/13	3, 5
Kdevelop	7,824	3,572	8/99-12/13	3, 4, 5
Kate	7,058	3,326	1/00-12/13	3, 4, 5
Lucene	5,327	3,035	4/02-12/13	3, 5
Kopete	9,824	2,957	10/01-9/13	3, 4, 5
Hibernate	8,366	2,737	10/00-12/13	3, 5
Ant	5,848	2,612	4/03-12/13	3, 5
Apache Cassandra	3,609	2,463	8/04-12/13	3, 5
digikam	6,107	2,400	3/02-12/13	3, 4, 5
Apache httpd	7,666	2,334	2/03-10/13	3, 4, 5
Dolphin	7,097	2,161	6/02-12/13	3, 4, 5
K3b	4,009	1,380	4/04-11/13	3, 4, 5
Apache Maven	2,586	1,332	10/01-12/13	3, 5
Portable OpenSSH	2,206	1,061	3/09-12/13	3, 5
Total	*1,259,758*	*422,583*		

Table 2.1: Overview of examined projects for desktop.

Android				
Project	Bugs		Time span	Used Chapter
	Reported	Fixed		
Android Platform	64,158	3,497	11/07-12/13	3, 5
Firefox for Android	11,998	4,489	9/08-12/13	3, 5
K-9 Mail	6,079	1,200	6/10-12/13	3, 5
Chrome for Android	3,787	1,601	10/08-12/13	3, 5
OsmAnd Maps	2,253	1,018	1/12-12/13	3, 5
AnkiDroid Flashcards	1,940	746	7/09-12/13	3, 5
CSipSimple	2,584	604	4/10-12/13	3, 5
My Tracks	1,433	525	5/10-12/13	3, 5
Cyanogen-Mod	788	432	9/10-1/13	3, 5
Andro-minion	623	346	9/11-11/13	3, 5
WordPress for Android	532	317	9/09-9/13	3, 5
Sipdroid	1,149	300	4/09-4/13	3, 5
AnySoft-Keyboard	1,144	229	5/09-5/12	3, 5
libphone-number	389	219	11/07-12/13	3, 5
ZXing	1,696	218	5/09-12/12	3, 5
SL4A	701	204	10/09-5/12	3, 5
WebSMS-Droid	815	197	7/10-12/13	3, 5
OpenIntents	553	188	12/07-6/12	3, 5
IMSDroid	502	183	6/10-3/13	3, 5
Wikimedia Mobile	261	166	1/09-9/12	3, 5
OSMdroid	494	166	2/09-12/13	3, 5
WebKit	225	157	11/09-3/13	3, 5
XBMC Remote	729	129	9/09-11/11	3, 5
Mapsforge	466	127	2/09-12/13	3, 5
libgdx	384	126	5/10-12/13	3, 5
WiFi Tether	1,938	125	11/09-7/13	3, 5
Call Meter NG/3G	904	116	2/10-11/13	3, 5
GAOSP	529	114	2/09-5/11	3, 5
Open GPS Tracker	391	114	7/11-9/12	3, 5
CM7 Atrix	337	103	3/11-5/12	3, 5
Transdroid	481	103	4/09-10/13	3, 5
MiniCM	759	101	4/10-5/12	3, 5
Connectbot	676	87	4/08-6/12	3, 5
Synodroid	214	86	4/10-1/13	3, 5
Shuffle	325	77	10/08-7/12	3, 5
Eyes-Free	322	69	6/09-12/13	3, 5
Omnidroid	184	61	10/09-8/10	3, 5
VLC for Android	151	39	5/12-12/13	3, 5
Total	*112,894*	*18,579*		

Table 2.2: Overview of examined projects for Android.

iOS				
Project	Bugs		Time span	Used Chapter
	Reported	Fixed		
WordPress for iPhone	1,647	892	7/08-9/13	3
Cocos2d for iPhone	1,506	628	7/08-5/13	3
Core Plot	614	218	2/09-12/13	3
Siphon	586	162	4/08-11/11	3
Colloquy	542	149	12/08-12/13	3
Chrome for iOS	365	129	6/09-12/13	3
tweetero	142	109	8/09-6/10	3
BTstack	360	106	2/08-12/13	3
Mobile Terminal	311	82	8/07-3/12	3
MyTime	247	101	7/11-11/13	3
VLC for iOS	188	80	8/07-12/13	3
Frotz	214	78	9/10-9/12	3
iDoubs	164	74	9/07-7/13	3
Vnsea	173	58	4/08-10/10	3
Meta-syntactic	145	50	7/08-4/12	3
Tomes	148	51	8/07-5/08	3
Total	*7,352*	*2,967*		

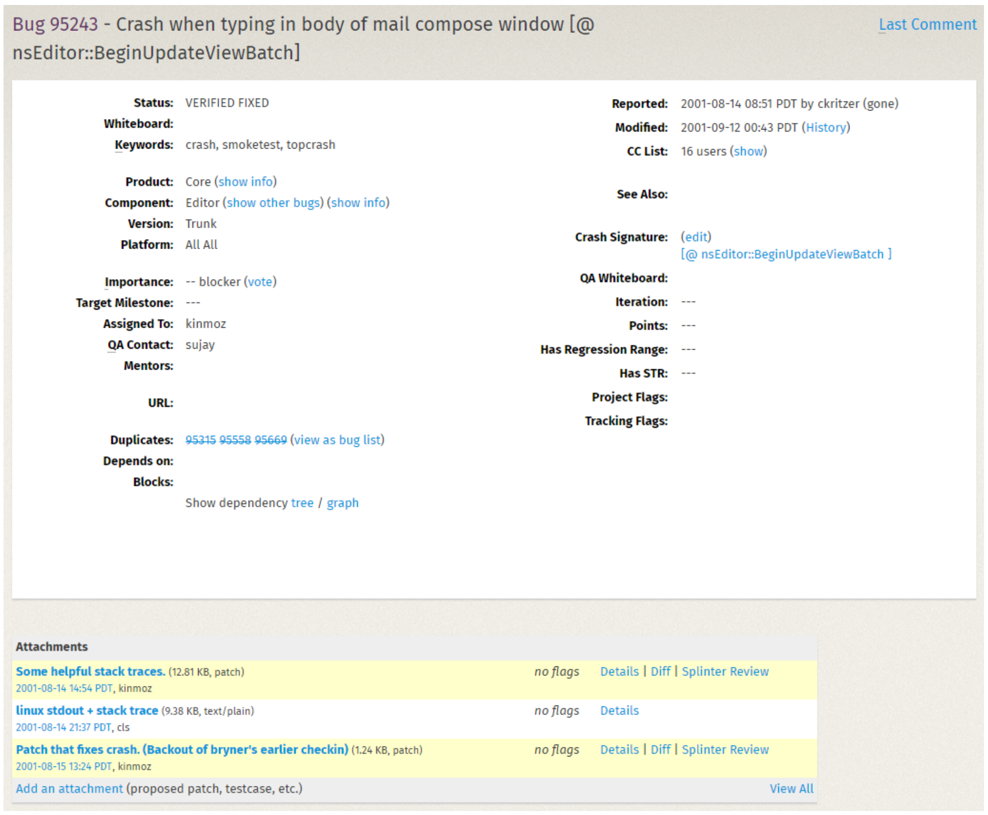
Table 2.3: Overview of examined projects for iOS.

2.2 Collecting Data From Bug Reports

Bug report repositories archive all bug reports and feature enhancement requests for a project. Each bug report includes pre-defined fields, free-form text, attachments and dependencies. In Figures 2.1-2.4 we show parts of a sample bug report from Mozilla and the activity related to it. We collect the following data from bug reports:

1. *BugID:* the id of the bug report.

2. *FixTime:* the time required to fix the bug, in days, computed from the day the bug was reported to the day the bug was closed.



Bug 95243 - Crash when typing in body of mail compose window [@ nsEditor::BeginUpdateViewBatch]

Last Comment

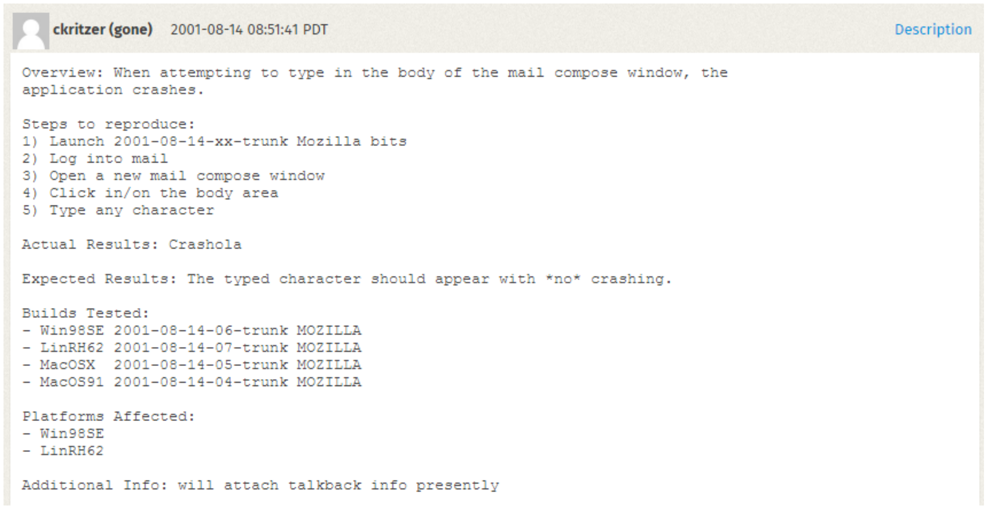
Status:	VERIFIED FIXED	**Reported:**	2001-08-14 08:51 PDT by ckritzer (gone)
Whiteboard:		**Modified:**	2001-09-12 00:43 PDT (History)
Keywords:	crash, smoketest, topcrash	**CC List:**	16 users (show)
Product:	Core (show info)	**See Also:**	
Component:	Editor (show other bugs) (show info)		
Version:	Trunk	**Crash Signature:**	(edit) [@ nsEditor::BeginUpdateViewBatch]
Platform:	All All		
Importance:	-- blocker (vote)	**QA Whiteboard:**	
Target Milestone:	---	**Iteration:**	---
Assigned To:	kinmoz	**Points:**	---
QA Contact:	sujay	**Has Regression Range:**	---
Mentors:		**Has STR:**	---
URL:		**Project Flags:**	
Duplicates:	~~95315~~ ~~95558~~ ~~95669~~ (view as bug list)	**Tracking Flags:**	
Depends on:			
Blocks:			
	Show dependency tree / graph		

Attachments

Some helpful stack traces. (12.81 KB, patch) 2001-08-14 14:54 PDT, kinmoz	*no flags*	Details | Diff | Splinter Review
linux stdout + stack trace (9.38 KB, text/plain) 2001-08-14 21:37 PDT, cls	*no flags*	Details
Patch that fixes crash. (Backout of bryner's earlier checkin) (1.24 KB, patch) 2001-08-15 13:24 PDT, kinmoz	*no flags*	Details | Diff | Splinter Review

Add an attachment (proposed patch, testcase, etc.) View All

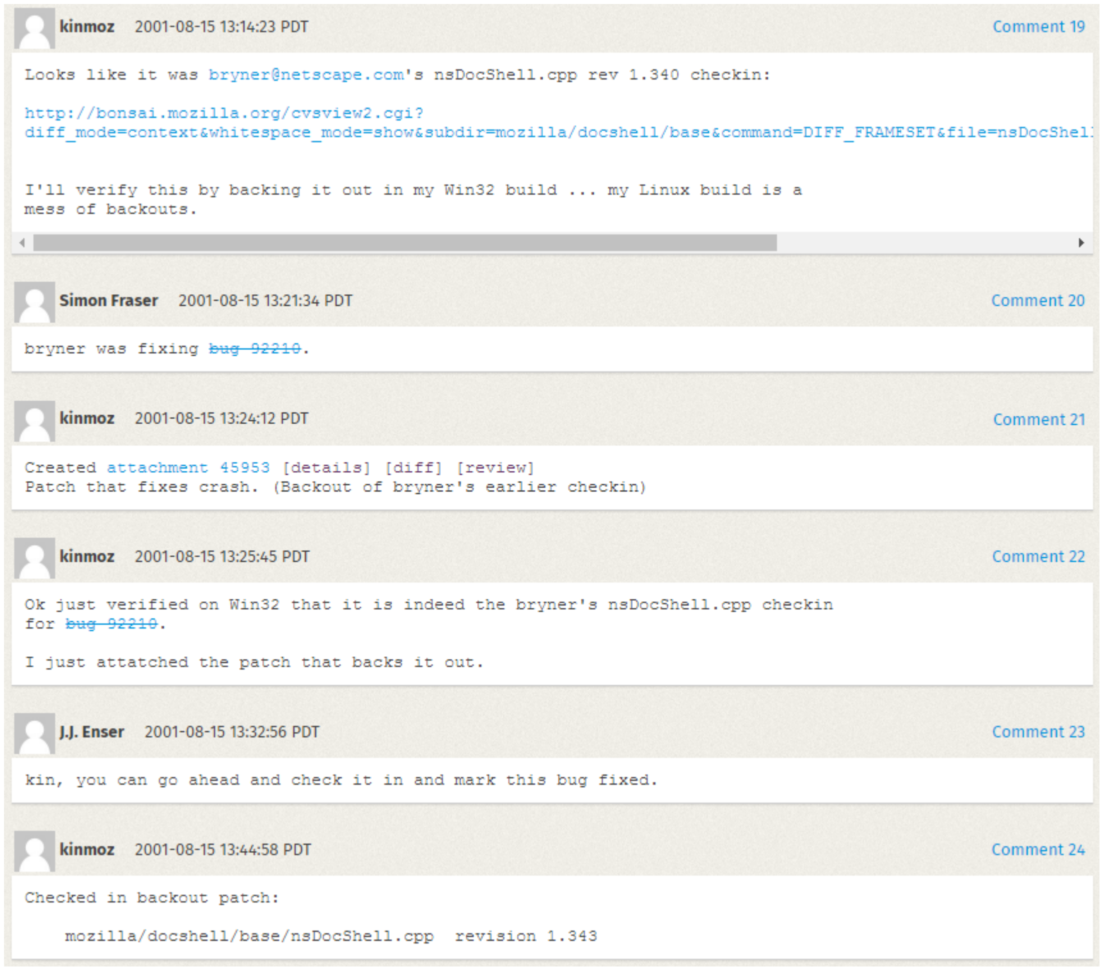
Figure 2.1: Bug report header information (sample bug ID 95243 in Mozilla).



ckritzer (gone) 2001-08-14 08:51:41 PDT Description

```
Overview: When attempting to type in the body of the mail compose window, the
application crashes.

Steps to reproduce:
1) Launch 2001-08-14-xx-trunk Mozilla bits
2) Log into mail
3) Open a new mail compose window
4) Click in/on the body area
5) Type any character

Actual Results: Crashola

Expected Results: The typed character should appear with *no* crashing.

Builds Tested:
- Win98SE 2001-08-14-06-trunk MOZILLA
- LinRH62 2001-08-14-07-trunk MOZILLA
- MacOSX  2001-08-14-05-trunk MOZILLA
- MacOS91 2001-08-14-04-trunk MOZILLA

Platforms Affected:
- Win98SE
- LinRH62

Additional Info: will attach talkback info presently
```

Figure 2.2: Bug description (sample bug ID 95243 in Mozilla).


kinmoz 2001-08-15 13:14:23 PDT Comment 19

```
Looks like it was bryner@netscape.com's nsDocShell.cpp rev 1.340 checkin:

http://bonsai.mozilla.org/cvsview2.cgi?
diff_mode=context&whitespace_mode=show&subdir=mozilla/docshell/base&command=DIFF_FRAMESET&file=nsDocShel


I'll verify this by backing it out in my Win32 build ... my Linux build is a
mess of backouts.
```

Simon Fraser 2001-08-15 13:21:34 PDT Comment 20

```
bryner was fixing ~~bug 92210~~.
```

kinmoz 2001-08-15 13:24:12 PDT Comment 21

```
Created attachment 45953 [details] [diff] [review]
Patch that fixes crash. (Backout of bryner's earlier checkin)
```

kinmoz 2001-08-15 13:25:45 PDT Comment 22

```
Ok just verified on Win32 that it is indeed the bryner's nsDocShell.cpp checkin
for ~~bug 92210~~.

I just attatched the patch that backs it out.
```

J.J. Enser 2001-08-15 13:32:56 PDT Comment 23

```
kin, you can go ahead and check it in and mark this bug fixed.
```

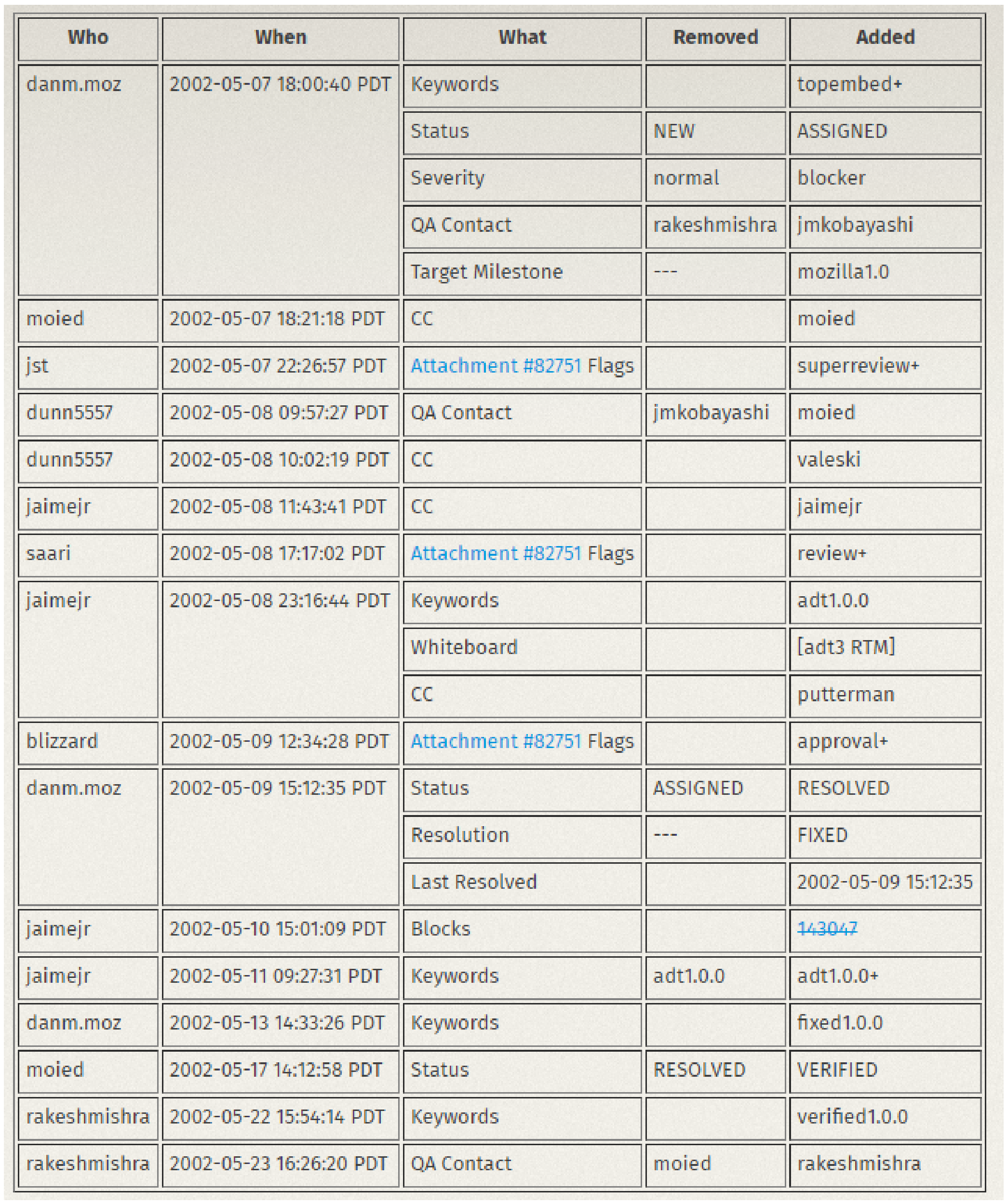
kinmoz 2001-08-15 13:44:58 PDT Comment 24

```
Checked in backout patch:

    mozilla/docshell/base/nsDocShell.cpp  revision 1.343
```

Figure 2.3: Comments for a bug report (sample bug ID 95243 in Mozilla).

3. *Severity:* an indicator of the bug's potential impact on customers. When a bug is reported, the administrators first review it and then assign it a severity rank based on how severely it affects the program. Since severity levels differ among trackers, we mapped severity from different trackers to a uniform 10-point scale. Table 2.4 shows the levels of bug severity and their ranks.

4. *Priority:* a bug's priority rates the urgency and importance of fixing the bug, relative to the stated project goals and priorities. It is set by the maintainers or developers



Who	When	What	Removed	Added
danm.moz	2002-05-07 18:00:40 PDT	Keywords		topembed+
		Status	NEW	ASSIGNED
		Severity	normal	blocker
		QA Contact	rakeshmishra	jmkobayashi
		Target Milestone	---	mozilla1.0
moied	2002-05-07 18:21:18 PDT	CC		moied
jst	2002-05-07 22:26:57 PDT	Attachment #82751 Flags		superreview+
dunn5557	2002-05-08 09:57:27 PDT	QA Contact	jmkobayashi	moied
dunn5557	2002-05-08 10:02:19 PDT	CC		valeski
jaimejr	2002-05-08 11:43:41 PDT	CC		jaimejr
saari	2002-05-08 17:17:02 PDT	Attachment #82751 Flags		review+
jaimejr	2002-05-08 23:16:44 PDT	Keywords		adt1.0.0
		Whiteboard		[adt3 RTM]
		CC		putterman
blizzard	2002-05-09 12:34:28 PDT	Attachment #82751 Flags		approval+
danm.moz	2002-05-09 15:12:35 PDT	Status	ASSIGNED	RESOLVED
		Resolution	---	FIXED
		Last Resolved		2002-05-09 15:12:35
jaimejr	2002-05-10 15:01:09 PDT	Blocks		~~143047~~
jaimejr	2002-05-11 09:27:31 PDT	Keywords	adt1.0.0	adt1.0.0+
danm.moz	2002-05-13 14:33:26 PDT	Keywords		fixed1.0.0
moied	2002-05-17 14:12:58 PDT	Status	RESOLVED	VERIFIED
rakeshmishra	2002-05-22 15:54:14 PDT	Keywords		verified1.0.0
rakeshmishra	2002-05-23 16:26:20 PDT	QA Contact	moied	rakeshmishra

Figure 2.4: Bug activity (sample bug ID 142918 in Mozilla).

who plan to work on the bug; there are 5 levels of priority, with P1 the highest and P5 the lowest.[3]

[3]We use the priority definition from Bugzilla: `http://wiki.eclipse.org/WTP/Conventions_of_bug_priority_and_severity`.

Bug Severity	**Description**	**Score**
Blocker	Blocks development testing work	10
Critical	Crashes, loss of data, severe memory leak	9
Major/Crash/High	Major loss of function	8
Normal/Medium	Regular issue, some loss of functionality	6
Minor/Low/Small	Minor loss of function	5
Trivial/Tweak	Cosmetic problem	2
Enhancement	Request for enhancement	1

Table 2.4: Bug severity: descriptions and ranks.

5. *BugReporter:* the ID of the contributor who reported the bug.

6. *BugOwner:* the ID of the contributor who eventually fixed the bug.

7. *DevExperience:* the experience of developer X in year Y, defined as the difference, in days, between the date of the X's last contribution in year Y and X's first contribution ever.

8. *BugTitle:* the text content of the bug report title.

9. *BugDescription:* the text content of the bug summary/description.

10. *DescriptionLength:* the number of words in the bug summary/description.

11. *BugComment:* the text content of the comments in the bug report.

12. *TotalComments:* the number of comments in the bug report.

13. *CommentLength:* the number of words in all the comments attached to the bug report.

2.3 Quantitative Analysis

To find quantitative differences in bug-fixing processes we performed an analysis on various features (attributes) of the bug-fixing process, e.g., fix time, severity, comment length defined in the previous section. We employed three statistical tests in our analysis:

Pairwise comparison test. To check whether feature values differ between different groups, we conducted pairwise comparisons using the Wilcoxon-Mann-Whitney test (which is also known as Mann Whitney U test or Wilcoxon rank-sum test).

Trend test. To test whether a feature increases/decreases over time, we build a linear regression model where the independent variable is the time and the dependent variable is the feature value for each project. We consider that the trend is increasing (or decreasing, respectively) if the slope β of the regression model is positive (or negative, respectively) and $p < 0.05$.

Non-zero test. To test whether a set of values differs significantly from 0, we perform a one-sample t-test where the specified value was 0; if $p < 0.05$, we consider that the samples differ from 0 significantly.

All statistical tests in our work are implemented by the statistical package *R* [121].

2.4 Topic Modeling

For the other thrust of our study, we used a qualitative analysis to understand the nature of the bugs by extracting topics from bug reports. Topic models are a suite of algorithms that uncover the hidden thematic structure in document collections [24]. Topic models provide a simple way to analyze large volumes of unlabeled text. A “topic” consists of a cluster of words that frequently occur together. Using contextual clues, topic models can connect words with similar meanings and distinguish between uses of words with multiple meanings. These algorithms help us develop new ways to search, browse and summarize large archives of texts.

We used the bug title, bug description and comments for topic extraction. We applied several standard text retrieval and processing techniques for making text corpora amenable to text analyses [140] before applying Latent Dirichlet allocation (LDA) algorithm: stemming, stop-word removal, non-alphabetic word removal, programming language keyword removal. For example, we removed all the special characters (e.g., "&&","->"); identifier names were split into multiple parts (e.g., "fooBar","foo_bar"); programming language keywords (e.g., "while","if") and English keywords (e.g., "a", "the") were removed. Finally we stemmed each word. We then used MALLET [103] for topic training.

Chapter 3

A Cross-platform Analysis of Bugs

As smartphones continue to increase in popularity, understanding how software processes associated with the smartphone platform differ from the traditional desktop platform is critical for improving user experience and facilitating software development and maintenance. Empirical bugs and bug-fixing studies so far have mostly focused on traditional software; few efforts [21, 99] have investigated the differences between desktop and smartphone software. Therefore, in this chapter we analyzed the similarities and differences in bug reports and bug-fixing processes between desktop and smartphone platforms. Our study covers 88 projects (34 on desktop, 38 on Android, 16 on iOS) encompassing 444,129 bug reports. We analyzed bugs in a time span beginning in 1998 for desktop and 2007 for Android/iOS, and ending at the end of December 2013 (Section 3.1.1 shows projects details).

In particular, we studied the bug-fix process features, bug nature, and the reporter/fixer relationship to understand how bugs, as well as bug-fixing processes, differ between desktop and smartphone. The study has two thrusts. First, a *quantitative* thrust (Section 3.2) where we compare the three platforms in terms of attributes associated with bug reports and the bug-fixing process, how developer profiles differ between desktop and smartphone, etc. Second, a *qualitative* thrust (Section 3.3) where we apply LDA to extract topics from bug reports on each platform and gain insights into the nature of bugs, how bug categories differ from desktop to smartphone, and how these categories change over time. Our study, findings, and recommendations are potentially useful to smartphone researchers and practitioners.

3.1 Methodology

We first provide an overview of the examined projects, and then describe how we extracted bug features and topics.

3.1.1 Examined Projects

We choose all the projects mentioned in Chapter 2.1 for our study. Tables 3.1–3.3 show a summary of the projects we examined. For each platform, we show the project's name, the number of reported bugs, the number of closed and fixed bugs, the FixRate (i.e., the percentage of fixed bugs in the total number of reported bugs), and finally, the dates of the first and last bugs we considered.

Desktop			
Project	Bugs		Time span
	Reported	Fixed (FixRate)	
Mozilla Core	247,376	101,647 (41.09%)	2/98-12/13
OpenOffice	124,373	48,067 (38.65%)	10/00-12/13
Gnome Core	160,825	42,867 (26.65%)	10/01-12/13
Eclipse platform	100,559	42,401 (42.17%)	2/99-12/13
Eclipse JDT	50,370	22,775 (45.22%)	10/01-12/13
Firefox	132,917	19,312 (14.53%)	4/98-12/13
SeaMonkey	91,656	18,831 (20.55%)	4/01-12/13
Konqueror	38,156	15,990 (41.91%)	4/00-12/13
Eclipse CDT	17,646	10,168 (57.62%)	1/02-12/13
WordPress	26,632	9,995 (37.53%)	6/04-12/13
KMail	21,636	8,324 (38.47%)	11/02-12/13
Linux Kernel	22,671	7,535 (33.24%)	3/99-12/13
Thunder-bird	39,323	5,684 (14.45%)	4/00-12/13
Amarok	18,212	5,400 (29.65%)	11/03-12/13
Plasma Desktop	22,187	5,294 (23.86%)	7/02-12/13
Mylyn	8,461	5,050 (59.69%)	10/05-12/13
Spring	15,300	4,937 (32.27%)	8/00-12/13
Tomcat	11,332	4,826 (42.59%)	11/03-12/13
MantisBT	11,484	4,141 (36.06%)	2/01-12/13
Hadoop	11,444	4,077 (35.63%)	10/05-12/13
VLC	9,674	3,892 (40.24%)	5/05-12/13
Kdevelop	7,824	3,572 (45.65%)	8/99-12/13
Kate	7,058	3,326 (47.12%)	1/00-12/13
Lucene	5,327	3,035 (56.97%)	4/02-12/13
Kopete	9,824	2,957 (30.10%)	10/01-9/13
Hibernate	8,366	2,737 (32.72%)	10/00-12/13
Ant	5,848	2,612 (44.66%)	4/03-12/13
Apache Cassandra	3,609	2,463 (68.25%)	8/04-12/13
digikam	6,107	2,400 (39.30%)	3/02-12/13
Apache httpd	7,666	2,334 (30.45%)	2/03-10/13
Dolphin	7,097	2,161 (30.45%)	6/02-12/13
K3b	4,009	1,380 (34.42%)	4/04-11/13
Apache Maven	2,586	1,332 (51.51%)	10/01-12/13
Portable OpenSSH	2,206	1,061 (48.10%)	3/09-12/13
Total	*1,259,758*	*422,583 (33.54%)*	

Table 3.1: Projects examined, bugs reported, bugs fixed, and time span on desktop.

Android			
Project	Bugs		Time span
	Reported	Fixed (FixRate)	
Android Platform	64,158	3,497 (5.45%)	11/07-12/13
Firefox for Android	11,998	4,489 (37.41%)	9/08-12/13
K-9 Mail	6,079	1,200 (19.74%)	6/10-12/13
Chrome for Android	3,787	1,601 (42.28%)	10/08-12/13
OsmAnd Maps	2,253	1,018 (45.18%)	1/12-12/13
AnkiDroid Flashcards	1,940	746 (38.45%)	7/09-12/13
CSipSimple	2,584	604 (23.37%)	4/10-12/13
My Tracks	1,433	525 (36.64%)	5/10-12/13
Cyanogen-Mod	788	432 (54.82%)	9/10-1/13
Andro-minion	623	346 (55.54%)	9/11-11/13
WordPress for Android	532	317 (59.59%)	9/09-9/13
Sipdroid	1,149	300 (26.11%)	4/09-4/13
AnySoft-Keyboard	1,144	229 (20.02%)	5/09-5/12
libphone-number	389	219 (56.30%)	11/07-12/13
ZXing	1,696	218 (12.85%)	5/09-12/12
SL4A	701	204 (29.10%)	10/09-5/12
WebSMS-Droid	815	197 (24.17%)	7/10-12/13
OpenIntents	553	188 (34.00%)	12/07-6/12
IMSDroid	502	183 (36.45%)	6/10-3/13
Wikimedia Mobile	261	166 (63.60%)	1/09-9/12
OSMdroid	494	166 (33.60%)	2/09-12/13
WebKit	225	157 (69.78%)	11/09-3/13
XBMC Remote	729	129 (17.70%)	9/09-11/11
Mapsforge	466	127 (27.25%)	2/09-12/13
libgdx	384	126 (32.81%)	5/10-12/13
WiFi Tether	1,938	125 (6.45%)	11/09-7/13
Call Meter NG/3G	904	116 (12.83%)	2/10-11/13
GAOSP	529	114 (21.55%)	2/09-5/11
Open GPS Tracker	391	114 (29.16%)	7/11-9/12
CM7 Atrix	337	103 (30.56%)	3/11-5/12
Transdroid	481	103 (21.41%)	4/09-10/13
MiniCM	759	101 (13.31%)	4/10-5/12
Connectbot	676	87 (12.87%)	4/08-6/12
Synodroid	214	86 (40.19%)	4/10-1/13
Shuffle	325	77 (36.56%)	10/08-7/12
Eyes-Free	322	69 (21.43%)	6/09-12/13
Omnidroid	184	61 (33.15%)	10/09-8/10
VLC for Android	151	39 (25.83%)	5/12-12/13
Total	*112,894*	*18,579 (27.28%)*	

Table 3.2: Projects examined, bugs reported, bugs fixed, and time span on Android.

iOS			
Project	Bugs		Time span
	Reported	Fixed (FixRate)	
WordPress for iPhone	1,647	892 (54.16%)	7/08-9/13
Cocos2d for iPhone	1,506	628 (41.70%)	7/08-5/13
Core Plot	614	218 (35.50%)	2/09-12/13
Siphon	586	162 (27.65%)	4/08-11/11
Colloquy	542	149 (27.49%)	12/08-12/13
Chrome for iOS	365	129 (35.34%)	6/09-12/13
tweetero	142	109 (76.76%)	8/09-6/10
BTstack	360	106 (29.44%)	2/08-12/13
Mobile Terminal	311	82 (26.37%)	8/07-3/12
MyTime	247	101 (40.89%)	7/11-11/13
VLC for iOS	188	80 (42.55%)	8/07-12/13
Frotz	214	78 (36.45%)	9/10-9/12
iDoubs	164	74 (45.12%)	9/07-7/13
Vnsea	173	58 (33.53%)	4/08-10/10
Meta-syntactic	145	50 (34.48%)	7/08-4/12
Tomes	148	51 (34.46%)	8/07-5/08
Total	*7,352*	*2,967 (37.40%)*	

Table 3.3: Projects examined, bugs reported, bugs fixed, and time span on iOS.

3.1.2 Quantitative Analysis

To find quantitative differences in bug-fixing processes we performed an analysis on various features (attributes) of the bug-fixing process, e.g., fix time, severity, comment length, which is defined in Chapter 2.2.

Data preprocessing: feature values and trends. We computed per-project values at monthly granularity, for several reasons: (1) to also study differences between projects within a platform; (2) to avoid data bias resulting from over-representation, e.g., Mozilla Core bugs account for 24% of total desktop bugs, hence conflating all the bug reports into a single "desktop" category would give undue bias to Mozilla; and (3) we found monthly to be a good granularity for studying trends. For each feature, e.g., FixTime, we compute the geometric mean (since the distributions are skewed, arithmetic mean is not an appropriate measure [88], and we therefore used the geometric mean in our study) and the trend (slope) as follows:

```
Input: Feature value per bug
  for each project do
    for $i$ = start month to last month do
      feature[$i$] = geometric.mean(input)
    end for
    FeatureMean = geometric.mean(feature)
    FeatureBeta = slope(feature $\sim$ time)
  end for
Output: FeatureMean, FeatureBeta
```

We employed three statistical tests in our analysis:

Trend test. To test whether a feature increases/decreases over time, we build a linear regression model where the independent variable is the time and the dependent variable is the feature value for each project. We consider that the trend is increasing (or decreasing, respectively) if the slope β of the regression model is positive (or negative, respectively) and $p < 0.05$.

Non-zero test. To test whether a set of values differs significantly from 0, we perform a one-sample t-test where the specified value was 0; if $p < 0.05$, we consider that the samples differ from 0 significantly.

Pairwise comparison test. To check whether feature values differ significantly between platforms, we conducted pairwise comparisons (desktop v. Android; desktop v. iOS; and Android v. iOS) using the Wilcoxon-Mann-Whitney test.

3.1.3 Qualitative Analysis

For the second thrust of our study, we used a qualitative analysis to understand the nature of the bugs by extracting topics from bug reports. We used the bug title, bug description and comments for topic extraction. We applied several standard text retrieval and processing techniques for making text corpora amenable to text analyses [140] before applying LDA: stemming, stop-word removal, non-alphabetic word removal, programming language keyword removal. We then used MALLET [103] for topic training. The parameter settings are presented in Section 3.3.1.

3.2 Quantitative Analysis

The first thrust of our study takes a quantitative approach to investigating the similarities and differences between bug-fixing processes on desktop and smartphone platforms. Specifically, we are interested in how bug-fixing process attributes differ across platforms; how the contributor sets (bug reporters and bug owners) vary between platforms; how the bug-fix rate varies and what factors influence it.

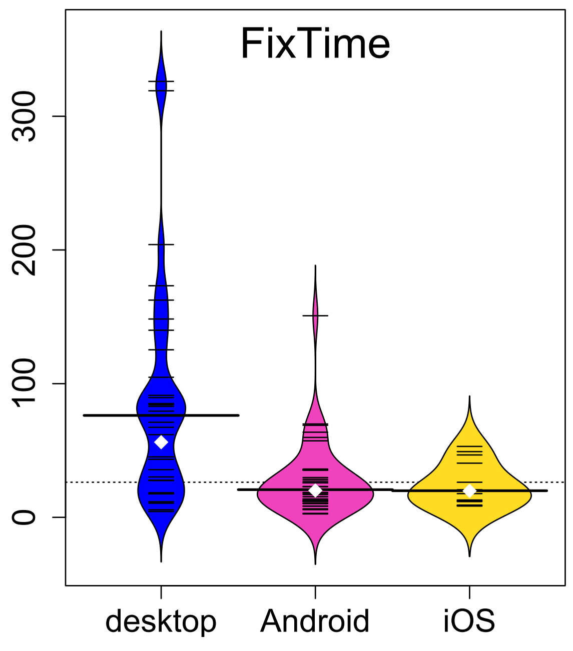
3.2.1 Bug-fix Process Attributes

We start with the quantitative analysis of bug characteristics and bug-fixing process features. Moreover, to avoid undue influence by outliers, we have excluded the top 5% and bottom 5% when computing and plotting the statistical values. We show the results, as beanplots, which is an alternative to the boxplot for visual comparison of univariate data between groups, in Figures 3.1 through 3.14. The shape of the beanplot is the entire

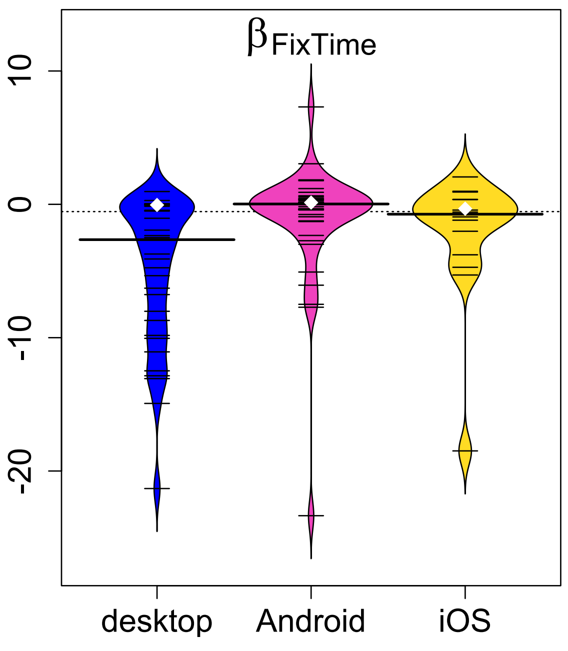
	Min	**1st Q**	**Median**	**Mean**	**3rd Q**	**Max**	**Non-zero test p**
Desktop							
FixTime	4.361	28.366	77.844	59.990	120.192	500.773	
Severity	3.148	5.060	5.421	5.500	6.121	7.463	
Desc.Len	32.09	46.18	57.73	71.674	132.37	159.87	
TotalComm.	1.780	3.225	4.459	4.268	5.249	9.501	
Comm.Len	16.44	43.74	65.87	63.323	93.40	260.38	
β_{FixTime}	-21.314	-9.551	-2.650	-5.122	-0.086	0.960	< 0.01
betaSeverity	-0.025	-0.002	0.004	0.004	0.007	0.031	0.027
betaDesc.Len	-0.738	-0.152	0.006	0.053	0.166	1.138	0.470
betaTotalComm.	-21.314	-9.551	-2.650	-5.122	-0.086	0.959	< 0.01
betaComm.Len	-3.699	-0.375	-0.122	-0.251	0.187	1.893	0.159
Android							
FixTime	2.556	12.097	20.694	20.080	33.847	150.800	
Severity	3.737	6.001	6.068	6.094	6.305	7.074	
Desc.Len	19.24	60.20	69.63	64.136	83.18	105.50	
TotalComm.	1.861	2.580	3.555	3.779	4.632	14.064	
Comm.Len	11.18	24.78	43.37	40.179	60.73	129.26	
betaFixTime	-23.352	-1.164	0.025	-1.165	0.391	7.306	0.124
betaSeverity	-0.070	-0.010	-0.001	-0.003	0.002	0.105	0.523
betaDesc.Len	-1.874	0.107	0.519	0.703	1.017	5.869	0.003
betaTotalComm.	-23.352	-1.164	0.025	-1.165	0.391	7.306	0.124
betaComm.Len	-22.148	-0.798	-0.149	0.256	1.417	12.608	0.762
iOS							
FixTime	8.423	12.257	19.906	19.793	29.828	53.043	
Severity	5.985	6.011	6.054	6.236	6.250	7.148	
Desc.Len	26.73	47.12	69.10	63.269	85.86	159.41	
TotalComm.	1.492	2.547	3.271	3.298	3.980	6.221	
Comm.Len	7.844	17.591	37.740	32.730	68.245	143.207	
betaFixTime	-18.492	-2.461	-0.740	-2.141	0.361	2.055	0.095
betaSeverity	-0.093	-0.002	-0.000	-0.001	0.004	0.043	0.908
betaDesc.Len	-18.354	-1.758	0.503	-0.250	1.073	12.345	0.870
betaTotalComm.	-18.492	-2.461	-0.740	-2.141	0.361	2.055	0.095
betaComm.Len	-11.047	-0.627	-0.122	-0.069	0.994	17.249	0.964

Table 3.4: Statistical summary of bug-fix process attributes.

density distribution, which is a better choice for large range of non-normal data, the short horizontal lines represent each data point, the longer thick lines are the medians, and the



(a)



(b)

Figure 3.1: Beanplot of fix time distributions trends per project.

white diamond points are the geometric means. Also we show the statistical summary of each feature on both platforms in Table 3.4. We now discuss each feature.

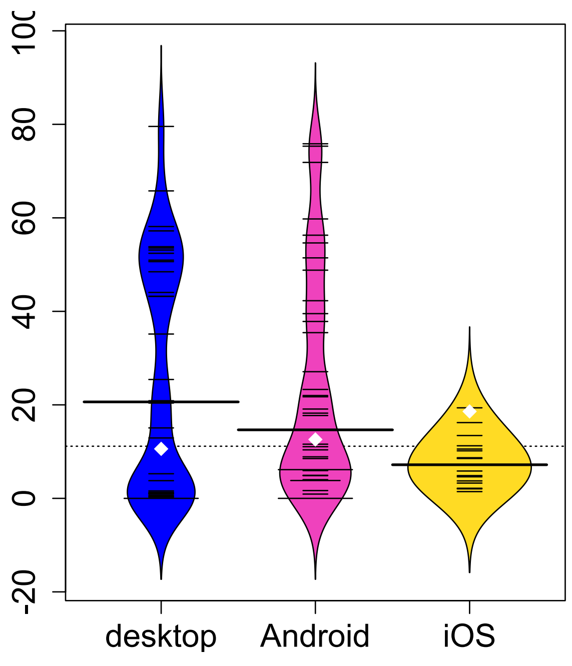
FixTime. Figure 3.1a shows the time to fix bugs on each platform and Figure 3.1b shows how the FixTime change for each project on different platforms. Several observations emerge. First, *desktop bugs took longer to fix than smartphone bugs: 60 days on desktop, 20 days on Android, 19 days on iOS* (Figure 3.1a). The pairwise comparison test indicates that FixTime on desktop differs from Android and iOS ($p \ll 0.01$ for both); there is no statistical difference between Android and iOS ($p = 0.8$). This is due to multiple reasons, mainly low severity and large number of comments. According to previous research [59,167], FixTime is correlated with many factors, e.g., positively with number of comments or bug reports with attachments, and negatively with bug severity. As can be seen in Figure 3.5a, the number of comments for desktop is larger. The severity of desktop bugs is lower, as shown in Figure 3.3a. We have also observed (as have Lamkanfi and Demeyer [82]) that on desktop many bugs are reported in the wrong component of the software system, which prolongs fixing. Also desktop applications are usually more complicate than smartphone application, it is harder to find root cause and proper fix strategy for desktop applications.

Second, *bug-fix time tends to decrease over time on desktop and iOS*. In fact, FixTime is the only feature where the non-zero test for β's turned out significant or suggestive for all platforms ($p < 0.01$ for desktop, $p = 0.124$ for Android, $p = 0.095$ for iOS based on Table 3.4). As Figure 3.1b shows, most desktop projects (29 out of 34) and iOS projects (11 out of 16) have decreasing trends, i.e., negative β's, on FixTime. For Android, only half of the projects (19 out of 38) have the same trends. The reasons are again multiple.

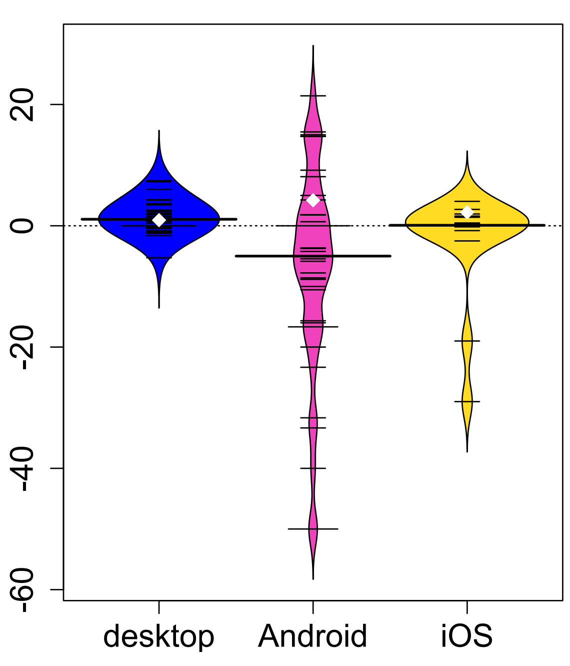
The first reason is increasing developer experience: as developers become more experienced, they take less time to fix bugs. The second reason is increased developer engagement. High overlap of bug reporters and bug owners results in shorter bug fixing time, since project developers are more familiar with their own products.

Figure 3.2 shows the percentage of owners who have also reported at least one bug for each project and their corresponding trend—the graph reveals higher engagement over time for desktop and iOS, but not for Android (for Android, 23 out of 38 projects show lower engagement over time).

Other researchers had similar findings: Giger et al. [48] found that older bugs (e.g., Mozilla bugs opened before 2002 or Gnome bugs opened before 2005) were likely to



(a)



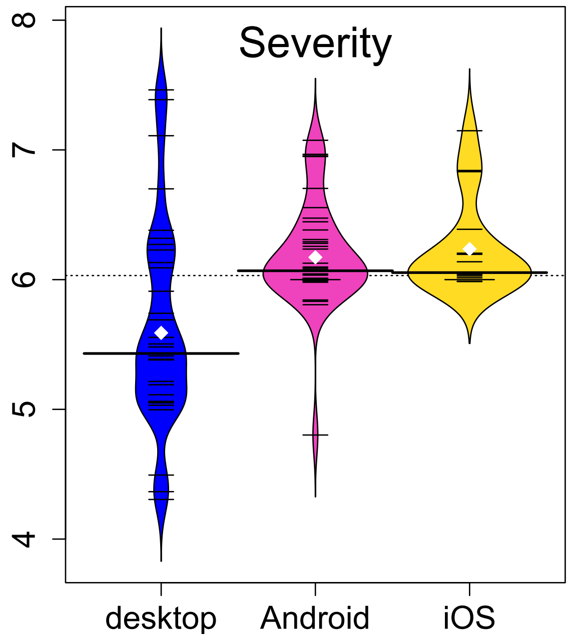
(b)

Figure 3.2: Percentage of bug owners who have reported bugs (a) and their trends (b).

take more time to fix than recently-reported bugs; and more recent bugs were fixed faster because of the increasing involvement of external developers and the maturation of the project [106].

Severity. High-severity bug reports indicate those issues that the community considers to be of utmost priority on each platform.

Figure 3.3a shows that desktop bug severity is lower than smartphone bug severity. When looking at severity trends, as Figure 3.3b indicates, severity is steady at level 6 (Normal/Medium) for Android and iOS and has a small increasing trend for desktop (22 out of 34 projects on desktop have increasing trend). The pairwise comparison indicates severity on desktop differs from Android and iOS ($p \ll 0.01$ for both), and no statistical



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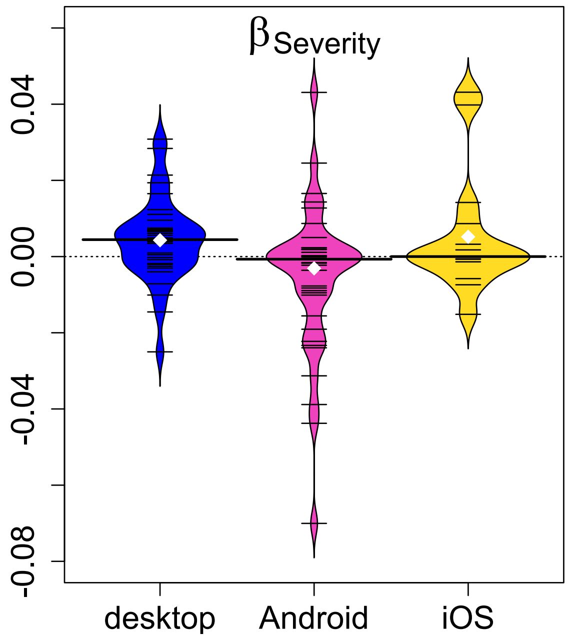
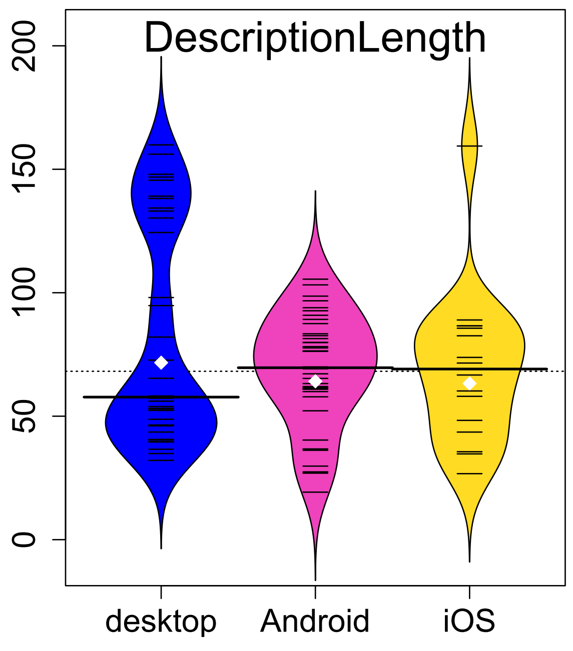


(b)

Figure 3.3: Beanplot of severity distributions trends per project.

difference between Android and iOS ($p = 0.769$). Upon investigation, we found that on desktop, over time, the frequency of high-severity bugs (e.g., crashes or compilation issues) increases, which raises the mean severity level. We examined projects' release frequency, and saw an increasing frequency for desktop [76], meaning for desktop there is less time for validating new releases and a higher incidence of severe bugs.

DescriptionLength. The number of words in the bug description reflects the level of detail in which bugs are described. A higher DescriptionLength value indicates a higher bug report quality [167], i.e., bug fixers can understand and find the correct fix strategy easier. The pairwise test indicates there is no statistical significant difference in DescriptionLength among platforms ($p > 0.659$ for all three cases). DescriptionLength stays constant on desktop and iOS (Figure 3.4b), but on Android increased significantly ($p = 0.003$). We



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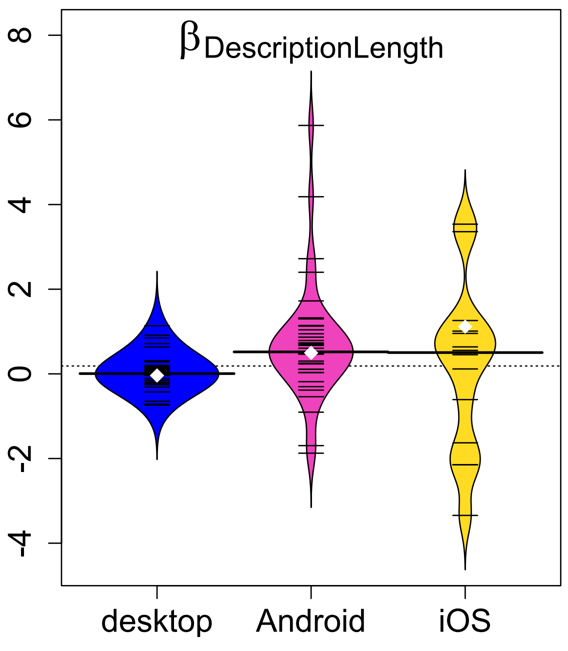
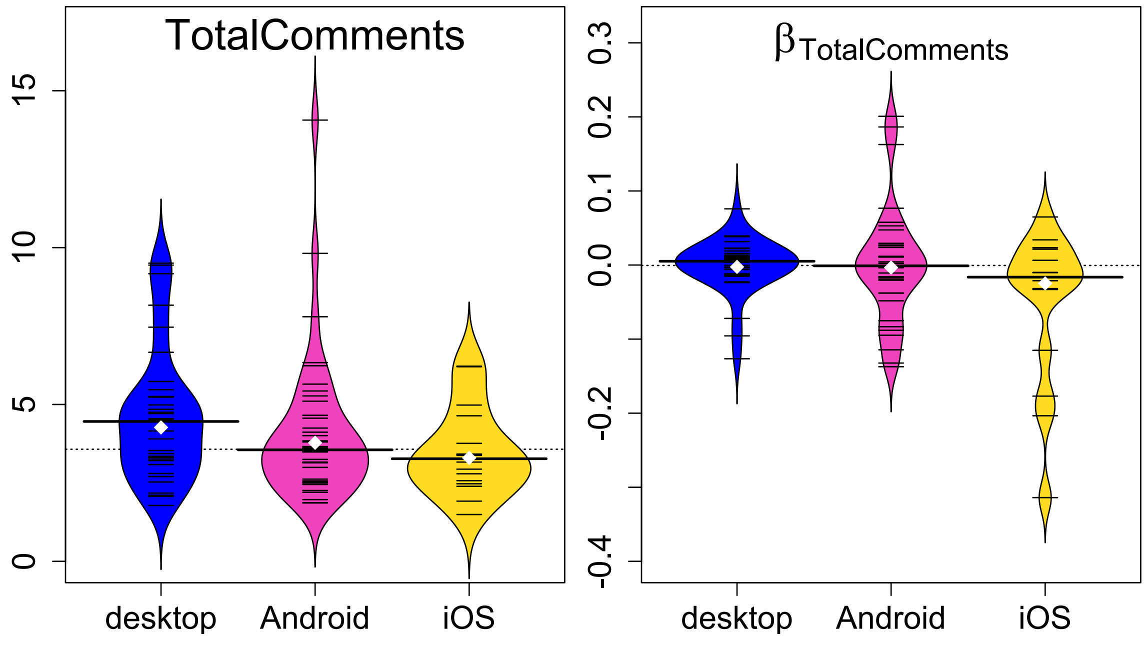


(b)

Figure 3.4: Beanplot of description length distributions trends per project.

found that the increase on Android is due to more stringent reporting requirements (e.g., asking reporters to provide steps-to-reproduce [7]).

TotalComments. Bugs that are controversial or difficult to fix have a higher number of comments. The number of comments can also reflect the amount of communication between application users and developers—the higher the number of people interested in a bug report, the more likely it is to be fixed [54]. The means differ (4.6 for desktop, 4.14 for Android, 3.5 for iOS, as shown in Figure 3.5a) but not significantly (all $p > 0.07$); TotalComments also tends to stay constant on all three platforms (non-zero test $p > 0.46$ in each case). For iOS, TotalComments starts lower and stays lower than for desktop and Android; we found that this is due to a smaller number of reporters and owners (which

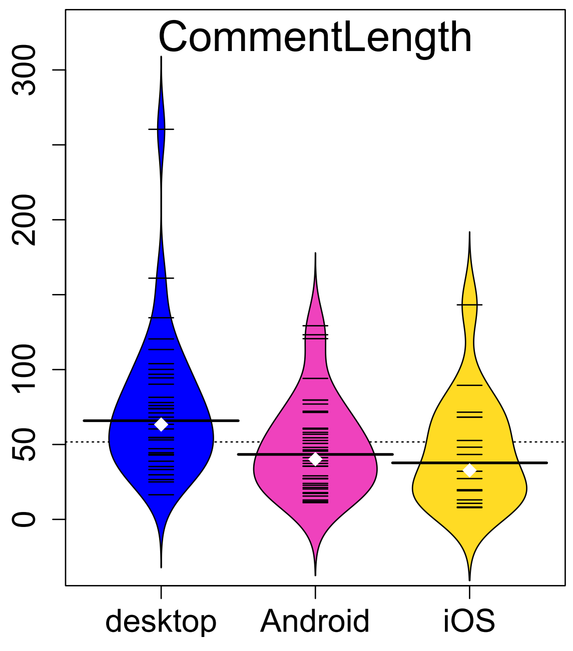


(a) (b)

Figure 3.5: Beanplot of total comments distributions trends per project.

reduces the amount of communication), as well as overlap between reporters and owners (Figure 3.2), which reduces the need for commenting; we will provide an example shortly, from the Colloquy project.

CommentLength. This measure, shown in Figures 3.6a and 3.6b, bears some similarity with TotalComments, in that it reflects the complexity of the bug and activity of contributor community. Results were similar to TotalComments'. However, iOS has smaller CommentLength values (33) than desktop (63) and Android (40). The pairwise tests show that desktop differs with Android and iOS ($p = 0.005$ and 0.01, respectively), but there is no statistical difference between Android and iOS ($p = 0.48$). Upon examining iOS bug reports we found that fewer users are involved in iOS apps' bug-fixing—bug fixers frequently locate



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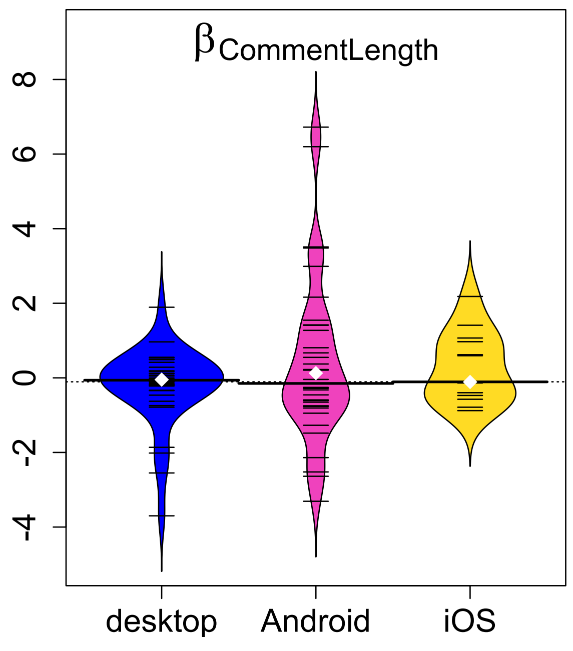

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Figure 3.6: Beanplot of comments length distributions trends per project.

the bug by themselves and close the report, with little or no commenting. For instance, the mean CommentLength in the Colloquy project is just 9.63 words. Even for high-severity bugs such as Colloquy bug #3442 (an app crash, with severity Blocker) there is no communication between the bug reporter and bug owner—rather, the developer has just fixed the bug and closed the bug report.

Generality. We also performed a smaller-scale study where we control for process, and to a smaller extent developers, by using cross-platform projects. The study, which will be presented in Section 3.2.4, has yielded findings similar to the aforementioned ones.

3.2.2 Management of Bug-fixing

Software developers have to collaborate effectively and communicate with their peers in order to avoid coordination problems. Resource allocation and management of the bug-fixing process have a significant impact on software development [153]; for example, traditional software quality is affected by the relation between bug reporters and bug owners [17]; information hiding lead development teams to be unaware of other teams work, resulting in coordination problems [36]. We defined the two roles in Section 2.2 and now set out to analyze the relationship between bug reporters and bug owners across the different platforms.

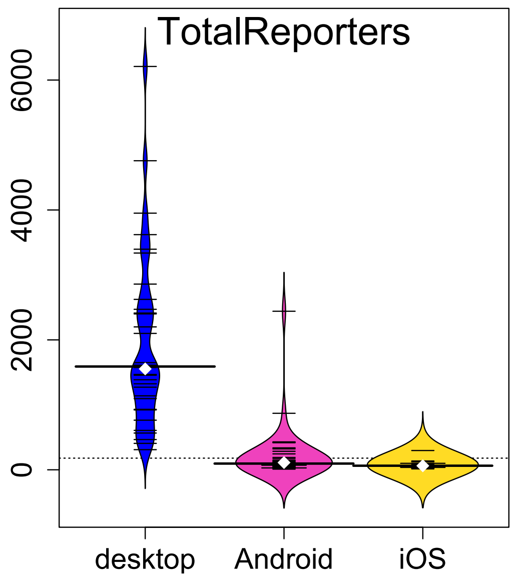
Developer Change

We examined the distribution and evolution of bug reporters, as well as bug owners, for the three platforms. Table 3.5 shows the results. The second and third columns show the number of bug reporters and bug owners, respectively. The fourth and fifth columns show the top reporters' IDs (for privacy reasons, where the ID refers to an individual, we use developer numbers instead of developers' real names) and the number of bugs they have reported in that year. The sixth column shows the turnover in top-10 reporters. Columns 7–8 contain the ID and number of bugs of the top bug owner that year, while the last column is the turnover in top-10 bug owners.

To investigate how reporters (or owners) change overtime, we introduce a new metric, *Turnover*, i.e., the percentage of bug reporters (or owners) changed compared to the previous year. In Figure 3.7 and Figure 3.8 we plot the numbers of bug reporters and

Year	Reporters	Owners	Top reporter	# of bugs	Turn-over (%)	Top owner	# of bugs	Turn-over (%)
Desktop								
1998	164	64	dev 1	116		dev 2	67	
1999	949	214	dev 3	287	30	dev 4	279	40
2000	3,270	449	dev 5	656	20	Konqueror	3,675	10
2001	5,471	664	issues@www	299	40	Konqueror	5,333	40
2002	7,324	995	dev 6	570	20	Konqueror	2,030	60
2003	7,654	1,084	dev 7	421	50	Konqueror	961	70
2004	8,678	1,273	dev 7	520	60	Konqueror	775	60
2005	8,990	1,327	dev 8	471	50	dev 9	636	40
2006	7,988	1,408	dev 10	448	60	Amarok	872	50
2007	7,292	1,393	dev 10	593	60	dev 11	357	60
2008	8,474	1,546	dev 10	444	40	Plasma	1,188	40
2009	8,451	1,537	dev 12	330	70	Plasma	1,476	40
2010	7,799	1,475	dev 10	351	50	Plasma	1,014	80
2011	6,136	1,381	dev 13	295	40	gnome	790	80
2012	5,132	1,352	dev 13	331	30	gnome	674	50
2013	4,884	1,432	dev 14	325	60	gnome	661	60
Android								
2007	8	2	dev 15	3		dev 15	3	
2008	429	41	dev 16	32	10	dev 16	28	20
2009	987	104	dev 17	24	10	dev 18	62	30
2010	1,875	163	dev 19	47	30	dev 20	89	70
2011	2,045	218	dev 21	70	10	dev 22	72	20
2012	1,998	340	dev 23	162	40	dev 23	262	60
2013	1,492	419	dev 24	125	80	dev 25	159	70
iOS								
2007	70	8	dev 26	23		dev 27	28	
2008	159	23	dev 28	27	10	dev 28	34	30
2009	292	36	dev 28	38	20	dev 29	47	30
2010	209	34	dev 30	53	30	dev 31	52	40
2011	245	18	dev 30	61	30	dev 30	55	70
2012	179	28	dev 32	165	40	dev 32	63	60
2013	182	51	dev 33	31	50	dev 33	58	40

Table 3.5: Bug reporters and bug owners.



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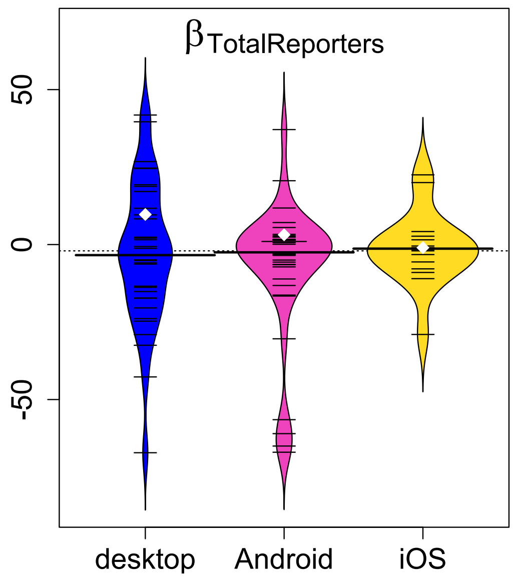


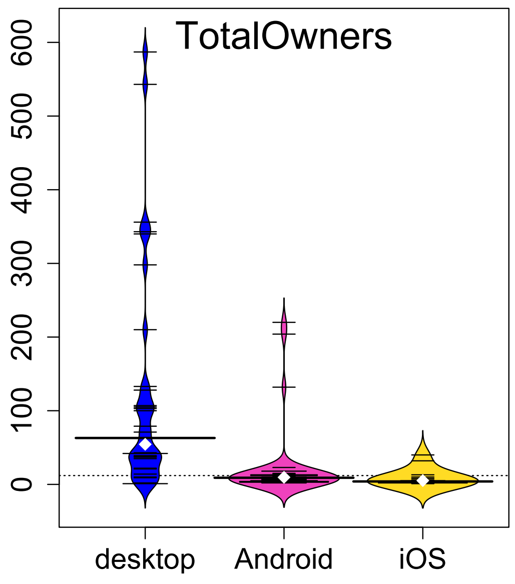
(b)

Figure 3.7: Bug reporters and trends distribution.

owners for each project; we will discuss the evolution of the numbers of reporters and owners shortly. Figures 3.9 and 3.10 show the turnover per project for each platform. We make several observations.

First, desktop projects have larger sets of bug reporters and bug owners. Desktop projects also have a more hierarchical structure with front accounts for filing and fixing bugs (e.g., "issues@www" in OpenOffice for reporters, "Konqueror Developers", "Tomcat Developers Mailing List" for owners).

Second, among individual reporters and owners, the top contributors on desktop contribute (report or own, respectively) many more bugs than the top contributors on smartphone, as seen in the "# of bugs" columns.



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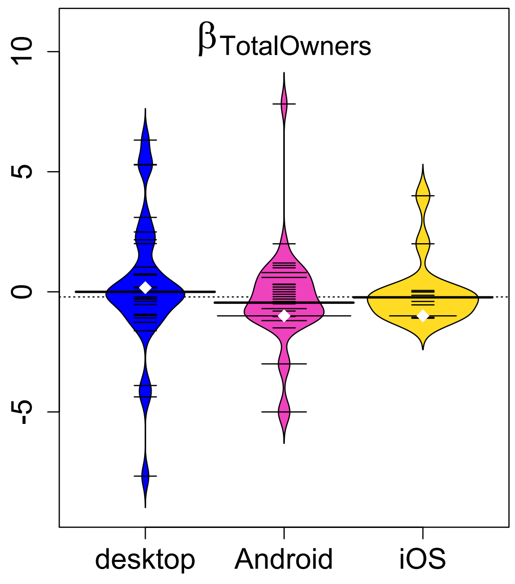

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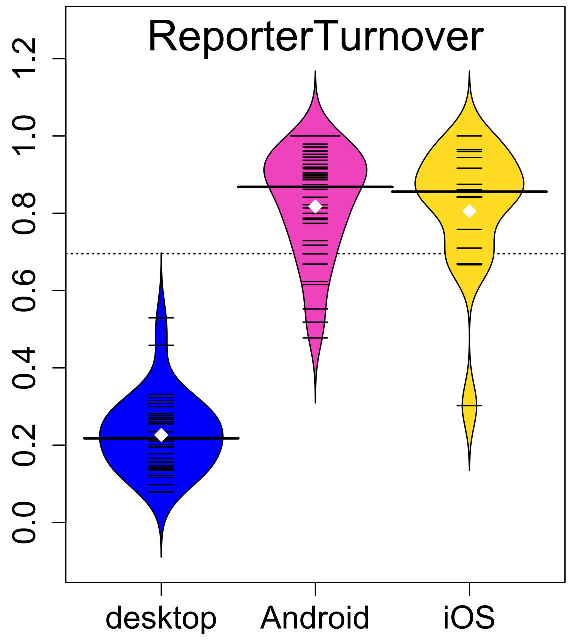
Figure 3.8: Bug owners and trends distribution.

Third, owner turnover is lower than reporter turnover, echoing one of our findings on bug reporting ramping up and down faster than bug owning (end of Section 3.2.2). The turnover of bug reporters differs significantly between desktop and smartphone ($p \ll 0.01$ for both), but not between Android and iOS ($p = 0.917$). Furthermore, the turnover of bug owners differs between desktop and iOS ($p = 0.015$) as well as Android and iOS ($p = 0.018$); the difference is not significant between desktop and Android ($p = 0.644$).

The number of fixed bugs differs across platforms, so to be able to compare reporter and owner activity between platforms, we use the number of bug reporters and bug owners in each month divided by the number of fixed bugs in that month (which we name ReporterFixed, OwnerFixed and Reporter/Owner, respectively). Figures 3.11–3.13 show the result.



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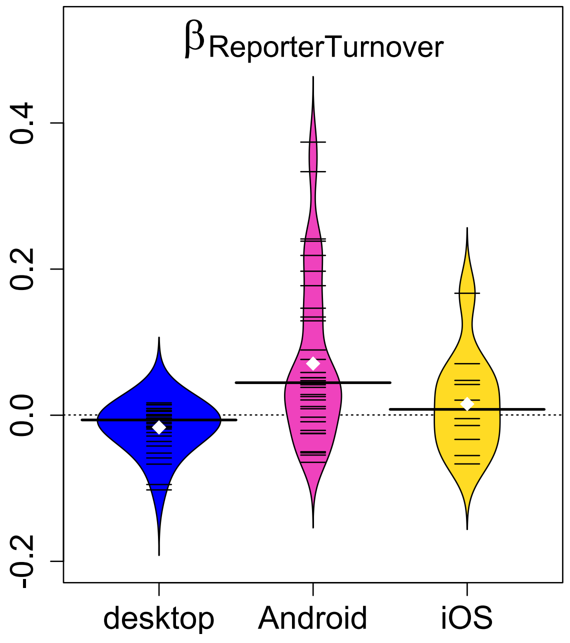
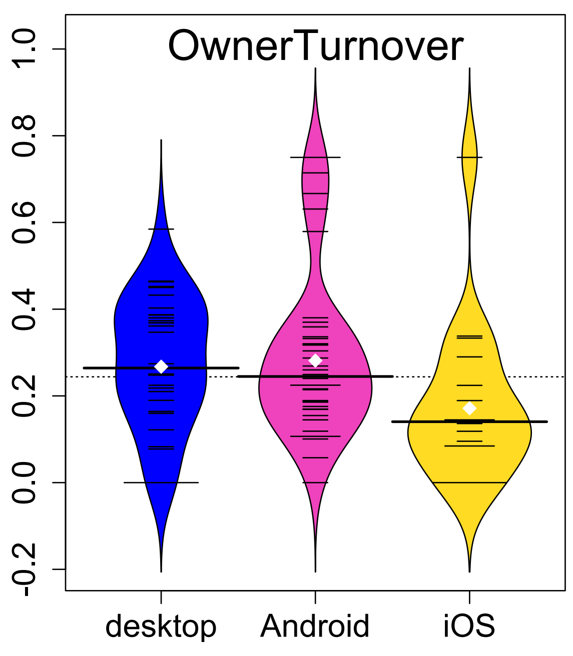


(b)

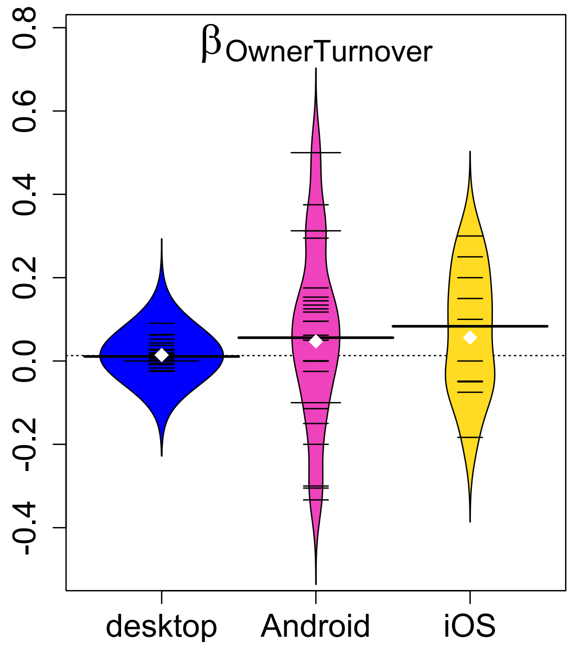
Figure 3.9: Bug reporters turnover and trends distribution.

The ratio of reporter to fixed bugs can reflect the popularity of the applications. According to Figures 3.11a and 3.11b, ReporterFixed values for Android and iOS are higher than for desktop, which we believe is due to two reasons: higher user base and popularity of smartphone apps, and a lower effort/barrier for reporting bugs (e.g., no need to provide steps-to-reproduce as required on desktop [7]). Pairwise test results show significant differences between Android and desktop/iOS ($p \ll 0.01$ for both), but not between desktop and iOS ($p = 0.715$).

OwnerFixed is lower on desktop (Figure 3.12a); this measures the inverse of workload and effort associated with bug-fixing (high ratio = low workload); given the low OwnerTurnover rates for all platforms, it is unsurprising that OwnerFixed (workload) tends to



(a)

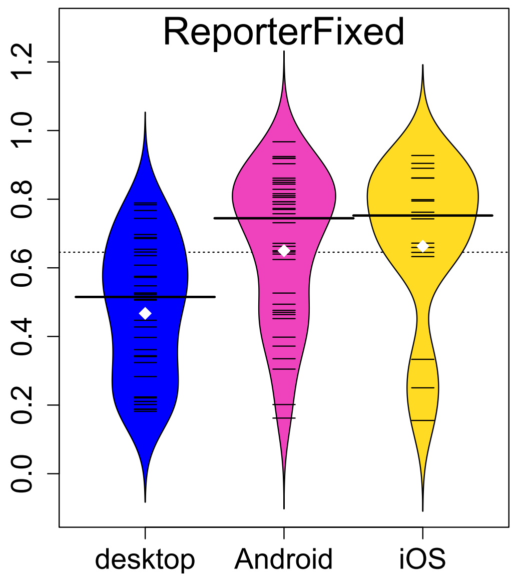


(b)

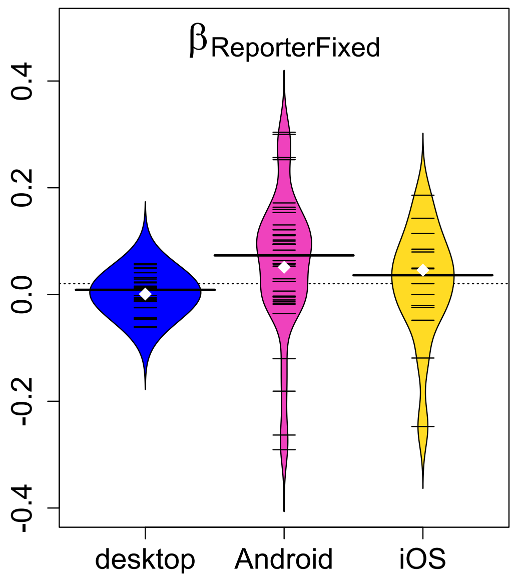
Figure 3.10: Owners, reporters, their turnover and trends.

stay constant for all platforms (Figure 3.12b). The pairwise test shows that desktop differs from smartphone platforms ($p < 0.01$) but the difference is not significant between Android and iOS ($p = 0.323$).

The ratio of reporters to owners (Figures 3.13 and 3.13b) changes in an interesting way on all platforms—increase, then decrease—which is due to users adopting applications (and finding/reporting bugs) at a faster pace than the development team is growing, hence the initial increase; eventually, as applications mature, their reporter base decreases at a faster pace than their owner base. There are no significant differences between platforms ($p > 0.19$ in all cases).

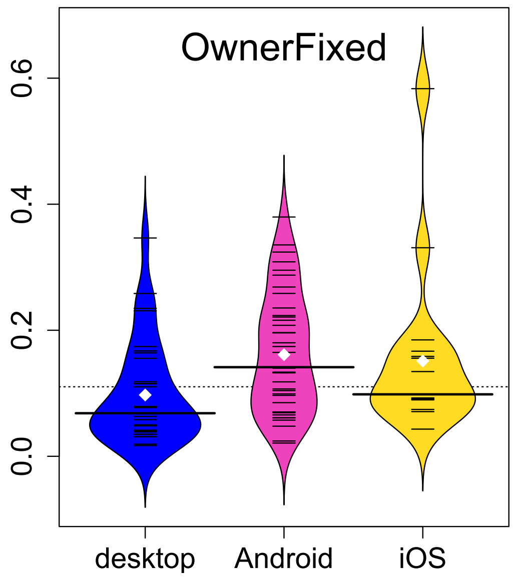


(a)



(b)

Figure 3.11: Beanplot of bug reporter fixed metric and trend.



(a)

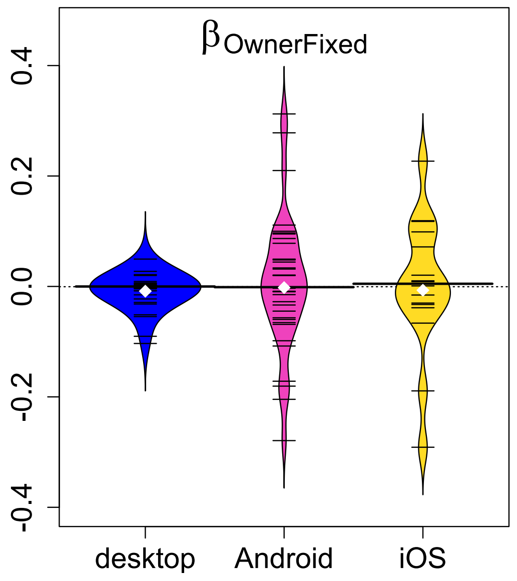


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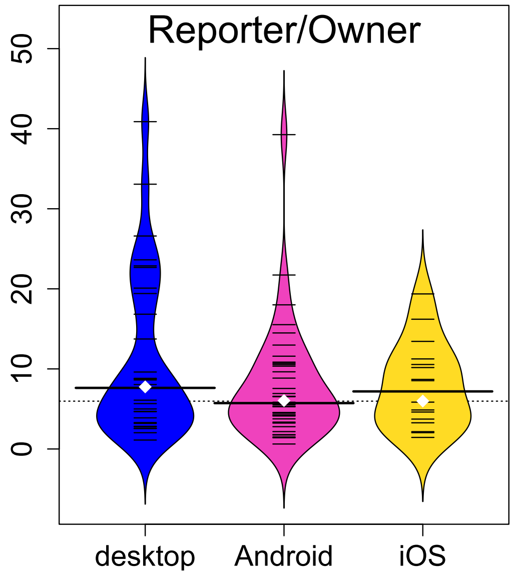
Figure 3.12: Beanplot of bug owner fixed metric and trend.



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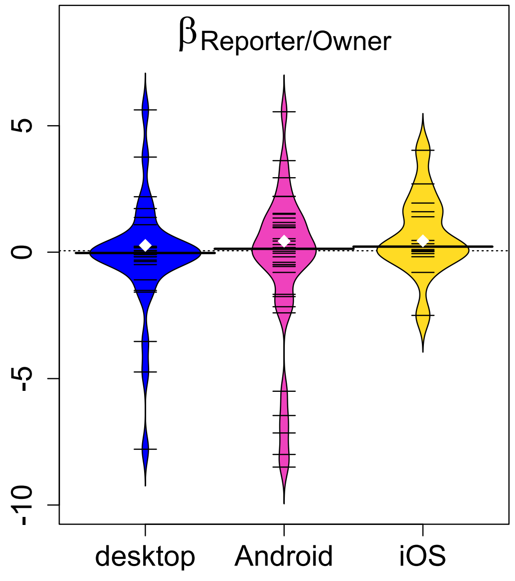


(b)

Figure 3.13: Beanplot of bug reporter/owner metric and trend.

Case Study: Contributor Activity in 2012

We now elaborate on the overlap between developer and owner sets which was also visible in Table 3.5—we found that for Android and iOS, many developers both reported and owned bugs. We chose 2012 for the case study.

Table 3.6 provides the top-7 contributors for each platform in 2012 (we chose 7 for consistency with Table 5.6). The first column is the developer ID, the second and fourth columns are the number of bugs reported and fixed by that developer, respectively. The third and fifth columns are the rank of that developer based on the number of bugs reported/fixed. Note how for desktop, top bug reporters and top bug owners are separate sets, indicating a strong separation of responsibilities. In contrast, for Android and iOS, the situation is opposite: top bug reporters also fix bugs as indicated by the large overlap in

Name	**Bugs reported**	**Rank**	**Bugs owned**	**Rank**
Desktop				
dev 13	331	1	21	276
dev 35	309	2	280	5
dev 14	273	3	246	7
dev 10	239	4	6	508
dev 36	202	5	0	N/A
dev 37	105	36	325	2
dev 38	192	8	223	8
Android				
dev 23	162	1	262	1
dev 21	148	2	6	76
dev 39	126	3	10	57
dev 40	101	4	177	3
dev 41	95	5	176	4
dev 24	80	6	178	2
dev 42	62	10	161	5
iOS				
dev 32	165	1	63	1
dev 30	64	2	48	2
dev 43	59	3	44	3
dev 44	30	4	6	10
dev 34	17	5	20	4
dev 33	7	7	9	5
dev 45	9	6	9	6

Table 3.6: Top bug reporters in 2012.

membership between top reporters and top owners. Previous work [69] has similar findings: 21.8% of the sampled participants in an Android contributor survey were developers who have submitted changes.

3.2.3 Bug Fix Rate Comparison

The bug fix rate is an indication of the efficiency of the bug-fixing process: a low fix rate can be due to many spurious bug reports being filed, or when reports are legitimate,

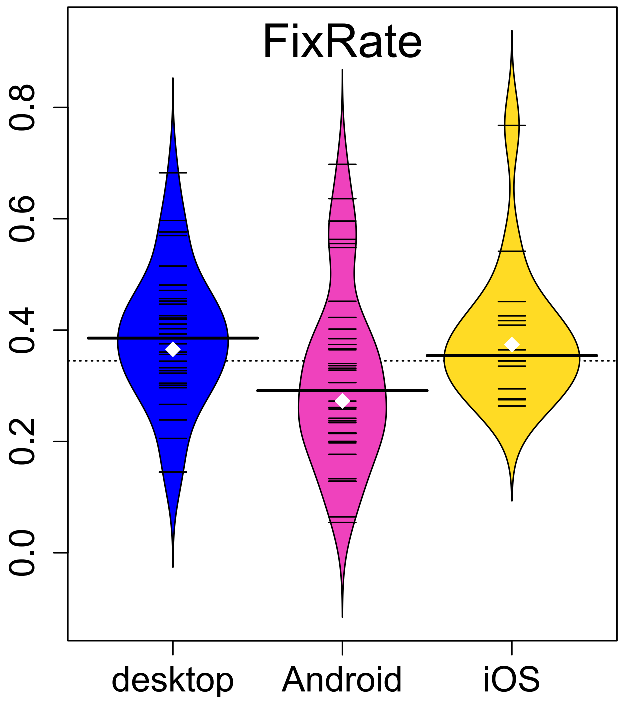


Figure 3.14: Bug fix rate.

developers are unable to cope with the high workload required for addressing the issues. Figure 3.14 shows the fix rate.

The mean bug fix rate for Android (27.28%) is lower than for desktop (36.56%) and iOS (37.40%). Our investigation has revealed that this is due to differences in bug reporter profiles and developer workloads.

In Android, two projects have much lower fix rates than others: Android platform (5.45%) and Wifi Tether (6.45%). When examining their workload compared to other projects, we found it to be very high (Android platform has 2,433 bug reporters and 130 bug owners, while Wifi Tether has 117 reporters but only 3 owners), which results in a low fix rate. On the other hand, WebKit, the project with the highest fix rate (69.78%), has 29 bug reporters and 18 bug owners—the high fix rate is unsurprising, given the lighter workload.

For desktop, the fix rate for Firefox (14.53%) and Thunderbird (14.45%) are the lowest. In contrast, Cassandra (68.25%), Mylyn (59.69%), and Eclipse CDT (57.62%) have much higher fix rates. The high rate of duplicate bug reports (27.18% for Firefox and 32.02% for Thunderbird) certainly plays a role in the low fix rate. Note, however, that Firefox and Thunderbird, a Web browser and email client respectively, are used by broad categories of people that have varying levels of expertise. In contrast, Mylyn is a task management system, Eclipse CDT is an IDE, Cassandra is a distributed database management system; their users have higher levels of expertise. Hence we believe that users of the latter applications are more adept at filing and fixing bugs than Firefox and Thunderbird users, leading to a higher fix rate.

For iOS, no application stands out as having a much lower fix rate than others. While Chrome for iOS has a low fix rate (35.34%), it is comparable with Chrome for Android (42.28%); tweetero has the highest fix rate (76.76%), understandably so as the project has 14 bug reporters and 5 bug owners.

Pairwise tests for fix rates show that the rates for desktop and Android projects differ ($p = 0.010$), as do Android and iOS projects ($p = 0.039$); the difference in fix rate between desktop and iOS projects is not significant ($p = 0.673$).

3.2.4 Case Study: Cross-platform Projects

We now present a method and case study for comparing process features in a more controlled setting, using cross-platform projects. We chose four apps, Chrome, Firefox, WordPress and VLC: the first two are dual-platform, while the last two are present on all three platforms. This comparison method is somewhat orthogonal to our approach so far: on one hand, it compares desktop, Android and iOS while eliminating some confounding factors, as within each project, processes and some developers are common across platforms; on the other hand it uses a small set of projects.

For Chrome, there are 337 bug reporters and 218 bug owners for Android, while the iOS version has 62 bug reporters and 38 bug owners. We found that 16 bug reporters and 13 bug owners contribute to both platforms; in fact, 6 of them reported and fixed bugs on both Android and iOS. For Firefox, we found 3,380 and 423 bug reporters for desktop and Android, respectively; 216 of them reported bugs on both platforms. We also found that Firefox has 911 and 203 bug owners on desktop and Android, respectively, with 80 owning bugs on both platforms. Finally, there were 58 developers that have reported and owned bugs on both platforms. In charge of WordPress bugs, there were 2352, 37, and 99 bug reporters (in desktop, Android and iOS, respectively) and 205, 8, and 31 bug owners (in desktop, Android and iOS). We found that 3 reporters open bug reports on all three platforms. For bug owners, we did not find developers who contribute to both desktop and Android; though 4 developers fixed bugs in both Android and iOS, while 3 developers fixed bugs for desktop and iOS. For VLC, there were 1451, 28, and 27 bug reporters and 98, 4, and 5 bug owners in desktop, Android and iOS, respectively; only one developer has contributed to all the platforms as bug reporter and owner.

Table 3.7 shows the geometric mean of features and bug-fixing management metrics for each app on different platforms; differences between the means were significant ($p < 0.01$), with few exceptions. We again ran a Wilcoxon-Mann-Whitney test between feature sets on different platforms but within the same project; non-significant features were

Project		FixTime	Severity	Description Length	Total Comments	Comment Length	Fix Rate	Reporter Turnover	Owner Turnover	Reporter Fixed	Owner Fixed	Reporter Owner
Chrome	Android	20.82	5.82	57.69	7.95	61.12	42.28%	0.61	0.22	0.40	0.26	1.50
	iOS	14.11	5.94	50.61	6.05	41.73	35.34%	0.30	0.10	0.79	0.58	1.44
Firefox	Desktop	86.20	5.61	45.19	8.59	86.30	14.53%	0.28	0.45	0.36	0.16	2.56
	Android	28.29	6.16	40.50	8.64	68.41	37.41%	0.52	0.24	0.30	0.21	1.79
WordPress	Desktop	9.54	5.79	38.37	3.38	42.01	37.53%	0.27	0.46	0.34	0.04	8.82
	Android	9.70	7.22	22.12	1.87	12.20	59.59%	0.48	0.17	0.16	0.12	2.17
	iOS	6.03	6.97	26.34	2.84	27.12	54.16%	0.76	0.34	0.25	0.13	2.04
VLC	Desktop	23.20	6.21	36.77	2.48	15.76	40.24%	0.21	0.39	0.40	0.08	5.00
	Android	18.40	6.27	22.02	2.82	11.52	25.83%	1.00	0.00	0.80	0.22	3.76
	iOS	8.96	6.77	22.30	2.24	12.02	42.55%	0.67	0.00	0.33	0.09	3.73

Table 3.7: Mean feature values for cross-platform projects.

Severity and DescriptionLength for Chrome; TotalComment for Firefox; FixTime on desktop v. Android, Severity ($p = 0.873$) and DescriptionLength ($p = 0.069$) on Android v. iOS. for WordPress; and Android v. iOS on VLC.

We make two observations. First, several findings (e.g., iOS bugs are fixed faster; Android bugs have larger ReporterTurnover; OwnerTurnover and CommentLength are higher on desktop) are consistent with the findings in Section 5.2.2, which gives us increased confidence in the generality of those results. Second, researchers and practitioners can use these findings to start exploring why, within a project, the subproject associated with a certain platform fares better than the other platforms.

3.3 Qualitative Analysis

We now turn to a *qualitative analysis* that investigates the nature of the bugs. Specifically, we are interested in what kinds of bugs affect each platform, what are the most important issues (high-severity bugs) on each platform, and how the nature of bugs changes as projects evolve.

We use topic analysis; we first extract topics (sets of related keywords) via LDA from the terms (keywords) used in bug title, descriptions and comments, as described in Section 2.2 used each year in each platform, and then compare the topics to figure out how topics change over time in each platform, how topics differ across platforms, and what were the prevalent bug topics in smartphone projects.

3.3.1 Topic Extraction

The number of bug reports varies across projects, as seen in Tables 3.1–3.3. Moreover, some projects are related in that they depend on a common set of libraries, for instance SeaMonkey, Firefox and Thunderbird use functionality from libraries in Mozilla Core, e.g., handling Web content. It is possible that a bug in Mozilla Core cascades and actually manifests as a crash or issue in SeaMonkey, Firefox, or Thunderbird, which leads to three separate bugs being filed in the latter three projects. For example, Mozilla Core bug #269568 cascaded into another two bugs in Firefox and Thunderbird.

Hence we extract topics using two strategies: `Original` and `Sampled`. In the `Original` strategy, we use all bug reports from each project. In the `Sampled` a *sampling* strategy, where we sampled bug reports to reduce possible over representation due to large projects and shared dependences. More concretely, for `Sampled` we extracted topics from 1,000 "independent" bug reports for each project group, e.g., Mozilla, KDE. The independent bug report sets were constructed as follows: since we have 10 projects from KDE, we sampled 100 bugs from each KDE-related project. We followed a similar process for Mozilla, Eclipse and Apache. Android and iOS had smaller number of bug reports, so for Android we sampled 100 bug reports from each project, and for iOS we sampled 50 bug reports from each project. For those projects have less bug reports (e.g., VLC for Android) than the sample number, we choose all the bug reports.

We used LDA (as described in Section 2.4) on both `Original` and `Sampled` sets; For `Sampled` set, since there were only 2 bug reports on 1998 for desktop and 1 for Android in 2007, we have omitted those years. For `Original` set, the preprocessing of desktop bug reports resulted in 35,083,363 words (510,600 of which were distinct). For Android bug reports, the preprocessing resulted in 1,535,307 words (36,411 of which were distinct). For iOS bug reports, the preprocessing resulted in 202,263 words (10,314 of which were distinct). For `Sampled` set, The preprocessing of desktop, Android, and iOS sets resulted in 824,275 words (37,891 distinct), 238,027 words (12,046 distinct) and 71,869 words (5,852 distinct), respectively.

In the next step, we used MALLET [103] for LDA computation. We ran for 10,000 sampling iterations, the first 1,000 of which were used for parameter optimization. For `Original` set, we modeled bug reports with $K = 400$ topics for desktop, 90 for Android and 50 for iOS. For `Sampled` set, We modeled bug reports with $K = 100$ topics for desktop, 60 for Android, and 30 for iOS; we choose K based on the number of distinct words for each platform; Section 3.5 discusses caveats on choosing K. Finally, we labeled topics according to the most representative words and confirmed topic choices by sampling bug reports for each topic to ensure the topic's label and representative words set were appropriate.

3.3.2 Bug Nature and Evolution

How Bug Nature Differs Across Platforms

Table 3.8 shows the top-5 topics in each platform, in each year, for the `Original` data set. As expected, some projects, e.g., "Qt", the shared library used in KDE, was the strongest topic in 2008; Mozilla or Android platform, dominate and bugs associated with them have a high preponderance among topics. Nevertheless, differences among platforms are clear: on desktop, crashes and GUI issues are preponderant; on Android, the Android runtime is a major source of issues; on iOS, crashes are preponderant. Note that the analysis of `Original` or `Sampled` serve different purposes, depending on whether our interest is in where the bulk of the bugs are in a certain year (`Original`), or how the nature of the bugs exhibits similarity across projects `Sampled`.

Table 3.9 shows the topics extracted from `Sampled` data set. We found that for desktop, application crash is the most common bug type, and application logic bugs (failure to meet requirements) are the second most popular. For Android, bugs associated with the user interface (GUI) are the most prevalent. For iOS, application logic bugs are the most prevalent.

There are topics related to specific applications, e.g., Hadoop. The reason is that with partial assignments, LDA will not try to find mutually exclusive topics, since a document can be partly about one topic and partly about another [110].

How Bug Nature Evolves

To study macro-trends in how the nature of bugs changes over time, we analyzed topic evolution in each platform. We discuss our findings on `Sampled` data set. For desktop, application logic and crashes are a perennial presence, which is unsurprising. However, while in the early years (before 2005), compilation bugs were a popular topic, after 2005 new kinds of bugs, e.g., concurrency (topic “thread”) and multimedia (topics “audio”, “video”) take center stage.

For Android, it is evident that in the beginning, developers were still learning how to use the platform correctly: intents are a fundamental structure for intra- and inter-app

Year	Top 5 topics (topic weight)				
Desktop					
1998	layout (33%)	scrollbar (22%)	crash (11%)	toolbar/sidebar (11%)	event handler (8%)
1999	scrollbar (29%)	Mozilla dogfood (20%)	toolbar/sidebar (12%)	crash (10%)	event handler (9%)
2000	nsbeta (19%)	scrollbar (18%)	toolbar/sidebar (13%)	crash (13%)	konqueror (12%)
2001	konqueror (15%)	compile (14%)	crash (14%)	toolbar/sidebar (11%)	event handler (11%)
2002	widget (21%)	crash (15%)	compile (14%)	event handler (11%)	toolbar/sidebar (9%)
2003	widget (20%)	Mozilla Firebird (14%)	crash (14%)	event handler (10%)	toolbar/sidebar (7%)
2004	crash (14%)	UI (14%)	widget (13%)	Firefox clobber (12%)	event handler (10%)
2005	crash (15%)	OSGI (13%)	UI (11%)	widget (10%)	event handler (9%)
2006	crash (16%)	Amarok (12%)	UI (10%)	plugin (10%)	event handler (10%)
2007	crash (18%)	plugin (12%)	Equinox (12%)	Cairo lib (10%)	event handler (10%)
2008	Qt (21%)	crash (17%)	plugin (12%)	event handler (9%)	UI (7%)
2009	thread (32%)	crash (17%)	plugin (10%)	event handler (9%)	concurrency (7%)
2010	thread (32%)	crash (20%)	plugin (10%)	event handler (9%)	concurrency (9%)
2011	crash (20%)	widget crash (13%)	concurrency (10%)	plugin (10%)	event handler (9%)
2012	crash (20%)	Hadoop (18%)	Gnome (12%)	dll (11%)	plugin (9%)
2013	Hadoop (26%)	crash (20%)	audio (15%)	event handler (8%)	plugin (7%)
Android					
2007	sdk (24%)	layout (17%)	Android runtime (16%)	crash (9%)	mail (6%)
2008	sdk (25%)	Android runtime (17%)	mail (11%)	layout (11%)	crash (9%)
2009	mail (15%)	Android runtime (15%)	crash (11%)	layout (10%)	Email client (9%)
2010	Android runtime (15%)	crash (12%)	thread (10%)	AnkiDroid (9%)	mail (7%)
2011	Android runtime (18%)	crash (12%)	thread (9%)	battery (9%)	layout (8%)
2012	Android runtime (15%)	Firefox (13%)	crash (13%)	layout (8%)	bookmark (7%)
2013	Firefox (17%)	Android runtime (13%)	crash (10%)	Chrome (10%)	layout (9%)
iOS					
2007	connection (22%)	book (21%)	screen display (13%)	UI (10%)	crash (10%)
2008	graphics (16%)	multimedia (13%)	crash (11%)	screen display (11%)	MobileTerminal (10%)
2009	Siphone (13%)	memory (12%)	connection (11%)	graphics (11%)	crash (10%)
2010	crash (14%)	graphics (11%)	connection (11%)	screen display (10%)	BTstack (8%)
2011	book (22%)	crash (17%)	plot (9%)	memory (8%)	graphics (8%)
2012	plot (20%)	crash (17%)	screen display (15%)	UI (14%)	memory (8%)
2013	sync (37%)	crash (16%)	connection (10%)	memory (8%)	screen display (7%)

Table 3.8: Top-5 topics in each platform per year for `Original` data set.

Year	**Top 5 topics (topic weight)**				
Desktop					
1999	layout (30%)	reassign (20%)	application logic (15%)	crash (14%)	php (8%)
2000	database (22%)	reassign (20%)	crash (15%)	layout (15%)	application logic (9%)
2001	crash (16%)	compilation (16%)	reassign (16%)	application logic (14%)	php (13%)
2002	application logic (14%)	compilation (14%)	crash (12%)	SCSI (12%)	ssh (12%)
2003	compilation (21%)	application logic (15%)	crash (11%)	config (9%)	connection (9%)
2004	UI (33%)	application logic (13%)	crash (12%)	config (9%)	compilation (7%)
2005	sql (28%)	application logic (15%)	crash (12%)	compilation (8%)	php (7%)
2006	application logic (17%)	Spring (16%)	crash (15%)	sql (9%)	php (7%)
2007	crash (14%)	application logic (13%)	graphic (13%)	php (10%)	connection (9%)
2008	application logic (16%)	crash (15%)	component mgmt. (12%)	UI (10%)	php (9%)
2009	crash (17%)	application logic (14%)	thread (13%)	UI (11%)	connection (7%)
2010	crash (17%)	application logic (16%)	audio (11%)	php (10%)	video (8%)
2011	debug symbol (20%)	crash (19%)	application logic (14%)	video (7%)	php (7%)
2012	crash (21%)	application logic (14%)	Hadoop (12%)	video (11%)	connection (9%)
2013	crash (21%)	Hadoop (21%)	application logic (17%)	video (8%)	connection (7%)
Android					
2008	intent (26%)	sensor (22%)	UI (21%)	thread handler (14%)	phone call (8%)
2009	UI (17%)	phone call (15%)	thread handler (12%)	intent (10%)	wifi (10%)
2010	phone call (18%)	UI (16%)	thread handler (13%)	battery (9%)	wifi (8%)
2011	thread handler (19%)	UI (14%)	network (12%)	phone call (10%)	reboot (9%)
2012	thread handler (18%)	map (16%)	UI (14%)	phone call (10%)	locale (9%)
2013	UI (21%)	scale (17%)	API (12%)	phone call (11%)	thread handler (11%)
iOS					
2007	ebook (29%)	screen display (29%)	general (15%)	UI (13%)	compilation (4%)
2008	general (30%)	multimedia (27%)	screen display (19%)	compilation (4%)	MyTime (3%)
2009	Siphon (28%)	general (26%)	message (15%)	screen display (9%)	compilation (5%)
2010	multimedia (22%)	general (19%)	graph plot (15%)	screen display (15%)	compilation (10%)
2011	SDK (44%)	general (19%)	compilation (8%)	screen display (8%)	graph plot (8%)
2012	BTstack (30%)	general (21%)	graph plot (16%)	UI (10%)	screen display (9%)
2013	sync (39%)	compilation (20%)	general (16%)	UI (7%)	WordPress (6%)

Table 3.9: Top-5 topics in each platform per year for `Sampled` data set.

Label	**Most representative words**
Desktop	
crash	crash fail call check log process item size expect event state titl menu point block
application logic	messag updat configur link control task access thread directori cach method displai correct command modul
Android	
UI	android screen applic messag menu button text select option error fail wrong mode crash icon
thread handler	android app thread log type init intern phone zygot event handler window displai looper invok
phone call	call phone send account press devic server servic network mobil stop receiv wait confirm lock
iOS	
general	phone file call updat crash touch applic support point type menu post delet upgrad network
screen display	screen button displai view click error scroll bar game imag left load tap keyboard landscap
compilation	user run page receiv attach fail error compil mode revision map enabl crash devic handl

Table 3.10: Top words associated with major topics.

communication, and "intent" is a predominant topic in 2007 and 2008. The GUI ("UI"), concurrency ("thread handler"), and telephony ("phone call") are perennial issues.

For iOS, the GUI ("UI") and display ("screen display") are perennial issues, but in contrast to Android, concurrency and the platform do not appear to pose as much difficulty, and in later years application bugs take over. However, compilation issues seem to be a perennial problem as well, whereas for Android they are not. Table 3.10 shows the major topics and the top keywords within each topic.

Platform	**Rank 1**	**Rank 2**	**Rank 3**	**Rank 4**	**Rank 5**
Desktop	site mgmt.	style	codex	error msg.	user mgmt.
Android	null pointer	post error	upload fail	user mgmt.	codex
iOS	post error	error msg.	upload fail	landscape	codex

Table 3.11: Top-5 topics for WordPress.

3.3.3 Case Study: WordPress

We now focus on studying topic differences in a single app that exists on all three platforms: WordPress. We chose WordPress as our case study app for two reasons. First, it is one of the most popular blogging tools, used by 21.5% of all the websites – a content management system market share of 60.1% [145]. Second, WordPress is a cross-platform application and mature on all three platforms—desktop, Android and iOS—which reduces confounding factors (we employed the same strategy in Section 3.2.4).

To study differences across platforms for WordPress, we used the Section 2.4 process and set the number of topics K to 80. Table 3.11 shows the resulting top-5 topics for each platform. The power of topic analysis and the contrast between platforms now becomes apparent. "Post error" and "upload fail" are topics #2/#3 on Android, and #1/#3 on iOS: these are bugs due to communication errors, since spotty network connectivity is common on smartphones; "codex" (semantic error) is a hot topic across all platforms, which is unsurprising and in line with our findings from Section 5.3.2. For desktop, the #1 topic, "site management" is due to desktop-specific plugins and features. Since the Android version of WordPress is developed in Java, null pointer bugs stand out ("null pointer" is topic #1 in Android). For iOS, there are many critical bugs when using landscape mode, e.g. issues #392, #403 and #768.

3.3.4 Smartphone-specific Bugs

As mentioned in Chapter 1, smartphone software differs substantially from desktop software in many regards: app construction, resource constraints, etc. For example, the data that smartphone software collects from GPS and accelerometer raises significant privacy concerns that did not exist on the desktop platform. Furthermore, due to device portability, issues such as performance and energy bugs are significantly more important on smartphone than on fixed platforms. Understandably, significant research efforts have been dedicated to smartphone bugs such as location privacy or energy consumption. Hence we aimed to quantify the prevalence of energy, security, and performance bugs in the topic model.

We found that *energy-related* bugs (containing keywords such as "power," "battery," "energy," "drain") as a topic only ranked high (in top-5) once, in 2010 for Android—the reason was the release of Android platform version 2.2 (Froyo) in 2010, which contained a higher number of energy bugs (e.g., Android platform issues #8478, #9307 and #9455). In all other years, energy did not appear as a topic in top-20.

For *security bugs*, keywords within the topic included "security," "vulnerability," "permission," "certificate", "attack". We found that, although such bugs are marked with high severity, their representation among topics was low. We did not find them in top-5 topics; the highest was rank 7 in 2009 and rank 11 in 2010, in Android. For iOS we could not find security bugs among the top-20 topics.

For *performance bugs*, associated keywords included "performance," "slow," "latency," "lagging". We could not find performance-related topics in top-20 on Android or iOS platform.

3.4 Actionable Findings

We now discuss how our findings can help point out potential improvements.

3.4.1 Addressing Android's Concurrency Issues

Android's GUI framework is single-threaded and requires the application developer to manage threads manually, offering no thread-safety guarantees. For example, to build a responsive UI, long-running operations such as network and disk IO have to be performed in background threads and then the results posted to the UI thread's event queue; as a consequence, the happens-before relationship between GUI and other events is not enforced, leading to concurrency bugs [97]. In contrast, the iOS framework handles concurrency in a safer manner by using `GCD` (Grand Central Dispatch) to manage inter-thread communication; as a result, there are fewer concurrency bugs on iOS.

Hence there is an impetus for (1) improving the Android platform with better orchestration of concurrency, (2) improving programing practice, e.g., via the use of `AsyncTask` as suggested by Lin et al. [89], and (3) constructing analyses for Android race detection [97].

3.4.2 Improving Android's Bug Trackers

Many of the Android projects we have examined (27 out of 38) are hosted on, and use the bug tracking facilities of, Google Code, in contrast to desktop programs, whose bugs are hosted on traditional bug trackers such as Bugzilla, JIRA and Trac. On Google Code, bug tracking is conveniently integrated with the source code repository. However, Google

Code's tracker has no support for: (1) bug component—while easier for new users to file bugs as there is no need to fill in bug components, the lack of a component makes it harder for developers to locate the bug; and (2) bug resolution—they use labels instead. These aspects complicate bug management (triaging, fixing).

Hence there is an impetus for improving bug tracking in Google Code, which will in turn improve the bug fixing process for the projects it hosts.

3.4.3 Improving the Bug-fixing Process on All Platforms

As Figure 3.2 in Section 3.2 shows, the overlap between bug reporters and bug owners is higher on desktop projects. This is good for speeding up the bug-fixing process since usually bug reporters are more familiar with the bugs they report [28]. Smartphone projects' development teams should aim to increase this overlap.

According to Sections 3.2.2 and 3.2.3, Android projects have the lowest workload (highest OwnerFixed rate), and the lowest fix rate as well, which suggests a need for improving developer engagement. The ReporterTurnover rate on Android and iOS is higher than that of desktop (Figure 3.9a, Section 3.2.2)—this indicates that there are many new users of smartphone apps, which can potentially increase product quality [22]. Hence desktop projects can improve the bug-fixing process by encouraging more users to report issues in the bug tracking system [164], e.g., via automatic bug reporting [147].

Furthermore, bug reports containing attachments, e.g., stack traces, tend to be fixed sooner [59, 167]. Yet, few Android bug reports have a system trace (`logcat`) or crash report attached. Hence the Android bug-fixing process would benefit from automatically attaching the `logcat` to the bug report, which is also recommended in previous research [72].

3.4.4 Challenges for Projects Migrating to GitHub

For our examined period, we found that many smartphone projects have "migrated" to GitHub: 7 Android projects and 3 iOS projects have fully migrated to GitHub (source code and bug tracking), while 10 Android projects only moved the source code repositories to GitHub.[1] The rationale was developers' concern with Google Code's lack of features compared to GitHub, e.g., forks and pull requests, source code integration [13,124]. However, the issue tracking system on GitHub lacks several critical features, e.g., severity, component (instead they only use labels); furthermore, bug reports cannot have attachments; a bug report template is missing as well. Unless GitHub adds those missing bug management features, the projects will suffer, as it is harder for developers to manage and ultimately fix the bugs.

3.5 Threats to Validity

We now discuss possible threats to the validity of our study.

3.5.1 Selection Bias

We only chose open source applications for our study, so the findings might not generalize to closed-source projects. Our chosen projects use one of four trackers (Bugzilla, Trac, JIRA, Google Code); we did not choose projects hosted on GitHub since several bug features (e.g., severity) are not available on GitHub, hence our findings might not generalize to GitHub-hosted projects.

[1]For details please visit our online supplementary material: `http://www.cs.ucr.edu/~bzhou003/cross_platform.html`.

We studied several cross-platform projects (Chrome, Firefox, WordPress, and VLC) to control for process. However, we did not control for source code size—differences in source code size might influence features such as FixTime.

3.5.2 Data Processing

For the topic number parameter K, finding an optimal value is an open research question. If K is too small, different topics are clustered together, if K is too large, related topics will appear as disjoint. In our case, we manually read the topics, evaluated whether the topics are distinct enough, and chose an appropriate K to yield disjoint yet self-contained topics.

Google Code does not have support for marking bugs as reopened (they show up as new bugs), whereas the other trackers do have support for it. About 5% of bugs have been reopened in desktop, and the FixTime for reopened bugs is usually high [130]. This can result in FixTime values being lower for Google Code-based projects than they would be if bug reopening tracking was supported.

3.5.3 IDs vs. Individuals

Some projects (especially large ones) have multiple individuals behind a single ID, as we showed in Section 3.2.2. Conversely, it is possible that a single individual operates using multiple IDs. This affects the results in cases where we assume one individual per ID.

3.6 Summary

We have conducted a study to understand how bugs and bug-fixing processes differ between desktop and smartphone software projects. A quantitative analysis has revealed that, at a meta level, the smartphone platforms are still maturing, though on certain bug-fixing measures they fare better than the desktop. By comparing differences due to platforms, especially within the same project, researchers and practitioners could get insights into improving products and processes. After analyzing bug nature and its evolution, it appears that most frequent issues differ across platforms.

Chapter 4

Empirical Study of Concurrency Bugs

Our studies (e.g., Section 3.4) have revealed that concurrency is an important issue on both desktop and mobile platforms. Concurrent programming is challenging, and concurrency bugs are particularly hard to diagnose and fix for several reasons, e.g., thread interleaving and shared data complicate reasoning about program state [95], and bugs are difficult to reproduce due to non-determinism and platform-specific behavior. As a result, it appears that fixing concurrency bugs takes longer, requires more developers, and involves more patches, compared to fixing non-concurrency bugs.

To help with finding and fixing concurrency bugs, prior research has mostly focused on static or dynamic analyses for finding specific classes of bugs. Hence in this chapter, we present an approach whose focus is understanding the nature of concurrency bugs and the differences between concurrency and non-concurrency bugs, the differences among various concurrency bug classes, and predicting bug quantity, type, and location, from patches, bug reports and bug-fix metrics. We use statistics and machine learning as our main tools. First, we show that bug characteristics and bug-fixing processes vary significantly among different kinds of concurrency bugs and compared to non-concurrency bugs. Next, we build a quantitative predictor model to estimate concurrency bugs appearance in future releases. Then, we build a qualitative predictor that can predict the type of concurrency bug for a newly-filed bug report. Finally, we build a bug location predictor to indicate the likely source code location for newly-reported bugs. We validate the effectiveness of our approach on three popular projects, Mozilla, KDE, and Apache.

4.1 Concurrency Bug Types

We now briefly review the four main types of concurrency bugs, as introduced by previous research [39, 93, 95].

Atomicity violations result from a lack of constraints on the interleaving of operations in a program. Atomicity violation bugs are introduced when programmers assume some code regions to be atomic, but fail to guarantee the atomicity in their implementation. In Figure 4.1 we present an example of an atomicity violation, bug #21287 in Apache: accesses to variable obj in function decrement_refcount are not protected by a lock, which causes the obj to be freed twice.

Order violations involve two or more memory accesses from multiple threads that happen in an unexpected order, due to absent or incorrect synchronization. An order violation

Thread 1	**Thread 2**
`apr_atomic_dec(&obj->refcount);`	
	`apr_atomic_dec(&obj->refcount);`
	`if (!obj->refcount) {`
`if (!obj->refcount) {`	`    cleanup_cache_object(obj);`
`    cleanup_cache_object(obj);`	`}`
`}`	

Figure 4.1: Atomicity violation bug #21287 in Apache (`mod_mem_cache.c`).

Thread 1	**Thread 2**
`nsThread::Init(...){`	`nsThread::Main(...){`
`    ...`	`    ...`
	`    mState = mThread->GetState(...);`
	`    ...`
`    mThread = PR_CreateThread(Main`	
`        ,...);`	
`    ...`	

Figure 4.2: Order violation bug #61369 in Mozilla (`nsthread.cpp`).

example, bug #61369 in Mozilla, is shown in Figure 4.2: nsThread::Main() in Thread 2 can access mThread's state before it is initialized (before PR_CreateThread in Thread 1 returns).

Data races occur when two different threads access the same memory location, at least one access is a write, and the accesses are not ordered properly by synchronization.

Deadlocks occur when two or more operations circularly wait for each other to release acquired resources (e.g., locks).

4.2 Methodology

We now present an overview of the three projects we examined, as well as the methodology we used for identifying and analyzing concurrency bugs and their bug-fix process.

4.2.1 Projects Examined

We selected three large, popular, open source projects for our study: Mozilla, KDE and Apache. The Mozilla suite is an open-source web client system implementing a web browser, an email client, an HTML editor, newsreader, etc. Mozilla contains many different sub-projects, e.g., the Firefox web browser, and the Thunderbird mail client. In this chapter, we mainly focus on the core libraries, and the products related to the Firefox web browser. KDE is a development platform, a graphical desktop, and a set of applications in diverse categories. Apache is the most widely-used web server; we analyzed the HTTP server and its supporting library, APR, which provides a set of APIs that map to the underlying operating system. The evolution time span and source code size are presented in Table 4.1.

We focus on these three projects for several reasons. First, their long evolution (more than 10 years), allow us to observe the effect of longer or shorter histories on prediction accuracy. Second, they are highly concurrent applications with rich semantics, and have large code bases, hence predicting bug type and location is particularly helpful for finding and fixing bugs. Finally, given the popularity of their core components that constitute the object of our study, finding and fixing concurrency bugs is a key priority for these projects. We believe that these characteristics make our chosen projects representative of some of the biggest challenges that the software development community faces as complex applications become more and more concurrent.

Project	**Time span**	**SLOC**		**Bug reports**		**Concurrency Bugs**				
		First release	Last release	Fixed & closed	Matching concurrency keywords	Atomicity violation	Order violation	Data race	Deadlock	*Total*
Mozilla	1998-2012	1,459k	4,557k	114,367	1,149	60	34	10	30	*134*
KDE	1999-2012	956k	14,330k	118,868	887	14	13	29	19	*75*
Apache	2000-2012	110k	223k	22,370	423	18	8	10	5	*41*
				Total	2,459	*92*	*55*	*49*	*54*	*250*

Table 4.1: Bug reports and concurrency bug counts.

4.2.2 Identifying Concurrency Bugs

We now describe the process for collecting concurrency bugs and computing the attributes of their bug-fixing process. All three projects offer public access to their bug trackers [12, 75, 108]. We first selected the fixed bugs; then we split the fixed bugs into concurrency and non-concurrency bugs using a set of keywords and cross-information from the commit logs; finally we categorized the concurrency bugs into the four types. Our process is similar to previous research [46, 93]. Potential threats to the validity of our process will be discussed in Section 4.7. The results, explained next, are given in Table 4.1.

Identifying "true" bugs. To identify the viable bug report candidates, we only considered bugs that have been confirmed and fixed; that is, we only selected bug reports marked with resolution `FIXED` and status `CLOSED`. We did not consider bugs with other statuses, e.g., `UNCONFIRMED` and other resolutions (e.g., `INVALID`, or `WONTFIX`)—the reason is that for bugs other than `FIXED` and `CLOSED`, the bug reports did not have detailed information and discussions also in general, they will not contain correct patches. Without reasonably complete bug reports it would be impossible for us to completely understand the root cause of the bugs.

We limited the searching process to those parts of the project with a long history and large source code base. For Mozilla, we only selected 8 products which are directly related to the core and browser parts: *Core, Firefox, Directory, JSS, NSPR, NSS, Plugins*, and *Rhino* [19]. For Apache, we only chose C/C++ products: the *Apache HTTP Server* and the *Apache Portable Runtime.* For KDE, we considered all products in the KDE Bugtracking System.

Candidate concurrency bug reports. As the 5th column of Table 4.1 shows, there were more than 250,000 bugs left after the previous step. To make our study feasible, we automatically filtered bugs that were not likely to be relevant to concurrency by performing a search process on the bug report database. We retained reports that contained a keyword from our list of relevant concurrency terms; the list included terms such as "thread", "synchronization", "concurrency", "mutex", "atomic", "race", "deadlock". Note that similar keywords were used in the previous research [46,93]. In Table 4.1 (6th column), we show the number of bug reports that matched these keywords. Many bugs, however, are mislabeled, as explained shortly. Our keyword-based search for bug reports could have false negatives, i.e., missing some of the real concurrency bugs (which we identify as a threat to validity in Section 4.7). However, we believe that a concurrency bug report that did not contain any of the aforementioned keywords is more likely to be incomplete and much more difficult to analyze its root cause.

Determining the concurrency bug type. We then manually analyzed the 2,459 bug reports obtained in the previous step to determine (1) whether they describe an actual concurrency bug and if yes, (2) what is the concurrency bug type. In addition to the bug description, some reports also contain execution traces, steps to reproduce, discussion between the developers about how the bug was triggered, fix strategies, and links to patches. We used all these pieces of information to determine whether the bug was a concurrency bug and its type.

For all bugs we identified as concurrency bugs, we analyzed their root cause and fix strategy, and binned the bug into one of the four types described in Section 4.1. In the end, we found 250 concurrency bugs: 134 in Mozilla, 75 in KDE, and 41 in Apache; the numbers for each category are presented in the last set of grouped columns of Table 4.1; the Mozilla and Apache numbers are in line with prior findings by other researchers, though their study has analyzed bugs up to 2008 [93]. We found that, in Mozilla and Apache, atomicity violations were the most common, while in KDE, data races were the most frequent.

Note that searching bug reports alone is prone to false positives (incorrectly identifying a non-concurrency bug as a concurrency bug) and false negatives (missing actual concurrency bugs) [46]. To reduce the incidence of such errors, we also keyword-searched the commit logs (e.g., CVS and Mercurial for Mozilla) and then cross-referenced the information obtained from the bug tracker with the information obtained from the commit logs. For instance, Mozilla bug report #47021, did not contain any of the keywords but we found the keyword *race* in the commit log associated with the bug, so based on this information we added it to our set of concurrency bugs to be categorized.

Concurrency bug types and keywords. We found many bug reports that contained keywords pertaining to other types of bugs. The following table shows the percentage of bug reports in each category (computed after our manual categorization) containing each of the four keywords that one would naturally associate with the corresponding bug type.

	Percentage of bug reports containing the keyword			
Keyword	Atomicity bug reports	Order bug reports	Race bug reports	Deadlock bug reports
"atomic"	29.35	14.54	8.16	1.85
"order"	21.74	40.00	16.33	14.81
"race"	70.65	63.64	51.02	7.41
"deadlock"	16.30	16.36	12.24	94.44

Note how 70.65% of the atomicity violation reports contain the keyword "race", while only 29.35% contain the keyword "atomic". In fact, a higher percentage of atomicity violation and order violation bug reports contain the term “race” (70.65% and 63.64%, respectively) compared to the race bug reports (51.02%). These findings suggest that: (1) while searching for concurrency bug reports using an exhaustive keyword list followed by manual analysis has increased our effort, it was essential for accurate characterization, as many bugs contain misleading keywords, and (2) using approaches that can assign weights to, and learn associations between, keywords, are likely to be promising in automatically classifying bug types—we do exactly that in Section 4.5.

4.2.3 Collecting Bug-fix Process Data

To understand the nature of, and differences in, bug-fixing processes associated with each concurrency bug type, we gathered data on bug features—the time, patches, developers, files changed, etc., that are involved in fixing the bugs. We now provide details and definitions of these features.

Patches represents the number of patches required to fix the bug; we extract it from the bug report. *Days* represents the time required to fix the bug, computed as the difference between the date the bug was opened and the date the bug was closed. *Files* is the number of files changed in the last successful patch. We extracted the number of files changed by analyzing the bug report and the commit information from the version control system. *Total patch size* indicates the combined size of all patches associated with a bug fix, in KB. *Developers* represents the number of people who have submitted patches. *Comments* is the number of comments in the bug report. *Severity:* to capture the impact that the bug has on the successful execution of the applications, our examined projects use a numerical scale for bug severity. Mozilla uses a 7-point scale[1], while KDE and Apache use 8-point scales. To have a uniform scale, we mapped KDE[2] and Apache[3] severity levels onto Mozilla's.

4.3 Quantitative Analysis of Bug-fixing Features

Prior work has found that fixing strategies (that is, code changes) differ widely among different classes of concurrency bugs [93]; however, their findings were qualitative, rather than quantitative. In particular, we would like to be able to answer questions such as: *Which concurrency fixes require changes across multiple files? Do atomicity violation fixes require more patches to "get it right" compared to deadlock fixes? Which concurrency bug types take the longest to fix? Are concurrency bugs more severe than non-concurrency bugs? Do concurrency bugs take longer to fix than non-concurrency bugs?*

Therefore, in this section we perform a quantitative assessment of the bug-fix process for each concurrency bug type, as well as compare concurrency and non-concurrency bugs, along several dimensions (features). While bug-fixing effort is difficult to measure, the features we have chosen provide a substantive indication of the developer involvement associated with each type of bug. Moreover, this assessment is essential for making inroads into predicting the number of concurrency bugs in the code that are yet to be discovered.

To compare concurrency bugs and non-concurrency bugs, we randomly selected 250 non-concurrency bugs found and fixed in the same product, component, software version and milestone with the 250 concurrency bugs we found. The reason why we used the same

[1]0=Enhancement, 1=Trivial, 2=Minor, 3=Normal, 4=Major, 5=Critical, 6=Blocker.
[2]0=Task, 1=Wishlist, 2=Minor, 3=Normal, 4=Crash, 4=Major, 5=Grave, 6=Critical.
[3]0=Enhancement, 1=Trivial, 2=Minor, 3=Normal, 4=Major, 4=Regression, 5=Critical, 6=Blocker.

product/component/version/milestone for concurrency and non-concurrency bugs was to reduce potential confounding factors. We manually validated each non-concurrency bug and bug report for validity, as we did with concurrency bugs.

4.3.1 Feature Distributions

We now present our findings. For each feature, in Figure 4.3 we show a boxplot indicating the distribution of its values for each concurrency bug type. Each boxplot represents the minimum, first quartile, third quartile and maximum values. The black horizontal bar is the median and the red diamond point is the mean. The second-from-right boxplot shows the distribution across all concurrency bugs. The rightmost boxplot shows the distribution for non-concurrency bugs. For legibility and to eliminate outliers, we have excluded the top 5% and bottom 5% when computing and plotting the statistical values. We now discuss each feature.

Patches are one of the most important characteristics of bug fixing. Intuitively, the number of patches could be used to evaluate how difficult the bugs are—the more patches required to "get it right," the more difficult it was to fix that bug. We found (Figure 4.3) that atomicity violations take the highest number of patches (usually 2–5, on average 3.5), while order violations take on average 2.4 patches, followed by races at 1.7 patches and deadlocks at 1.6 patches. Non-concurrency bugs require on average 1.4 patches.

Days. Predicting the bug-fix time is useful for both concurrency bugs and non-concurrency bugs, as it helps managers plan the next releases. We found (Figure 4.3) that the average bug-fix time is longer than 33 days for all 4 types of concurrency bugs, which

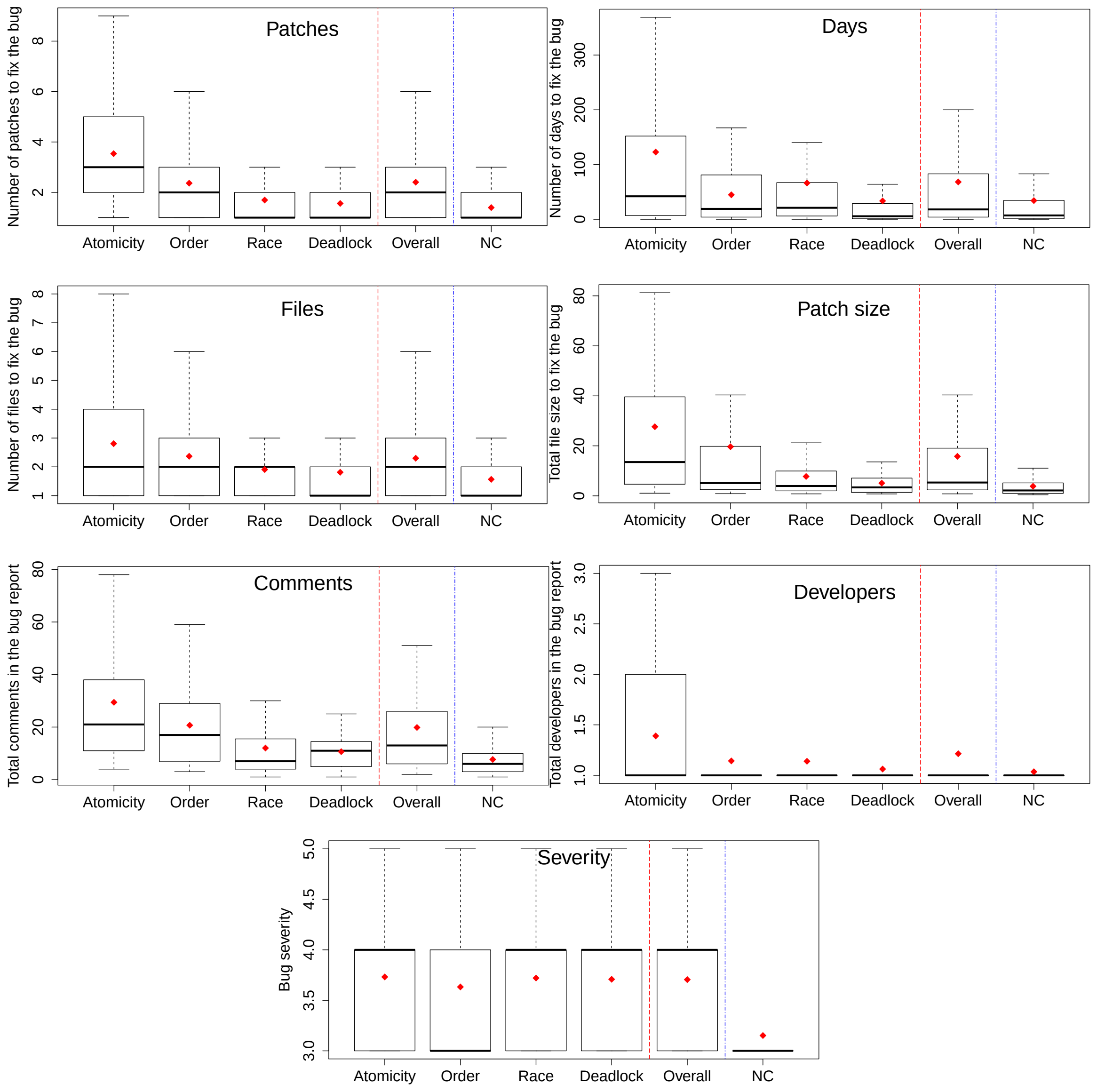


Figure 4.3: Feature distributions for each class of concurrency bugs (Atomicity, Order, Race, Deadlock), all concurrency bugs combined (Overall) and non-concurrency bugs (NC).

means that usually the time cost associated with concurrency bugs is high. Similar to the number of patches, atomicity violation bugs took the longest to fix (123 days on average), order violations and races took less (66 days and 44 days, respectively), while deadlocks were fixed the fastest (33.5 days on average). Non-concurrency bugs take on average 34 days to be fixed.

One example of why atomicity bugs take long to resolve is Mozilla bug #225525. This bug, reported on 2003/11/12, was first identified as a data race and the same day the developer added a condition check to fix it. However the issue resurfaced on 2006/03/30, the bug was deemed to actually be an atomicity violation, and after a lengthy fixing process, was finally marked as `FIXED` on 2006/08/22. On the other hand, the root cause of Mozilla #165639 is deadlock, it was got fixed the next day.

Files. This characteristic can be used to estimate the extent of changes and also the risk associated with making changes in order to fix a bug—the higher the number of affected files, the more developers and inter-module communications are affected. We found (Figure 4.3) that bug fixes affect on average 2.8 files for atomicity, 2.4 files for order violations, 1.9 files for races and 1.8 files for deadlocks. Non-concurrency bugs affect on average 1.6 files.

Total patch size. The total size of all patches, just like the number of files, can be used to indicate the risk associated with introducing the bug-fixing changes: if the size of the patches is large, many modifications have been made to the source code (e.g., pervasive changes, large-scale restructuring). We found that average concurrency patch sizes tend to be large, with atomicity (27.6KB) and order violations (19.7KB) far ahead of races (7.7KB) and deadlocks (5.1KB). Non-concurrency patches are smaller, 3.8KB on average.

Comments. The number of comments in the report can indicate hard-to-find/hard-to-fix bugs that developers solicit a lot of help with. Examples of such bugs that are hard to reproduce and fix include Mozilla bugs #549767, #153815, #556194, where even after removing the "mark as duplicate" comments, there are more than 100 comments dedicated to reproducing and fixing the bug. We found that the average number of comments is again highest for atomicity violations (29.4) followed by order violations (20.7), races (12.0) and deadlocks (10.6). The number is much smaller for non-concurrency bugs (7.6).

Developers. The more developers are involved into submitting patches for a bug, the more difficult it was to find and fix that bug. We found that atomicity fixes involve on average 1.39 developers while the other bugs involve fewer developers (1.21). Non-concurrency bugs involve, on average, 1.03 developers.

Severity. Bug severity is important as developers are more concerned with higher severity bugs which inhibit functionality and use. We found that all types of concurrency bugs have average severity between 3.6 and 3.7. Since severity level 3 is Normal and level 4 is Major, we can infer that concurrency bugs are higher-priority bugs. Non-concurrency bugs tend to be lower severity (mean 3.1), which underlines the importance of focusing on concurrency bugs.

4.3.2 Differences Among Concurrency Bugs

We now set out to answer another one of our initial questions: *Are there significant differences in the bug-fix process among different categories of concurrency bugs?*

To answer this question we performed a pairwise comparison across all pairs of concurrency bug types. For generality and to avoid normality assumptions, we performed the comparison via a non-parametric test, the Wilcoxon signed-rank test. To avoid type I errors, we performed a Wilcoxon signed-rank test by applying *false discovery rate* (FDR)

Features	**Category**	Order	Race	Deadlock
Patches	Atomicity	0.0116*	<0.0001**	<0.0001**
	Order		0.0168*	0.0084**
	Race			0.8427
Days	Atomicity	0.0790	0.1728	0.0002**
	Order		0.6302	0.0790
	Race			0.0270*
Files	Atomicity	0.4654	0.1215	0.0868
	Order		0.6378	0.5034
	Race			0.7363
Patch size	Atomicity	0.0079**	<0.0001**	<0.0001**
	Order		0.2666	0.0412*
	Race			0.2814
Comments	Atomicity	0.0367*	<0.0001**	<0.0001**
	Order		0.0034**	0.0063**
	Race			0.5370
Developers	Atomicity	0.0110*	0.0110*	0.0005**
	Order		0.9690	0.2695
	Race			0.2695
Severity	Atomicity	0.7933	0.7933	0.9228
	Order		0.7933	0.7933
	Race			0.7933

Table 4.2: Wilcoxon Rank Sum and Signed Rank Tests results; p-values were adjusted using the FDR procedure; ** indicates significance at $p = 0.01$ while * at $p = 0.05$.

procedures [18]. We present the results, obtained after the correction, in Table 4.2. The starred values indicate significance at $p = 0.01$ (**) and $p = 0.05$ (*), respectively. We found that atomicity and deadlock tend to be significantly different from the other categories, while for order and race, it depends on the feature. We also found that bug severity does not differ significantly among concurrency bug types.

4.3.3 Discussion

Concurrency bugs v. non-concurrency bugs. We found significant differences *for all these features* between concurrency and non-concurrency bugs. In Figure 4.3, the last two boxplots in each graph show the distribution of values for that feature for all concurrency bugs (Overall) and non-concurrency bugs (NC). We found that, compared to non-concurrency bugs, concurrency bugs involve 72% more patches for a successful fix, take twice as long to fix, bug-fixes affect 46% more files, require patches that are four times larger, generate 2.5 times as many comments, involve 17% more developers, and have a 17% higher severity.

For each feature, the differences between concurrency and non-concurrency bugs are significant ($p < 2e^{-16)}$); we used Cliff's delta to compute the effect size measure; the results indicated significance (effect size *Large* for all features except severity, where they were *Medium*). For brevity, we omit presenting the individual results.

Differences among types. Based on our findings, we infer that (1) concurrency bugs are usually difficult to find the root cause of and get the correct fix for, and (2) there are significant differences between different types of concurrency bugs hence these types should be considered separately. These two points provide the impetus for the work presented in the remainder of the chapter.

4.4 Predicting the Number of Concurrency Bugs

Costs associated with software evolution are high, an estimated 50%–90% of total software production costs [80,131]. Predicting the number of extant bugs, that will have to be fixed in upcoming releases, helps managers with release planning and resource allocation, and in turn can reduce software evolution costs. Therefore, in this section we focus on predicting the future number of concurrency bugs.

In Section 4.3, we observed relationships between the number of concurrency bugs and the features we analyzed. Hence, to estimate the likelihood of concurrency bugs in the project, we naturally turn to using the features as inputs. In this section we focus on (1) understanding the effect of each feature on each type of concurrency bug, as well as its prediction power for the number of those concurrency bugs, (2) using the features to build predictor models and evaluating the accuracy of the models, and (3) understanding the effect of time and autocorrelation on prediction accuracy. In particular, we explore two predictors models—one based on multiple linear regression and one based on time series.

Time granularity. There is an accuracy–timeliness trade-off in how long a window we use for bug prediction. A time frame too short can be susceptible to wild short-term variations or lack of observations, while too long a time frame will base predictions on stale data. Therefore, we built several models, with varying time spans, for computing past values of independent variables and bug numbers. In the first model, named *Monthly*, we counted the dependent variable (number of bugs) and independent variables (patches, days, files, patch size, etc.) at a monthly granularity based on the open date of the bugs, e.g., one observation corresponds to May 2010, the next observation corresponds to June 2010, and so on. We also tried coarser granularities, 3-months, 6-months, and 12-months, but the predictions were less accurate (albeit slightly). Therefore, in the remainder of this section, monthly granularity is assumed.

4.4.1 Generalized Linear Regression

To analyze the relationship between the number of concurrency bugs and each feature, we built a *generalized linear regression* model to avoid the normality assumption. We choose the number of bugs as dependent variable and the features, i.e., *patches*, *days*, *files*, *patch size*, *comments*, *developers*, and *severity*, as independent variables.

In Table 4.3 we present the regression results for each type of concurrency bug and across all concurrency bugs (again, this is using the monthly granularity). For each independent variable, we show the regression coefficient and the p-value, that is, the significance of that variable. We found that not all independent variables contribute meaningfully to the model. For example, for data race bugs, *files*, *patch size*, *developers* and *severity* are good predictors (low p-value), but the other features are not; moreover, the regression coefficients for files, developers and severity are positive. Intuitively, these results indicate that past changes to files, high number of developers and high bug severity are correlated with a high incidence of data race bugs later on; since the coefficient for patch size is negative, it means that past patches will actually *reduce* the incidence of data races in upcoming releases. For atomicity violations and order violations we have similar results. When predicting the number of all concurrency bugs (last two columns in Table 4.3), we found that three variables contribute to the model: *files*, *developers* and *severity*.

Features	**Atomicity violation**		**Order violation**		**Data race**		**Deadlock**		**All conc.**	
	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value
Patches	0.0196	0.014*	0.0197	0.094	0.0171	0.173	-0.0090	0.607	0.0032	0.709
Days	-0.0001	0.004**	<0.0001	0.912	<0.0001	0.360	<0.0001	0.950	-0.0001	0.084
Files	0.0147	0.001**	0.0321	<0.001**	0.0161	0.002**	0.0313	<0.001**	0.0136	0.003**
Patch size	-0.0011	<0.001**	-0.0011	<0.001**	-0.0038	<0.001**	0.0017	0.141	-0.0004	0.122
Comments	-0.0006	0.176	-0.0017	0.003**	0.0008	0.126	0.0017	0.049*	-0.0004	0.354
Developers	0.1517	<0.001**	0.2035	¡0.001**	0.1847	<0.001**	0.2086	<0.001**	0.1757	<0.001**
Severity	0.1257	<0.001**	0.1055	<0.001**	0.1173	<0.001**	0.1035	<0.001**	0.1331	<0.001**
Pseudo R^2		*0.9388*		*0.9572*		*0.9701*		*0.9653*		*0.9165*

Table 4.3: Results of the generalized regression model; ** indicates significance at $p = 0.01$; * indicates significance at $p = 0.05$.

Bug category	Independent variables						
	Patches	Days	Files	Patch size	Comments	Developers	Severity
Atomicity	✓	✓	✓	✓	✓	✓	✓
Order	✓		✓	✓	✓	✓	✓
Race	✓		✓	✓	✓	✓	✓
Deadlock	✓		✓	✓	✓	✓	✓
All concur.		✓	✓	✓	✓	✓	✓

Table 4.4: Summary of stepwise regression model.

Finally, we used the Cox & Snell pseudo R^2 to measure how well the model fits the actual data—the bigger the R^2, the larger the portion of the total variance in the dependent variable that is explained by the regression model and the better the dependent variable is explained by the independent variables. We show the results in the last row of Table 4.3; the results indicate high goodness of fit, 0.91–0.97, which confirms the suitability of using the model to predict the number of concurrency bugs based on feature values.

Finding parsimonious yet effective predictors. To balance prediction accuracy with the cost of the approximation and avoid overfitting, we looked for more parsimonious models that use fewer independent variables. We applied backward stepwise regression, a semi-automated process of building a model by successively adding or removing independent variables based on their statistical significance, then computing the Akaike Information Criterion (AIC) for finding the important variables. Table 4.4 shows the result of stepwise regression; we use '✓' to mark the independent variables that should be used when constructing predictor models. For example, for races, we can still get a good prediction when eliminating the *days* feature.

4.4.2 Times Series-based Prediction

Since our data set is based on time series, and prior work has found bug autocorrelation (temporal bug locality [78]), we decided to investigate the applicability of time series forecasting techniques for predicting concurrency bugs. In particular, we used ARIMA (Autoregressive integrated moving average), a widely-used technique in predicting future points in time series data, to build a concurrency bug prediction model. In a nutshell, given a time series with t observations $X_1, \ldots, X_t$ and error terms $\varepsilon_1, \ldots, \varepsilon_t$, an ARIMA model predicts the value of an output variable $\hat{X}_{t+1}$ at time step $t+1$; that is, $\hat{X}_{t+1} = f(X_1, \ldots, X_t, \varepsilon_1, \ldots, \varepsilon_t)$. Note that prior values for X, i.e., $X_1, \ldots, X_t$ are part of the model, hence the term "autocorrelation". The quality of the model is measured in terms of goodness of fit (adjusted R^2) and other metrics such as RMSE—the root mean squared error between the predicted ($\hat{X}_t$) and actual (X_t) values.

Concretely, we constructed ARIMA predictor models for each bug class. In each case $X_1, \ldots, X_t$ were the number of bugs; $\varepsilon_1, \ldots, \varepsilon_t$ were the values of independent variables (patches, days, files, etc.); and $\hat{X}_1 \ldots, \hat{X}_t$ were the predicted values; the differences between X_i and $\hat{X}_i$ were used when computing the prediction accuracy. For example, if $X_{May\,2010}$ was the actual number of atomicity bugs in May 2010, then the time series model used $X_{April\,2010}$, $X_{March\,2010}$, ..., as lagged (true) values; $Patches_{April\,2010}$, $Patches_{March\,2010}$, ..., $Days_{April\,2010}$, $Days_{March\,2010}$, ..., $Files_{April\,2010}$, $Files_{March\,2010}$, ..., etc. as error terms; and $\hat{X}_{May\,2010}$, $\hat{X}_{April\,2010}$, ... as predicted values.

Table 4.5 shows the ARIMA results for each concurrency bug type and each time granularity; we performed this analysis using the R toolkit. The first column shows the

Bug category	**RMSE**	**Adjusted $\mathbf{R^2}$**	**ARIMA parameter**
Atomicity	0.3485	0.8626	ARIMA(1,1,1)
Order	0.1947	0.9149	ARIMA(0,0,0)s
Race	0.1832	0.9285	ARIMA(1,0,0)
Deadlock	0.1728	0.9244	ARIMA(2,0,0)s
All conc.	0.5400	0.8965	ARIMA(0,0,0)

Table 4.5: Time series based prediction model result.

concurrency bug type, the second column shows the root mean square error (the lower, the better); the third column shows the goodness of fit R^2; the last column shows the ARIMA parameter that was automatically chosen by R as best-performing model. ARIMA has three parameters: (p, d, q) where p is the autoregressive (AR) parameter, d is the number of differencing passes and q is the moving average (MA) parameter; put simply, p and q indicate the number of past samples involved in the prediction. For example, for Atomicity, the best model was ARIMA(1,1,1) meaning it got best results when $\hat{X}_t$ was computed using just the prior observation X_{t-1} and the prior error term ε_{t-1}, and differencing once. The time series analysis has also found *seasonal* patterns in the bug time series. Such entries are marked with a trailing 's', e.g., for Order and Deadlock bugs. In all cases, the season length was determined to be 12 months—this is not surprising, given that certain projects follow a fixed release cycle; we leave further investigation of seasonal patterns to future work. We observed that the RMSE is low for our data sets—the typical difference between the predicted and actual bug numbers was 0.17–0.54, depending on the bug type. To illustrate the accuracy of time series-based prediction, in Figure 4.4 we show the predicted (blue, triangle marks) and actual (red, round marks) time series for the total number of concurrency bugs each month.

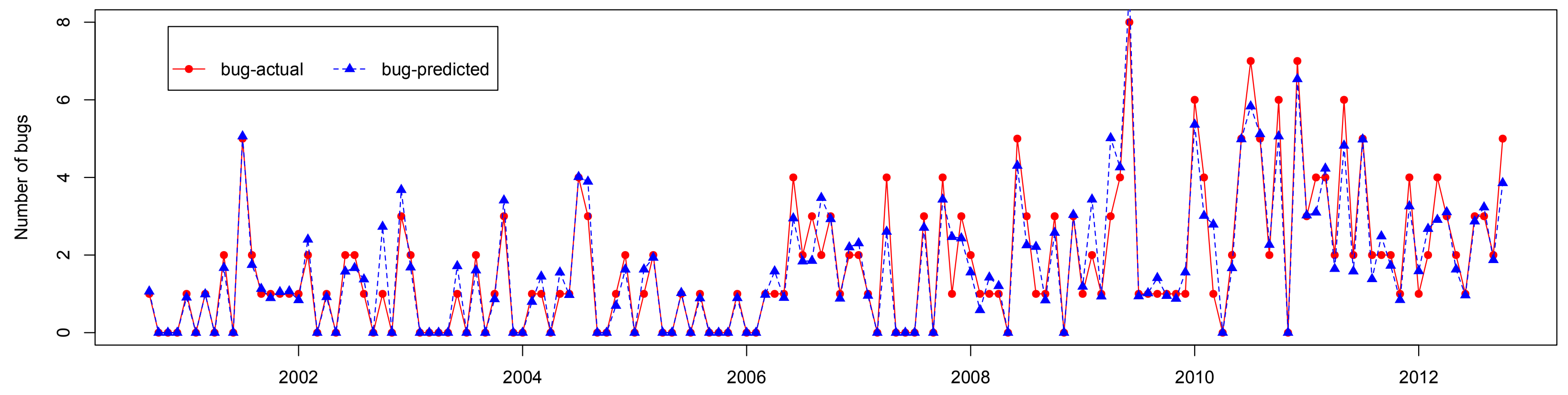


Figure 4.4: Time series of predicted and actual numbers of concurrency bugs each month.

Discussion. We now discuss why multiple models are needed. ARIMA is based on autocorrelation, that is, it works well when the current value X_t and the lagged value X_{t-l} are *not* independent. While accurate in helping managers forecast the number of bugs, the autoregressive nature of ARIMA models in a sense espouses the time locality of concurrency bugs: if the prior release was buggy, the next release is likely to be buggy, too—in that case the managers can delay the next release to allow time for finding and fixing the bugs. However, at the risk of stating the obvious, the managers cannot control the *past* number of bugs, but by examining the model and the non-autoregressive features (number of patches, files, developers, etc.) they can adjust the software process so that future values of the non-autoregressive features will permit the number of bugs to decrease. It is also up to the project managers to decide whether a one-month horizon is enough for release planning, or longer horizons (e.g., 3- or 6-months) would be more suitable.

4.5 Predicting the Type of Concurrency Bugs

When a new bug report has been filed and is examined, determining the nature of the bug is essential for a wide range of software engineering tasks, from bug triaging to knowing whom to toss a bug to [68], to finding the root cause and eventually fixing the bug.

In particular for concurrency bugs, the root causes and fixing strategies can vary widely among bug categories (Section 4.1). Therefore, when a concurrency bug report is filed, it is essential that the developers determine its category in order to speed up the fixing process. To support this task, using the categorized bugs reports described in Section 4.3, we built a predictor model that, given a newly-filed bug report, predicts which type it is:

atomicity violation, order violation, deadlock or race. We next describe the approach and then the results.

4.5.1 Approach

The approach is based on machine learning, i.e., classifiers that use relevant keywords extracted from bug reports as input features and learn the association between keywords and specific concurrency bug types based on a Training Data Set (TDS). Next, we verify the prediction accuracy by presenting the classifier with validation inputs and comparing the classifier output with the true output; the set of bug reports used for validation is called a Validation Data Set (VDS). We now describe the predictor construction process.

Textual data preparation. We applied standard information retrieval techniques to extract relevant keywords from bug reports: we used Weka to transform bug reports from the textual description available in the bug tracker into a set of keywords usable by the classifier[4] and build our TDS.

Classifier choice. After preparing the TDS, the next step was to train the classifier and validate the learned model. We use Weka's built-in Naïve Bayes, Bayesian Network, C4.5 and Decision Table classifiers in our approach.

Training and validation. As shown in our prior work [20], using a larger dataset for training bug classifiers does not necessarily yield better results; in fact, training a classifier

[4]To extract keywords from bug reports, we employed TF-IDF, stemming, stop-word and non-alphabetic word removal [101], using Weka's `StringtoWordVector` class.

Training set	**Validation set**	**Classifier**			
		Naïve Bayes	Bayesian Net	C4.5	Decision Table
All	Mozilla	39.39	**63.64**	45.45	60.61
	KDE	37.50	**56.25**	**56.25**	31.25
	All projects	38.00	**60.00**	48.00	50.00
2004+	Mozilla	50.00	60.00	40.00	**63.33**
	KDE	63.64	**72.73**	36.36	**72.73**
	All projects	52.38	61.90	38.10	**66.67**
Mozilla	Mozilla	60.00	**65.00**	55.00	50.00
KDE	KDE	46.67	**60.00**	**60.00**	53.33
Apache	Apache	57.14	**71.43**	**71.43**	**71.43**

Table 4.6: Accuracy of bug category prediction (%); highest accuracy indicated in bold.

with old samples can *decrease* prediction accuracy as the classifier is trained with stale input-output pairs that do not match the current project state.

To quantify the effect of recent vs. old training samples, we constructed two bug training/validation sets: one set, referred to as *All*, contained all the concurrency bug reports since project inception (that is 1998–2012 for Mozilla, 1999–2012 for KDE, and 2000–2012 for Apache); the other set, referred to as *2004+*, contained only more recent samples, i.e., bug reports from 2004–2012 for each project. We chose threshold 2004 as a trade-off between still having a significant history yet eliminate the initial evolution period.

In both cases, the TDS/VDS split was 80%/20%, as follows. To construct the VDS, we sorted the bug reports in the *2004+* dataset chronologically. For the *2004+* scenario, we set aside the most recent 20% as the VDS. For the *All* scenario, to preserve the 80/20 proportion, we kept the same VDS but from the TDS we discarded a random set so that the TDS size for *All* was the same as for *2004+*.

4.5.2 Results

Table 4.6 shows each classifier's accuracy. The first column indicates the training set we used, while the second column indicates the validation set. The rest of the columns show the prediction accuracy, in percents, using different classifiers. We highlight the best results in bold; in a nutshell, Bayesian Net performs best (as it is usable across the board).

The first set of rows shows the results when the *All* training set was used, that is bug reports selected from all projects across the entire time span. In the second column we show the VDS used: bugs from Mozilla, KDE, or from all three projects (we did not perform this validation for Apache due to its low representation in the VDS). We found that the best classifier was Bayesian Net, which attained 56.25%–63.64% prediction accuracy in identifying the concurrency bug type.

The second set of rows shows the results when the *2004+* (recent history) training set was used. We found that the best classifier was Decision Table, which attained 63.33%–72.73% prediction accuracy in identifying the concurrency bug type. We consider a predictor with this level of accuracy to be potentially very useful to developers. Also, the deleterious effect of "stale" training samples is readily apparent, as all classifiers except C4.5 perform better on this more recent data set, *2004+*, than on the *All* data set.

In the last three rows we show the results obtained by using project-specific TDS/VDS sets. We used the complete-history data set for Mozilla and Apache; in KDE we could not find any concurrency bugs prior to 2004. We found that Bayesian Net performs best for Mozilla (65%), Bayesian Net and C4.5 perform best for KDE (60%), while for Apache, Bayesian Net, C4.5 and Decision Table are tied, with 71.43%.

Training /Validation set	**Bug category**	**Evaluation measure**		
		precision	recall	F-measure
All /All projects	Atomicity	0.647	0.524	0.579
	Order	0.600	0.429	0.500
	Race	0.429	0.750	0.545
	Deadlock	0.778	1.000	0.875
2004+ /All projects	Atomicity	0.625	0.625	0.625
	Order	0.571	0.333	0.421
	Race	0.545	0.750	0.632
	Deadlock	0.750	1.000	0.857

Table 4.7: Detailed result of the Bayesian Net classifier.

Overall the Bayesian Net classifier had the best performance in most cases (7 out of 9). Hence in Table 4.7 we show the precision, recall and F-measure attained with this classifier. We found that deadlock bugs have the highest precision, recall and F-measure value since they are quite different from the other three classes. Order violation has the lowest precision, recall and F-measure value. Upon manual inspection, we found that in several cases order bugs were classified as data races (the nature of order and race bugs makes them difficult to distinguish in certain cases). For instance, KDE bug #301166 was classified as data race due to the keywords “thread” and “asynchronously”, but it could be considered both an order violation and data race bug.

Observations. These results reveal several aspects. First, for a new project we recommend that project managers choose Bayesian Net as classifier, since it has performed best in most cases. Second, recent training sets achieve the highest accuracy (compare *2004+* with *All*) when using the right classifier—Decision Table in our case. Third, a large, cross-project training dataset can yield better results than per-project training sets—compare KDE trained on *2004+* with KDE trained on its own data sets; this might be due to lower

Mozilla	**KDE**	**Apache**	**All projects**
deadlock	deadlock	between	deadlock
moztrap	cef	mac	warhammer
structure	synchron	crash	concur
race	concur	import	first
network	hang	got	atom
spin	order	id	network
xpcom	callback	call	race
semaphore	backport	determine	spin
gclevel	manage	intern	lock
runtime	cur	subsequ	backgroundparser

Table 4.8: Strongest prediction keywords.

bug report quality in KDE. This might be promising for predicting bugs in a new project for which we have no large concurrency bug sets; we leave this to future work.

What do classifiers learn? To gain insight into how classifiers learn to distinguish among bug types, we extracted the 10 "strongest" nodes, i.e., with the highest conditional probability in the trained Bayesian Nets, on the data sets used in the last four rows of Table 4.6 (that is, each project trained on its own bug reports and an all-projects VDS trained on the *2004+* TDS). Table 4.8 lists the keywords in these nodes, in the order of strength. We found that, in addition to textual keywords (e.g., "deadlock", "race", "spin", "hang"), the network has learned to use names of program classes, variables and functions (e.g., "gclevel", "cef", "cur", "backgroundparser"). We believe that the high prediction power of these program identifiers could be a useful starting points for static analysis, an investigation we leave to future work. Interestingly, another high-probability node was the developer ID of a frequent Mozilla contributor ("warhammer" in the last column).

Note that we have built our classifier assuming the input is a concurrency bug report. However, as future bug reports will not be subject to our manual analysis to decide whether they are concurrency or non-concurrency (our goal is to avoid manual intervention) we will not have ground truth on whether they represent a concurrency or a non-concurrency bug. To solve this, we have built a high-accuracy (90%) "pre-classifier" that triages bug reports into concurrency and non-concurrency. For brevity, we leave out details of this classifier. Since the proportion of concurrency bugs is small compared to other bugs, we would still have some false positives to manually eliminate among the classified bug reports, but the workload is reduced greatly thanks to the pre-classifier.

4.6 Predicting Concurrency Bugs' Location

The previous section showed one useful step for finding and fixing a bug: predicting its type. It is also useful to figure out *where*, in the source code, the new bug is likely to be located; hence in this section we present our approach for predicting the likely location of a concurrency bug.

4.6.1 Approach

We used a classifier that takes a bug report as input and produces a set of source code paths as output. More specifically, the classifier's output is a vector of binary values, and each position in this vector corresponds to a source code path. For example, consider three bugs #1, #2, and #3, such that #1's location was code path /foo/, #2's location was path /bar/, and #3 has affected both code paths /bar/ and /baz/. Suppose the order in the output vector is (/foo/, /bar/, /baz/). Then the correct classifier output for bug #1 would be (1,0,0); for bug #2 it would be (0,1,0); and for bug #3 it would be (0,1,1).

4.6.2 Results

The training process is similar to the one used in the prior section, that is, we used 80% of the bug set for training and 20% for validation. Measuring prediction accuracy is slightly more convoluted, because a bug can affect multiple files, and we are interested in predicting a Top-k of most likely locations, rather than a single location.

We now explain how we compute Top-k accuracy when a single bug spans multiple code paths. For each bug i in the VDS, assuming the bug has affected j paths, we have a list of true source code paths $\{tpath_{i1}, \ldots, tpath_{ij}\}$ (each unique path is called a "class"; we employed Mulan [142] for this part). We present the bug report i to our classifier, which returns a list of m likely output paths $\{opath_{i1}, \ldots, opath_{im}\}$. More specifically, for each validation input, Mulan returns as output a vector of real numbers indicating the probability of the sample belonging to each class; probabilities under a threshold are replaced with 0. Next, from the set $\{opath_{i1}, \ldots, opath_{im}\}$ we select the highest-ranked k output paths, in order of probability, i.e., a subset $\{opath_{i1}, \ldots, opath_{ik}\}$. Then, we check if the set $\{tpath_{i1}, \ldots, tpath_{ij}\}$ is a subset of $\{opath_{i1}, \ldots, opath_{ik}\}$. Finally, we compute Top-k accuracy: for Top-1 accuracy, we count a hit if the probability value assigned to the true path class is the highest-ranked in output vector; for bugs affecting multiple files, say 2, if the 2 highest probabilities correspond to the true path classes, and so on. To compute Top-10% accuracy, we check whether the bug location(s) is(are) in the Top-10% highest output class probabilities; similarly for Top-20%.

In Table 4.9 we present the results. In the first column we show the project, and in the columns 2–4 we present the attained accuracy for each of the three metrics. The last

Project	**Accuracy (%)**			**Classifier**
	Top-1	Top-10%	Top-20%	
Mozilla	31.82	50.00	59.09	Decision Table
KDE	25.00	50.00	56.25	Naïve Bayes
Apache	22.22	44.44	55.56	Bayesian Net
All projects	26.09	47.83	52.17	Naïve Bayes

Table 4.9: Source path prediction results.

column shows the classifier used to achieve that accuracy (we only present the best results across the four classifiers).

We achieve 22.22%–31.82% Top-1 accuracy, depending on the project (column 2). We consider this to be potentially very useful for locating bugs, because it means the developer is presented with the *exact bug location* in 22.22%–31.82% of the cases, depending on the project (we had 45 path locations for Mozilla, 47 for KDE and 19 for Apache). When measuring Top-10% accuracy, the accuracy increases to 44.44%–50%. When measuring Top-20% accuracy, we obtained higher values, 55.26%–59.09%, which is expected. That is, in more than half the cases, the bug location is in the Top-20% results returned by the classifier. Since all our projects have large code bases, narrowing down the possible bug location can considerably reduce bug-fixing time and effort.

On a qualitative note, we found that certain locations are more prone to concurrency bugs: Mozilla had 6 bugs in files under /mozilla/netwerk/cache/src and 4 bugs files under /mozilla/xpcom/base, whereas KDE had 6 bugs in /KDE/extragear/graphics/digikam/libs. Our method can guide developers to these likely bug-prone locations after receiving a bug report to help speed up bug finding and fixing.

4.7 Threats to Validity

4.7.1 Selection Bias

We have chosen three projects for our study. These projects are mostly written in C/C++ and are, we believe, representative for browsers, desktop GUI, and server programs that use concurrency. However, other projects, e.g., operating systems, database applications or applications developed in other programming language (Java), might have different concurrency bug characteristics. For example, prior efforts [46, 93] have found that deadlocks in MySQL represent 40% of the total number of concurrency bugs, whereas for our projects, deadlocks account for 22% (Mozilla), 25% (KDE), and 12% (Apache) of concurrency bugs. Nevertheless, for atomicity violation and order violation, our results are similar to prior findings [93].

4.7.2 Data Processing

Our keyword-based search for bug reports could have missed some concurrency bugs—a weakness we share with other prior studies [46, 93]. However, a concurrency bug report that did not contain any keywords on our list is more likely to be incomplete and more difficult to analyze its root cause. To reduce this threat, we used an extensive list of concurrency-related keywords, and searched both the bug tracker and the commit logs. Completely eliminating this threat is impractical, as it would involve manual analysis (which itself is prone to errors) for more than 250,000 bug reports.

4.7.3 Unfixed and Unreported Bugs

Some concurrency bugs might go unfixed or unreported because they strike infrequently, on certain platforms/software configurations only, and are hard to reproduce. It would be interesting to consider these kinds of bugs, but they are not likely to have detailed discussions and they will not have patches. As a result, these bugs are not considered as important as the reported and fixed concurrency bugs that are used in our study.

4.7.4 Short Histories

When relying solely on machine learning and statistics for training, our approach works better for projects with larger training data sets—this could be problematic for projects with short histories or low incidence of concurrency bugs, though cross-project prediction could be useful in that case, as we have shown.

4.7.5 Bug Classification

We used four categories and manual categorization for concurrency bugs. We excluded bugs which did not have enough information to be categorized. This can lead to missing some concurrency bugs, as discussed previously. As a matter of fact, some concurrency bugs may belong to multiple categories, e.g., an order violation could also be considered a data race.

4.8 Summary

We have performed a study of concurrency bugs in three large, long-lived, open source projects. We have found that concurrency bugs are significantly more complicated, taking more time and resources to fix, than non-concurrency bugs. We have also found that concurrency bugs fall into four main categories (atomicity violations, order violations, races, and deadlocks) and that among these categories, deadlocks are easiest, while atomicity violations are hardest to fix. We have shown that effective forecast methods can be constructed to help managers and developers predict the number of concurrency bugs in upcoming releases, as well as the bug type and location for new concurrency bug reports.

Chapter 5

Bug Analysis Across Severity Classes

Severity is important for effort planning and resource allocation during the bug-fixing process; we illustrate this with several examples. First, while our intuition says that bugs with different severity levels need to be treated differently, for planning purposes we need to know how bug severity influences bug characteristics, e.g., fix time or developer workload. Second, assigning the wrong severity to a bug will lead to resource mis-allocation and wasting time and effort; a project where bugs are routinely assigned the wrong severity level might have a flawed bug triaging process. Third, if high-severity bugs tend to have a common cause, e.g., concurrency, that suggests more time and effort needs to be allocated to preventing those specific issues (in this case concurrency). Hence understanding bug severity can make development and maintenance more efficient. Most of the prior work on bug severity has focused on severity prediction [83, 84, 105, 141]; there has been no research on how severity is assigned and how it changes, on how bugs of different severities differ in terms of characteristics (e.g., in fix time, developer activity, and developer profiles), and on the topics associated with different classes of severity. To this end, in this chapter we perform a thorough study of severity in a large corpus of bugs on two platforms, desktop and Android. To the best of our knowledge, we are the first to investigate differences in bug characteristics based on different severity classes.

Our study is based upon 72 open source projects (34 on desktop and 38 on Android) comprising of 441,162 fixed bug reports. The study has two thrusts, centered around nine research questions, RQ1–RQ9. First, a *quantitative* thrust (Section 5.2) where we study how severity assigned to a bug might change; next, we compare the three severity classes in terms of attributes associated with bug reports and the bug-fixing process, how developer profiles differ between high, medium and low severity bugs, etc. Second, a *topic* thrust (Section 5.3) where we apply LDA (Latent Dirichlet Allocation [25]) to extract topics from bug reports and gain insights into the nature of bugs, how bug categories differ among bug severity classes, and how these categories change over time.

Since our study reveals that bug-fixing process attributes and developer traits differ across severity levels, our work confirms the importance of prior work that has focused on accurately predicting bug severity [84, 105, 141].

5.1 Methodology

We now present an overview of the projects we examined, as well as the methodology we used to extract the bug features and topics.

5.1.1 Examined Projects

We choose the projects mentioned in Chapter 2.1 for our study. Tables 5.1 and 5.2 show a summary of the projects we examined. For each platform, we show the project name, the number of fixed bugs, the percentage of bugs in each severity class (High, Medium, and Low), the percentage of bugs that had severity changes, and finally, the time span, i.e., the dates of the first and last bugs we considered.

5.1.2 Severity Classes

Since severity levels differ among bug tracking systems, we mapped severity from different trackers to a uniform 10-point scale, as follows: 1=Enhancement, 2=Trivial/Tweak, 5=Minor/Low/Small, 6=Normal/Medium, 8=Major/High, 9=Critical/Crash, 10=Blocker. Then we classified all bug reports into three classes, *High*, with severity level ≥ 8, *Medium*, with severity level=6, and *Low*, with severity level ≤ 5. This classification is based on previous research [83, 84]; we now describe each category.

– *High severity bugs* represent issues that are genuine show-stoppers, e.g., crashes, data corruption, privacy leaks.

– *Medium severity bugs* refer to issues such as application logic issues or occasional crashes.

– *Low severity bugs* usually refer to either nuisances or requests for improvement.

5.1.3 Quantitative Analysis

To find quantitative differences in bug-fixing processes we performed an analysis on various features (attributes) of the bug-fixing process, e.g., fix time, as defined in Chapter 2.

Desktop						
Project	Fixed bugs	Severity(%)				Time span
		Hi	Med	Low	Change	
Mozilla Core	101,647	20	73	7	8	2/98-12/13
OpenOffice	48,067	14	73	13	1	10/00-12/13
Gnome Core	42,867	13	71	17	8	10/01-12/13
Eclipse platform	42,401	15	71	14	10	2/99-12/13
Eclipse JDT	22,775	11	71	18	10	10/01-12/13
Firefox	19,312	9	79	12	6	4/98-12/13
SeaMonkey	18,831	21	64	14	13	4/01-12/13
Konqueror	15,990	18	72	10	3	4/00-12/13
Eclipse CDT	10,168	12	74	14	10	1/02-12/13
WordPress	9,995	14	67	19	8	6/04-12/13
KMail	8,324	15	57	27	4	11/02-12/13
Linux Kernel	7,535	18	76	5	3	3/99-12/13
Thunder-bird	5,684	14	69	17	7	4/00-12/13
Amarok	5,400	20	58	22	6	11/03-12/13
Plasma Desktop	5,294	24	62	14	6	7/02-12/13
Mylyn	5,050	8	50	41	11	10/05-12/13
Spring	4,937	63	0	37	NA	8/00-12/13
Tomcat	4,826	21	55	24	9	11/03-12/13
MantisBT	4,141	26	0	74	2	2/01-12/13
Hadoop	4,077	82	0	18	NA	10/05-12/13
VLC	3,892	19	72	9	8	5/05-12/13
Kdevelop	3,572	24	57	19	5	8/99-12/13
Kate	3,326	15	61	24	5	1/00-12/13
Lucene	3,035	65	0	35	NA	4/02-12/13
Kopete	2,957	18	60	22	8	10/01-9/13
Hibernate	2,737	80	0	20	NA	10/00-12/13
Ant	2,612	14	47	39	9	4/03-12/13
Apache Cassandra	2,463	54	0	46	NA	8/04-12/13
digikam	2,400	20	56	25	5	3/02-12/13
Apache httpd	2,334	21	52	27	9	2/03-10/13
Dolphin	2,161	32	51	17	5	6/02-12/13
K3b	1,380	18	70	13	8	4/04-11/13
Apache Maven	1,332	85	0	15	NA	10/01-12/13
Portable OpenSSH	1,061	11	57	31	5	3/09-12/13
Total	*422,583*	*20*	*69*	*11*	*7*	

Table 5.1: Projects examined, number of fixed bugs, severity classes percentage, severity level change percentage and time span on desktop.

Android						
Project	Fixed bugs	Severity(%)				Time span
		Hi	Med	Low	Change	
Android Platform	3,497	1	97	2	1	11/07-12/13
Firefox for Android	4,489	12	86	2	4	9/08-12/13
K-9 Mail	1,200	4	94	2	4	6/10-12/13
Chrome for Android	1,601	2	79	19	14	10/08-12/13
OsmAnd Maps	1,018	2	97	1	8	1/12-12/13
AnkiDroid Flashcards	746	41	48	10	50	7/09-12/13
CSipSimple	604	5	92	3	7	4/10-12/13
My Tracks	525	11	87	2	5	5/10-12/13
Cyanogen-Mod	432	1	99	0	1	9/10-1/13
Andro-minion	346	2	92	5	3	9/11-11/13
WordPress for Android	317	78	0	22	0	9/09-9/13
Sipdroid	300	0	100	0	0	4/09-4/13
AnySoft-Keyboard	229	41	59	0	32	5/09-5/12
libphone-number	219	4	95	1	4	10/10-12/13
ZXing	218	6	62	32	13	11/07-12/13
SL4A	204	0	100	0	0	5/09-5/12
WebSMS-Droid	197	44	52	4	46	10/09-12/13
OpenIntents	188	28	61	10	5	12/07-6/12
IMSDroid	183	1	99	0	1	6/10-3/13
Wikimedia Mobile	166	15	37	48	8	1/09-9/12
OSMdroid	166	1	96	3	4	2/09-12/13
WebKit	157	1	98	1	0	11/09-3/13
XBMC Remote	129	37	58	5	33	9/09-11/11
Mapsforge	127	23	73	4	NA	2/09-12/13
libgdx	126	0	100	0	0	5/10-12/13
WiFi Tether	125	2	96	2	3	11/09-7/13
Call Meter NG&3G	116	47	52	1	46	2/10-11/13
GAOSP	114	6	89	5	11	2/09-5/11
Open GPS Tracker	114	30	68	2	12	7/11-9/12
CM7 Atrix	103	0	95	5	5	3/11-5/12
Transdroid	103	23	73	4	22	4/09-10/13
MiniCM	101	0	100	0	4	4/10-5/12
Connectbot	87	3	94	2	6	4/08-6/12
Synodroid	86	29	63	8	20	4/10-1/13
Shuffle	77	9	87	4	9	10/08-7/12
Eyes-Free	69	7	91	1	9	6/09-12/13
Omnidroid	61	22	68	10	20	10/09-8/10
VLC for Android	39	17	81	3	8	5/12-12/13
Total	*18,579*	*10*	*85*	*5*	*8*	

Table 5.2: Projects examined, number of fixed bugs, severity classes percentage, severity level change percentage and time span on Android.

5.1.4 Topic Analysis

For the second thrust of our study, we used a topic analysis to understand the nature of the bugs by extracting topics from bug reports. We follow the process mentioned in Section 2.4. The parameter settings are presented in Section 5.3.1.

5.2 Quantitative Analysis

The first thrust of our study takes a quantitative approach to investigating the similarities and differences between bug-fixing processes on severity classes. Specifically, we are interested in how bug-fixing process attributes differ across severity classes on each platform; how the contributor sets (bug reporters and bug owners) differ across classes; and how the contributor profiles vary over time.

The quantitative thrust is centered around several specific research questions:

RQ1 *Does the severity level change and if so, how does it change?*

RQ2 *Are bugs in one severity class fixed faster than in other classes?*

RQ3 *Do bug reports in one severity class have longer descriptions than in other classes?*

RQ4 *Are bugs in one severity class more commented upon than in other classes?*

RQ5 *Do bugs in one severity class have larger comment sizes than other classes?*

RQ6 *How do severity classes differ in terms of bug owners, bug reporters, and owner or reporter workload?*

RQ7 *Are developers involved in handling one severity class more experienced than developers handling other classes?*

5.2.1 Severity Change

As mentioned in the beginning of this chapter, bug severity is not always fixed for the lifetime of a bug—after the initial assignment by the bug reporter, the severity can be changed, e.g., by the developers: it can be changed upwards, to a higher value, when it is discovered that the issue was more serious than initially thought, or it can be changed downwards, when the issue is deemed less important that thought initially. In either case, the result is that not enough resources (or too many resources, respectively) are allocated to a bug, which not only makes the process inefficient, but it affects users negatively, especially in the former case, as it prolongs bug-fixing. Hence severity changes should be avoided, or at least minimized. We now quantify the frequency and nature of severity changes.

We show the percentage of bugs that have at least one change in severity in the 6th columns of Table 5.1 and Table 5.2, respectively. The overall change rates are less than 10% for both desktop and Android. For desktop, severity change is not available for projects hosted on JIRA; we marked these as 'NA' in the table. The low change rates in both platforms indicate that bug reporters are accurate in assessing severity when a bug is reported. Still, for Android, the change rate is higher in some projects, e.g., AnkiDroid and WebSMS. We investigated the reasons for high change rates in AnkiDroid (50%) and WebSMS (46%) and found that it was apparently due to a project-specific configuration—large numbers of bugs being filed with severity initially set to 'undecided'. In the next step, we will shed light on the nature of severity changes.

We found that, for those bug reports that did change severity, 89.40% of desktop bugs and 98.63% of Android bugs have changed severity once; 8.6% of desktop bugs and 1.11% of Android bugs changed severity twice; finally, only 2% of desktop bugs and 0.26% of Android bugs have more than 3 severity changes. Repeated severity changes naturally lead to higher bug-fixing effort and longer fix times. For example, Firefox bug #250818 changed severity level *13 times*, the highest number of severity changes of all the bugs. It took developers 329 days to finally fix this bug. Next, we are going to show how severity changes.

We show the top-5 most common severity change patterns in Table 5.3.[1] We found that 'Normal→Major' and 'Medium→High' are the most common severity changes for desktop and Android, respectively. We also found the common pattern 'Undecided→High' on Android platform. These patterns indicate that *bug reporters tend to underestimate bug severity more than they overestimate it.* For instance, Mozilla Core bug #777005 was assigned Normal severity initially, but the severity level increased from Normal to Critical, and eventually further increased to Blocker, which indicates the bug had to be fixed as soon as possible. The pattern 'Undecided →High' only exists on Android since issue tracking systems on desktop have Normal as default severity level.

***RQ1**: Less than 10% of bugs change severity on both desktop and Android; in those cases where severity does change, it tends to only change once. Normal→Medium and Major→High are the most common change patterns on desktop and Android, respectively.*

[1]We only used the 10-point scale in Table 5.3 since the 3-category scale would be too coarse-grained. The rest of the study uses only the 3-category scale.

Rank	Desktop	Android
1	Normal→Major (18.2%)	Medium→high (33.5%)
2	Normal→Critical (16.3%)	Medium→Low (13.2%)
3	Normal→Enhancement (13.1%)	Medium→Critical (12.7%)
4	Normal→Minor (8.3%)	Undecided→High (8.9%)
5	Normal→Blocker (3.9%)	Undecided→Normal (5.5%)

Table 5.3: Top 5 severity change patterns.

5.2.2 Bug-fix Process Attributes

We now proceed with the quantitative analysis of bug characteristics and bug-fixing process features. Rather than presenting aggregate values across the entire time span, we analyze the evolution of values on each platform, at yearly granularity, for two main reasons: (1) as feature values change over time, changes would not be visible when looked at in aggregate, and (2) we want to study the trends of severity classes. The evolution graphs, presented in Figures 5.1 through 5.8, will be discussed at length.

Data preprocessing. For each feature, e.g., FixTime, we compute the geometric mean for feature values in each year. Since the distributions are skewed, arithmetic mean is not an appropriate measure [88], and we therefore used the geometric mean in our study. Moreover, to avoid undue influence by outliers, we have excluded the top 5% and bottom 5% when computing and plotting the statistical values.

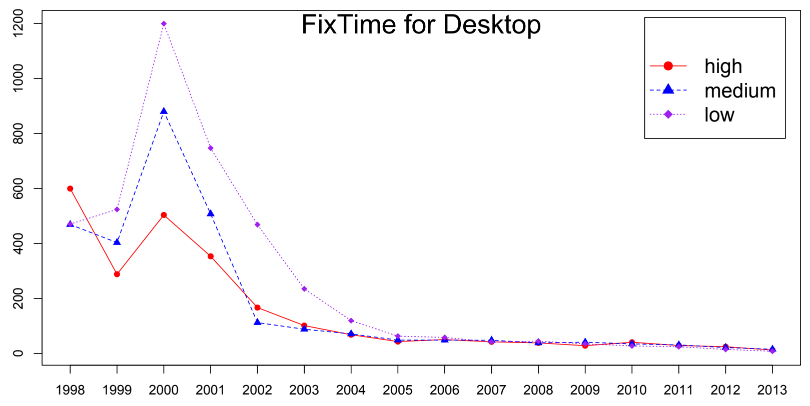
Pairwise tests between classes. To test whether the differences in bug characteristics between classes are significant, we performed a non-parametric Mann-Whitney U test (aka Wilcoxon rank sum test) *for each year, for each platform* comparing the distributions of each attribute, e.g., FixTime for high vs medium severity, high vs. low severity, and medium vs. low severity. For brevity, when we discuss the results of the pairwise tests, we only provide summaries, e.g., the year, platform, and class pair for which differences are significant.

FixTime. Figures 5.1a–5.1c show how the bug fixing time has changed over the years for each severity class on desktop and Android. Since the values after 2007 on desktop are much smaller than those pre-2007, we provide a zoom-in of FixTime for years 2007 to 2013 in Figure 5.1b. We make several observations regarding FixTime.

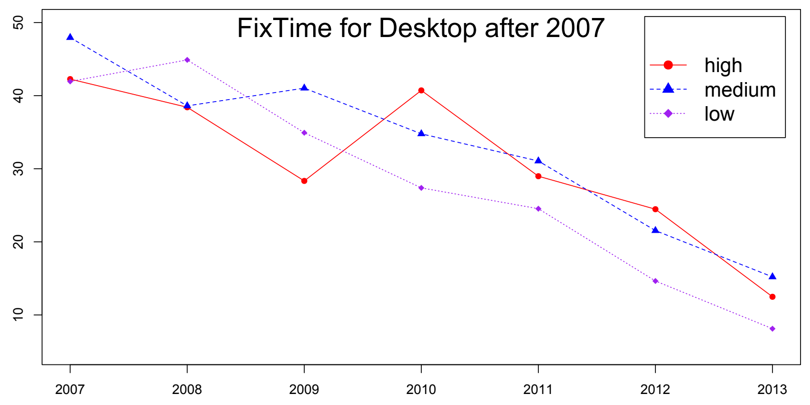
We found that *in addition to severity, priority also affects FixTime.* However, not all bug reports have an associated priority, as not all bug trackers support it: for our datasets, 67.68% of desktop bugs have an associated priority while only 6.44 of Android bugs do (Google Code does not support priority). We first provide several examples of how priority and severity can influence FixTime; later we will show the results of a statistical analysis indicating that severity influences FixTime more than priority does:

- *High Severity & High Priority:* major functionality failure or crash in the basic work-flow of software. These bugs usually took less time to fix since they have huge and deleterious effects on software usage. For instance, Mozilla Core bug #474866, which caused plugins to fail upon the second visit to a website, is a P1 blocker bug; it took developers just two days to fix it.

- *High Severity & Low Priority:* the application crashes or generates an error message, but the cause is a very specific situation, or a hard-to-reproduce circumstance. Usually developers need more time to fix these kind of bugs. For example, Mozilla Core bug



(a)



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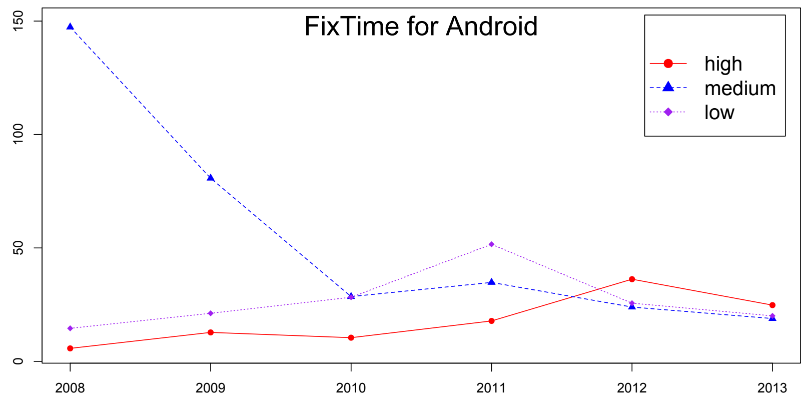


(c)

Figure 5.1: FixTime distribution per year; units are defined in Section 5.1.3.

Features	**Desktop**		**Android**	
	coefficient	p-value	coefficient	p-value
Severity	-95.850	$< 2e$-16	-20.892	6.44e-13
Priority	4.162	0.108	-14.891	0.00109

Table 5.4: Results of the generalized regression model.

92322 had severity Blocker (highest) but priority P5 (lowest). The bug took 2 months to fix because it required adding functionality for an obscure platform (at the time).

- *Low Severity & High Priority:* this characterizes bugs such as a typo in the UI, that do not impact functionality, but can upset or confuse users, so developers try to fix these bugs quickly. For instance, Eclipse JDT bug #13141, whose severity is trivial, had priority P1 since it was a typo in the UI; it was fixed in one day.
- *Low Severity & Low Priority:* bugs in this class comprise nuisances such as misspellings or cosmetic problems in documents or configuration files. Developers would fix these bugs when the workload is low. For example, Apache httpd bug #43269, a typo in the server error message with trivial severity and P5 priority, took more than 3 years to be fixed.

To check the influence of severity and priority on FixTime, we built a linear regression model in which FixTime was the dependent variable, while severity and priority were independent variables. Table 5.4 shows the results. We found that severity is a better FixTime predictor than priority, with p-values much smaller than those of priority, but nevertheless the priority's p-values, 0.1 for desktop and 0.001 for Android suggest a relationship between priority and FixTime.

Year	**Severity**			**Priority**		
	Hi. vs. Med.	Hi. vs. Low	Med. vs. Low	Hi. vs. Med.	Hi. vs. Low	Med. vs. Low
Desktop						
1998	0.0189	0.2183	0.5654	< 0.01	< 0.01	0.7325
1999	< 0.01	< 0.01	< 0.01	< 0.01	0.0102	< 0.01
2000	< 0.01	< 0.01	< 0.01	0.3180	< 0.01	0.0346
2001	< 0.01	< 0.01	< 0.01	< 0.01	0.6562	< 0.01
2002	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
2003	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
2004	0.4082	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
2005	< 0.01	< 0.01	< 0.01	0.9191	< 0.01	< 0.01
2006	0.2646	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
2007	< 0.01	0.9771	0.0102	< 0.01	< 0.01	< 0.01
2008	0.9800	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
2009	< 0.01	< 0.01	< 0.01	< 0.01	0.7295	< 0.01
2010	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
2011	0.2227	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
2012	< 0.01	< 0.01	< 0.01	< 0.01	0.0267	< 0.01
2013	< 0.01	< 0.01	< 0.01	< 0.01	0.2575	0.2535
Android						
2008	< 0.01	0.0831	< 0.01	NA	NA	NA
2009	< 0.01	0.2286	< 0.01	< 0.01	NA	NA
2010	< 0.01	< 0.01	0.9944	< 0.01	NA	NA
2011	< 0.01	< 0.01	0.0105	0.0429	0.2958	0.0304
2012	< 0.01	0.0604	0.3382	0.0347	0.0711	0.9072
2013	< 0.01	0.1118	0.4905	0.4140	0.5035	0.8857

Table 5.5: Significance values of whether FixTime differs between classes on Desktop and Android.

We now present the results of a per-year statistical analysis that shows FixTimes tend to differ significantly among severity classes and among priority classes. The "Severity" columns of Table 5.5 provide the p-values of pairwise two-means tests of FixTimes between different severity classes. The results indicate that on desktop, with few exceptions (1998, 2007), FixTimes do differ significantly between classes. On Android, though, FixTimes differ less among severity classes.

The "Priority" columns of Table 5.5 show the results of a similar analysis—how does FixTime differ between priority classes. To make comparisons with severity easier, we used a 3-point scale for priority. *High* means priority level ≤ 2; *Medium* means priority level=3; and *Low* means priority level ≥ 4.

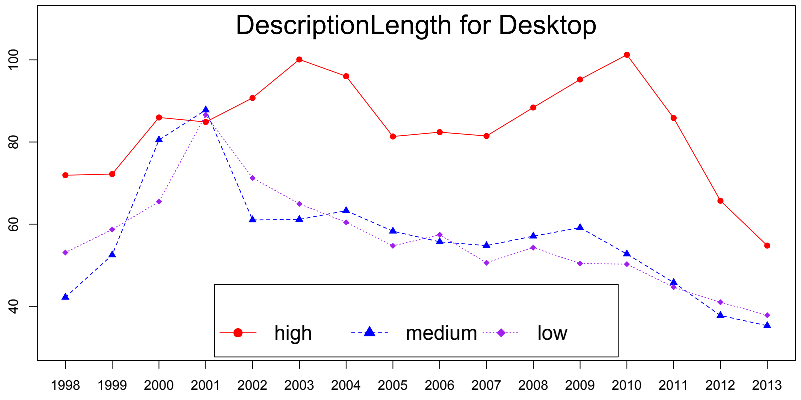
The table values indicate that differences in FixTime across priority classes again tend to be significant on desktop, but not on Android; the "NA" entries indicate that most of the Android bugs in that class were hosted on Google Code, which does not support priority.

For Android, FixTime differs significantly between high and medium severity bugs in all years, but does not differ significantly between high and low severity or between medium and low severity: this is explained by the fact that the Wilcoxon test is not transitive [49]. For high severity vs. low severity, only 2010 and 2011 have significant differences; for medium severity vs. low severity, the differences are only significant in 2008 and 2009.

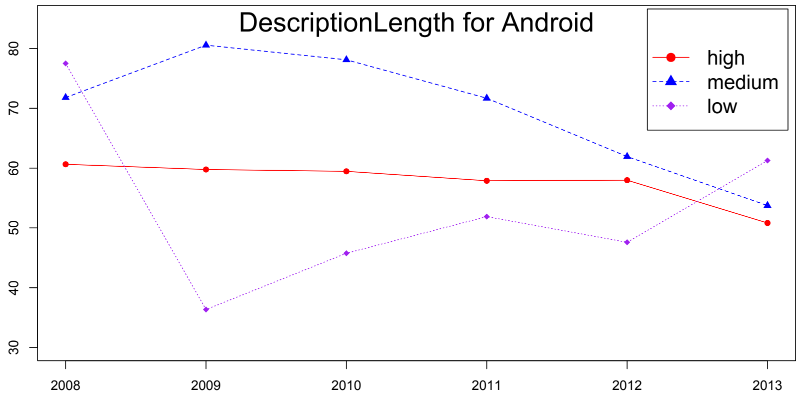
Figures 5.1a–5.1c indicate how the population means vary for each class, year, and platform. We can now answer RQ2:

RQ2: *Fix time for desktop bugs is affected by severity and to a lesser extent by priority. FixTime does vary significantly across severity classes for desktop, but for Android the only significant difference is between high and medium severity.*

DescriptionLength. The number of words in the bug description reflects the level of detail in which bugs are described. A higher DescriptionLength value indicates a higher bug report quality [59], i.e., bug fixers can understand and find the correct fix strategy easier. As shown in Figure 5.2a, high-severity bugs on desktop have significantly higher description



(a)



(b)

Figure 5.2: DescriptionLength distribution per year; units are defined in Section 5.1.3.

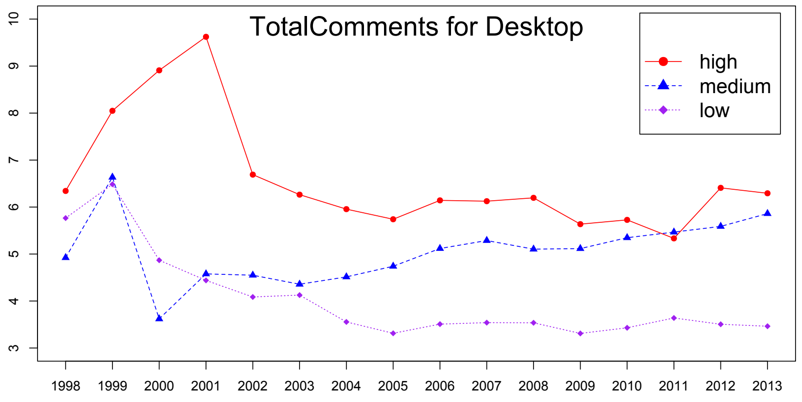
length values while medium and low-severity bugs have lower values (the DescriptionLength differences between medium and low-severity bugs is significant in only 10 out of 16 years). We found that the reason for high DescriptionLength for high-severity bugs is that reporters usually provide stack traces or error logs for the bugs.

However, as shown in Figure 5.2b, we found different trends on Android: medium severity bugs have the highest values of DescriptionLength, followed by high-severity bugs, while low-severity bugs usually have the smallest DescriptionLength. The difference between classes is small. The pairwise tests show that only during half of the studied time frame (2009–2011), the differences between severity classes are significant, for other years they are not. The reason for high-severity bugs not having the highest DescriptionLength is that unlike on desktop, for projects hosted on Google Code, reporters do not adhere to providing a stack trace or error log as strictly as they do on desktop.

RQ3*: On desktop, DescriptionLength is significantly higher for high-severity bugs compared to medium and low-severity bugs. DescriptionLength differences are not always significant between medium and low-severity on desktop, or between classes on Android.*

TotalComments. Bugs that are controversial or difficult to fix have a higher number of comments. The number of comments can also reflect the amount of communication between application users and developers—the higher the number of people interested in a bug report, the more likely it is to be fixed [54]. According to Figure 5.3a, there are more comments in high-severity bug reports on desktop, while low-severity bug reports have the least number of comments. This indicates that high-severity bugs are more complicated, and harder to fix, while low-severity bugs are in the opposite situation.

The pairwise tests show that all classes are different from each other except for a few years (medium vs. low in 1999 and 2001). TotalComments evolution is similar on Android (Figure 5.3b), i.e., high-severity bugs have the highest value while low-severity bugs have the lowest value. The pairwise tests indicate that differences are significant between all class pairs, except for 2008 and 2009.



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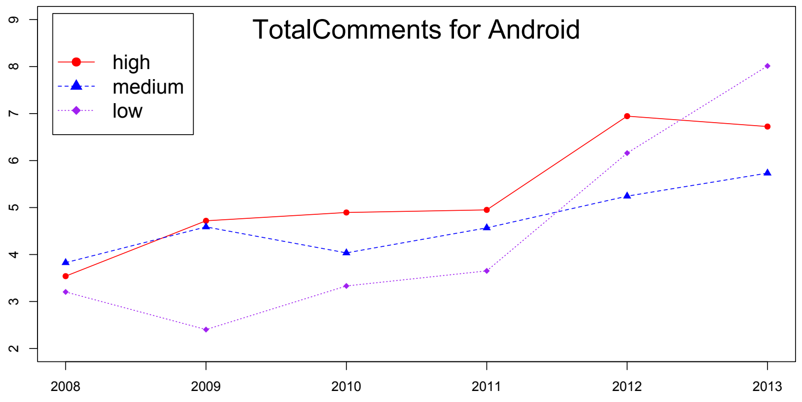
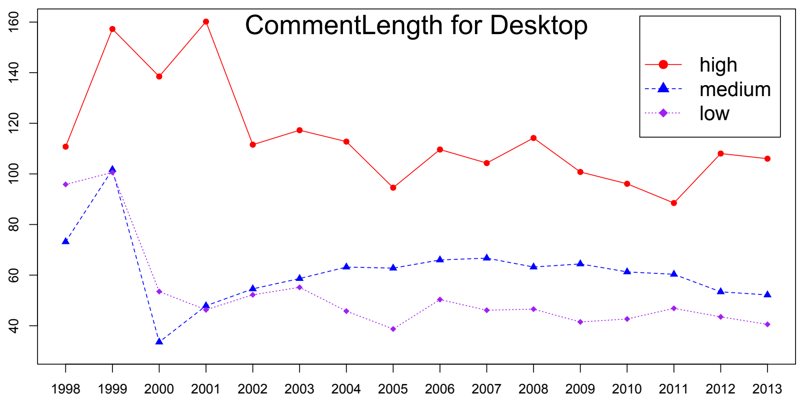


(b)

Figure 5.3: TotalComments distribution per year; units are defined in Section 5.1.3.

RQ4: *On desktop and Android, high-severity bugs are more commented upon than the other classes, whereas low-severity bugs are less commented upon.*

CommentLength. This measure, shown in Figures 5.4a and 5.4b, bears some similarity with TotalComments, in that it reflects the complexity of the bug and activity of contributor community. We found similar results as for TotalComments on desktop. Pairwise tests indicate that high-severity bugs do differ from medium and low in all the cases while medium and low-severity bugs have significant differences only after 2004. For Android, the trends



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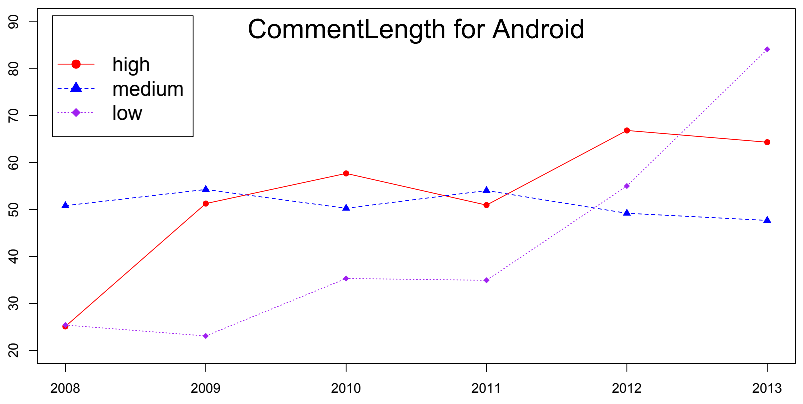


(b)

Figure 5.4: CommentLength distribution per year; units are defined in Section 5.1.3.

are not so clear: the pairwise tests show that the difference between high and medium are not significant in 2009 to 2011. But differences between high and low, and medium and low, are significant in all years.

RQ5*: High severity bugs on desktop have higher CommentLength than other classes. On Android, the differences between high and medium severity classes are not significant, but they both are significantly higher than for the low-severity class.*

5.2.3 Management of Bug-fixing

Resource allocation and management of the bug-fixing process have a significant impact on software development [153]; for example, software quality was found to be impacted by the relation between bug reporters and bug owners [17]. We defined the BugOwner and BugReporter roles in Section 5.1.3 and now set out to analyze the relationship between bug reporters and bug owners across the different severity classes.

Developer Changes

We examined the distributions and evolutions of bug reporters, as well as bug owners, for the three severity classes on the two platforms. Table 5.6 summarizes the results. Column 2 shows the total number of bug reporters in each year; columns 3–5 show the percentages of bug reporters who have reported high, medium, and low-severity bugs. Columns 6 through 9 show the numbers and percentages of bug owners.

We make several observations. First, the sums of percentages for high, medium, and low severity are larger than 100%, which indicates that there are reporters or owners who contribute to more than one severity class. Second, high-severity bug owners have larger contribution (percentage) values than those of corresponding bug reporters, because fixing high-severity bugs requires more resources.

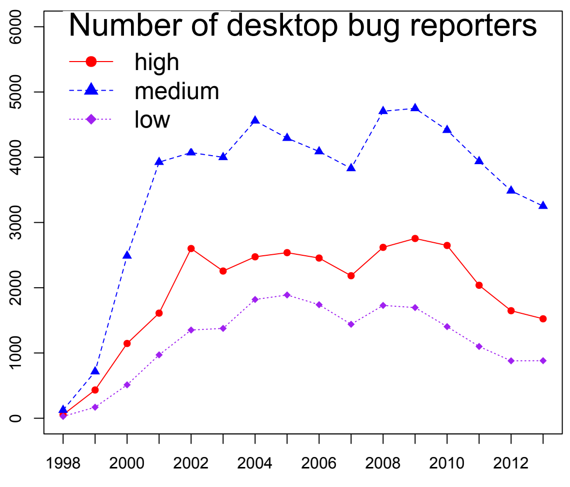
Figure 5.5 shows the trend of bug reporters and owners of each severity class. For desktop, according to Figures 5.5a and 5.5b, we found similar evolutions for the numbers of high, medium and low severity classes for both bug reporters and owners. For Android, Figures 5.5c and 5.5d indicate that there are many more medium severity reporters and

Year	**Reporters**				**Owners**			
	#	*(%)*			#	*(%)*		
		High	Med.	Low		High	Med.	Low
Desktop								
1998	164	33.5	76.2	17.1	64	43.8	78.1	29.7
1999	949	45.6	75.3	17.8	214	58.9	86.4	38.3
2000	3,270	35.0	76.1	15.7	449	42.5	80.0	35.0
2001	5,471	29.4	71.7	17.7	664	44.4	69.0	39.2
2002	7,324	35.5	55.6	18.5	995	41.2	60.5	33.9
2003	7,654	29.5	52.2	18.0	1,084	34.3	55.2	31.9
2004	8,678	28.5	52.5	21.0	1,273	36.4	56.2	32.8
2005	8,990	28.2	47.8	21.0	1,327	37.8	56.7	33.5
2006	7,988	30.7	51.2	21.8	1,408	39.9	58.9	33.7
2007	7,292	30.0	52.5	19.7	1,393	39.1	64.0	32.7
2008	8,474	30.9	55.5	20.4	1,546	39.7	65.3	32.5
2009	8,451	32.6	56.2	20.1	1,537	41.9	64.7	34.2
2010	7,799	34.0	56.6	18.0	1,475	45.5	65.5	32.4
2011	6,136	33.2	64.2	17.9	1,381	43.7	75.7	31.1
2012	5,132	32.1	67.9	17.1	1,352	47.4	76.0	29.6
2013	4,884	31.2	66.6	18.1	1,432	47.3	72.8	27.7
Android								
2008	429	4.4	97.7	2.6	41	36.6	95.1	17.1
2009	987	8.1	95.1	2.9	104	29.8	92.3	12.5
2010	1,875	12.6	87.0	7.3	163	33.1	88.3	21.5
2011	2,045	10.6	91.5	4.1	218	33.0	93.6	16.1
2012	1,998	11.6	89.6	6.4	340	26.8	87.9	20.3
2013	1,492	7.8	84.2	11.3	419	16.2	89.5	29.4

Table 5.6: Numbers of bug reporters and bug owners and the percentage of them who contribute to each severity class.

owners than other severity classes. The differences in these trends between desktop and Android are due to the percentage of medium severity bugs on Android (Table 5.1 and Table 5.2) being larger than the percentage of medium-severity bugs on desktop.

The number of fixed bugs differs across platforms, so to be able to compare reporter and owner activity between platforms, we use the number of bug reporters and bug owners



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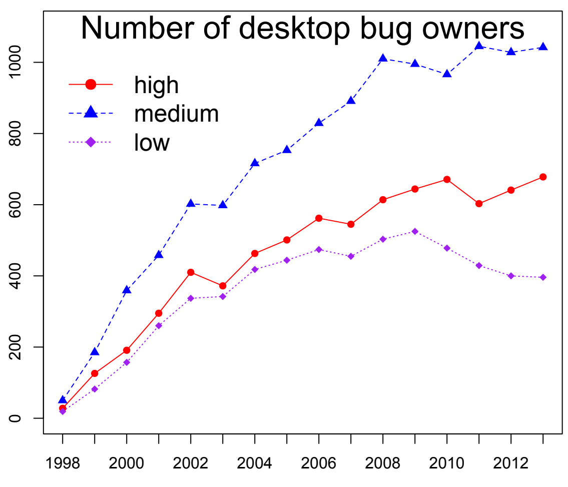

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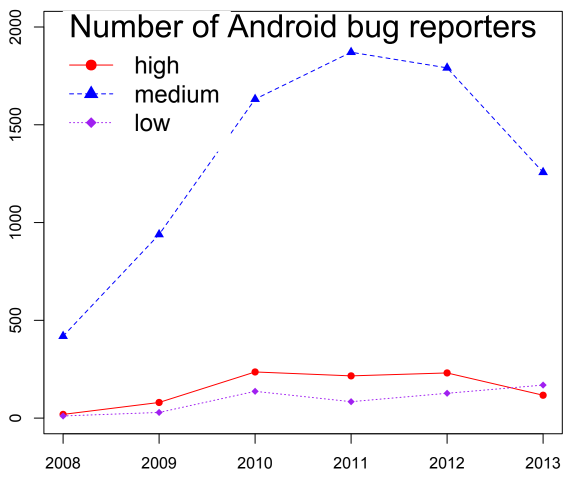

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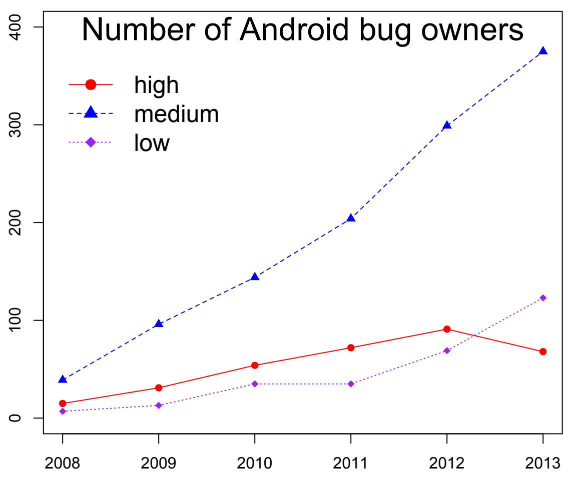
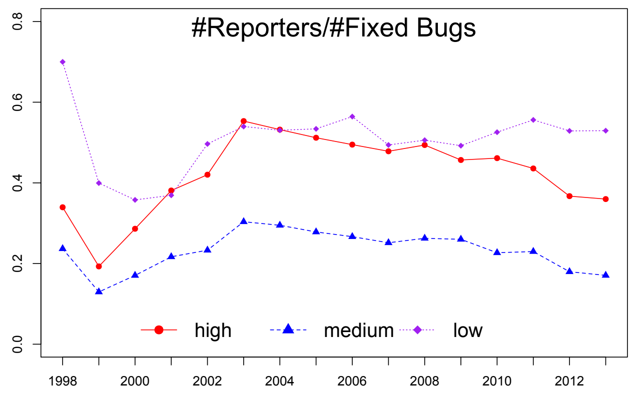


(d)

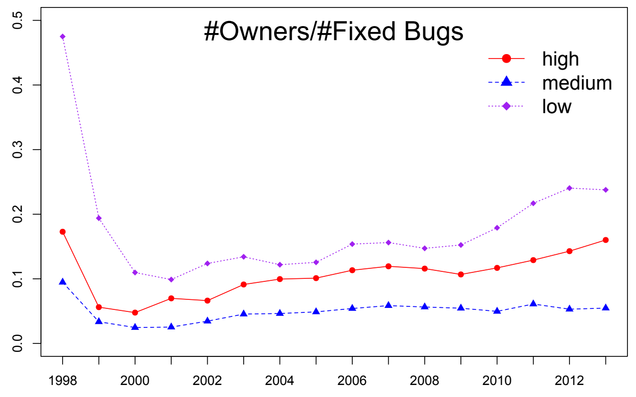
Figure 5.5: Number of bug reporters and owners for each platform.

in each year divided by the number of fixed bugs in that year. Figures 5.6a, 5.6b, 5.7a and 5.7b show the results; we will explain them one by one.

For desktop, the ratio of reporter or owner to fixed bugs have similar trends (Figures 5.6a, 5.6b): low-severity bugs have large values as they are easier to find and fix.



(a)



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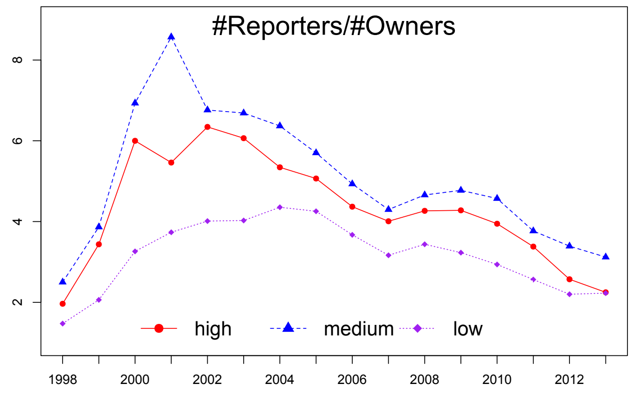

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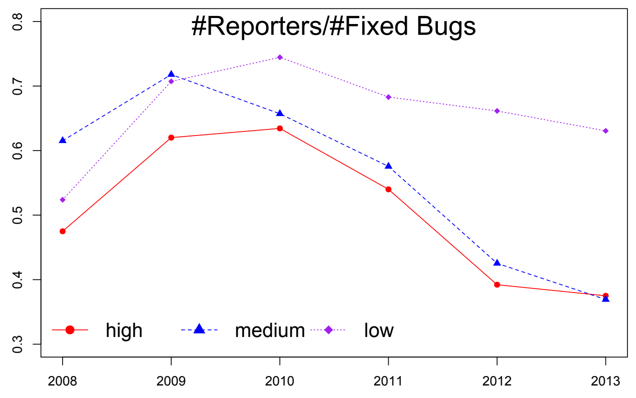
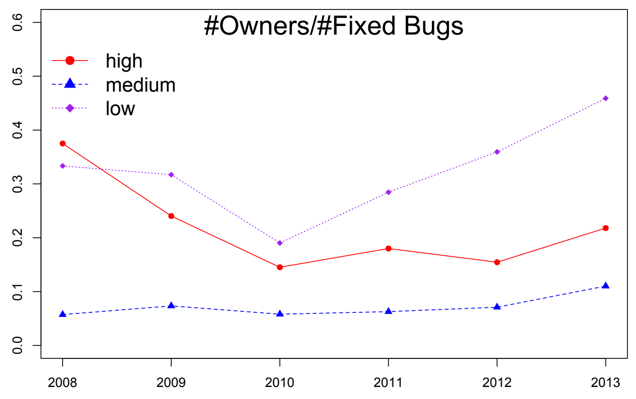
Figure 5.6: Developer trends on desktop.



(a)



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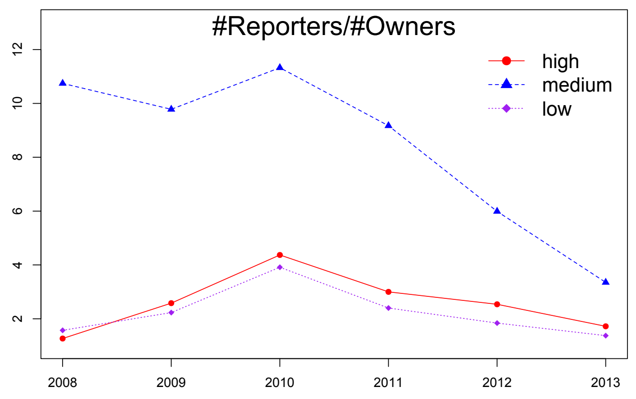


(c)

Figure 5.7: Developer trends on Android.

They are followed by high-severity bugs since, although hard to fix, the importance of high-severity bugs plays a significant role and instills urgency. For Android, the ratios of bug owners to fixed bugs (Figure 5.7b) have similar trends as on desktop, since the bug-fixing process is similar on both platforms. On the contrary, the ratio of bug reporters to fixed bugs (Figure 5.7a) on Android and desktop are different. On Android, high severity has the lowest value for this ratio while the medium severity class has the lowest value on desktop. The reason is that the percentage of high-severity bugs on Android is less than that of desktop. Also the severity classification on Android is not as strict as on desktop (most projects hosted on Google Code only have 3 severity levels); and finally, the difference between high and medium is smaller on Android.

Furthermore, the ratio of owners to fixed bugs can reflect the inverse of workload and effort associated with bug-fixing (high ratio value = low workload). We find that for both desktop and Android (Figures 5.6b and 5.7b), low-severity bugs have the lowest workload (the highest curve) since they are easiest to fix. Medium-severity bugs require most resources due to their large quantity.

The ratio of reporters to owners (Figures 5.6c and 5.7c) reveals that medium-severity bugs have the highest ratio— this is unsurprising since most reports are at this severity level. Low severity has the smallest ratio as these bugs are the easiest to report and fix.

RQ6*: Medium-severity bugs have the most reporters, most owners, and highest workload. Low-severity bugs are at the opposite end of the spectrum; high-severity bugs are in-between.*

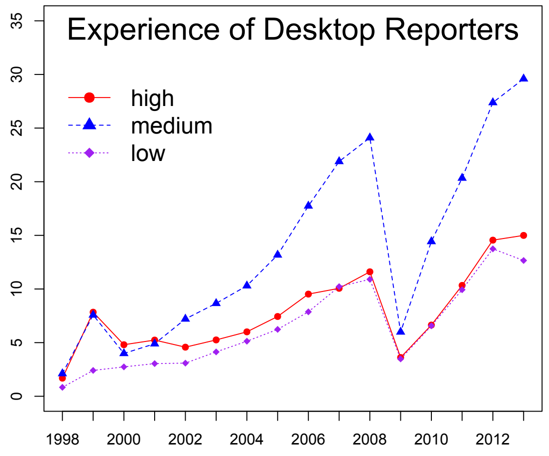
Developer Experience

To analyze differences in contributors' level of experience, we use the DevExperience metric defined in Section 2.2.[2] Figure 5.8 shows the evolution of DevExperience, in days, for bug reporters and bug owners of each severity class on desktop and Android. For bug reporters and owners, the experience on all severity classes increases with time. The dip in DevExperience for bug reporters on desktop in 2009 is caused by a large turnover that year; the fast rise afterwards is due to a surge in popularity of several projects (mainly Gnome Core, Amarok and Plasma).

For desktop, as Figures 5.8a and 5.8b show, bug reporters and bug owners of medium-severity bugs are more experienced than the other two severity classes due to there being more medium-severity bugs, hence contributors can gain more experience. Low-severity bug reporters and owners have the lowest levels of experience since the number of low-severity bugs is small and these bugs are easiest to find and fix.

For Android, bug owners have similar trends as on desktop, medium-severity bug owners have more experience than high and low-severity owners. On the other hand, high-severity bug reporters on Android are more experienced than medium severity than low severity, but the difference in experience levels between severity classes is smaller than on desktop. Upon further investigation, we found that the portion of new bug reporters on Android is much larger than that of desktop, which we attribute to the lower "barrier to entry": it is easier to report a bug in an Android project than in a desktop project since

[2] A handful of developers have made a lot of contributions over a short period while some made few contributions over a long period. Since these situations are extremely rare, they will not affect the overall result.



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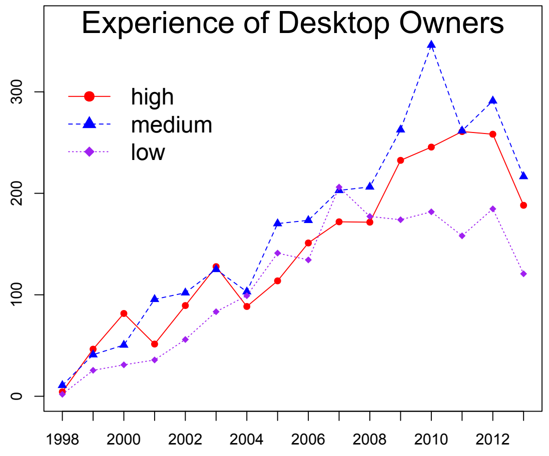

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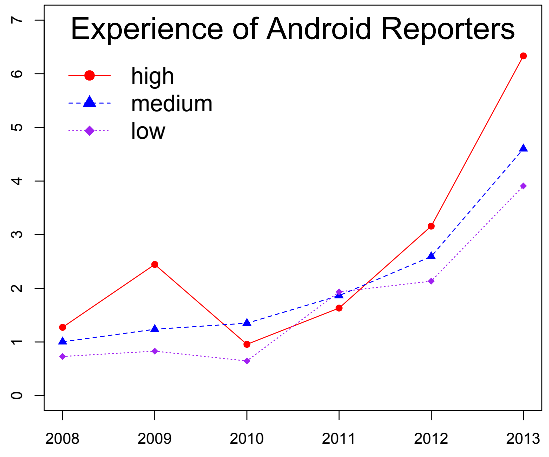

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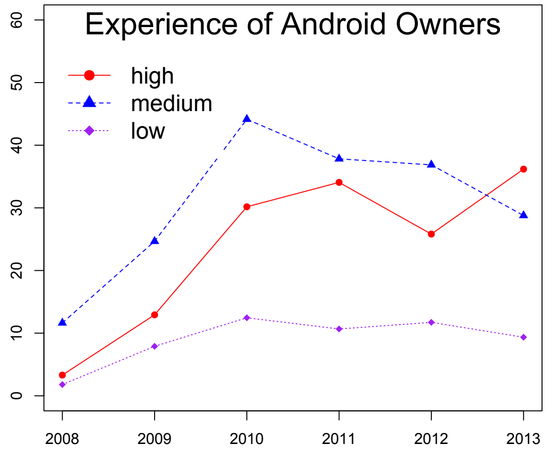


(d)

Figure 5.8: DevExperience for each severity class and each platform, in days.

most apps include a streamlined bug reporting functionality (send the crash report and/or Android `logcat` to developers by just pressing a button).

Also as Figure 5.7a shows, the high-severity class has the lowest ratio of reporters-to-fixed bugs, which indicates there are fewer new bug reporters for high severity. As a result, high-severity bug reporters are more experienced than others on Android.

RQ7*: Medium-severity class developers are more experienced (have been active for longer) than high-severity class developers than low-severity class developers.*

5.3 Topic Analysis

So far we have focused on a *quantitative analysis* of bugs and bug fixing. We now turn to a *topic analysis* that investigates the nature of the bugs in each severity class. More concretely, we are interested in what kinds of bugs comprise each severity class on different platforms and how the nature of bugs changes as projects evolve.

We use topic analysis for this purpose: we extract topics (sets of related keywords) via LDA from the terms (keywords) used in bug title, descriptions and comments, as described in Section 2.4. We extract the topics used each year in each severity class of each platform, and then compare the topics to figure out how topics change over time in each class and how topics differ across severity classes.

For the topic analysis, to investigate the difference between severity classes on bug nature, we designed the following research questions:

RQ8 *Do bug topics differ between severity classes?*

RQ9 *How do topics evolve over time?*

5.3.1 Topic Extraction

The number of bug reports varies across projects, as seen in Table 5.1 and Table 5.2. Moreover, some projects are related in that they depend on a common set of libraries, for instance SeaMonkey, Firefox and Thunderbird use functionality from libraries in

Mozilla Core for handling Web content. It is possible that a bug in Mozilla Core cascades and actually manifests as a crash or issue in SeaMonkey, Firefox, or Thunderbird, which leads to three separate bugs being filed in the latter three projects. For example, Mozilla Core bug #269568 cascaded into another two bugs in Firefox and Thunderbird. A similar issue may appear in projects from the KDE suite, e.g., Konqueror, Kdevelop, or Kate might crash (and have a bug filed) due to a bug in shared KDE libraries.

Hence we extract topics using a *proportional* strategy where we sample bug reports to reduce possible over-representation due to large projects and shared dependences. [3]

More concretely, for high/medium/low severity classes on desktop, we extracted topics from 500/1,000/400 "independent" bug reports for each severity class, respectively. The independent bug report sets were constructed as follows: since we have 10 projects from KDE, we sampled 100 medium severity bugs from each KDE-related project. We followed a similar process for Mozilla, Eclipse and Apache. Android projects had smaller number of bug reports, so for Android we sampled 50/100/50 bug reports from high/medium/low severity classes, respectively.

With the proportional sets at hand, we followed the LDA preprocessing steps described in Section 5.1.4; since there are only two bug reports in 1998 for desktop and one for Android in 2007, we have omitted those years. For desktop, the preprocessing of high, medium, and low severity sets resulted in 755,642 words (31,463 distinct), 758,303 words (36,445 distinct) and 352,802 words (19,684 distinct), respectively. For Android, the preprocessing of high, medium, and low severity sets resulted in 116,010 words (7,230

[3]We performed a similar analysis using the original data sets in their entirety, with no sampling. As expected, the topic analysis results were influenced by the large projects, e.g., "Qt", the shared library used in KDE, was the strongest topic in 2008. We omit presenting the results on the original sets for brevity.

distinct), 289,422 words (13,905 distinct) and 31,123 words (3,825 distinct), respectively. Next, we used MALLET [103] for LDA computation. We ran for 10,000 sampling iterations, the first 1,000 of which were used for parameter optimization. We modeled bug reports with $K = 100$ topics for high and medium severity classes on desktop, 60 for low severity class on desktop, 50 for high and medium classes on Android and 40 for low severity bugs on Android; we choose K based on the number of distinct words for each platform; in Section 5.4 we discuss caveats on choosing K.

5.3.2 Bug Nature and Evolution

We now set out to answer RQ8 and RQ9.

How Do Bug Topics Differ Across Severity Classes?

Tables 5.7 and 5.8 show the highest-weight topics extracted from the proportional data set. We found that for both desktop and Android, bug topics with highest weight differ across severity classes.

On desktop, build- and compilation-related bugs are the most common bug type in the high-severity class; for medium severity, application logic bugs (failure to meet requirements) are the most popular, followed by installation errors; for low severity, configuration bugs and feature requests are most prevalent. It was interesting to see that bug severity is somewhat more developer-centric than user-centric: note how build/compile errors which mostly affect developers or highly-advanced users appear in the high-severity class, whereas install errors, which mostly affect end-users, are in the medium-severity class.

Label	**Most representative words**	**Weight**
High		
build	build gener log option link config select resolv duplic depend level	12%
compile	server sourc compil output local project info path search util tag expect tool	11%
crash	crash load relat size caus broken good current instanc paramet trace stop properli valid trigger affect unabl assum condition	9%
GUI	swt widget ui editor dialog jface gnome content enabl handler mod send kei	6%
concurrency	thread lwp pthread event wait process mutex cond thread oper qeventdispatch qeventloop	5%
Medium		
application logic	window call page displai log connect start add data output check support current appli enabl apach	17%
install	instal select item control option move linux directori core debug icon start correct server thing info save statu place edit account	15%
crash	warn good crash layout limit buffer affect lock confirm miss screenshot trigger quick	8%
widget	widget descript action select plugin workbench dialog swt progress jdt wizard max	6%
communication	ssh debug local kei ssl protocol sshd authent messag password cgi login client channel launch exec	3%
Low		
config	configur support sourc instal size exist url inform util cach document info load custom src path move	22%
feature request	add option suggest gener find updat good local applic miss content address point data correct bit save duplic	20%
I/O	output space mous index block invalid separ net oper workaround stop foo wait timeout delet keyboard	9%
install	instal makefil icon dialog home build edit helper select normal page leav progress site bugzilla verifi	8%
database	db queri method menu php filter map sql jdbc execut databas count gecko init	8%

Table 5.7: Top words and topic weights for desktop.

Label	**Most representative words**	**Weight**
High		
concurrency	handler init handl dispatch looper event htc samsung galaxi loop sm mobil enabl post option launch miss	22%
runtime error	runtim error fail code press screen happen doesn exit queri finish notic process edit didn wait lock delet trace	16%
runtime crash	crash thread patch doesn repli state code updat stack good resourc beta hit verifi unknown window	13%
Medium		
runtime crash	runtim doesn result fail item remov wrong happen input action file app system data	27%
runtime error	output error messag correct forc due requir complet specif debug occur count	19%
phone call	call devic task sip galaxi samsung servic hardwar motorola	12%
Low		
feature request	suggest client find guess support messag phone output account system log option applic check format displai send screen result user market latest	23%
application logic	android app file error correct wrong bit page librari nofollow map correctli didn fail full data launch logcat screenshot	21%
GUI	report menu screen button gener ad user link browser load press item url mode action context keyboard previou widget	12%

Table 5.8: Top words and topic weights for Android.

For Android, in the high-severity class, bugs associated with the Android concurrency model (event/handler) are the most prevalent, followed by runtime errors (the app displays an error) and then runtime crashes (the app silently crashes without an error or restarts); in the medium-severity class, runtime crashes and runtime errors are also popular, followed by problems due to phone calls. In the low-severity class, feature requests are the most popular, followed by problems due to application logic and GUI.

While some commonalities exist between desktop and Android (runtime errors, crashes, and feature requests are well-represented in the high-weight topics on both platforms), there are also some notable differences: build/compile/install errors do not pose a problem on Android, which might suggest that the Android build process is less error-prone. Second, owing to the smartphone platform, phone call issues appear more frequently among high-weight topics on Android. Third, concurrency is still posing problems: it appears as a high-weight topic on both desktop on Android.

RQ8*: Topics differ across severity classes and across platforms, e.g., for high-severity bugs, build/install/compile-related issues are the most prevalent on desktop, while concurrency and runtime error/crash-related bugs are the most prevalent on Android.*

How Do Bug Topics Evolve?

To study macro-trends in how the nature of bugs changes over time, we analyzed topic evolution in each severity class on each platform. We found that high-severity bugs on desktop are the only class where topics change substantially over time; in other classes, high-frequency topics tend to be stable across years. We limit our discussion to high-severity topics; Table 5.9 shows the top-3 topics and their corresponding weight for each year.

We make several observations. On desktop, concurrency started to be a big issue in 2009, and has remained so. This is unsurprising, since multi-core computers have started to become the norm around that time, and multi-threading programming has been seeing increased adoption. Furthermore, we found that cloud computing-related bugs have started to appear in 2012, again understandably as cloud computing has been getting more traction.

Year	**Top 3 topics (topic weight)**		
Desktop			
1999	make (58%)	install (12%)	layout (10%)
2000	widget (27%)	layout (24%)	install (16%)
2001	layout (38%)	install (10%)	compile (7%)
2002	GUI (17%)	compile (14%)	build (10%)
2003	compile (20%)	GUI (13%)	build (10%)
2004	crash (19%)	build (12%)	compile (9%)
2005	plugin (17%)	build (10%)	compile (10%)
2006	GUI (14%)	build (10%)	compile (8%)
2007	build (14%)	GUI (11%)	compile (9%)
2008	debug (16%)	compile (11%)	widget (9%)
2009	concurrency (33%)	GUI (11%)	compile (11%)
2010	concurrency (15%)	compile (11%)	debug (7%)
2011	concurrency (16%)	compile (12%)	plugin (11%)
2012	cloud (14%)	compile (12%)	build (11%)
2013	concurrency (22%)	build (11%)	cloud (11%)
Android			
2008	email (39%)	runtime error (24%)	concurrency (11%)
2009	connection (23%)	runtime error (22%)	concurrency (14%)
2010	concurrency (18%)	database (17%)	call (13%)
2011	map (27%)	concurrency (26%)	database (12%)
2012	concurrency (21%)	runtime crash (17%)	runtime error (17%)
2013	browser (18%)	runtime crash (16%)	concurrency (15%)

Table 5.9: Top-3 bug topics per year for high-severity class on desktop and Android.

For Android, concurrency bugs rank high every year, suggesting that developers are still grappling to use the Android's event-based concurrency model correctly.

RQ9*: Bug topics tend to be stable in low- and medium-severity classes. In the high-severity class, on desktop, there have been more concurrency and cloud-related bugs since 2009 and 2012, respectively; on Android, concurrency bugs have been and continue to be prevalent.*

5.4 Threats to Validity

5.4.1 Selection Bias

We only chose open source applications for our study, so the findings might not generalize to closed-source projects. Our chosen projects use one of five trackers (Bugzilla, Trac, JIRA, MantisBT and Google Code); we did not choose projects hosted on GitHub since severity levels are not available on GitHub, hence our findings might not generalize to GitHub-hosted projects.

Furthermore, we did not control for source code size—differences in source code size might influence features such as FixTime.

5.4.2 Severity Distribution on Android

According to Table 5.1 and Table 5.2, many Android projects have skewed severity distributions (for 17 out of 38 Android projects, more than 90% of the bugs have medium severity). We believe this to be due to medium being the default value for the severity field on Google Code and most Android reporters or developers on Android not considering the severity level as important as on desktop.

5.4.3 Priority on Google Code and JIRA

We could not quantify the effect of priority on those projects hosted on Google Code and JIRA, as Google Code and JIRA do not have a priority field.

5.4.4 Data Processing

For the topic number parameter K, finding an optimal value is an open research question. If K is too small, different topics are clustered together, if K is too large, related topics will appear as disjoint. In our case, we manually read the topics, evaluated whether the topics are distinct enough, and chose an appropriate K to yield disjoint yet self-contained topics.

Google Code does not have support for marking bugs as reopened (they show up as new bugs), whereas the other trackers do have support for it. About 5% of bugs have been reopened on desktop, and the FixTime for reopened bugs is usually high [130]. This can result in FixTime values being lower for Google Code-based projects than they would be if bug reopening tracking was supported.

5.5 Summary

We presented the results of a study on desktop and Android projects that shows bugs of different severity have to be treated differently, as they differ in terms of characteristics and topics. We defined three severity classes, high, medium and low. We showed that across classes, bugs differ quantitatively e.g., in terms of bug fixing time, bug description length, bug reporters/owners. A topic analysis of bug topics and bug topic evolution has revealed that the topics of high-severity bugs on desktop have shifted over time from GUI and compilation toward concurrency and cloud, whereas on Android concurrency is a perennial topic. Our approach can guide severity assignment, e.g., compile/make bugs should have higher severity, and configuration errors should have lower severity.

Chapter 6

Minimizing Bug Reproduction Steps on Android

We have shown that Android apps have become rich featured and are increasing in popularity. Mobile apps enable user interaction via a touchscreen and a diverse set of sensors (e.g., accelerometer, ambient temperature, gyroscope, and light) which also present new challenges for software development, testing, debugging, and maintenance. Unfortunately, existing trace size minimization techniques are not adequate on Android due to the difference between Android apps and traditional desktop applications.

In this chapter, we present an approach to collect execution data automatically and extract minimized reproduction steps from captured data by using a record/replay scheme. We capture the event sequence while running the app and generate an event dependency graph (EDG). Then we use the EDG with event sequence to guide the delta debugging algorithm by eliminating irrelevant events.

6.1 Background

As mentioned in Chapter 1, bug reproducing is the first and crucial step in debugging process since without reproducing the bug, the developer will have trouble diagnosing and verifying the problem and figure out the correct fixing strategy. To reproduce a particular bug, developers need information about reproduction steps, i.e., the sequence of program statement, system events or user steps to trigger the bug, and information about the failure environment, i.e., the setting in which the bug occurs [156].

Developers can obtain reproduction steps and failure environment information mainly in two ways: bug report and collection of field data. Bug reports submitted by users often do not contain reproduction steps or the information provided by users is wrong or incomplete [85, 167]. Alternatively, developers can execute the application and collect field data, i.e., data about the runtime behavior and runtime environment of deployed programs [115]. Such approaches usually generate enormous amounts of tracing data which not only makes the debugging process difficulty but also risky, as the developer cannot predict when a particular bug will be found. Although execution traces are usually very long, very few of them are critical to exposing the behavior that causes the bug. Therefore, simplification of the bug-revealing trace is an important and essential step towards debugging.

Delta Debugging [157, 159] has been introduced as an effective and efficient procedure for simplification of the failing test-case. Given a program input on which the execution of a program fails, delta debugging automatically simplifies the input such that the resulting simplified input causes the same failure. In particular, it finds a 1-minimal input, i.e., an input from which removal of any entity causes the failure to disappear. This is achieved by carrying out a search in which: new simpler inputs are generated; the program is executed to determine if same failure is caused by the simpler input; and the above steps are repeatedly applied until the input cannot be simplified any further. Overall, Delta Debugging behaves very much like a binary search. Delta Debugging is an extremely useful algorithm and widely used in practice [123, 135, 136] to automatically simplify or isolate a failure inducing input [157, 159], produce cause effect chains [158] and to link cause transitions to the faulty code [34].

6.2 Problem Overview

Android apps differ from traditional desktop application since they have the rich capabilities for user interaction via touchscreens, as well as the diverse set of sensors (e.g., accelerometer, compass, GPS) that can be leveraged to drive app behavior. Users interact with apps through their Graphical User Interface (GUI). The app developers evolve the GUI overtime to improve the user experience. The GUI of Android apps consist of a set of separate screens names as *activities*. An activity defines a set of tasks that can be grouped together in terms of their behavior and corresponds to a window in a conventional GUI [16]. Each activity corresponds to a top-level view of the user interface (UI). Furthermore, each app has only one main activity, which is the initial state when the app is executed. When interacting with GUI of an application, the user commonly transitions between different activities, as actions in one activity trigger another activity, by triggering the corresponding *event*.

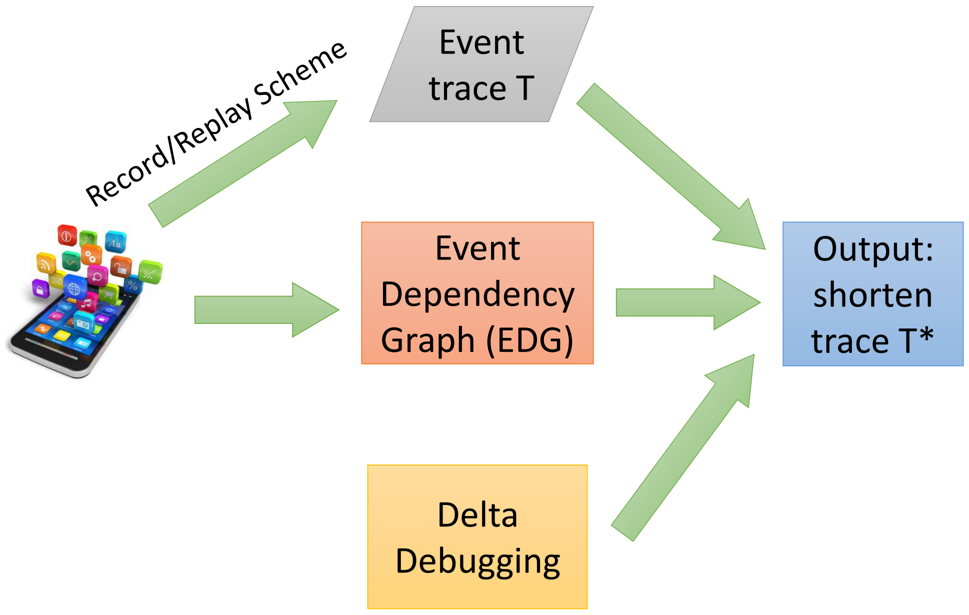


Figure 6.1: Overview of our approach.

Android app are event-driven: an app responds to an event by executing a piece of code (the *event handler* for that event). A GUI event trace is a sequence of user interface events such as screen taps, physical keyboard key presses and complete multi-touch gestures. One way to obtain such a trace is to record the actions of a user or extracting from the bug report. Another option uses a random or programmatic input generation tool to generate the trace automatically (e.g., Monkey [6], an official random input generation tool for Android). In our study, we us both ways.

6.3 Approach

Figure 6.1 gives the overview of the approach. We first collect the event execution sequence by using record&replay. In the next step, we build the event dependency graph

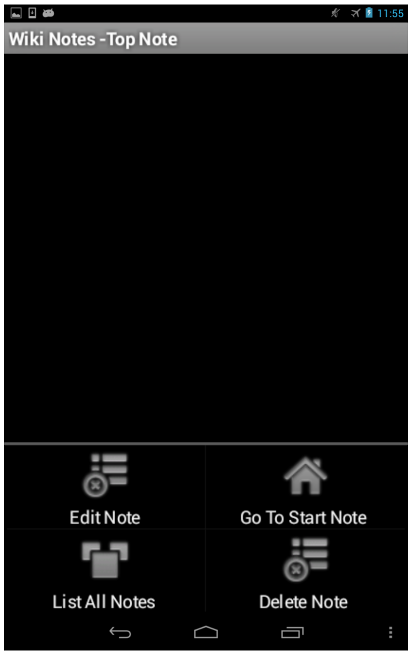
(EDG) of the app. Then we use the information extracted from EDG to guide the delta debugging process. We repeat the delta debugging process until we trigger the crash again with the simplified trace.

Next, we use a simple Android app, WikiNotes, to illustrate how our approach works. There are 3 activities in WikiNotes: WikiNotes, WikiNoteEditor and WikiNotesList and one dialog DeleteNote. Figure 6.2 shows the screenshot. As a matter of fact, it use the class WikiActivityHelper to jump between activities.

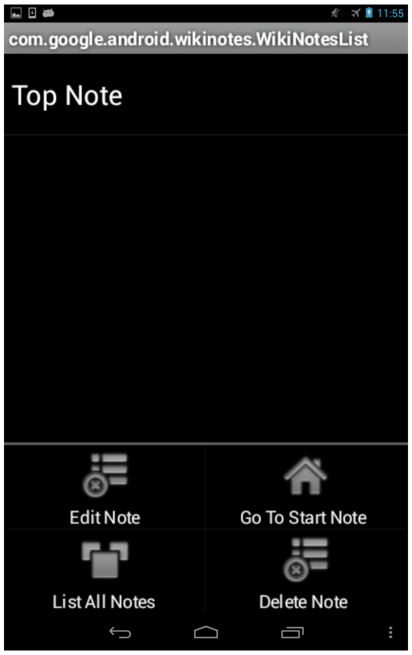
According to the bug report, there is a crash bug in WikiNotes. Based on the stack trace in the bug report (Figure 6.3), the crash happens when the method onResume() in activity WikiNotes is called. However, after analyzing the source code, we found that the real cause of crash is the deletion of a note that was created in activity WikiNotesList. More specifically, in WikiNotesList when the user clicks the "Delete Note" button, the event handler onMenuItemSelected is invoked. Next we call the function deleteNote in class WikiActivityHelper. Following note deletion, we update the cursor; however, since we have deleted the note, the number of elements in the cursor is 0, and a CursorIndexOutOfBoundsException is raised. Figure 6.4 shows the patch for this bug. We can fix the crash by checking the number of notes that exist.

6.3.1 Creating Event Traces

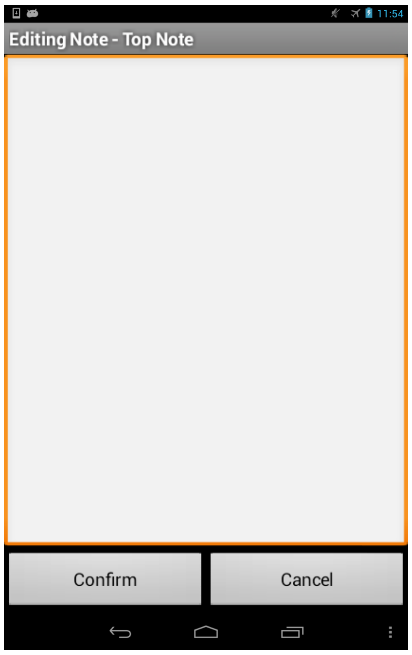
The ability to record and replay the execution of a smartphone app is useful to bug reproduction step in debugging process. Reproducing bugs in the development environment



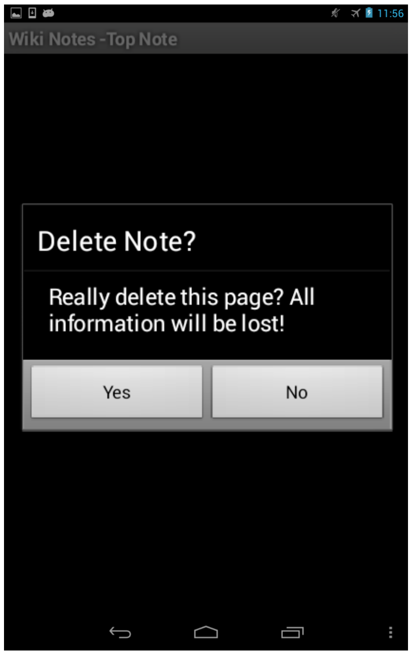
(a) Main Activity: WikiNoteEditor



(b) Activity WikiNotesList



(c) Activity WikiNoteEditor



Really delete this page? All information will be lost!

(d) Dialog DeleteNote

Figure 6.2: UI elements in app WikiNotes

```
Caused by:
android.database.CursorIndexOutOfBoundsException:
Index 0 requested, with a size of 0
    at android.database.AbstractCursor.checkPosition (AbstractCursor.java:426)
    at android.database.AbstractWindowedCursor.checkPosition
        (AbstractWindowedCursor.java:136)
    at android.database.AbstractWindowedCursor.getString(AbstractWindowedCursor.java:50)
    at android.database.CursorWrapper.getString (CursorWrapper.java:114)
    at com.google.android.wikinotes.WikiNotes.getString_aroundBody76(WikiNotes.java:159)
    at com.google.android.wikinotes.WikiNotes.getString_aroundBody77
        $advice(WikiNotes.java:122)
    at com.google.android.wikinotes.WikiNotes.onResume_aroundBody78(WikiNotes.java:159)
    at com.google.android.wikinotes.WikiNotes.onResume_aroundBody79
        $advice(WikiNotes.java:68)
    at com.google.android.wikinotes.WikiNotes.onResume(WikiNotes.java:1)
    at android.app.Instrumentation.callActivityOnResume(Instrumentation.java:1184)
    at android.app.Activity.performResume(Activity.java:5132)
    at android.app.ActivityThread.performResumeActivity(ActivityThread.java:2669)
    ... 10 more
```

Figure 6.3: Stack trace of the crash of WikiNotes.

```
1  protected void onResume() {
2      super.onResume();
3      Cursor c = mCursor;
4      // Patch start
5      if (c.getCount() < 1) {
6          // if the note can't be found, don't try to load it -- bail out
7          // (probably means it got deleted while we were frozen;
8          finish();
9          return;
10     }
11     //Patch end
12     c.requery();
13     c.moveToFirst();
14     showWikiNote(c.getString(
15         c.getColumnIndexOrThrow(
16         WikiNote.Notes.BODY)));
17     }
```

Figure 6.4: Crash of WikiNotes in activity WikiNotes. Lines 4–11 are the patch for this bug.

can be difficult, especially in the case of software that behaves non-deterministically, relies on remote resources, or has complex reproduction steps (the users may not even know what led up to triggering the flaw, particularly in the case of software interacting with external devices, databases, etc. in addition to human users). We use a record&replay approach to capture the state of the system just before a bug is encountered, so the steps leading up to this state can be replayed later. In our study, we use VALERA [61], a lightweight record-and-replay tool for Android.

As discussed in Section 6.1, we have three possible ways to get the crash event traces by using the record/replay scheme:

1. *Directly extract reproduction steps from the bug report.* When the crash reproduction steps are available, we can record the event trace following these steps and run our step minimization algorithm. However, the quality of bug reports (and user reviews) for Android apps in the wild varies considerably as they are often incomplete or noninformative [31].

2. *Use the Monkey tool to randomly generate events to trigger the crash.* The downside is for many apps, we need to login with account and password (e.g., WordPress and K-9 Mail). But Monkey cannot automatically login and record the following events.

3. *Recruit volunteer testers.* We can invite our lab colleagues to manually run the app as normal users and try to trigger the crash. We ask them to write their each action and record the event traces they used to find the crash.

As mentioned in the bug report description, we can reproduce the crash in WikiNotes in 6 steps:

Type	**Listener**	**Callback**
View	OnClickListener	onClick
	OnLongClickListener	onLongClick
	OnFocusChangeListener	onFocusChange
	OnTouchListener	onTouch
	OnDragListener	onDrag
Adapter View	OnItemClickListener	onItemClick
	OnItemLongClickListener	onItemLongClick
	OnItemSelectedListener	onItemSelectedClick
		onNothingSelected
ListView	onListItemClick	onItemClick
MenuItem	OnMenuItemClickListener	onMenuItemClick
AbsListView	OnScrollListener	onScroll
		onScrollStateChanged

Table 6.1: Event and their call backs we consider.

1. Open the app and create one note (either empty or not);
2. Click the "List All Notes" button; the app will go to activity WikiNotesList;
3. Select the note and will go back to WikiNotes;
4. Delete the note by clicking the "Delete Note" button;
5. When the confirmation dialog appears, click "Yes";
6. Click the "Back" button; then the crash happens.

In our study, we only focus on user events the app evolved with, which represent a human users interaction with the app. Other events like internet, database connections are not our concerns. Also we do not consider the inputs, i.e. exact strings we type. Table 6.1 shows the event listeners and their corresponding call back methods we consider in our study.

6.3.2 Generating the Event Dependency Graph

Android apps use event-driven model. There are dependence relations between events in the program. To use the dependency information to guide our approach, we need to build the event dependency graph (EDG) first. There are many works that focus on this process [162, 165].

In our study, we first apply static analysis on the app. There are two steps to generating an EDG for the app:

1. The EDG could be specified manually or generated automatically through one of the model generation techniques. We use GATOR [154] to generate sub-EDGs for each activity in the app;

2. Based on the event traces we collect in the previous step, we link the activities and events executed together and get the whole EDG for the app.

There are 12 events in WikiNotes in total. Figure 6.5 gives the EDG of WikiNotes. Based on the reproduction steps mentioned in Section 6.3.1 and the EDG we have, there are two ways to trigger the crash in WikiNotes. The event sequence to trigger the crash is $\{e_4$, e_7 or e_8, e_1, e_2, $e_9\}$ or $\{e_4$, e_7 or e_8, e_3, e_{11} or e_5, e_2, e_9, $e_{12}\}$. Here e_4 can be committed if we install the app and run it for the first time. When we enter the main activity WikiNotes, it first checks the database; if there is no note in the database, it will automatically jump to the activity WikiNoteEditor.

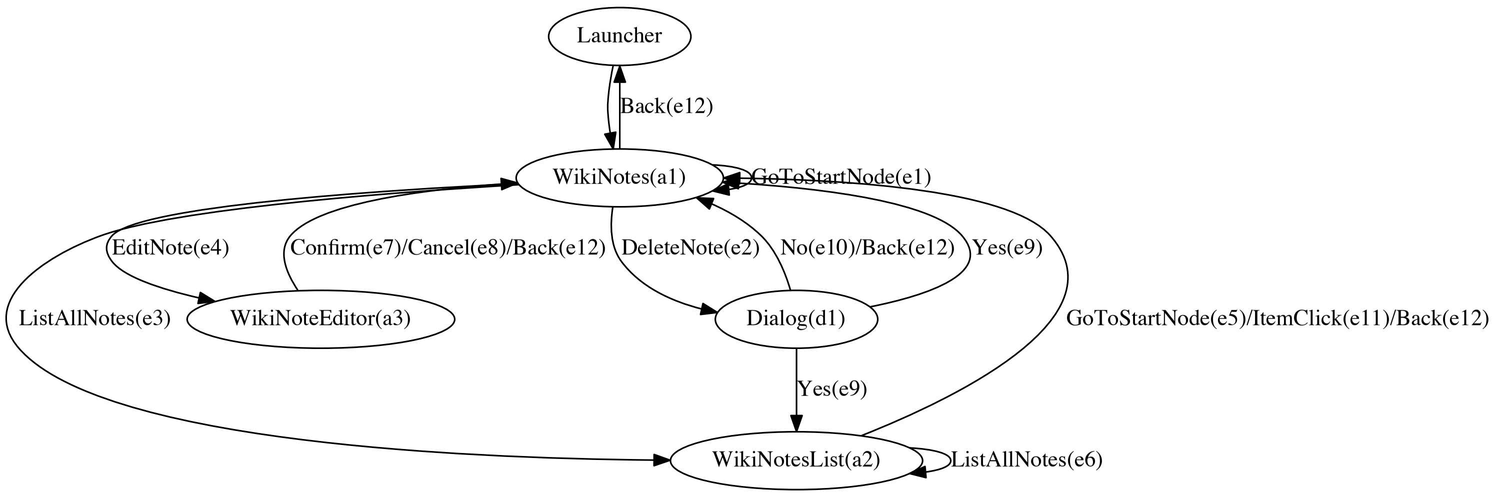


Figure 6.5: Event dependency graph of app WikiNotes.

6.3.3 Our Approach for Delta Debugging

Traditional Delta Debugging (DD) performs a binary search on the inputs. It splits the inputs into two sub groups and test each of them individually. If any of the two sub groups trigger the fault, DD marks it as minimal group and recursively searching in it until no single input can be removed from the group [159].

In our case, since on Android events are not independent, we cannot apply the traditional DD, and need to find another way to reduce the event trace size. We propose two approaches for adapting the idea of delta debugging to the problem of reducing the size of an event trace.

EDG based Delta Debugging Approach

Algorithm 1 shows the EDG-based DD approach. For each trace, we first intialize trace list T' to the shortest path from starting point to crash point. Then we expand the T' by adding possible events into it based on the EDG.

In the first step, we exclude irrelevent events based on the EDG generated in Section 6.3.2. Since we know the crash causing event and activities, we can mark those events that cannot be reached in the EDG as irrelevant.

In the next step, we use the replay tool to rerun the app to check whether it crashes or not until all the events in the traces are marked as "relevant". During this step, we might mark some trace as "important" and others as "unimportant" based on their relation with the crash point.

We use the crash bug of WikiNotes as example. We get the event trace $T =$

Algorithm 1 EDG based Delta Debugging algorithm

```
Input: Event trace $T \leftarrow \{E_0, E_1, ..., E_n\}$
Output: Candidate traces $T' \subseteq T$ of minimum events trigger the crash
 1: procedure DELTADEBUGGINGALGORITHM($T$)
 2:     $T' \leftarrow$ null
 3:     for each trace $T$ do
 4:         $T' \leftarrow \{E_0, E_n\}$
 5:         $T' \leftarrow$ SHORTESTPATH($E_0, E_n$, EDG)
 6:         Replay $T'$
 7:         if No crash triggered then
 8:             $T' \leftarrow$ EXPANSION($level$, $T'$)
 9:             $level \leftarrow level + 1$
10:         end if
11:     end for
12: end procedure
13: procedure SHORTESTPATH($E_i, E_j$, EDG)
14:     Find parent activity $A_i$ of $E_i$
15:     Find child activity $A_j$ of $E_j$
16:     Find shortest path from $A_i$ to $A_j$
17: end procedure
18: procedure EXPANSION(level, $T'$)
19:     level $\leftarrow$ 1
20:     for activities $A_{i,j,...,k}$ at the same level of $A_n$ which is the parent of $E_n$ do
21:         Find all event combinations from parent of $A_{i,j,...,k}$ to each of them with Breadth First
    Search (BFS)
22:         Add event into $T'$
23:     end for
24: end procedure
```

$\{e_7, e_1, e_3, e_{11}, e_4, e_8, e_4, e_7, e_3, e_5, e_2, e_{10}, e_1, e_4, e_7, e_2, e_9\}$. In the first step, we put the *start* and *end* event into the candidate set $T' = \{e_7, e_9\}$, since e_7 pointed to a_1 and e_9 came from d_1; next we use the generateShortestFirst function to get the shortest path from a_1 to d_1, we will get $T' = \{e_7, e_2, e_9\}$. When we replay with this trace, we do not trigger the crash; thus, we take one step back, and consider all the event combinations that came from a_1. There are 3 possible events, e_1, e_3, and e_4. Also we need to consider all possible ways coming back from one activity to another, for example, from a_3 to a_1, we can have e_7, e_8 or e_{12}. Finally, from one step back, combined with trace T, we can get reduced candidate $T' = \{e_7, e_1, e_2, e_9\}, \{e_7, e_3, e_5, e_2, e_9\}, \{e_7, e_3, e_{11}, e_2, e_9\}, \{e_7, e_4, e_7, e_2, e_9\}, \{e_7, e_4, e_8, e_2, e_9\}$. Then, by replaying with these 5 candidate traces, we can trigger the crash by using $\{e_7, e_1, e_2, e_9\}$.

After the analysis, it appears that we only need 4 steps to trigger the crash:

1. Open the app and create one note (either empty or not);
2. Click "Go To Start Note"; the app will go to activity WikiNotes;
3. Delete the note by clicking "Delete Note";
4. When the confirmation dialog appears, click "Yes"; the crash happens.

Improved Delta Debugging Approach

During our study, we found that in the EDGs of many apps, there are many activities at the same level, hence we have to execute the app too many times to validate all the possible candidate traces. To reduce the replay times and improve efficiency, we propose an improved delta debugging approach. We use static information that may be

Algorithm 2 Improved Delta Debugging algorithm

```
1: procedure EXPANSION(level, $T'$)
2:     level $\leftarrow 1$
3:     for activities $A_{i,j,\ldots,k}$ at the same level of $A_n$ which is the parent of $E_n$ do
4:         Find all event combinations from parent of $A_{i,j,\ldots,k}$ to them with Breadth First Search
5:         Sort $A_{i,j,\ldots,k} \leftarrow$ RELEVANCE($A_{i,j,\ldots,k}$,$A_n$)
6:         Add sorted events into $T'$
7:     end for
8: end procedure
9: procedure RELEVANCE($A_{i,j,\ldots,k}$,$A_n$)
10:    for each method ($m$)/variable ($v$) used in $A_n$ do
11:        if $m/v$ defined in $A_i$ then
12:            Put $A_i$ in the top
13:        end if
14:    end for
15: end procedure
```

readily available because the developers, who are familiar with their own code, are often the ones who debug and fix their apps [163].

In this approach, we consider the dependencies of the activities, for example, if the crash happened in activity A, and in A the method defined in activity B was called, then we first consider adding events involved in activity B. The only difference of updated algorithm comparing with the previous one is Expansion function, the updated algorithm is given by Algorithm 2.

We use AnkiDroid app to illustrate this approach. The EDG of AnkiDroid is shown in Figure 6.6. The crash happens when we enter activity Reviewer (a_6) after enabling the

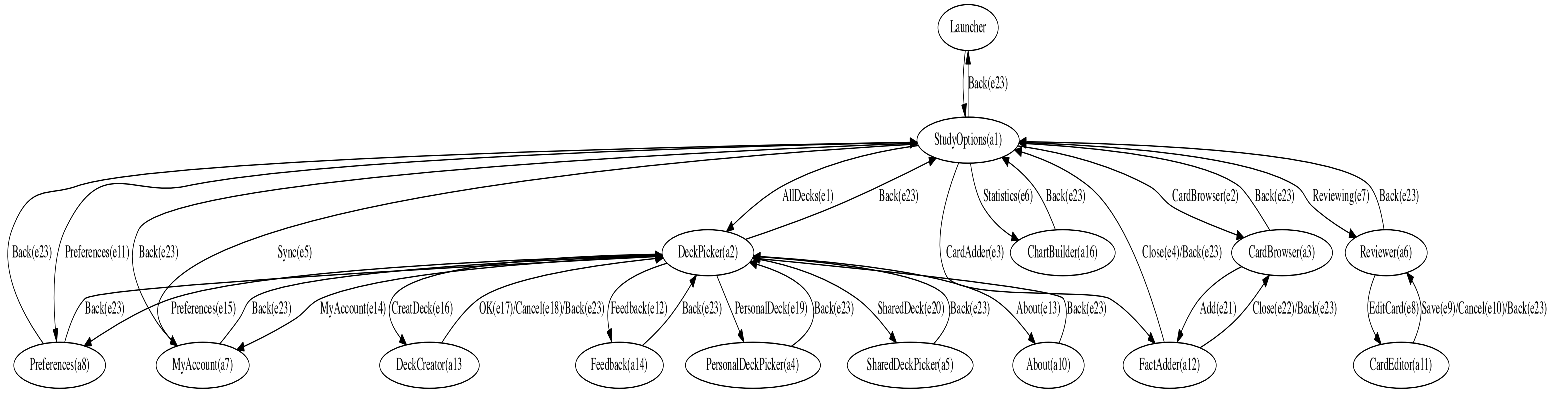


Figure 6.6: Event dependency graph of app AnkiDroid.

```
Caused by:
android.database.CursorIndexOutOfBoundsException:
Index 0 requested, with a size of 0
    at android.database.AbstractCursor.checkPosition(AbstractCursor.java:424)
    at android.database.AbstractWindowedCursor.checkPosition
        (AbstractWindowedCursor.java:136)
    at android.database.AbstractWindowedCursor.getString(AbstractWindowedCursor.java:50)
    at com.ichi2.anki.Field.fieldValuefromDb(Field.java:24)
    at com.ichi2.anki.Card.getComparedFieldAnswer(Card.java:1037)
    at com.ichi2.anki.Reviewer$8.onProgressUpdate(Reviewer.java:549)
    ...
    at dalvik.system.NativeStart.main(Native Method)
```

Figure 6.7: Stack trace of the crash of AnkiDroid.

setting "Write answers" in Preference (a_8). By applying the algorithm in Section 6.3.3, we first get the shortest path from a_1 to a_6, that is $T' = \{e_7\}$. Then we replay T' but this does not trigger the crash. In the next step, we find all the activities at the same level as a_6. We have 6 activities at the same level as a_6 which include a_2, a_3, a_7, a_8, a_{12}, and a_{16}. For each of these 6 activities, we find all possible events that go out from them. This gives us 11 candidate events. We find that, since there are too many possibilities to validate from activity StudyOptions (a_1), we would spend too much time and effort to validate all possible combinations. Therefore we need a better solution to speed up the candidate selection process.

Based upon the stack trace given in Figure 6.7, and the source code of AnkiDroid in Figure 6.8, we find that the crash actually happened in method getComparedFieldAnswer which is called by function onProgressUpdate of activity Reviewer (a_6) (line 39 in Figure 6.8). The method call uses the variable mPrefWriteAnswers (line 30 in Figure 6.8), which is defined in the activity Preference (a_8). Therefore we first add events in a_8 and validate them first.

```
Card.java
public String[] getComparedFieldAnswer() {
    String[] returnArray = new String[2];
    CardModel myCardModel = this.getCardModel();
    String typeAnswer = myCardModel.getTypeAnswer();
    // fix: Check if we have a valid field to use as the answer to type.
    if (null == typeAnswer || 0 == typeAnswer.trim().length()) {
      returnArray[0] = null;
  // fix:
  // return returnArray;
    }
    Model myModel = Model.getModel(mDeck, myCardModel.getModelId(), true);
    ...
    /* fix:
    // Just in case we do not find the matching field model.
    if (myFieldModelId == 0) {
        Log.e(AnkiDroidApp.TAG, "could not find field model for type answer: " +
             typeAnswer);
        returnArray[0] = null;
        return null;
    }
    */
    returnArray[0] = com.ichi2.anki.Field.fieldValuefromDb(this.mDeck, this.mFactId,
        myFieldModelId);
    returnArray[1] = "fm" + Long.toHexString(myFieldModelId);
    return returnArray;
}

Reviewer.java
private SharedPreferences restorePreferences() {
    ...
    mPrefWriteAnswers = preferences.getBoolean("writeAnswers", false);
    ...
}
...
public void onProgressUpdate(DeckTask.TaskData... values) {
    ...
    // Start reviewing next card
    mCurrentCard = newCard;
    if (mPrefWriteAnswers) { //only bother query deck if needed
        String[] answer = mCurrentCard.getComparedFieldAnswer();
        comparedFieldAnswer = answer[0];
        comparedFieldClass = answer[1];
    } else {
        comparedFieldAnswer = null;
    }
    ...
}
```

Figure 6.8: Fix strategy for the crash of AnkiDroid.

6.4 Summary

We prototyped the approach described in Section 6.3. Our approach is useful for bug reproduction and bug localization. However, currently it can only handle clickable GUI events. We plan to evaluate our algorithm using more real world apps.

Chapter 7

Related Work

This chapter summarizes various research in software engineering community and problems addressed by this thesis. We first summarize previous research on empirical software engineering including bug characteristic studies, using bug reports, e.g., bug location prediction, bug triaging, duplicate bug report detection. Next we review various studies on specific types of bugs, e.g., smartphone related bugs, concurrency bugs. Finally, we summarize work on existing software testing and debugging techniques on Android platform.

7.1 Empirical Software Engineering

7.1.1 Bug Characteristic Studies

Bug characteristic studies have been performed on other large software systems [138], though the objectives of those studies were different, e.g., understanding OS [32] errors. In contrast, our study focuses specifically on understanding and predicting concurrency bugs. Many other efforts [15,78,83,90,117] have mined bug and source code repositories to study and analyze the behavior and contributions of developers and their effects on software quality. Some of the efforts used machine learning for analysis and prediction. In contrast, we do in-depth analysis and prediction for bugs on different platforms.

7.1.2 Bug Severity Studies

All the existing bug severity studies are focused on predicting severity levels from a newly-filed bug report. Menzies et al. [105] proposed a classification algorithm named RIPPER and applied it to bug reports in NASA to output fine-grained severity levels. Lamkanfi et al. [84] apply various classification algorithms to compare their performance on severity predicting. They grouped bug reports into two classes, severe and non-severe. Tian et al. [141] have applied the Nearest Neighbor algorithm to predict the severity of bug reports in a fine-grained way.

All these works are using information retrieval techniques to predict severity level of bug reports, but they did not consider the question whether there are differences in bug characteristics across severity classes. Our findings validate the importance and necessity of these previous works, and show that severity is an important factor not only for bug reporters but also for project managers.

7.1.3 Predicting Bug Location

Ostrand et al. [116] used multivariate negative binomial regression model and revealed that variables such as file size, the number of prior faults, newly-introduced and changed files can be used to predict faults in upcoming releases. Based on the model they predict the number of faults in each file, and fault density. They found that their Top-20%

files predicted to be buggy contained 71%–92% of the detected bugs. Their study, like ours, has revealed that bug numbers are autocorrelated. However, we use different variables to construct the predictor model, and instead of predicting the number of bugs per file and bug density per file, we predict the number of concurrency bugs in the system, and type/location for newly-filed concurrency bug reports. Kim et al. [78] proposed bug cache algorithms to predict future bugs at the function/method and file level by observing that bugs exhibit locality (temporal, spatial) and the fact the entities that have been introduced or changed recently tend to introduce bugs. Their study was performed on 7 large open source projects (including Apache). Their accuracy was 73%–95% for files and 46%–72% for functions/methods. Their study, like ours, has revealed that bug numbers are autocorrelated. We do not investigate localities beyond temporal; however, they might help improve our prediction accuracy.

Wu et al. [151] used time series for bug prediction but did not consider the impact of independent variables on the time series, as we do. Rao et al. [122] compared five information retrieval models for the purpose of locating bugs. Their work mainly focused on comparing models (concluding that Unigram and Vector Space work best) and calculating the likelihood that one file would be buggy based on its similarity with known buggy files. We use a different model; we focused on finding the exact location one concurrency bug would affect; and we had to solve the multi-label classification problem. Moin et al. [107] used commit logs and bug reports to locate bugs in the source file hierarchy. However, their method is coarser-grained than ours, e.g., if two bugs are in `mozilla/security/nss/lib/certdb` and `mozilla/security/nss/lib/pki` respectively, they considered the bugs to be in the same location, `mozilla/security/nss/lib/`, but our prediction model can distinguish the difference between these two locations.

7.1.4 Topic Modeling

Topic models have been used widely in software engineering research. Prior efforts have used topic model for bug localization [113], source code evolution [140], duplicate bug detection [114, 127] and bug triaging [152]. Han et al. [57] studied how fragmentation manifests across the Android platform and found that labeled-LDA performed better than LDA for finding feature-relevant topics. Their work focused on two vendors, HTC and Motorola; we compare bug topics between desktop, Android and iOS. Martie et al. [102] studied topic trends on Android Platform bugs. They revealed that features of Android are more problematic in a certain period. They only analyzed bug trends in the Android Platform project; in our study, we examined 87 additional projects on Android, desktop and iOS. Our work applies a similar process with previous work [140], but we use topic modeling technique for a different purpose: finding differences in bug topics across severity classes, and how bug topics evolve over time.

7.2 Specific Type of Bugs

7.2.1 Studies on Smartphone Bugs

Maji et al. [99] compared defects and their effect on Android and Symbian OS. They found that development tools, web browsers and multimedia apps are the most defect-prone; and most bugs require only minor code changes. Their study was focused on the relation between source code and defects, e.g., bug density, types of code changes required for fixes. We also analyze bugs in Android Platform, but we mainly focus on bug-fixing process features. Besides Android Platform, we also consider 87 other projects on Android, desktop and iOS.

Syer et al. [137] compared 15 Android apps with 2 large desktop/server applications and 3 small Unix utilities on source code metrics and bug fixing time. We examined 38 Android projects, 34 desktop projects and 16 iOS projects. Besides fixing time, we also consider other features, e.g., severity, description length; we also analyze topics and reporter/owner trends for each platform.

Zhang et al. [160] tested three of Lehman's laws on VLC and ownCloud for desktop and Android. Their work was based on source code metrics, e.g., code churn, total commits. Our work focuses on bug reports/nature/fixing process.

Our own prior work [21] studied bug reports on Android platform and apps. The study found that for Android app bugs (especially security bugs), bug report quality is high while bug triaging is still a problem on Google Code. While there we compared bug report features across Android apps, in this work we compare bug-fixing process features across three platforms, study topics, and study feature evolution.

7.2.2 Studies on Concurrent Programs

Lu et al. [93] analyzed 105 concurrency bugs collected from four open source projects (Mozilla, Apache, OpenOffice, MySQL). Their study focused on understanding concurrency bug causes and fixing strategies. Fonseca et al. [46] studied internal and external effects of concurrency bugs in MySQL. They provide a complementary angle by studying the effects of concurrency bugs (e.g., whether concurrency bugs are latent or not, or what type of failures they cause). We use a similar methodology for deciding which bugs to analyze, but with different objectives and methods: characterizing bug features, a quantitative analysis of the bug-fixing process and constructing prediction models for bug number, type and location.

7.3 Software Testing & Debugging on Android

7.3.1 Mobile App Testing

Yang et al. [155] implement Orbit tool based on grey-box approach for automatic exploration. Their approach uses static analysis on the apps source code to detect actions associated with GUI states and then use a dynamic crawler (built on top of Robotium) to fire the actions. Anand et al. [11] developed an approach named ACTEVE based on concolic testing. It can generate sequences of events automatically and systematically. Their focus is on covering branches while avoiding the path explosion problem. Similarly, Jensen et al. [67] apply symbolic execution technique to derive event sequences that can lead to a specific target state in an Android app. Their approach can reach states that could not be reached using Monkey tool. Mahmood et al. [96] presented EvoDroid, an evolutionary approach for system testing of Android apps. It extracts interface and call graph models automatically, and then generates test cases using search-based techniques. White et al. [149] presents CRASHDROID, an approach for automating the process of reproducing a bug by translating the call stack from a crash report into expressive steps to reproduce the bug and a kernel event trace that can be replayed on-demand.

7.3.2 Delta Debugging

Delta debugging is a family of algorithms for sequence minimization and fault isolation, described originally by Zeller et al. [159] . Burger el al. [29] presented JINSI which used delta debugging to record and minimize the interaction between objects to the set of calls relevant for the failure. Roehm et al. [125] presented an approach to automatically extract failure reproduction steps from user interaction traces by applying both delta debugging and sequential pattern mining. It is used for desktop applications. Elyasov et al. [37, 38] proposed a two stage approach for reduction of the failing event sequence, that consists of 1) mining rewriting rules from the set of collected logs, and 2) applying these rules to the failing sequence with the purpose of sequence length reduction. Hammoudi et al. [56] presented an approach for recording reduction based on delta debugging that operates on recordings of web applications. Clapp et al. [33] propose a variant of delta debugging algorithm to handle non-determinism which is a pervasive issue in app behavior and solve the problem of trace minimization.

Chapter 8

Conclusions and Future Work

8.1 Contributions

The main contribution of this dissertation was to extract actionable information from bug reports, e.g., for evaluating product quality, reducing the time and human effort for bug fixing process and speeding up the debugging process. To this end, this dissertation makes the following fundamental contributions to the field of software engineering.

8.1.1 A Cross-platform Analysis of Bugs

Bug-fixing process features (e.g., fix time, number of comments) differ between desktop and the two smartphone platforms, but are similar for Android and iOS. We also found that the most frequent issues differ across platforms. Furthermore, concurrency bugs are much more prevalent on Android than on iOS. Despite the attention they have received in the research community, we found that issues commonly associated with smartphone apps such as energy, security and performance, are not very prevalent.

8.1.2 Empirical Study of Concurrency Bugs

For each bug type, we analyzed multiple facets (e.g., patches, files, comments, and developers involved) to characterize the process involved in, and differences between, fixing concurrency and non-concurrency bugs. We found that compared to non-concurrency bugs, concurrency bugs take twice as long to fix, require patches that are 4 times larger. Within concurrency bugs, we found that atomicity violations are the most complicated bugs, taking highest amounts of time, developers and patches to fix, while deadlocks are the easiest and fastest to fix.

Using the historic values of these bug characteristics, we construct two models to predict the number of extant concurrency bugs that will have to be fixed in future releases: a model based on generalized linear regression and one based on time series forecasting. Our predicted number of concurrency bugs differed very little from the actual number: depending on the bug type, our prediction was off by just 0.17–0.54 bugs.

While these quantitative predictors provide *managers* an estimate of the number of upcoming concurrency bugs, to help *developers* we constructed two additional, qualitative predictors. First, a *bug type* predictor that can predict the likely type of a newly-filed bug concurrency bug, e.g., atomicity violation or deadlock with at least 63% accuracy. Second, a *bug location* predictor that predicts the likely bug location from a new bug report with at least 22% Top-1 accuracy and 55% Top-20% accuracy.

8.1.3 Bug Analysis Across Severity Classes

Severity changes are more frequent on Android, where some projects have change rates in excess of 20%, than on desktop. Bug-fix time is affected by not only severity but also priority. Interestingly, there are marked quantitative difference between the three severity classes on desktop, but the differences are more muted on Android. Fixing medium-severity bugs imposes a greater workload than fixing high-severity bugs. Medium-severity bug reporters/owners are more experienced than high-severity bug reporters/owners. There have been more concurrency and cloud-related high-severity bugs on desktop since 2009, while on Android concurrency bugs have been and continue to be prevalent. Since our study reveals that bug-fixing process attributes and developer traits differ across severity levels, our work confirms the importance of prior work that has focused on accurately predicting bug severity [84, 105, 141].

8.1.4 Minimizing Bug Reproduction Steps on Android

We proposed an approach to collect execution data automatically and extract minimized reproduction steps from captured data by using a record/replay scheme. We generate an event dependency graph (EDG) based on app execution. Then we use the EDG with event sequences to guide the delta debugging algorithm by eliminating irrelevant events.

8.2 Future Directions

8.2.1 Mixture Use of Data Sources

In our quantitative studies in Sections 3.2, 4.3, and 5.2, we only extract bug fixing features from the bug tracking system, without looking at source code. Therefore, future work can extract metrics from source code repository, e.g., McCabe cyclomatic complexity, lines of code, number of classes, number of methods, number of parameters [166, 168], etc., and build quantitative studies using these metrics. Furthermore, we can build combined prediction models by applying both features extracted from source code repository and bug tracking system.

8.2.2 Study of General Applications

Our study focused on open source applications; thus the findings might not generalize to closed source applications. Therefore, future work can analyze the bug characteristics and topics on the specific domains.

Additionally, in Section 3.4 we introduced our finding on projects migrating to GitHub. We can investigate how we can extract actionable information from bug reports hosted on GitHub.

8.2.3 Minimizing Event Trace on Android

Our study in the dissertation only focused on click events on Android. There are other event types (e.g., input numbers/characters, system related) that we have not handled. To support these additional types of events, we can apply symbolic execution techniques. However, the existing symbolic execution tools [23] supporting Android cannot be used in our study since they can only cover part of the system calls. We can develop a new symbolic execution tool and continue our study in the future.

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