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EMPIRICAL METHODS FOR EVALUATING VULNERABILITY MODELS

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Abstract

This dissertation focuses on the following research question: *"how to independently and systematically validate empirical vulnerability models?"*. Based on the survey on past studies about the vulnerability discovery process, the dissertation has pointed out several critical issues in the traditional methodology for evaluating the performance of vulnerability discovery models (VDMs). Such issues did impact the conclusions of several studies in the literature. To address such pitfalls, a novel empirical methodology and a data collection infrastructure are proposed to conduct experiments that evaluate the empirical performance of VDMs. The methodology consists of two quantitative analyses, namely *quality* and *predictability* analyses, which enable analysts to study the performance of VDMs, and to compare them effectively.

The proposed methodology and the data collection infrastructure have been used to assess several existing VDMs on many major versions of the major browsers (*i.e.,* Chrome, Firefox, Internet Explorer, and Safari). The extensive experimental analysis reveals an interesting finding about the VDM performance in terms of quality and predictability: the simplest linear model is the most appropriate one for predicting vulnerability discovery trend within the first twelve months since the release date of browser versions; later than that, logistic models are more appropriate.

The analyzed vulnerability data exhibits the phenomenon of *after-life* vulnerabilities, which have been discovered for the current version but also attributed to browser versions out of support – *dead* versions. These vulnerabilities however may not actually exist, and may have an impact on past scientific studies, or on compliance assessment. Therefore, this dissertation has proposed a method to identify code evidence for vulnerabilities. The results of the experiments show that a significant amount of vulnerabilities has been systematically over-reported for old versions of browsers. Consequently, old versions of software seem to have less vulnerabilities than reported.

Acknowledgements

I would like to express my deep appreciation to many people, without whom, I could not finish the dissertation for my PhD graduation.

At first, I would like to thank Professor Fabio Massacci, who supervised my PhD work at University of Trento. It is my luck to be his student and colleague. I would like to thank a lot for his helpful advices, his endless patience, and his guidance during the last five years and beyond. I have received invaluable supports from him for my travels to summer schools, conferences, and project meetings. This helped to broaden not only my research horizonal, but also my social knowledge.

I would like to thank Dr. Riccardo Scandariato who was the mentor for my internship at University of Leuven. I have learnt many things from him. His working style has indeed influenced me a lot. I also want to thank all other colleagues at Ditri Net (University of Leuven) for their kindness and helpfulness.

I am grateful to Professor Laurie William (North Carolina State University, United States), Professor Alexander Pretschner (University of Munich, Germany), and Professor Massimiliano Di Penta (University of Sannio, Italy) for being committee members in my defence. They have taken their time for reading my dissertation carefully, giving me many helpful and constructive feedback, and for challenging me with interesting questions that helped to improve the quality of this dissertation.

I am thankful to Dr. Stephan Neuhaus for his collaboration in the very first year of my PhD study. I also would like to thank to my colleagues and my friends at University of Trento. However I decided not to list their names here because it is more likely that I would forget some of them at the time of writing. They have contributed a lot of useful advices, discussions, and also nice and welcome distraction.

I would like to thank to anonymous reviewers whom I will never know. Their comments have frustrated me at the first sight, but they really were fruitful criticism that dramatically helped me to improve my writing works, resulting in publications which the dissertation is built upon.

Finally I would like to dedicate this dissertation to my sweetheart, Le Minh Sang Tran, for her true love and deep understanding. Without her encouragements and supports I would not be able to achieve that success. And to my family, who are always in my side unconditionally, even if they do not really understand what I am doing.

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Acronyms

AE Average Error

AB Average Bias

AIC Akaike Information Criteria

AKB Apple Knowledge Base

BSIMM Building Security In Maturity Model

CDG Component Dependency Graph

CERT Computer Emergency Response Team/Coordination Center

CIT Chrome Issue Tracker

CSV Comma Separated Values

CVE Common Vulnerabilities and Exposures

CVS Concurrent Version System

CVSS Common Vulnerabilities Scoring System

LoC Line of Code

MBug Mozilla Bugzilla

MDG Member Dependency Graph

MFSA Mozilla Foundation Security Advisories

MSB Microsoft Security Bulletin

NIST National Institute of Standards & Technology

NVD National Vulnerability Database

OSVDB Open Source Vulnerability Database

PCI DSS	Payment Card Industry Data Security Standard
SCAP	Security Content Automation Protocol
SDL	Security Development Lifecycle
SQL	Structured Query Language
SVM	Support Vector Machine
VDM	Vulnerability Discovery Model

CHAPTER 1

INTRODUCTION

This chapter presents the motivation of this dissertation. It describes the overall research questions and research method that drive the subsequent chapters. It also summarizes the major contributions of this work, as well as published/in submission publications on which the dissertation is built upon.

RECENT years have seen major efforts addressing the insecurity of software from guidelines for secure software development [McG09; HL03; HL06] to studies attempting to understand the nature of vulnerabilities. Our survey of 59 recent studies in the field from 2005 to 2012 whose contributions were (partially) relied on (or validated by) empirical experiments shows *fact finding* papers (*i.e.,* reporting the findings with/without some statistics [Ozm05; OS06; Fre06; Res05; Li12; Sha12]), *modeling* papers (*i.e.,* proposing mathematical models, or metrics, or methodologies concerning vulnerabilities [Alh07; And02; Res05; You11; Joh08], or economic models [Shi12; AM13]), and *prediction* papers (*i.e.,* predicting the vulnerabilities in code base, [Shi11; CZ11; Geg09b; Neu07; Boz10]).

Vulnerability data sources now are employed not only in scientific studies, but also in the compliance assessment for deployed software. The US National Institute of Standards & Technology (NIST) Security Content Automation Protocol (SCAP) [Qui10], and Payment Card Industry Data Security Standard (PCI DSS)[WC12] have been applied to evaluate the compliance of software-related products. They both employ NVD. Any mistakes in NVD might result in unfair fines raking hundreds of thousand of euros in companies. For instance, if a product embeds an older version of browser (*e.g.,* Chrome v4), it might lose compliance with PCI DSS due to a large number of unfixed vulnerabilities. Then the product vendor might either update to new version, or pay a fine, or be kicked out of the market.

This dissertation does not aim to provide a novel model of the vulnerability discovery process, nor an outperform approach to early detect vulnerabilities. Instead, motivating by the fact that several models on vulnerabilities are based on empirical experiments, the dissertation lays its focus on the research question: *"how to independently and systematically validate empirical vulnerability models?"*.

The rest of this chapter is organized as follows. Section 1.1 briefly summarizes the main contributions of the dissertation. Section 1.3 describes the chapters in the dissertation, as well as a short summary for each chapter. Section 1.4 shows the ordinal publications that I have (co)authored during the course of the PhD study.

1.1 Contributions

This section briefs the major contributions of the dissertation as follows.

i) *An empirical methodology to evaluate the performance of time-based vulnerability discovery models (VDMs).* Several VDMs have been proposed *e.g.,* [Alh05; Joh08; You11], and have been claimed to be workable by their proponents. However, there were some criticisms that these models might not work due to the violation of their implicit assumptions [Ozm05]. We have pointed out some issues that might affect the validation experiments on the performance of VDMs. We have proposed a novel empirical methodology to validate the performance of VDMs. The methodology consists of two quantitative analyses, namely *quality* and *predictability*, which enable analysts to study the performance of VDMs, and to compare them effectively. Moreover, the methodology addresses all identified issues that might be problematic while validating VDMs.

ii) *A systematic assessment on the performance of existing VDMs* based on our proposed methodology. The conducted experiment assesses 8 out of 10 existing VDMs on 30 major versions of dominant web browsers (*i.e.,* Chrome, Firefox, IE, and Safari). The experiment results have revealed an interesting finding about the VDM performance in terms of quality and predictability: the simplest linear model ($\Omega(t) = Ax + B$) is the champion within first 12 months since the release date of browsers in predicting the future trend of vulnerabilities; later then, logistic models are more appropriate.

iii) *An empirical technique to quickly identify evidences for the existence of vulnerabilities in retro versions of software.* Apart from the findings about the majority of *foundational vulnerabilities* [OS06] which are introduced in the very first version and continue to survive in later versions, Chapter 5 shows that many of vulnerabilities have been reported for "dead" software, which we called *after-life vulnerabilities*. Such vulnerabilities are byproducts when researchers (or attackers) study and report security flaws in the latest release of the software. These vulnerabilities however may not actually exist, and may have an impact on past studies (*e.g.,* Ozment and Schechter [OS06]), or on compliance assessment (*e.g.,* [Qui10; WC12]). Therefore, we have proposed a method to quickly identify code evidence for vulnerabilities. The method has been empirically tested in an experiment showing that a significant amount of vulnerabilities has been systematically misreported for old versions of browsers. Consequently, old versions of software (*e.g.,* Chrome v4) seem to have less vulnerabilities than reported.

1.2 Terminology

Vulnerability is "an instance of a [human] mistake in the specification, development, or configuration of software such that its execution can [implicitly or explicitly] violate the security policy" [Krs98; Ozm07a].

Vulnerability entry is an entry, which reports security problem(s), in a vulnerability data source, for instance NVD entries (a.k.a Common Vulnerabilities and Exposusres (CVEs)) of the NVD data source.

Vulnerability claim is a statement by a data source that a particular software version is vulnerable to a particular vulnerability entry. Figure 8.1 shows an example of the claims of CVE-2008-7294.

Spurious vulnerability claim is a vulnerability claim which is not correct.

Data set is a collection of vulnerability data extracted from one or more data sources.

Release refers to a particular version of an application *e.g.,* Firefox v1.0.

Horizon is a specific time interval sample. It is measured by the number of months since the released date, *e.g.,* 12 months since the release date.

Observed vulnerability sample (or observed sample, for short) is a time series of monthly cumulative vulnerabilities of a major release since the first month after release to a particular horizon.

Evaluated sample is a tuple of an observed sample, a VDM model, and the goodness-of-fit of this model to this sample.

Commit is a unit of changes in source code, managed by the code base repository.

Bug-fix commit is a commit that contains changes to fix a (security) bug.

Vulnerable code footprint is a piece of code which is changed (or removed) in order to fix a security bug. The intuition to identify such vulnerable code footprints is to compare the revision where a security bug is fixed (*i.e.,* bug-fix commit) to its immediate parent revision. Pieces of code that appear in the parent revision, but not in the bug-fixed revision are considered vulnerable code footprints, see Section 8.2.3 for more details.

1.3 Structure of the Dissertation

Chapter 1: *Introduction*. This chapter presents the motivation and the contributions of the dissertation. It also describes the organization of the dissertation.

Chapter 2: *Research Roadmap*. This chapter presents the research objective of the dissertation, as well as research questions refined from the objective. It also describes how other chapters could help to attain the research objective.

Chapter 3: *A Survey of Empirical Vulnerability Studies*. This chapter presents a survey on empirical vulnerability studies. It focuses on the usage of data sources, and the major focuses of those studies.

Related publication(s): This chapter has been partially published in:

- Fabio Massacci and Viet Hung Nguyen. “Which is the Right Source for Vulnerabilities Studies? An Empirical Analysis on Mozilla Firefox”. In: *Proceedings of the International ACM Workshop on Security Measurement and Metrics (MetriSec’10)*. 2010

Chapter 4: *Data Infrastructure for Empirical Experiments*. This chapter presents the data infrastructure that will be used in the experiments conducted within the dissertation.

This chapter includes the software infrastructure, and some heuristic rules to collect the data from public sources.

Related publication(s): This chapter has been partially published in/ or being submitted to:

- Fabio Massacci and Viet Hung Nguyen. "Which is the Right Source for Vulnerabilities Studies? An Empirical Analysis on Mozilla Firefox". In: *Proceedings of the International ACM Workshop on Security Measurement and Metrics (MetriSec'10)*. 2010
- Fabio Massacci, Stephan Neuhaus, and Viet Hung Nguyen. "After-Life Vulnerabilities: A Study on Firefox Evolution, its Vulnerabilities and Fixes". In: *Proceedings of the 2011 Engineering Secure Software and Systems Conference (ESSoS'11)*. 2011
- Viet Hung Nguyen and Fabio Massacci. *An Empirical Methodology to Validated Vulnerability Discovery Models*. Tech. rep. (under submission to IEEE Transactions on Software Engineering). University of Trento, 2013

Chapter 5: *After-Life Vulnerabilities*. This chapter presents our findings based on the collected vulnerability data. We find that there are a lot of vulnerabilities discovered after the browsers are out-of-support. We also revisit the claim about the majority of foundation vulnerabilities made in [OS06].

Related publication(s): This chapter has been published in:

- Fabio Massacci, Stephan Neuhaus, and Viet Hung Nguyen. "After-Life Vulnerabilities: A Study on Firefox Evolution, its Vulnerabilities and Fixes". In: *Proceedings of the 2011 Engineering Secure Software and Systems Conference (ESSoS'11)*. 2011

Chapter 6: *A Methodology to Evaluate VDMs*. This chapter describes a methodology to empirically evaluate the performance of vulnerability discovery models (VDMs). The chapter reviews the traditional validation methodology in past studies, as well as critical issues that potentially bias the experiments in past studies. The proposed method addresses all these issues in its data collection and analysis steps. All notions and concepts in the methodology are exemplified by real data from the experiment on browsers.

Related publication(s): This chapters has been partially published in/or being submitted to:

- Viet Hung Nguyen and Fabio Massacci. "An Independent Validation of Vulnerability Discovery Models". In: *Proceeding of the 7th ACM Symposium on Information, Computer and Communications Security (ASIACCS'12)*. 2012
- Viet Hung Nguyen and Fabio Massacci. *An Empirical Methodology to Validated Vulnerability Discovery Models.* Tech. rep. (under submission to IEEE Transactions on Software Engineering). University of Trento, 2013

Chapter 7: *The Evaluation of Existing VDMs*. This chapter applies the methodology proposed in the previous chapter to conduct a validation experiment to review the performance of existing VDMs. The experiment assesses the performance of eight VDMs in different usage scenarios based on the vulnerability data of 30 major releases of dominant browsers (*i.e.,* Chrome, Firefox, IE, and Safari).

Related publication(s): This chapters has been partially published in/or being submitted to:

- Viet Hung Nguyen and Fabio Massacci. "An Idea of an Independent Validation of Vulnerability Discovery Models". In: *Proceedings of the 2012 Engineering Secure Software and Systems Conference (ESSoS'12)*. 2012
- Viet Hung Nguyen and Fabio Massacci. "An Independent Validation of Vulnerability Discovery Models". In: *Proceeding of the 7th ACM Symposium on Information, Computer and Communications Security (ASIACCS'12)*. 2012
- Viet Hung Nguyen and Fabio Massacci. *An Empirical Methodology to Validated Vulnerability Discovery Models.* Tech. rep. (under submission to IEEE Transactions on Software Engineering). University of Trento, 2013

Chapter 8: *A Method to Assess Vulnerabilities Retro Persistence*. This chapter describes an empirical method that automatically assess the retro persistence of vulnerabilities. The proposed method extends the work by Sliwerski *et al.* [Sli05] to identify evidences for the existence of vulnerabilities in retro versions of software.

Related publication(s): This chapter has been partially published in/or being submitted to:

- Viet Hung Nguyen and Fabio Massacci. “The (Un) Reliability of NVD Vulnerable Versions Data: an Empirical Experiment on Google Chrome Vulnerabilities”. In: *Proceeding of the 8th ACM Symposium on Information, Computer and Communications Security (ASIACCS'13)*. 2013
- Viet Hung Nguyen and Fabio Massacci. *An Empirical Assessment of Vulnerabilities Retro Persistence*. Tech. rep. (to be submitted to Empirical Software Engineering, journal, Springer). University of Trento, 2013

Chapter 9: *The Assessment of the NVD Vulnerability Claims*. This chapter applies the proposed assessment method for vulnerabilities retro persistence to conduct an experiment on 33 major versions of Chrome and Firefox. The purpose is to test the proposed method, and to validate the rule “version X and all its previous versions are vulnerable" adopted by NVD security team. The experiment results have shown that, on average, more than 30% of vulnerability claims to each of these versions are erroneous. The errors do not negligibly happen by chance, but are significant and systematic phenomenon along the browser age, and individual version age. Furthermore, we have shown that these errors could negatively impact the conclusions withdrawn from some vulnerability analyses.

Related publication(s): This chapter has been partially published in/or being submitted to:

- Viet Hung Nguyen and Fabio Massacci. “The (Un) Reliability of NVD Vulnerable Versions Data: an Empirical Experiment on Google Chrome Vulnerabilities”. In: *Proceeding of the 8th ACM Symposium on Information, Computer and Communications Security (ASIACCS'13)*. 2013
- Viet Hung Nguyen and Fabio Massacci. *An Empirical Assessment of Vulnerabilities Retro Persistence*. Tech. rep. (to be submitted to Empirical Software Engineering, journal, Springer). University of Trento, 2013

Chapter 10: *Conclusion*. This chapter summarizes the major contributions of the dissertation and describes possible future directions based on the results.

1.4 Publications

During my work as a PhD candidate I have (co)authored the following publications:

- Fabio Massacci and Viet Hung Nguyen. “Which is the Right Source for Vulnerabilities Studies? An Empirical Analysis on Mozilla Firefox”. In: *Proceedings of the International ACM Workshop on Security Measurement and Metrics (MetriSec'10).* 2010
- Viet Hung Nguyen and Le Minh Sang Tran. “Predicting Vulnerable Software Components using Dependency Graphs”. In: *Proceedings of the International ACM Workshop on Security Measurement and Metrics (MetriSec'10).* 2010
- Fabio Massacci, Stephan Neuhaus, and Viet Hung Nguyen. “After-Life Vulnerabilities: A Study on Firefox Evolution, its Vulnerabilities and Fixes”. In: *Proceedings of the 2011 Engineering Secure Software and Systems Conference (ESSoS'11).* 2011
- Viet Hung Nguyen and Fabio Massacci. “An idea of an independent validation of vulnerability discovery models”. In: *Proceedings of the 2012 Engineering Secure Software and Systems Conference (ESSoS'12).* 2012, pp. 89–96
- Viet Hung Nguyen and Fabio Massacci. “An Independent Validation of Vulnerability Discovery Models”. In: *Proceeding of the 7th ACM Symposium on Information, Computer and Communications Security (ASIACCS'12).* 2012
- Viet Hung Nguyen and Fabio Massacci. “The (Un) Reliability of NVD Vulnerable Versions Data: an Empirical Experiment on Google Chrome Vulnerabilities”. In: *Proceeding of the 8th ACM Symposium on Information, Computer and Communications Security (ASIACCS'13).* 2013
- Viet Hung Nguyen and Fabio Massacci. *An Empirical Methodology to Validated Vulnerability Discovery Models.* Tech. rep. (under submission to IEEE Transactions on Software Engineering). University of Trento, 2013
- Viet Hung Nguyen and Fabio Massacci. *An Empirical Assessment of Vulnerabilities Retro Persistence.* Tech. rep. (to be submitted to Empirical Software Engineering, journal, Springer). University of Trento, 2013
- Riccardo Scandariato, Viet Hung Nguyen, Fabio Massacci, and Wouter Joosen. *Evaluating Text Features as Predictors of Security Vulnerabilities.* Tech. rep. Univeristy of Trento, University of Leuven, 2013

CHAPTER 2

RESEARCH ROADMAP

This chapter presents the global research objective of the dissertation, as well as several research questions refined from this objective. The chapter discusses the research method to attain the research objective, and also discusses how various artifact presented in other chapters could fit together to obtain the global objective.

THIS chapter presents the general research objective of the dissertation, and the methodology to achieve the objective. The chapter describes various research questions refined from the general objective, and gives an overview how and where these questions are answered in the dissertation. The chapter is organized as follows. Section 2.1 presents the global research objective. Section 2.2 discusses the research methodology and various research questions refined from the objective. Section 2.3 summarizes the chapter.

2.1 Research Objective

Recent years have seen a growing interest of studies in quantitative security assessment and the use of empirical methods on software vulnerabilities. Most of studies address the knowledge problems such as *what are the interesting phenomena in vulnerabilities?"* or focus on the ability to capture characteristics of vulnerabilities: *e.g., what is the mathematical model for the discovery of vulnerabilities?* or *could we predict vulnerabilities?* Obviously, attaining such insights would help to improve the security of software.

This dissertation is inspired by two key observations on past studies. First, only few studies [Res05; OS06] provided some claims about the quality of the data sources they used in their experiments. Second, many proposed empirical models about vulnerabilities were evaluated by researchers who are the authors of the models, except few independent discussion [**OZMEN-07-QOP**]. This motivates for the research objective that drives the rest of this dissertation:

"How to perform an independent empirical evaluation of vulnerability models?"

2.2 Research Method and Research Questions

Figure 2.1 illustrates the steps of the research method used in this dissertation:

- *Experimental setup.* We gather background knowledge, facts, and requisites that need to carry out the research.
- *Observation.* We observe on collected information in the previous step for interesting phenomena.
- *Induction.* Based on observed phenomena plus background knowledge, we propose a technique, a method, or an artifact that explains in more general terms the observations. Since our research goal focuses on an independent empirical evaluation of vulnerability models, we have not invented our own version of a method or model that predicted the observed data. Rather during the induction phase we have invented methods to evaluate other work.

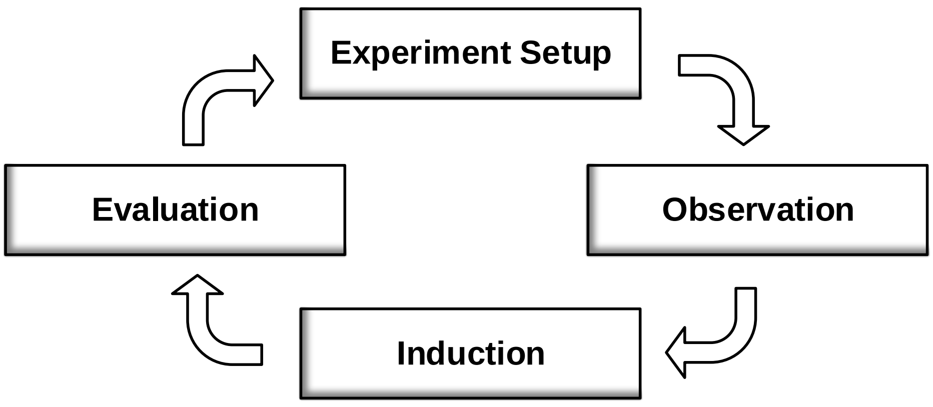


Figure 2.1: Essential steps of the research methodology.

Table 2.1: Summary of research questions.

Research Question		Answered In
Activity: Survey State-of-the-Art		
RQ1	Which are the popular data sources for vulnerability studies?	Chapter 3
RQ2	Which data sources and features are used for which studies?	Chapter 3
Activity: Invent Method(s)		
RQ3	How to evaluate the performance of a VDM?	Chapter 6
RQ4	How to compare between two or more VDMs?	Chapter 6
RQ5	How to estimate the validity of a vulnerability claim to a retro version of software?	Chapter 8
Activity: Evaluate Invented Method(s)		
RQ6	Is the proposed VDM evaluation methodology effective in evaluating VDMs?	Chapter 7
RQ7	Among existing VDMs, which one is the best?	Chapter 7
RQ8	Is the proposed assessment method effective in assessing the retro persistence of vulnerabilities?	Chapter 9
RQ9	To what extend are vulnerability claims by NVD trustworthy?	Chapter 9
RQ10	To what extend does the bias in vulnerability claims by NVD (if any) impact conclusions of a vulnerability analysis?	Chapter 9

- *Evaluation.* We conduct empirical experiments to evaluate the methods invented in the previous step.

Figure 2.2 shows how we apply the research method in this dissertation, and how various artifacts in subsequent chapters could fit to the research method. In this figure, rectangles are activities and parallelograms represent artifacts produced in each activity. In general the dissertation consists of following activities: *Survey State-of-the-Art* (Chapter 3), *Acquire Experimental Data* (Chapter 4), *Perform Observation on Experimental Data* (Chapter 5, and Chapter 6), *Invent Method(s)* (Chapter 6, Chapter 8), and *Evaluate Invented Method(s)* (Chapter 7, Chapter 9).

As parts of these activities, we have conducted several empirical experiments. In these experiments, we have refined the research objective into several technical research questions. Thus to achieve the final research objective, we are going to satisfy all these research

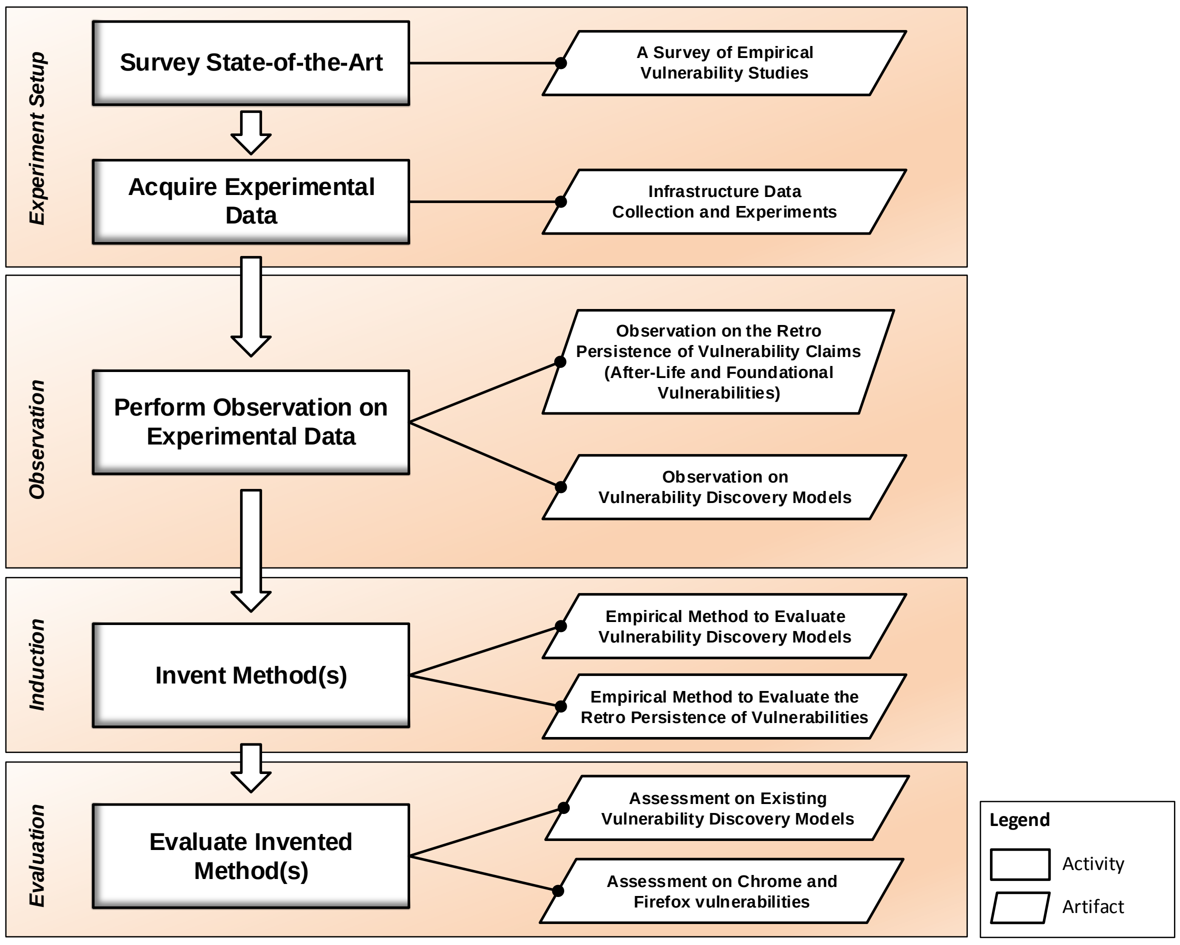

Experiment Setup
Survey State-of-the-Art
A Survey of Empirical Vulnerability Studies
Acquire Experimental Data
Infrastructure Data Collection and Experiments
Observation
Perform Observation on Experimental Data
Observation on the Retro Persistence of Vulnerability Claims (After-Life and Foundational Vulnerabilities)
Observation on Vulnerability Discovery Models
Induction
Invent Method(s)
Empirical Method to Evaluate Vulnerability Discovery Models
Empirical Method to Evaluate the Retro Persistence of Vulnerabilities
Evaluation
Evaluate Invented Method(s)
Assessment on Existing Vulnerability Discovery Models
Assessment on Chrome and Firefox vulnerabilities
Legend
Activity
Artifact

Figure 2.2: An overview to the research activities and produced artifacts.

questions, which will be described in the rest of this section, and are summarized in Table 2.1.

The details of these activities and research questions are discussed in the sequel.

2.2.1 Survey State-of-the-Art

This activity is a part of the experiment setup where we gather background knowledge for the research. Since the major focus of this dissertation lays on the area of empirical studies, we conduct a survey about empirical studies on software vulnerabilities. The survey aims to understand the following characteristics in past research studies: the research questions which past studies have addressed, and the vulnerability data sources, particularly data features, which past studies have used for their research topics. Formally, the survey addresses the following research questions:

RQ1 *Which are the popular data sources for vulnerability studies?*

RQ2 *Which data sources and features are used for which studies?*

The outcome of this activity is a *Survey of Empirical Vulnerability Studies*. The details of the survey is described in Chapter 3.

2.2.2 Acquire Experimental Data

Data is a common requisite for an empirical study about vulnerabilities since data plays a crucial role in an empirical experiment. As a part of the experiment setup, this activity leads to an *Infrastructure Data Collection and Experiments* to acquire vulnerability data. The infrastructure describes the software infrastructure and rules for compiling vulnerability data from various data sources discussed in the survey of the previous activity. The details of the data infrastructure are discussed in Chapter 4.

2.2.3 Perform Observation on Experimental Data

Based on the collected data, we can start the observation for interesting phenomena. We also challenge the claims in past studies on the same data sources as we have an independent validation of these claims. In particular, we have made the following observations:

- *Observation on the Retro Persistence of Vulnerabilities (After-Life Vulnerabilities and Foundational Vulnerabilities).* We observe Firefox vulnerabilities in order to look for an empirical evidence whether *software-evolution-as-a-security-solution* is actually a solution. This observation reveals that a non-negligible amount of after-life vulnerabilities is a counter-evidence the solution. We also use the vulnerability data to check the claim whether foundational vulnerabilities are the majority [OS06]. More detailed discussion on this observation is described in Chapter 5.

  On the other side, we observe an implicit rule in reporting vulnerability claims by the NVD security team: they will claim *all versions* of a software vulnerable to a particular vulnerability without any additional validation if its description has something like *"version X and its previous versions are vulnerable"*. This rule might be overdosed, and could be a threat to validity of not only empirical vulnerability studies, but also assessment of security compliance (*e.g.*, SCAP, PCI DSS). This observation is presented in Chapter 8.

- *Observation on Vulnerability Discovery Models.* We observe many issues that exist in the traditional validation method to evaluate VDMs. They bias the outcome of VDM validation experiments that follow this traditional method. Additionally, existing validation experiments in the past were conducted by the own authors of the model. This observation motivated the invention of an empirical method that could independently and systematically evaluate the performance of VDM. This observation is described in Chapter 6.

2.2.4 Invent Method(s)

From the observations done in the previous step, we propose two empirical methods:

- *Empirical Method to Evaluate Vulnerability Discovery Models.* During the observation activity, we have observed several issues in the traditional validation method for VDMs. This potentially biases the outcome of VDM validation experiments that follow this method. This motivates the following research questions:

  RQ3 *How to evaluate the performance of a VDM?*

  RQ4 *How to compare between two or more VDMs?*

  We answer the above research questions by proposing an empirical method to evaluate the empirical performance of VDMs. The method consists of two key analyses: *goodness-of-fit quality* analysis and *goodness-of-fit predictability* analysis. These analyses allow researchers (or practitioners) to evaluate the performance of VDM, as well as to compare VDMs. With these analyses, the proposed method delivers a better insight than the traditional method. Moreover, the proposed method addresses all issues of the traditional method. The outcome of a VDM validation experiment following the proposed method is thus more reliable than the traditional analysis. We describe the methodology in Chapter 6.

- *Empirical Method to Evaluate the Retro Persistence of Vulnerabilities.* The observation on the retro persistence of vulnerability claims motivates following research question:

  RQ5 *How to estimate the validity of a vulnerability claim to a retro version of software?*

  We propose an empirical method that could quickly identify whether a vulnerability claims made to a retro version of software is valid or not. The method quickly looks for vulnerable code footprints, whose occurrences relate to the validity of vulnerabilities, in the repository of the software. Then the method scans through the code base of a software version, searching vulnerable code footprints. If none of them exists, it is more likely that the vulnerability claim is not valid. The details of this method are presented in Chapter 8.

2.2.5 Evaluate Method(s)

We conduct two experiments on browser vulnerabilities to test the two proposed empirical methods. These experiments are:

- *Assessment on Existing Vulnerability Discovery Models.* We validate the methodology to evaluate VDMs described in Chapter 6 by conducting an evaluation experiment on several existing VDMs. The experiment addresses the following research questions:

  RQ6 *Is the proposed VDM evaluation methodology effective in evaluating VDMs?*

  RQ7 *Among existing VDMs, which one is the best?*

  By the word *"effective"*, we mean the proposed methodology is able to evaluate VDMs at least as good as the traditional methodology to conduct the experiment. We compare the outcomes of each methodology. The comparison shows that the proposed methodology provides more informative and interesting answers than the traditional one. The experiment also studies the quality and predictability of VDMs in different period of software lifetime. The details of this experiment are reported in Chapter 7.

- *Assessment on Vulnerabilities of Chrome and Firefox.* We test the method to assess the validity of (retrospective) vulnerability claims in an experiment with many major versions of Chrome and Firefox. The experiment address the following research questions:

  RQ8 *Is the proposed assessment method effective in assessing the retro persistence of vulnerabilities?*

  RQ9 *To what extend are vulnerability claims by NVD trustworthy?*

  RQ10 *To what extend does the bias in vulnerability claims by NVD (if any) impact conclusions of a vulnerability analysis?*

  Similarly, by the word *"effective"* we mean the proposed method is able to assess most of vulnerability claims for the target applications (*i.e.,* Chrome and Firefox). The outcomes of the experiment present an empirical evidence that vulnerability claims by

NVD contains significant biases, which may significantly impact the conclusion of a vulnerability analysis. The details of this experiment are presented in Chapter 9.

2.3 Chapter Summary

This chapter presented the research objective, as well as the research method to attain the objective in this dissertation. The major focus of this work is to propose empirical method(s) to evaluate empirical vulnerabilities. We followed the inductive inference research methodology to carry out the research. During the course of the dissertation, we have refined the objective into several technical research questions. The answers to these research questions will help to meet the research objective.

In the next section, we are going to describe the survey of empirical vulnerability studies.

CHAPTER 3

A Survey of Empirical Vulnerability Studies

This chapter describes a survey about empirical vulnerability studies. The survey focuses on the data usage of past studies, in which we study which data sources have been used, and which data features are available in these data sources. We present some descriptive statistics about the usage of data sources in these studies. Finally, the survey briefly reviews past studies.

An important stepping stone for conducting research is to have a sufficient knowledge about the literature. A traditional way, which is also very good, to achieve such knowledge is to conduct a survey. Since we are interested in evaluation of empirical studies, the objective of the survey on empirical vulnerability studies focuses on the following research questions:

RQ1 *Which are the popular data sources for vulnerability studies?*

RQ2 *Which data sources and features are used for which studies?*

To find the answers for these questions, we conduct a survey on the vulnerability studies that based their contributions on top of vulnerability data sources. For the first question, RQ1, we look at past studies to learn their research questions and which data sources are used in order to fulfill the research purposes. For the second one, RQ2, we examine the data sources for provided features and see which features are for which research questions.

The rest of this chapter is organized as follows. Section 3.1 describes the method that we follow to conduct the survey. Section 3.2 reviews past studies. Section 3.3 presents a qualitative analysis on data sources used in past studies. Section 3.4 summarizes the chapter.

3.1 The Method to Conduct the Survey

We partially adopt the guidelines of Kitchenham [Kit04] and Webster and Watson [WW02] to conduct the survey. We select candidate papers in leading journals, conferences, and workshops. We search the Scopus (`www.scopus.com`) for computer science publications with following keywords: *"empirical stud(ies)/analysis, software vulnerabilit(ies), software security"*. We also apply the similar search on Google Scholar. Finally we manually evaluate the relevance of the papers based on their title and abstract. For selected papers, we look at their bibliography for other candidates. Next, we describe the inclusion criteria for selected publications.

Included papers are published between 2005 and 2012. Moreover, selected papers should have their major contributions based on (or validated by) some vulnerability data sources. Some works in the same series by same authors and with very similar content such as a conference/workshop paper and its extended journal version are intentionally classified and evaluated as separate studies for a more rigorous analysis.

Indeed, research studies in the field of software vulnerabilities are diversity and cover different research topics which might or might not employ a vulnerability data set. Hence, this chapter mostly scopes out research works that explicitly relied on vulnerability data sets. Concretely, we focus on past papers in the following research horizons:

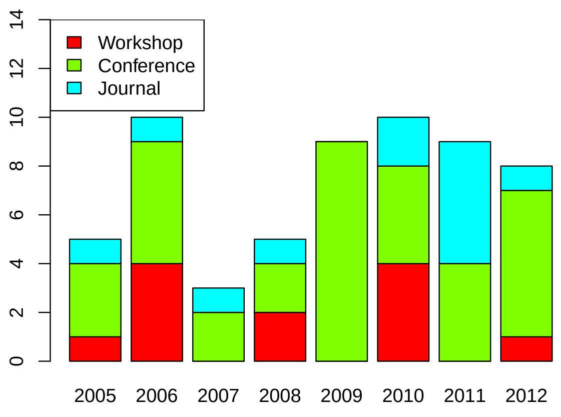
- **Fact Finding.** Works in this horizon describe the state of practice in the field, *e.g.,* [Ozm05; OS06; Res05]. These studies provide data and aggregate statistics but do not provide models for prediction. Some research questions picked from prior studies are *"What is the median lifetime of a vulnerability?"*[OS06], *"Are reporting rates declining?"*[OS06; Res05].

- **Modeling.** Studies in this area aim to find models that captures certain aspects of vulnerabilities. For example, in [Alh07; AM05b; AM08; And02; Res05], researchers invent mathematical models for the evolution of vulnerability, and collect vulnerability data to validate their models.

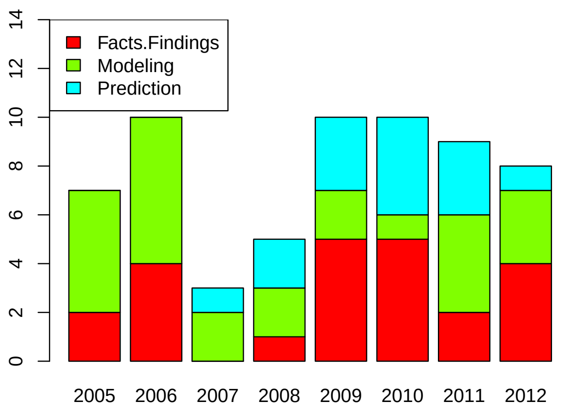
- **Prediction.** Such works in this horizon focus on predicting particular attributes of vulnerabilities based on historical data. Mostly they predict the existence of vulnerabilities in code base, *e.g.,* [CZ11; Geg09b; Jia08; Men07; Neu07; Ozm05; SW08b; SW08a; ZN09; Zim07]. The main concern of these papers is to find a metric or a set of metrics that correlates with vulnerabilities in order to predict vulnerable source files.

If we look at the issue of the lifetime of vulnerabilities, *Fact Finding* papers will provide statistics on various software and the related vulnerability lifetime. Meanwhile, *Modeling* papers will try to identify a mathematical law that describes the lifetime of vulnerabilities *e.g.,* a thermodynamic model [And02], or a logistics model [AM05b]. The good papers in the group will provide experimental evidences that support the models, *e.g.,* [Alh07; AM05b; AM08]. Studies on this topic aim to increase the goodness-of-fit of their models *i.e.,* try to answer the question *"How well does our model fit the facts?"*. *Prediction* studies identified software characteristics (or metrics) that correlate with the existence of vulnerabilities, and then used these metrics to predict whether a software component will exhibit a vulnerability during its lifetime. These papers usually use statistics and machine learning methods and back up their claim with some empirical evidence. These studies focus on the attribute and the quality of prediction, and they aim to answer the question *"How good are we at predicting?"*

We collected 59 papers that were in the scope of this study. These 59 papers are referred



(a) by publication type



(b) by research topics

Note: a paper could be classified into one or more research topics depended on its contributions.

Figure 3.1: Classification of primary studies yearly.

Table 3.1: Details of primary studies.

Studies are formatted according to their contributions: *FF* – fact findings, **M** – modeling, P – prediction.

Year	Type	Primary Studies	FF	M	P	All
2005	W	***[Ozm05]***	1	1	0	1
	J	***[Res05]***	1	1	0	1
	C	**[AM05b]**, **[AM05a]**, **[Alh05]**	0	3	0	3
			2	5	0	5
2006	W	**[Abe06]**, *[Fre06]*, **[Man06]**, *[Ozm06]*	2	2	0	4
	J	*[Aro06]*	1	0	0	1
	C	**[AM06b]**, **[AM06a]**, *[OS06]*, **[Woo06b]**, **[Woo06a]**	1	4	0	5
			4	6	0	10
2007	J	**[Alh07]**	0	1	0	1
	C	**[Kim07]**, [Neu07]	0	1	1	2
			0	2	1	3
2008	W	[Geg08b], *[SW08a]*	1	0	1	2
	J	**[AM08]**	0	1	0	1
	C	**[Joh08]**, [SW08b]	0	1	1	2
			1	2	2	5
2009	C	[Geg09a], [Geg09b], **[JM09]**, *[MW09b]*, *[SM09]*, *[Sch09b]*, *[Sch09a]*, *[Vac09]*, **[Wan09]**	5	2	3	9
2010	W	*[Fre10]*, *[MN10]*, [NT10], *[Ran10]*	3	0	1	4
	J	*[Aro10]*, **[LZ10]**	1	1	0	2
	C	[Boz10], [CZ10], *[Cla10]*, [Zim10]	1	0	3	4
			5	1	4	10
2011	J	[CZ11], **[MW11]**, *[Sch11]*, [Shi11], **[Woo11]**	1	2	2	5
	C	*[Gal11]*, **[Mas11]**, **[You11]**, [Zha11]	1	2	1	4
			2	4	3	9
2012	W	*[AM12]*	1	0	0	1
	J	[WD12]	0	0	1	1
	C	*[BD12]*, *[EC12]*, **[NM12c]**, **[NM12a]**, *[Sha12]*, **[Shi12]**	3	3	0	6
			4	3	1	8
Total			23	25	14	59

to as *primary studies* [Kit04]. Of these, 12 were published in workshops, 35 in conferences, and 12 in journals. Figure 3.1 classifies primary studies yearly by publication types (a), and research topics (b). It reveals a stable trend of publications in years.

Table 3.1 lists all primary studies with respect to their publication years, and types of the venue (*i.e.,* W–workshop, C–conference, and J–journal). We format the primary studies according to their research horizons: *italic*–fact finding studies, **bold**–modeling studies, and underline–prediction studies. Notice that some primary studies are classified into several research horizons. Their format will be the combination, such as ***bold italic*** for fact findings and modeling studies. Therefore, the sum of all studies might be different from the sums of all individual horizons.

Among the collected primary studies, I also included my own empirical studies during the PhD course. However, the reviews for these studies are not presented in this chapters as they will be presented in the rest of the dissertation.

3.2 A Qualitative Overview to Primary Studies

3.2.1 Fact Finding Studies

The work by Frei *et al.* [Fre06; Fre10] can be easily described as the representative of the security and economics fields. It offers a detailed landscape of which security vulnerabilities affect which systems but does not provide a concrete answer to any research questions.

Ozment [Ozm05] pointed out many problems that NVD database suffered, which are *chronological inconsistency*, *incomplete selection*, and *lack of effort normalization*. The chronological inconsistency referred to the inaccuracy in the versions affected by a vulnerability. The second problem was that NVD does not cover every vulnerability detected in a software system. In fact, only vulnerabilities that are discovered after 1999 and assigned CVE identifiers are included. The third problem referred to the fact that data is not normalized for the number of testers. The paper also discussed techniques to address the two first problems: the bugs' birth dates were approximated by adopting the repository log mining technique [Sli05], the incomplete selection was compensated by making use of additional data sources. The authors collected a vulnerability data set for OpenBSD, and used this data set to validate many software reliability models in another study [Ozm06].

Arora *et al.* [Aro06] conducted an analysis to understand how software vulnerability information should be made public. The study correlated the software attacks in the wild to vulnerabilities reported by NVD. The attack data was obtained from honeypots (www.

honeynet.org). The empirical result exhibited that vulnerabilities which were published and patched appealed more attacks than others. Additionally, the attacks on non-disclosed vulnerabilities increased slowly overtime until these vulnerabilities were published.

In another empirical analysis, Arora *et al.* [Aro10] analyzed the correlation between security patches and the disclosure of vulnerabilities. The authors collected vulnerability data from Computer Emergency Response Team/Coordination Center (CERT), Bugtraq to conduct their study. The outcome of the study was validated again vulnerability data reported by NVD. Their study revealed that vulnerabilities which were disclosed, or had high severity were quickly patched. Also, open source vendors tended to deliver patched faster than closed source vendors.

Ozment and Schechter [OS06] extended the data set discussed in their previous work [Ozm05] to study whether software security improves with age. The most important findings in that work was that foundation vulnerabilities were the majority in OpenBSD. However, their data set did not include data for the first version of OpenBSD, but started from version v2.3. This would be a validity threat to their findings.

Shin and Williams [SW08a] checked for whether code complexity could account for vulnerabilities. They collected known vulnerabilities reported by Mozilla Foundation Security Advisories (MFSA), and corresponding bugs reported by Mozilla Bugzilla (MBug). Their study reported a weak correlation between complexity metrics and the occurrences of vulnerabilities in Java Script Engine of Firefox v2.0 and retrospective versions.

Vache [Vac09] studied the vulnerability life cycle and the exploit appearance. They have studied 52000 vulnerabilities reported by Open Source Vulnerability Database (OSVDB) since December 1998. The study were mostly relied on the time features of the data entries. They found that they could use Beta distribution to characterize the distribution of the disclosure date, patch date, and exploit date.

Scarfone and Mell [SM09] performed an analysis on the Common Vulnerabilities Scoring System (CVSS) version 2, which is adopted by NVD to score the severity of its published vulnerabilities. They analyzed severity scores of NVD entries to understand the effectiveness of CVSS v2 with respect to CVSS v1. The analysis showed that most changes CVSS v2 have met the desire goals (*i.e.,* they are actually better than CVSS v1), but some changes complicated the calculation of severity score while providing negligible effect. Gallon [Gal11] developed another analysis on the distribution of CVSS scores in NVD vulnerabilities. The study pointed out some deficiencies which might impact the vulnerability discrimination of CVSS v2.

Schryen [Sch09a; Sch09b; Sch11] employed NVD data to conduct an empirical study about the security difference between two kinds of software: open source and closed source. The study compared 17 applications in several aspects: disclosed vulnerabilities, mean time between disclosure, vulnerability severity, and patches. The empirical results did not show any significant evidence about the difference between open source and close source.

Ransbotham [Ran10] studied the exploits on vulnerabilities of open source software to understand whether disclosing source code would improve the security of software. To conduct his analysis, the author employed data from three sources: intrusion detection system alert logs, vulnerabilities reported by NVD, and manual justification whether software was open source or closed source. The author employed Cox proportional hazard model to analyze the risk of first exploitation attempt, and two-stage Heckman model to study the number of alerts per each vulnerability. His study revealed that, compared with closed source software, vulnerabilities in open source software have higher risk of exploitation, the attacks diffused sooner and with higher total penetration, and higher volume of exploitation attempts.

Clark *et al.* [Cla10] worked on the honeymoon effect of 38 software systems (both close and open source) in various categories: operation systems, server applications, and common user applications. The honeymoon effect was defined as the period of time counting when a software product was released until its first vulnerability was publicly reported. They collected security advisories from seven sources: Securina, US-CERT, SecurityFocus, IBM ISS X-Force, SecurityTracker, iDefense's (VDC) and TippingPoint (ZDI). They calculated the honeymoon ratio p_0/p_{0+1}, in which p_0 was the honeymoon period, and p_{0+1} was time period between the discovery of the first and second vulnerabilities. All time measurements were done on the *initial disclosure date*, which was the earliest published date of an advisory in several sources. They find that most of software have a positive honeymoon ($p_0/p_{0+1} > 1$), and open-source software seem to have a longer honeymoon than close-source, contradict to the fact that attackers cannot study the source code of the close-source software. However, they did not show any analysis on code bases of software systems. It is obviously the limit in their study.

Allodi and Massacci [AM12] performed an analysis for the relation between vulnerabilities' severity score and their real attacks in the wild. That analysis focused on the question that whether severity scores by NVD (*i.e.*, CVSS), and Exploit-DB – a de facto standard data base showing proofs of concept to exploit vulnerabilities, are actually representative for attacks found in the wild. To identify real attacks, they relied on Symantec's Threat Explorer, and their own constructed data set called EKITS which contained vulnerabilities used by exploit kits in the black market. Their findings showed that NVD and Exploit-DB are no a reliable source of information for real attacks.

Shahzad *et al.* [Sha12] described a large scale analysis on the life cycle of software vulnerabilities. The analysis were based on data collected from NVD, OSVDB, and a data set from other study [Fre06]. The authors highlighted that the patching of vulnerabilities in close-source software is faster compared to open-source software. It is however contradict with findings by [Aro10]. Such contradiction in these two studies might because they were based on different data sources, and in different time frames.

Bilge and Dumitras [BD12] conducted an analysis on the data of real attacks in the wild. The data set was built on Worldwide Intelligence Network Environment (WINE) [Win], developed by Symantec Research Labs, and public vulnerability data sources such as OSVDB, Microsoft Security Bulletin (MSB), Apple Knowledge Base (AKB). The authors described a method to identify zero-day attacks by mining the conducted data sets. They have identified 18 zero-day vulnerabilities, and analyzed the evolution of their attacks in time. Their most important findings included: most zero-day attacks could not be detected in a timely manner using current policies and technologies, and most of them were targeted attacks; the public disclosure of vulnerabilities will significantly increase the volume of attacks (up to five orders of magnitude).

Edwards and Chen [EC12] studied the correlated between several metrics generated by Static Code Analyzers (SCAs), as well as SCA-identified issues, and the actual vulnerability rates (in terms of number of CVE entries). The study outcome showed that SCAs could be sued to make some assessment of risk due to the significant relation between the number of SCA-identified issues and the actual vulnerability rates in next releases of software. However, metrics generated by SCAs could not be used for the same purpose due to an insignificant correlations between metrics values and vulnerability rates.

3.2.2 Modeling Studies

Anderson [And02] discussed the trade-off in security in open source and close source systems. On one side 'to many eyes, all bugs are shallow', but in the other side, 'potential hackers have also had the opportunity to study the software closely to determine its vulnerabilities'. He proposed a VDM, namely Anderson's Thermodynamic – AT, based on reliability growth models. In the AT model, the probability of a security failure at time t, when n bugs have been removed, was in inverse ratio to t for alpha testers. This probability was even lower for beta testers, λ times more than alpha testers. However, he did not conduct any experiment to validate the proposed model

Rescorla [Res05] focused on the discovery of vulnerability. Although he discussed out many shortcomings of NVD, his study heavily relied on it. By studying vulnerability reports of several applications in NVD, Rescorla introduced two mathematical models to capture the discovery trends of vulnerabilities. These models were *Rescorla's Linear model* and *Rescorla's Exponential model*, to identify trends in vulnerability discovery.

Alhazmi *et al.* [AM05a; AM05b; Alh07] observed vulnerabilities of Windows and Linux systems from different sources. For Windows systems, the data sources were mostly NVD, other papers, and private sources. For Linux systems, data was from NVD and Bugzilla for Linux. The authors tried to model the cumulative vulnerabilities of these system into two models: the *logistic model* and the *linear model*. Based on the goodness of fit on each model, the authors gave a forecast about the number of undiscovered vulnerabilities, and emphasized the applicability of the new metric called *vulnerability density* which was obtained by dividing the total of vulnerabilities by the size of the software systems. Also based on these vulnerability data, Alhazmi and Malaiya [AM08] compare their proposed models with Rescorla's [Res05] and Anderson's [And02]. The result showed that their logistic model had a better goodness of fit than others.

Woo *et al.* [Woo06a] carried out an experiment with AML on three browsers IE, Firefox and Mozilla. However, it was unclear which versions of these browsers were analyzed. Most likely, they did not distinguish between versions. In their experiment, IE has not been fitted, Firefox was fairly fitted, and Mozilla was good fitted. From this result, we could not conclude anything about the performance of AML. In another experiment, Woo *et al.* [Woo06b] validated AML against two web servers: Apache and IIS. Also, they did not distinguish between versions of Apache and IIS. In this experiment, AML has demonstrated a very good performance on vulnerability data.

Kim *et al.* [Kim07] introduced AML for Multiple-Version (MVDM) which was the generalization of AML. MVDM divides vulnerabilities of a version into several fragments. The first fragment included vulnerabilities affecting a version and its past versions, and other fragments included shared vulnerabilities of a version and its future versions. The authors compared MVDM to AML on Apache and MySQL. Both models were well fitted the data. MVDM was slightly better, but not significant.

Joh *et al.* [Joh08] proposed JW model, and compared it to AML on WinXP, Win2K3 and Linux (RedHat and RedHat Enterprise). The goodness-of-fit of JW was slightly worse than AML. In other work, Younis *et al.* [You11] proposed YF model and compared it to AML on Win7, OSX 5.0, Apache 2.0, and IE8. The results showed that YF was sometime better than AML.

Abedin *et al.* [Abe06] proposed four security metrics to evaluate the state of security of software based on existing vulnerabilities and historical vulnerabilities in a software service. The metrics were derived from the severity of vulnerabilities. The authors conducted an experiment using NVD data to evaluate their metrics. However the result of the experiment was not clearly reported.

Manadhata *et al.* [MW09a; Man06; MW11] worked on a system-level metric called attackability, which estimated the opportunities to attack. This metric was first introduced in [How05]. Manadhata *et al.* categorized the attackability of a software system into different abstract dimensions. These dimensions together defined the attack surface of the system, which was how much the software was exposed to attacks. The attackability is therefore measured by the total area of the attack surface. The authors have conducted some experiments to validate the proposed metrics.

Liu and Zhang [LZ10] analyzed the severity scores of a large set of vulnerabilities in several data sources, including IBM ISS X-Force, Vupen, and NVD. Their analysis exhibited the significant difference between the severity scores of vulnerabilities by different data sources. Based on the outcome of the analysis, the author proposed a new system for rating and scoring vulnerabilities.

3.2.3 Prediction Studies

Hereafter, we briefly review studies on this area after 2005. For older studies, interested readers can find more details in the review of Catal and Diri [CD09].

Neuhaus *et al.* [Neu07] constructed a tool called Vulture to predict vulnerable components for Mozilla products with a hit rate of 50%. Vulture used a vulnerability database for Mozilla products for training its predictor. This database was compiled upon three main different sources: MFSA, MBug and Concurrent Version System (CVS) archive. Vulture collected the import patterns and function-call patterns in many known vulnerable modules and then applied the Support Vector Machine (SVM) technique classify new modules.

Meneely and Williams [MW09b] performed an empirical case study examining the correlation between the known vulnerabilities and developers' activities in Red Hat Enterprise Linux 4. They found that files developed by independent developers were move likely to have vulnerability. Files with changes from nine or more developers were more likely to have vulnerability than others.

Shin *et al.* [SW08a; SW08b] argued that software (in)security and software complexity are related. In order to validate these hypotheses, the authors conduct an experiment on the JavaScript Engine (JSE) module of the Mozilla Firefox browser. They mined the code base of four JSE's versions for complexity metric values. Meanwhile, faults and vulnerabilities for these versions are collected from MFSA and MBug. Their prediction model is based on the *nesting level* metric and logistic regression methods. Although the overall accuracy is quite high, their experiment still misses a large portion of vulnerabilities.

In another work, Shin *et al.* [Shi11] evaluated the prediction power of complexity metrics and code churn in combination with developers' activity metrics. They used 34 minor versions of Firefox between versions 1.0 and 2.0, which got combined into 11 releases. Their setup consist of a next-release experiment where each release is tested with a model built over the previous three releases. The authors used logistic regression and under-sampling of the training set, variable selection based on information gain and logarithmic transformation of the independent variables. In their results, recall is between 68% and 88% and the file inspection ratio is between 17% and 26% (precision is 3%).

Gegick *et al.* [Geg09a; Geg09b] employed Automatic Source Analysis tools (ASA) warnings, code churn and total line of code to implement their prediction model. However, their experiments were based on private defected data sources and they thus were difficult to reproduce.

Chowdhury *et al.*[CZ11; CZ10] claimed the combination of non-security realm such as combine complexity, coupling and cohesion (CCC) metrics were useful for vulnerability prediction. They conducted an experiments on fifty-two releases (including both major and minor releases) from v1.0 to v3.0.6. They collected a vulnerability data set for Firefox, which was assembled from MFSA and MBug, and calculate CCC metrics using a commercial tool (Understand C++). These values were then fed to a trained classifier to determine whether the source code is vulnerable. They obtained an average accuracy rate of 70% and recall rate of 58%.

Bozorgi *et al.* [Boz10] attempted to predict the exploitability of vulnerabilities using data mining and machine learning approach. In their experiment, a balanced set of 4,000 vulnerabilities of OSVDB and NVD is used to produce very high dimension vectors (95,378 features) for each vulnerability. These vectors were then fed into an SVM-based classifier to predict the exploitability of vulnerabilities. The exploitability was considered in two folds: whether a vulnerability likely was exploitable, and how long that a vulnerability was to be exploited. The experiment has showed a high accuracy of nearly 90% for the first fold, and 75%-80% for the second.

Zimmermann *et al.* [Zim10] conducted a large-scale empirical study on Windows Vista. In that study, they empirically evaluate the efficacy of classical metrics like complexity, code churn, coverage, dependency measures, and organizational structure of the company to predict vulnerabilities. Their study showed that classical metrics could predict vulnerabilities with a high precision but low recall rates. Meanwhile, the actual dependencies could predict vulnerabilities with lower precision but substantially higher recall.

Zhang *et al.* [Zha11] conducted an empirical study to predict the time-to-next-vulnerabilities of several software applications. The prediction models were based on time and severity score of NVD vulnerability data. The authors concluded that NVD in generally have poor prediction capability. Then they discussed several reasons that might decrease the prediction power of their models.

Walden and Doyle [WD12] proposed Static-Analysis Vulnerability Indicator (SAVI) to combine several types of static-analysis data to rank application vulnerability. Organizations could use SAVI to select a less vulnerable software applications based on the outcome ranks of vulnerability. The authors have conducted an experiment to evaluate the proposed metrics on several web applications. The outcome has shown a strong relation between the predicted ranks and the actual ranks, which were based on number of NVD entries.

3.3 A Qualitative Analysis of Vulnerability Data Sources

In this section, we study the data sources and their features that are used in primary studies.

3.3.1 Classification of Data Sources

Based on the owner of data sources, we have two types: *software vendor* (shortly, *vendor*), and *third-party organization* (shortly, *third-party*). The former indicates the data sources owned by the vendor who develop and/or distribute software targeted by the data sources. The latter, as name suggested, indicates data sources run by third-party organization who are not vendor of software targeted by the data sources.

Based on the level of abstraction, we also have two types: *advisory* and *bug tracker*. An advisory data source consists of high level reports which mostly target end-users. An advisory report usually provide textual description of the security issues, and solution for these issues, usually software patches to fix the problems. On contrary, a bug tracker data source mainly targets developers. A bug tracker report describes how to reproduce the problem and other technical information for developers to fix the corresponding bug.

Table 3.2 summarizes different categories of data sources. Each category has an abbreviation name (*i.e.,* code name), a full name, and a description. Among four categories, we have not found any data source being classified as *Third-party Bug Tracker*. The missing of

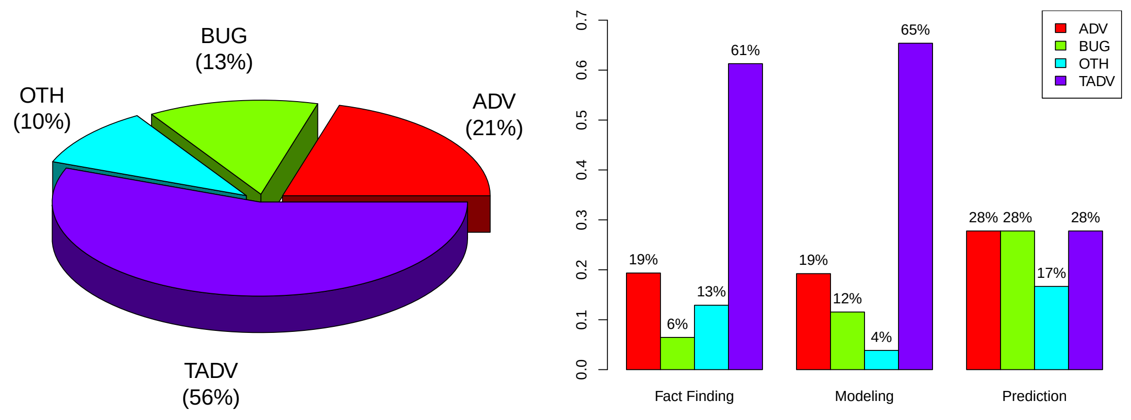


Figure 3.2: The usage of data sources in all research topics (left) and its breakdown (right).

data source in this category might come from the purpose of bug trackers which are mostly interested by software vendors in fixing bugs. Meanwhile, end-users and third-party organizations are not interested in this kind of data. However, we still keep the definition of this category for the completeness. We define an extra categories called *Other* (OTH). Other data sources determines ones that could not be classified in one of above categories, they could be a personal effort in synthesizing data from different sources, *e.g.,* Ozment's data source. We additional classify data sources with respect to their availability to public. From this dimensions, we have Public (PUB), Private (PRV), and Mix (MIX) data sources. The public data sources are publicly available to all. On the other hand, private data sources are limited to the data source providers or their clients. Mix data sources are something in the middle: some features are public, but some features are private.

Table 3.3 summarizes data sources used in primary studies. Each data source is reported with a short name and a full name. The full name is provided by the data source provider, but the short name is not necessary. Some short names are also well known such as Bugtraq, NVD, OSVDB, while many others are local in this chapter(denoted by a star in this table).

To investigate the usage of data sources in primary studies, we count how many times a kind of data sources was used. For example, a primary study use NVD, OSVDB, and MBug. Because both NVD and OSVDB are TDAV data source, and MBug is a BUG data source. We increase the usage of TADV by 1, and BUG also by 1 similarly.

Figure 3.2 exhibits the usage of data sources reported in Table 3.3 in primary studies. It reports the usage for all data source categories (left), and the usage breakdown in individual research topics (right). From the pie chart on the left, it is very easy to observe the domi-

Table 3.2: Classification of vulnerability data sources.

Category		Description
ADV	Vendor Advisory	A database of security advisories for one or more software. An security advisory is a security report that mostly targets end-users, which provides textual summary about the security issues as well as their solutions (or work-around) doable by end-user to prevent or mitigate the problems. The data source is maintained by the software vendor.
TADV	Third-party Advisory	A database of security advisories for one or more software. The data source is maintained by third-party organization who are not vendor of the software mentioned in the data source.
BUG	Vendor Bug Tracker	A database of bug reports for one or more software. A bug report contains technical information for developers to fix the bug. The data source is maintained by the software vendor.
TBUG	Third-party Bug Tracker	A database of bug reports for one or more software. The data source is maintained by third-party organization. Thus far, there is no data source in this category.
OTH	Other Source	A data sources that does not belong to above categories.
PRV	Private Source	The access to data source is limited to the data source provider and/or their clients.
PUB	Public Source	The access to data source is available to public. However, some entries might be restricted due to the policy of the data source provider.
MIX	Mix Source	The access to data source is available to public. However, some features in all entries are restricted to the data source provider and/or their clients.

Table 3.3: Vulnerability data sources in past studies.

Short Name	Name	Category	Provider
AKB	Apple Knowledge Base	PUB ADV	Apple
Bugtraq	Security Focus	PUB TADV	Security Focus
Bugzilla	Mozila Bugzilla	PUB BUG	Mozilla Foundation
Cisco	Cisco	PRV OTH	Cisco
CIT	Chrome Issue Tracker	PUB BUG	Google
iDef$^{(*)}$	iDefense	PUB TADV	Verisign
MFSA	Mozila Foundation Security Advisories	PUB ADV	Mozilla Foundation
MSB	Microsoft Security Bulletins	PUB ADV	Microsoft
NVD	National Vulnerability Database	PUB TADV	NIST
OpenBSD	OpenBSD Errata	PUB ADV	OpenBSD
OSVDB	Open Source Vulnerability Database	PUB TADV	Open Security Foundation
Ozmen	Ozmen's Data Source	PUB OTH	
RHBugzilla	RedHat Bugizlla	PUB BUG	RedHat
RHSA	RedHat Security Advisories	PUB ADV	RedHat
SAP	SAP	PRV ADV	SAP
Secunia	Secunia	MIX TADV	Secunia
ST$^{(*)}$	Security Tracker	PUB TADV	Security Tracker
STE$^{(*)}$	Symantec's Threat Explorer	PUB OTH	Symantec
US-CERT	US-CERT	PUB TADV	US-CERT
Vupen	Vupen	PRV TADV	VUPEN Security
WINE	Worldwide Intelligence Network Environment	PRV OTH	Symantec
Xforce$^{(*)}$	ISS/Xforce	PUB TADV	IBM
ZDI	Zero Day Initiative	PUB TADV	TippingPoint

$^{(*)}$: short names are given by me.

nance of the third-party databases (TADV) which occupies 56% of the data sources usage in primary studies. The other (OTH) data sources take a modest fraction, approximate 10%. BUG and ADV equivalently share the rest, more or less, which are orderly 13%, and 21%.

The clustered bar plot on the right of Figure 3.2 details the usage of data sources in individual research topics. The TADV data sources are preferred the most in *Fact Finding* and *Modeling* studies: 61% and 65% of the used data sources are TADV in these studies. The prediction studies more prefer both ADV and BUG data sources than others, 28% (for ADV) and 28% (for BUG). However, the share of TADV is still high, 28%, which confirms the preference for this kind of data sources in the community.

The rationale for the high usage ratios of both BUG and ADV data sources in *Prediction* studies is the relationship from vulnerabilities to their corresponding source files. This relationship is essential to set up (and/or validate) a prediction model. Researchers could establish this relationship thank to BUG and ADV data sources (and some repository mining technique [Sli05]). However, these kinds of data source usually do not provide version information, *i.e.,* which versions are vulnerable to which vulnerabilities. The missing data could be found in TADV ones. This reasons the relatively high usage ratio of TDAV data sources in the *Prediction* area, though they are not dominant.

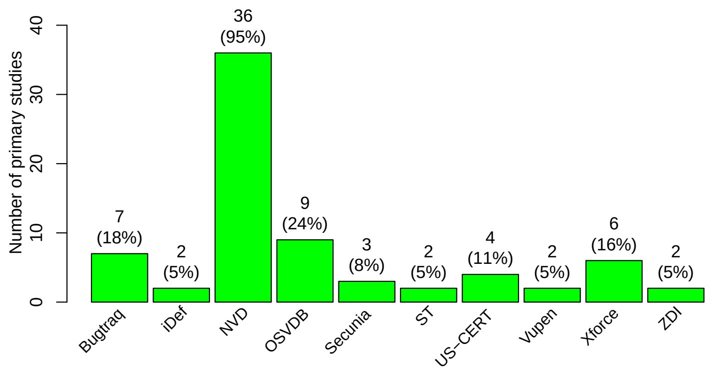
Some *Prediction* studies [Geg08a; Geg08b; GW08] employed PRV data sources to conduct their prediction models. This raises the usage ratio of PRV data sources in this area. However, this ratio is still lower than others (except OTH data sources which are not used) because these data sources usually could not be replicable due to the disclosure policy of the data source owners.

The repeatability is responsible for the low usage ratios of OTH data sources in all other research topics. Some OTH data sources are not public, or are out date, or require huge adhoc effort to reconstruct. Thus studies based on these sources are hard to reproduce.

In contrary, TADV data sources are publicly available to all researchers. These data sources also provide vulnerabilities data for a variety of software. Therefore, researchers can easily repeat studies based on TADV data sources. Moreover, experiments relied on TADV could be also applied to numerous applications, which increases the generality of the withdrawn conclusions. As the result, TADV are more frequently used than others in the community.

Figure 3.3 details the usage of individual TADV data sources. The bar plot indicates the number of *primary studies* that employs a particular data source. The numbers on top represent the percentage of primary studies that employ the corresponding data source to the primary studies that employ third-party data sources (non-parenthesized), and to the total primary studies (parenthesized). The bar plot shows that: 95% of TADV-based primary studies employ NVD. This confirms the top most popularity of NVD.

Though there are several similar TADV data sources (*e.g.,* OSVDB, Bugtraq), NVD becomes the top most popular one because of two reasons, probably. First, CVE-ID, the identi-



The numbers on top are the numbers of primary studies that use the corresponding data source, and its percentage to all studies that use third-party data sources.

Figure 3.3: The usage of third-party data sources.

fier of NVD, is used as a de-factor standard to identify vulnerabilities, and to link across data sources. Second, NVD supports most of features that provided by other data sources (this will be shown later).

3.3.2 Features in Data Sources

The data source features are summarized in Table 3.4. Each feature has a unique ID, a name, and a short description about the meaning of the feature. Features are grouped into following categories.

- *Reference* includes features describing the source of an entry *e.g.*, who creates an entry (R_{REP}), or cross references among different data sources, *e.g.*, unique id of an NVD entry (R_{CVE}), or hyperlinks to relevant entries in other data sources (R_{REF}).
- *Impact* includes features describing the impact of the problem reported by an entry in various perspectives: whether the problem is security related or not (I_C, I_V), textual description (I_D, I_T), severity of the consequence (I_S), and solution for the problem (I_P).
- *Target* includes features describing the target applications related an entry, such the version where the problem gets fixed (V_F), then version at discovery (V_D), and affected versions (V_A).
- *Life cycle* includes features about different milestone in the lifetime of the problem reported by an entry. Typically, a security problem (*i.e.*, vulnerability) has following

milestones in its lifetime: when the problem is committed to the code base (T_I), when the problem is discovered by either attacker or researcher (T_D), when the vendor acknowledges the problem (T_N), when the problem gets fixed (T_F), when the problem is publicly announce to public (T_A), when the problem is firstly exploited (T_E).

Table 3.5 presents the availability of the features listed in Table 3.4 in data sources used in past studies (see Table 3.3). The bullet at the cross between a feature in a column and a data source in a row indicates the feature is available in the data source. The availability of a feature is affirmed if we find an entry which has a field for a feature no matter this field is empty or not. Notice that for some private data source (*e.g.*, Cisco) or commercial data source (*e.g.*, Vupen) we do not have access to the data. Thus we could not make any assessment on these data sources.

Figure 3.4 reports the usage of data features in primary studies. Each feature is counted at most once in each study, no matter the feature could be belong to different data sources. For example, if a study used T_A of two data sources NVD and OSVDB, we still count the

Table 3.4: Potential features in a vulnerability data source.

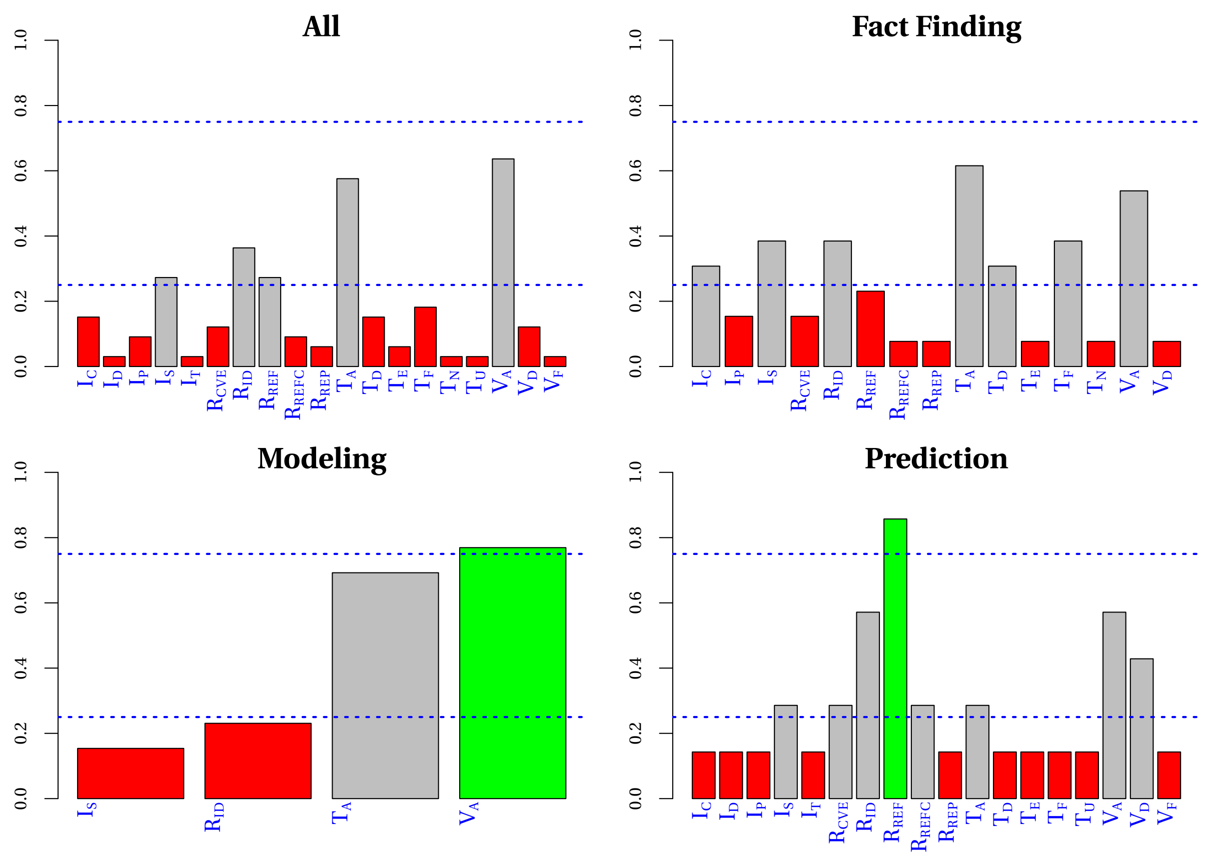
Cat.	ID	Name	Description
Reference	R_{ID}	Unique ID	The unique ID of this problem within a data source
	R_{CVE}	CVE ID	Reference to CVE/NVD entry
	R_{REP}	Reporter	Person who reports or files this problem
	R_{REF}	Reference Links	Reference to other confirmation sources
	R_{REFC}	Reference to Source Code	Reference to locations in codebase which are responsible for this problem
Impact	I_C	Category	Type of entry, *e.g.*, Bug, Security, Enhance, Feature
	I_D	Description	Text about the problem
	I_T	Title	Short description of this problem
	I_V	Vulnerability Discernibility	Determine whether this problem is a security vulnerability
	I_P	Patch/Solution	Solution for the vulnerability, *e.g.*, patches or work around.
	I_S	Impact Score	A qualitative (*e.g.*, low, high, medium) or quantitative (*e.g.*, CVSSv2 score) assessment of the problem's impact
Target	V_F	Fixed Version	The version containing fix for this problem
	V_D	Version at Discovery	The version that this problem is discovered
	V_A	Affected Versions	Versions impacted by this problem
Life cycle	T_I	Injection Date	The date when this problem is first introduced in the codebase
	T_D	Discovery Date	The date when this problem is discovered
	T_N	Acknowledge Date	The date when the software vendor get acknowledge about this problem
	T_F	Fixed Date	The date when this problem is fixed
	T_A	Announced Date	The date when this problem is publicly announced
	T_E	Exploit Publish Date	The date when this problem is known to be exploited
	T_U	Update Date	The date when this entry is updated

usage of T_A once in that study. The figure shows that almost features have been used in primary studies. Due to the variety of research topics, none of features is used in more than 75% of primary studies. However, we can observe that V_A and T_A are the most frequently used features (in more than 50% primary studies). It means that the life cycle (T_A) and the targets (V_A) of vulnerabilities were the major concern in primary studies. The features that are used more frequently than the rest are the reference features (R_{ID}, R_{REF}), and severity of vulnerabilities. The former features were mostly for correlating vulnerability data sources to obtain missing features. The latter feature was used primarily in fact findings studies.

According to Figure 3.4, the majority of primary studies employed V_A and T_A to conduct their research. The former V_A is used to indicate which software products (or versions of software product) are affected by an entry reported in a data source. However, we observe the process to attain data for this feature is not clear (or at least not public). The conversations

Table 3.5: Features of vulnerabilities data sources.

	Reference					Impact						Target			Life Cycle						
Data Source	R_{ID}	R_{CVE}	R_{REP}	R_{REF}	R_{REFC}	I_C	I_D	I_T	I_V	I_P	I_S	V_F	V_D	V_A	T_I	T_D	T_N	T_F	T_A	T_E	T_U
MFSA	•	•	•	•			•	•	•	•	•	•							•		
AKB	•	•	•	•		•	•	•		•	•	•							•		•
MSB	•	•	•				•	•	•	•	•	•		•				•	•		•
OpenBSD	•	•			•		•	•					•					•	•		
RHSA	•	•			•	•	•	•	•	•	•			•					•		•
SAP	•					•	•	•	•	•	•	•	•	•		•		•	•		•
Bugzilla	•	•	•		•		•	•			•					•		•			•
RHBugzilla	•	•	•		•		•	•			•					•		•			•
Ozmen	•	•	•	•	•	•	•	•	•		•	•	•	•	•	•		•	•		
Cisco																					
CIT	•	•	•	•	•	•	•	•	•							•					
Bugtraq	•	•	•	•			•	•	•			•		•					•		•
iDef	•	•	•	•			•	•	•	•	•			•			•		•		
Xforce	•	•		•			•	•	•	•	•		•	•					•		
NVD	•	•	•	•		•	•	•	•	•	•		•	•					•		•
OSVDB	•	•	•	•		•	•	•	•	•	•		•	•		•		•	•	•	•
Secunia	•	•		•			•	•	•	•	•			•					•		•
ST	•	•	•				•	•	•	•	•			•					•		
US-CERT	•	•		•			•	•	•		•	•		•			•	•	•		•
Vupen																					
ZDI	•	•	•	•			•	•	•		•			•			•		•		



Each feature is counted at most once for each study no matter it could belong to different data sources. The color of bars indicate the frequency of features: green – features are used in more than 75% of primary studies, red – features are used in less than 25%, gray – others.

Figure 3.4: Usage of features by primary studies in each research topic.

with the NVD research team reveal that they do not actually perform test to determine which versions are affected by which NVD entry. Importantly, they apply a strategy that “version X and all its previous versions are vulnerable” when they could not find any better information. This leads to noise in the NVD (and possibly other data sources). We will come back to this issue later in Chapter 9 where we discuss more details about the impact such noise to the validity of scientific studies.

The latter feature T_A were mostly used as a surrogate for the discovery time of vulnerability T_D. It is because T_D is only available in few TADV data source (*i.e.,* OSVDB, see Table 3.5), but data for this feature is empty in most entries of the data source (7%) [Vac09]. Such surrogate is a non-negligible threat to the validity of primary studies since the T_A feature depends on the disclosure policy of the data source providers. Such policy could change over time.

Thus it is very hard to approximate the discovery date by public announced date.

3.4 Chapter Summary

This chapter presented a survey about empirical vulnerability studies. The survey includes 59 primary studies in international workshops, conferences/symposium, and journals from 2005 to 2012. The survey studied the data sources and data features used in primary studies. It also summarized most common features in the used data sources. The analysis on data usage has revealed that third-party data sources were preferred more than other data sources to conduct empirical experiments. Among several data source, NVD was the most popular one, which was used in about 62% of primary studies across different research topics. Additionally, Affected Versions (V_A) and Announced Date (T_A) were the mostly used features in primary studies.

In the next chapter, we will present the data infrastructure for compiling experimental data which will be used in the rest of this dissertation.

CHAPTER 4

DATA INFRASTRUCTURE FOR EMPIRICAL EXPERIMENTS

This chapter focuses on the compilation of vulnerability data for further experiments in the dissertation. It discusses the vulnerability data infrastructure including the data sources and software infrastructure for data collection. It discusses potential biases in data sets that were collected based on the software infrastructure. The chapter also describes other data sources such as market share information and code base information of the target applications.

RECENTLY we have seen a substantial shift of vulnerability discovery from operating systems to web browsers and their plugins [You13]. Additionally, a study by Google [Raj11] shows that more than two-third of attacks to internet users have exploited vulnerabilities of browsing software or its plugins. Therefore in this dissertation, we mostly target our experiments on browsers, and select the most popular ones according to the main providers of market share information.

Table 4.1 presents the vulnerability data sources for compiling the data infrastructure of the dissertation. The category of the data source is based on the classification in the previous survey (see Table 3.2). The *Apply for* indicates the browsers of which the corresponding data source provides vulnerability data. Among different third-party data sources (see Table 3.3), we choose to use NVD because: first, it provides almost features which are supported by other third-party data sources; second, almost third-party data sources maintain references to NVD; third, it is the most popular data source in the literature (see Section 3.3), thus choosing NVD will enable us to compare the outcome of our experiments to the others.

The rest of this chapter is organized as follows. Section 4.1 presents the data sources as well as the software infrastructure to collect vulnerability data. Section 4.2 discusses potential biases in the data set collected by the infrastructure, and how to mitigate them. Section 4.3 describes how to obtain the market share data for browsers. Section 4.4 summarizes the chapter.

4.1 Software Infrastructure for Data Acquisition

Vulnerability data is not static, but keeps evolving as more and more vulnerabilities are discovered when time passes by. During the course of this dissertation we have to collect vulnerability data for several times, especially when we start new experiments so that we base the experiments on the up-to-date data. Therefore, in this chapter we will not present any snapshot of vulnerability data. Instead, we describe the software infrastructure to acquire the data. This infrastructure is consistently used throughout all experiments within this dissertation.

Moreover, from the perspective of researchers who are not inside the data source providers, we are in favor of an automated process to collect vulnerability data. This makes the collected data objective rather than subjective. Some sanitization activities could be applied to the collected data to improve the quality. However these activities should be clearly defined, and should not be subject to personal judgments, which could be different from person to person. Therefore the experiments based on the data could be easily and widely reproducible by other researchers.

Table 4.1: Vulnerability data sources of browsers.

Data Source	Category	Apply for
National Vulnerability Database (NVD)	TADV	All browsers
Mozilla Foundation Security Advisories (MFSA)	ADV	Firefox
Mozilla Bugzilla (MBug)	BUG	Firefox
Microsoft Security Bulletin (MSB)	ADV	IE
Apple Knowledge Base (AKB)	ADV	Safari
Chrome Issue Tracker (CIT)	BUG	Chrome

In the subsequent section we describe the software infrastructure to automate the data acquisition task.

4.1.1 Acquiring Vulnerability Data for Firefox

Figure 4.1 exhibits the software infrastructure for collecting Firefox vulnerability data. The infrastructure consists of a couple of scripts: Sphinx scripts (white rectangles) and R scripts (filled rectangles). The former scripts are written in the Sphinx script language, which is developed by myself and is optimized for extracting data in text files (*e.g.*, HTML pages). The latter scripts are written in R, a very popular language for data processing and statistics. Apart from the output data set (stack of cans), the figure also shows some intermediate data sources (filled cans), which are the outcome of the scripts.

The data collection process for Firefox starts by processing the MFSA dashboard (`www.mozilla.org/security/known-vulnerabilities/`) which lists all MFSA entries. The *MFSA Feature Extractor* invokes *Web Crawler* to download all HTML pages of all available MFSA entries for Firefox, and parses the content of these pages to produce three intermediate data sets: *MFSA Data*, *MFSA Refs*, and *Bug-CVE Links*. The first data set contains meta information of each MFSA entry; the second maintains cross-reference links between an MFSA entry to a CVE or an MBug entry; the third holds the associations between CVEs and MBugs mentioned in each MFSA report.

For each MBug detected in an MFSA, *MFSA Feature Extractor* passes it to *MBug Feature*

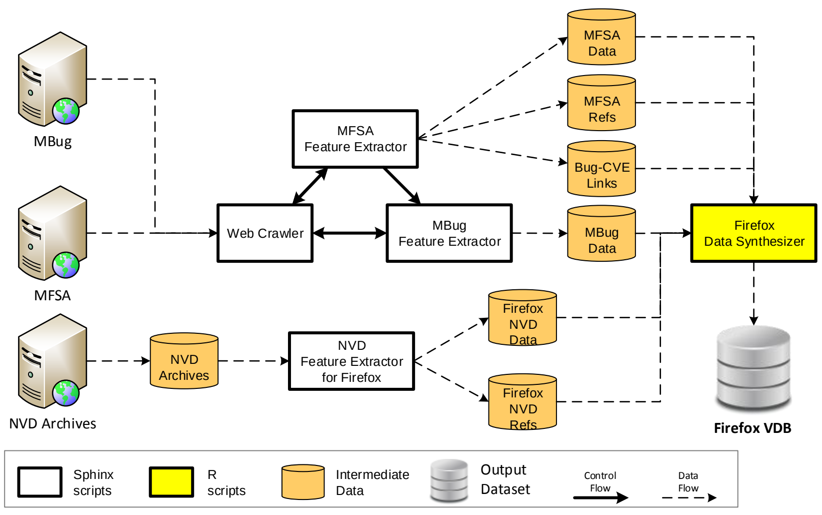


Figure 4.1: The infrastructure to collect vulnerability data for Firefox

Extractor which in turn asks *Web Crawler* to download its corresponding XML page, and parses the downloaded page to produce the data set *MBug Data*, which contains meta information of MBug.

On the other side, *NVD Feature Extractor for Firefox* mines the *NVD Archives* data set, which is provided by NVD (`nvd.nist.gov/download.cfm`), to produce two data sets: *Firefox NVD Data* and *Firefox NVD Refs*. The former contains CVEs that mention Firefox as the affected application. The latter maintains the all reference links of a CVE to either an MBug or an MFSA entry. Finally all the intermediate data sets are fed into the *Firefox Data Synthesizer* to produce the final output data set, *Firefox VDB*.

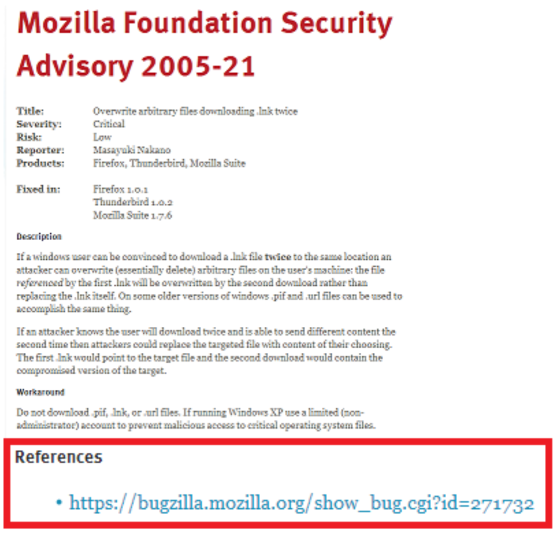
The schemas of all these data sets are described as follows:

$$
\begin{aligned}
&\textit{MFSA Data} && = (\mathsf{mfsaID},\ \mathsf{mfsaDate},\ \mathsf{title})\\
&\textit{MFSA Refs} && = (\mathsf{mfsaID},\ \mathsf{refType},\ \mathsf{refID})\\
&\textit{Bug-CVE Links} && = (\mathsf{bugID},\ \mathsf{mfsaID},\ \mathsf{cveID},\ \mathsf{patternType})\\
&\textit{MBug Data} && = (\mathsf{bugID},\ \mathsf{mfsaID},\ \mathsf{bugDate})\\
&\textit{Firefox NVD Data} && = (\mathsf{cveID},\ \mathsf{cveDate},\ \mathsf{affectedVersion})\\
&\textit{Firefox NVD Refs} && = (\mathsf{cveID},\ \mathsf{refType},\ \mathsf{refID})\\
&\textit{Firefox VDB} && = (\mathsf{bugID},\ \mathsf{bugDate},\ \mathsf{mfsaID},\ \mathsf{mfsaDate},\\
& && \mathsf{cveID},\ \mathsf{cveDate},\ \mathsf{minAffectedVersion},\ \mathsf{maxAffectedVersion})
\end{aligned}
$$

Some features are self-explained by their name, we only describe the meaning for the rest. Particularly, refType is one of strings `'CVE'`, or `'Bugzilla'`, or `'MFSA'`, which indicates the meaning of the refID feature. The feature patternType determines the heuristic rule used to associate CVE and MBug.

The heuristic rules to associate CVE and MBug are based on the relative positions of the hyperlinks to MBug and hyperlinks to NVD in an MFSA report. To clarify, we use the term `BUG` and `CVE` to denote hyperlinks to MBugs, and CVEs, respectively. If more than one similar term appears in a sequence, we use the star symbol (*). There are following cases for these relative positions.

- `BUG*`: one or more MBug hyperlinks, see Figure 4.2(a). We thus have no clue to link these MBug entries to any NVDs entries. However, this case only applies for Firefox v1.0. Thus we can safely assume that these MBug entries only affect Firefox v1.0 because they are fixed in Firefox v1.0.x. In other words, we still obtain the missing values for the I_V feature.



Mozilla Foundation Security Advisory 2005-21

Title:	Overwrite arbitrary files downloading .lnk twice
Severity:	Critical
Risk:	Low
Reporter:	Masayuki Nakano
Products:	Firefox, Thunderbird, Mozilla Suite
Fixed in:	Firefox 1.0.1 Thunderbird 1.0.2 Mozilla Suite 1.7.6

Description

If a windows user can be convinced to download a .lnk file **twice** to the same location an attacker can overwrite (essentially delete) arbitrary files on the user's machine: the file *referenced* by the first .lnk will be overwritten by the second download rather than replacing the .lnk itself. On some older versions of windows .pif and .url files can be used to accomplish the same thing.

If an attacker knows the user will download twice and is able to send different content the second time then attackers could replace the targeted file with content of their choosing. The first .lnk would point to the target file and the second download would contain the compromised version of the target.

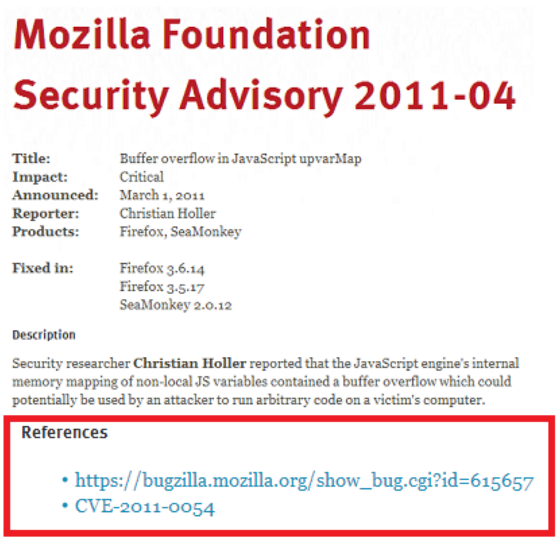
Workaround

Do not download .pif, .lnk, or .url files. If running Windows XP use a limited (non-administrator) account to prevent malicious access to critical operating system files.

References

- https://bugzilla.mozilla.org/show_bug.cgi?id=271732

(a) BUG*



Mozilla Foundation Security Advisory 2011-04

Title:	Buffer overflow in JavaScript upvarMap
Impact:	Critical
Announced:	March 1, 2011
Reporter:	Christian Holler
Products:	Firefox, SeaMonkey
Fixed in:	Firefox 3.6.14 Firefox 3.5.17 SeaMonkey 2.0.12

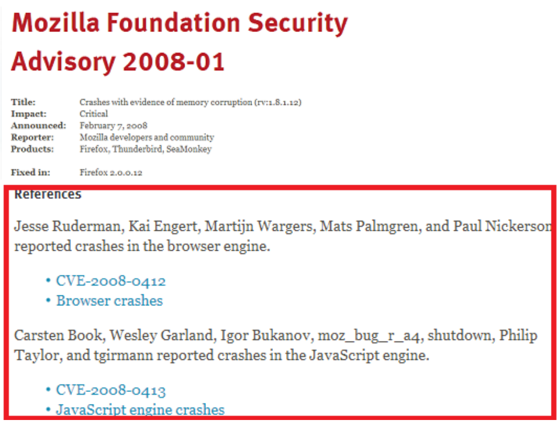
Description

Security researcher **Christian Holler** reported that the JavaScript engine's internal memory mapping of non-local JS variables contained a buffer overflow which could potentially be used by an attacker to run arbitrary code on a victim's computer.

References

- https://bugzilla.mozilla.org/show_bug.cgi?id=615657
- CVE-2011-0054

(b) BUG CVE



Mozilla Foundation Security Advisory 2008-01

Title:	Crashes with evidence of memory corruption (rv:1.8.1.12)
Impact:	Critical
Announced:	February 7, 2008
Reporter:	Mozilla developers and community
Products:	Firefox, Thunderbird, SeaMonkey
Fixed in:	Firefox 2.0.0.12

References

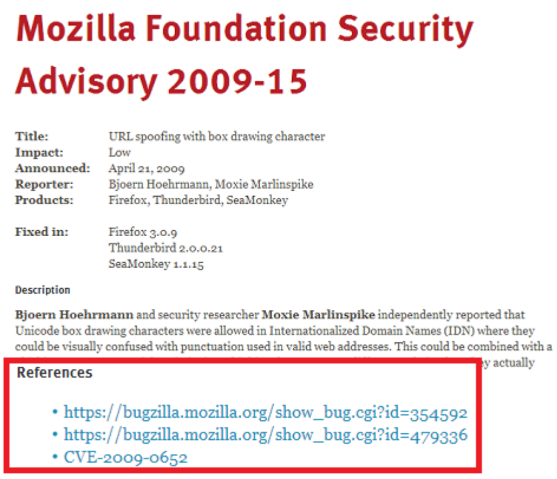
Jesse Ruderman, Kai Engert, Martijn Wargers, Mats Palmgren, and Paul Nickerson reported crashes in the browser engine.

- CVE-2008-0412
- Browser crashes

Carsten Book, Wesley Garland, Igor Bukanov, moz_bug_r_a4, shutdown, Philip Taylor, and tgirmann reported crashes in the JavaScript engine.

- CVE-2008-0413
- JavaScript engine crashes

(c) CVE BUG*



Mozilla Foundation Security Advisory 2009-15

Title:	URL spoofing with box drawing character
Impact:	Low
Announced:	April 21, 2009
Reporter:	Bjoern Hoehrmann, Moxie Marlinspike
Products:	Firefox, Thunderbird, SeaMonkey
Fixed in:	Firefox 3.0.9 Thunderbird 2.0.0.21 SeaMonkey 1.1.15

Description

Bjoern Hoehrmann and security researcher **Moxie Marlinspike** independently reported that Unicode box drawing characters were allowed in Internationalized Domain Names (IDN) where they could be visually confused with punctuation used in valid web addresses. This could be combined with a y actually

References

- https://bugzilla.mozilla.org/show_bug.cgi?id=354592
- https://bugzilla.mozilla.org/show_bug.cgi?id=479336
- CVE-2009-0652

(d) BUG* CVE

Figure 4.2: Different patterns of BUG and CVE references in MFSA.

- `BUG CVE`: one MBug hyperlink followed by an NVD hyperlink, see Figure 4.2(b). We assume that the mentioned MBug entry correlates to the mentioned NVD entry. We then correlate these entries together. This case occurs in most MFSA entries.

- `(CVE BUG*)*`: one NVD entry is followed by one or more MBug entries, and then another NVD entry and MBug entries, see Figure 4.2(c). We assume that the NVD entry correlates to the immediately followed MBug entries.

- `(BUG* CVE)*`: this case is the opposite of the previous one, see Figure 4.2(d). There is one or more MBug entries followed by an NVD entry, then other MBug entries and another NVD entry. Similarly, we assume that MBug entries correlate to their followed NVD entry.

By correlating NVD and MBug, we assume that all affected versions of the NVD entry are also applied for the MBug entry.

4.1.2 Acquiring Vulnerability Data for Chrome, IE, and Safari

The software infrastructure to download vulnerability data for Chrome, IE and Safari is illustrated in Figure 4.3.

For Chrome, first we download the *CIT Data* data set which contains a list of security bugs of Chrome. The GUI of CIT allows users to query the data. The queried results then could be exported to Comma Separated Values (CSV) file. Since we are only interested in security bugs, we set the query parameter to acquire only this type of bugs, *i.e.,* `type:Security-Bug`. Second, the *NVD Feature Extractor for Chrome*, as similar as *NVD Feature Extractor for Firefox*, also mines the *NVD Archives* to produce two intermediate data sets *Chrome NVD Data* and *Chrome NVD Refs*. The meaning of these two data sets are similar to *Firefox NVD Data* and *Firefox NVD Refs*, which have been discussed above. Finally, all intermediate data sets are fed into the *Chrome Data Synthesizer* to produce the final vulnerability data set for Chrome, *i.e., Chrome VDB*.

The acquisition of vulnerability for IE and Safari are mostly the same as Chrome. In this dissertation we have no interest in any features of MSB as well as AKB, except their IDs. Therefore, we will not present the infrastructure to collect features form these data sources, but only for collecting vulnerabilities for IE and Safari from the *NVD Archives* data set.

The schemas of the data sets in Figure 4.3 are described as follows.

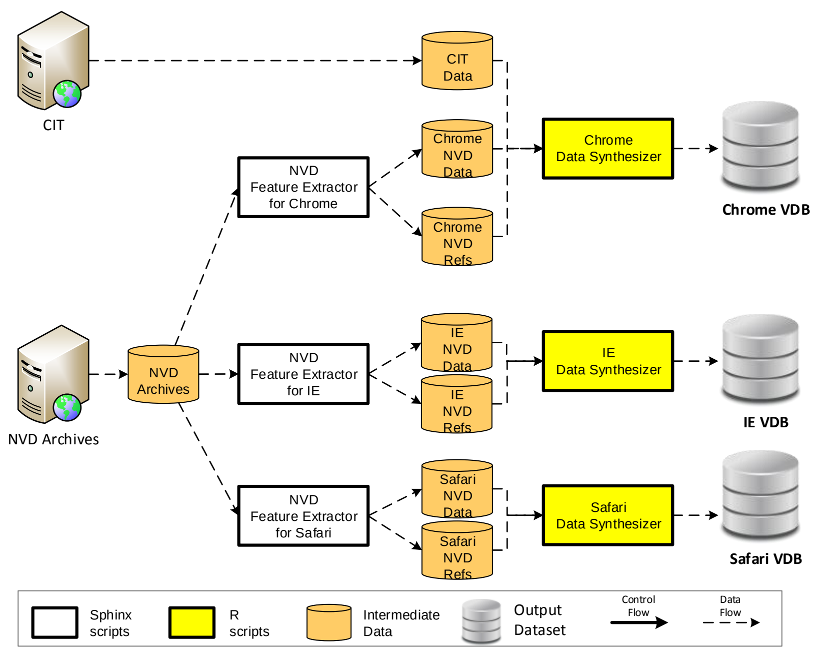


Figure 4.3: The infrastructure to collect vulnerability data for Chrome, IE, and Safari.

CIT Data	= (bugID, bugDate, cveID)
Chrome NVD Data	= (cveID, cveDate, affectedVersion)
Chrome NVD Refs	= (cveID, bugID)
IE NVD Data	= (cveID, cveDate, affectedVersion)
IE NVD Refs	= (cveID, msbID)
Safari NVD Data	= (cveID, cveDate, affectedVersion)
Safari NVD Refs	= (cveID, akbID)
Chrome VDB	= (bugID, bugDate, cveID, cveDate, minAffectedVersion, maxAffectedVersion)
IE VDB	= (cveID, cveDate, msbID, minAffectedVersion, maxAffectedVersion)
Safari VDB	= (cveID, cveDate, akbID, minAffectedVersion, maxAffectedVersion)

4.2 Potential Biases in Collected Data Sets

We have identified some validity threats to the collection of vulnerability data. These threats are classified to the *Construction validity* to any experiments relying on this infrastructure to attaining data. These threats are described as follows.

Bugs in the implementation scripts. The software infrastructure in Figure 4.1 and Figure 4.3 consists of some implemented scripts. These scripts might be buggy, leading to mistakes in the collected data. We have tried to remove programming bugs as much as possible. We first ran all the scripts in some samples, and then manually check the outputs of these scripts to see if there was any mistakes. If yes, we fixed the scripts and ran the test again. When all identified bugs have been eliminated. We ran the scripts to collect all data sets. Then we randomly sampled the data sets for mistakes. If there was any, we fixed the bugs and started over the data collection.

Bias in correlating MBug to NVD entries. Some MBug entries explicitly indicate the corresponding NVD in their titles, but the most of them do not. We employ the heuristic rules described in the previous section to link. The rules might not hold for all cases, leading to mistakes in the collected data. We tried to mitigate the mistakes by manually checking the description of MBug and NVD entries in some samples.

Figure 4.4 reports the distribution of number of MBugs per NVD entry reported by MFSA entries (up to January 2014). In most of cases (86%), each NVD is associated with a single MBug. This means that the associations between MBug and NVD established via MFSA apparently contain less bias. However, we have still manually verified many correlations between NVD and MBug entries. Fortunately all of them are found consistent.

Example 4.1 This example illustrates the corresponding between NVD and MBug entries.

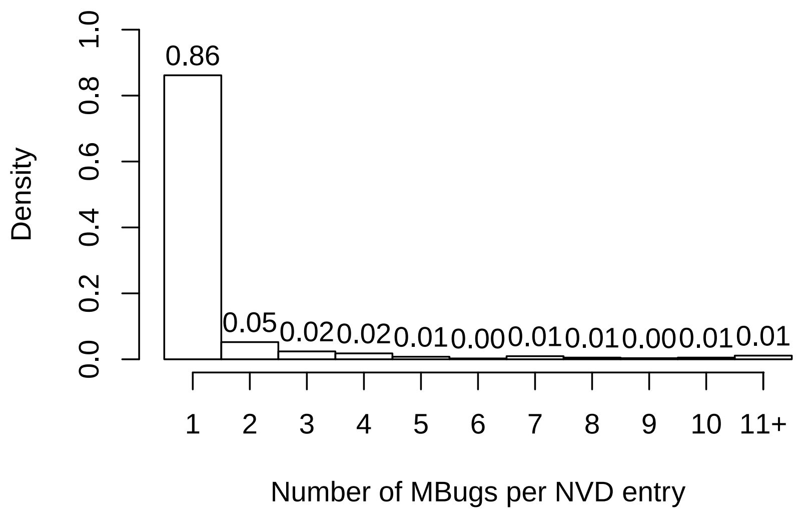


Figure 4.4: Histogram of number of MBugs per NVD entry, reported by MFSA.

Figure 4.2(d) shows the screenshot of MFSA-2009-15. The description of this MFSA entry said:

> *"Bjoern Hoehrmann and security researcher Moxie Marlinspike independently reported that Unicode box drawing characters were allowed in Internationalized Domain Names (IDN) where they could be visually confused with punctuation used in valid web addresses. This could be combined with a phishing-type scam to trick a victim into thinking they were on a different website than they actually were."*

Also, this MFSA has two reference hyperlinks to two MBugs, and one reference hyperlink to an NVD entry. The former are 479336 and 354592. The latter is CVE-2009-0652. The description of the CVE-2009-0652 said:

> *"The Internationalized Domain Names (IDN) blacklist in Mozilla Firefox 3.0.6 and other versions before 3.0.9; Thunderbird before 2.0.0.21; and SeaMonkey before 1.1.15 does not include box-drawing characters, which allows remote attackers to spoof URLs and conduct phishing attacks, as demonstrated by homoglyphs of the / (slash) and ? (question mark) characters in a subdomain of a .cn domain name, a different vulnerability than CVE-2005-0233. NOTE: some third parties claim that 3.0.6 is not affected, but much older versions perhaps are affected."*

The titles of the MBug entries said:

> MBug 479336: *" (CVE-2009-0652) IDN blacklist needs to include box-drawing characters."*
>
> MBug 354592: *"Handling of U+2571 and U+FF1A in IDNs allows URL spoofing."*

By looking at the description of CVE-2009-0652 and the title of the two MBug 479336, 354592, it is clearly that they were talking about the same problem but at different levels of abstraction. ■

4.3 Market Share Data

The information about market share of browsers are provided from several providers, *e.g.*, Net Application (`www.netmarketshare.com`), StatCounter Global (`gs.statcounter.com`), and W3Schools Online (`www.w3schools.com/browsers/`). Due to the lack of a standard way

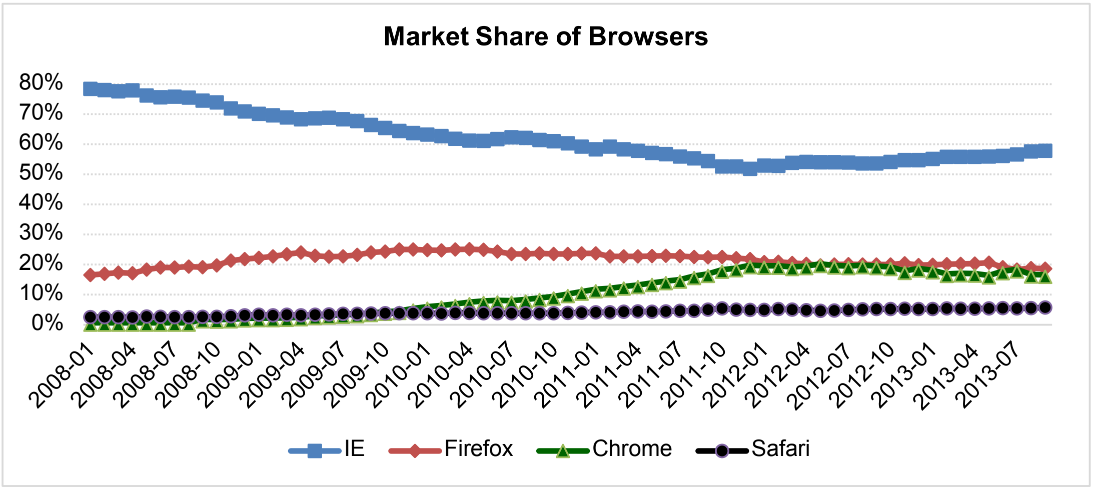


Figure 4.5: The market share of browsers since Jan 2008.

to calculate software market share, these data providers use their own methods to achieve the information. These methods could be classified into two classes: counting the number of unique visitors (*e.g.,* Net Application), or counting the number of page views (*e.g.,* StatCounter Global).

The latter method, counting the number of page views, might only be an approximation for the traffic share of browsers. This stats might be a good indicator for understanding bandwidth-dominating browsers, but might be not appropriate for estimating the choice of individual users which represents the market share. Since we are more interested in studying the browser choice of individual people, we prefer to use the number of unique visitors in this work.

Hereafter, we use the term *market share* to refer to the percentage of unique users of a particular browser to the total unique users. Notably, users who interchangeably use more than one browsers are counted multiple times.

We acquire market share of browsers from Net Application. The data is provided in monthly percentage starting from January 2008 to September 2013. The market share of each browser is the sum of all unique visitors (in percentage) of all versions of a browser. We mostly focus on the share of top 4 dominant browsers. The market shares of these browsers are exhibited in Figure 4.5.

Table 4.2 reports the yearly descriptive statistics of market shares of these browsers. All the values are in percentage. The market share of Chrome in 2008 was below 1% because this browser joint the market in December 2008.

Table 4.2: Descriptive statistics of browsers market share.

Market share values are in percentage.

Year	IE				Firefox				Chrome				Safari			
	μ	σ	min	max	μ	σ	min	max	μ	σ	min	max	μ	σ	min	max
2008	75.54	[2.38]	70.92	78.42	18.80	[1.67]	16.56	21.83	0.39	[0.58]	0.00	1.41	2.65	[0.19]	2.47	3.14
2009	67.55	[2.08]	63.69	70.17	23.54	[0.95]	22.27	25.05	2.68	[1.03]	1.53	4.71	3.52	[0.25]	3.19	3.88
2010	61.54	[1.07]	59.26	63.22	24.21	[0.67]	23.52	25.13	7.57	[1.49]	5.32	10.36	3.89	[0.08]	3.73	4.02
2011	55.87	[2.51]	51.87	59.22	22.67	[0.46]	21.83	23.72	14.60	[2.71]	11.15	19.11	4.63	[0.40]	4.13	5.43
2012	53.88	[0.59]	52.84	54.77	20.24	[0.38]	19.71	20.92	18.72	[0.59]	17.24	19.58	5.04	[0.23]	4.62	5.33
2013	56.30	[0.88]	55.14	57.80	19.57	[0.85]	18.29	20.63	16.58	[0.72]	15.74	17.76	5.46	[0.16]	5.24	5.77

4.4 Chapter Summary

This chapter presented the data infrastructure for the empirical experiments that will be discussed in the rest of the dissertation. We focused the data compilation for four browsers: Chrome, Firefox, IE, and Safari. These browsers are top dominant in the market of browsing software. The chapter described the software infrastructure for acquiring vulnerability data. The chapter also presented the market share information for each browsers

In the next chapters, we are going to describe the observations based on the data collected by the presented software infrastructure.

CHAPTER 5

AFTER-LIFE VULNERABILITIES

This chapter reports our first observational study and studies the interplay in the evolution of source code and known vulnerabilities in Firefox over six major versions (v1.0–v3.6) spanning almost ten years of development. We observe a large fraction of vulnerabilities apply to code that is no longer maintained in older versions. We call these after-life vulnerabilities. *Through an analysis of that code's market share, we also conclude that vulnerable code is still very much in use both in terms of instances and as global code base: CVS evidence suggests that Firefox evolves relatively slowly.*

PUBLIC vulnerability databases such as National Vulnerability Database (NVD, `web.nvd.nist.gov`), Open Source Vulnerability Database (OSVDB, `www.osvdb.org`), Bugtraq (`www.securityfocus.com`) have been used by both academics and industry to study and assess the security of a software. Among these, NVD emerges as one of the most popular source of vulnerabilities for a vast range of software types. Each entry in NVD (a.k.a CVE) is assigned with a unique CVE-ID which has been used as a de-factor vulnerability identifier among other vulnerability data sources. Each CVE is 'assessed[1]' against individual versions (both older and recent ones) to understand which ones are vulnerable.

Besides the academic interests, the presence of "vulnerable" software, according to the NVD, in a company's deployment has a major impact on its compliance with regulation. Some security protocol, such as US Government NIST SCAP [Qui10], evaluates the compliance of software products based on the existence of vulnerabilities as well as their severity

[1]In fact, we do not known the assessment process.

score (*e.g.,* CVSS). However, an analysis by Allodi and Fabio [AF12; All13b] on the exploits of vulnerabilities in the wild has shown that basing on CVSS is not an effective strategy since vulnerabilities with high CVSS score only represent a negligible amount of actual attacks.

Moreover, if you are a credit card merchant, you may need to obtain the compliance with the PCI DSS[WC12] even if it is now not a regulation or a law[2]. If you use, *e.g.,* Chrome v4 embedded in your products, then you might have a software that is vulnerable and may lose the PCI DSS compliance since one of PCI DSS specific regulatory requirement is that: “fix all medium- and high-severity vulnerabilities" [WC12, Chap. 9]. This may lead to fines raking hundreds of thousands of euros.

Meanwhile the current strategy among software vendors is to *counter the risk of exploits by software evolution*: security patches are automatically pushed to end customers, support for old versions is terminated, and customers are pressured to move to new versions. The idea is that, as new software instances replace the old vulnerable instances, the ecosystem as a whole progresses to a more secure state. Additionally, this strategy also has some economic advantages for software vendors: software market is a market of lemons [And01; Ozm07b] the first comers have to change to gain market share, and the simultaneous maintenance of many old versions is simple too costly to continue. However such strategy leaves many old, out-of-support versions, which we refer to as *end-of-life* versions – or simply *dead* versions, with many unpatched vulnerabilities. This might be troubles for organizations who still rely on end-of-life versions as discussed above.

The major concern that we try to address in this chapter is whether there is some empirical evidence that software-evolution-as-a-security-solution is actually a solution, *i.e.,* leads to less vulnerable software over time.

The remainder of this chapter is structured as follows. Section 5.1 presents the findings in the ecosystem of software evolution. Section 5.2 reports the findings in the ecosystem of vulnerabilities. Section 5.3 analyzes the threats to validity. Section 5.4 summarizes the chapter.

5.1 The Ecosystem of Software Evolution

We looked at six Firefox versions, namely v1.0, v1.5, v2.0, v3.0, v3.5 and v3.6. Their lifetimes [Wik12a] can be seen from Figure 5.1. At the time of writing, the versions of Firefox that were actively maintained were v3.5 and v3.6. Therefore, the rectangles representing version v3.5

[2]Some states in US (*i.e.,* Nevada and Minnesota) have adopted PCI DSS as a actual law for some business operating in these states [WC12, Chap.3]

and v3.6 actually extend to the right. There is very little overlap between two versions that are one release apart, *i.e.,* between v1.0 and v2.0, v1.5 and v3.0, v2.0 and v3.5, or v3.0 and v3.6. This is consistent with the conscious effort by the Mozilla developers to maintain only up to two versions simultaneously.

Figure 5.2 illustrates the evolution of Firefox code base from version v1.0 to v3.6. From this figure, the large fraction of code re-use reconciliate the seemingly contradictory information that vulnerability discovery is an hard process with the existence of zero-day attacks: when a new release gets out, the 40% of old code have been already analyzed by over 6 months. Therefore the zero-day attack of version X could well be in reality a six month mounting attack on version X-1.

There is a long held belief in the community that security exploits are a social phenomenon: the wider a user base the more economic appeal it has as a target, the more vulnerabilities are likely to be found. In order to evaluate the impact of social economic aspect of vulnerabilities we consider the market share of the various versions in order to calculate the attack surface of code that is around. The intuition is to calculate the Line of Code (LoC) on each version that are currently available to attackers, either by directly attacking that version or by attacking the fraction of that version that was inherited in later versions.

Let $users(v,t)$ be the number of users of Firefox version v at time t, and let $loc(p,c)$ be the number of lines of code that the *c*urrent version c has inherited from the *p*revious version p. Then the total number of lines of code in version c is $\sum_{1 \le p \le c} loc(p,c)$. In order to get an idea how much inherited code is used, we define a measure *LOC-users* as:

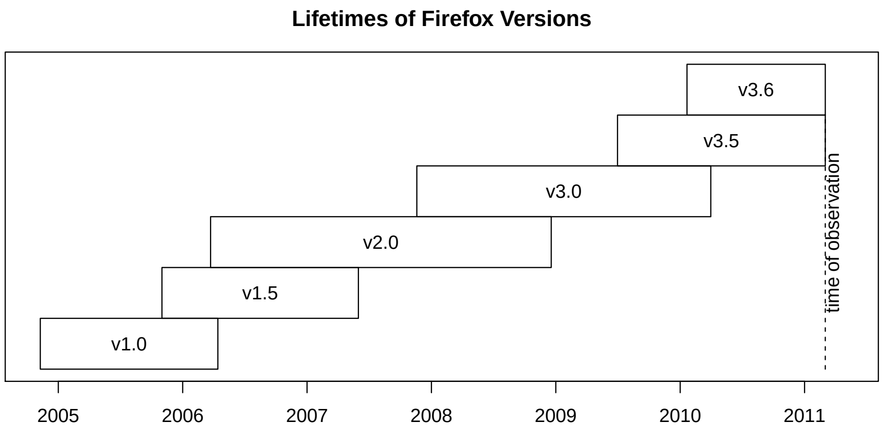
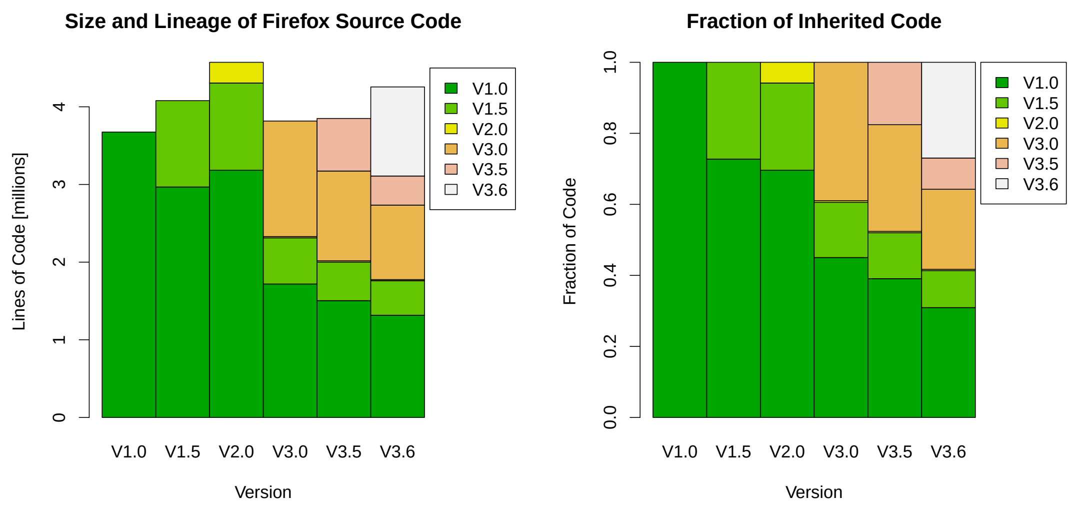


Figure 5.1: Release and retirement dates for Firefox.



Evolution of Firefox codebase in absolute terms (left) and fraction of codebase (right). The left diagram shows the size of the Firefox releases, and the right diagram normalizes all columns to a common height.

Figure 5.2: Size and lineage of Firefox source code

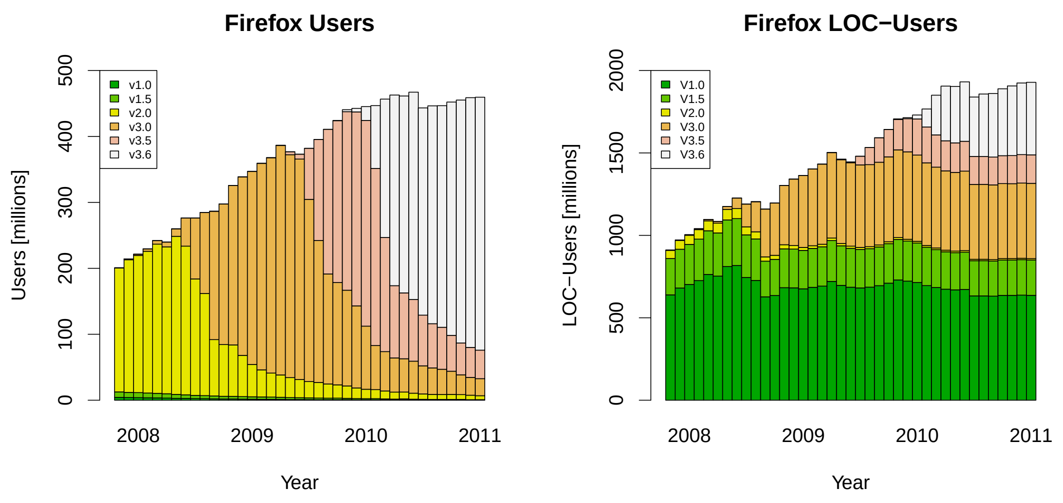
$$\mathit{LOC\text{-}users}(v,t) = \sum_{1\le p\le v} \mathit{users}(p,t)\cdot \mathit{loc}(p,v). \tag{5.1}$$

This is an approximation because the amount of code inherited into version v varies with time, therefore, $\mathit{loc}(p,v)$ is time-dependent. In this way, we eliminate transient phenomena for this high-level analysis.

Figure 5.3 shows the development of the number of users and of LOC-users over time. It is striking to see the number of Firefox v1.0 go down to a small fraction, while the LOC-users for v1.0 stays almost constant.

An important observation is that even the "small" fraction of users of older versions accounts to millions of users. You can imagine wandering in Belgium and each and every person that you meet in the city still uses old Firefox v1.0.

This might have major implications in terms of the possibility of achieving herd immunity as the number of vulnerable hosts would be always sufficient to allow propagation of infections, see [Het00] for discussion on threshold for epidemics.



Number of Firefox users (left) and LOC-users (right). While the number of users of Firefox v1.0 is very small, the amount of Firefox v1.0 *code* used by individual users is still substantial.

Figure 5.3: Firefox Users vs. LOC Users

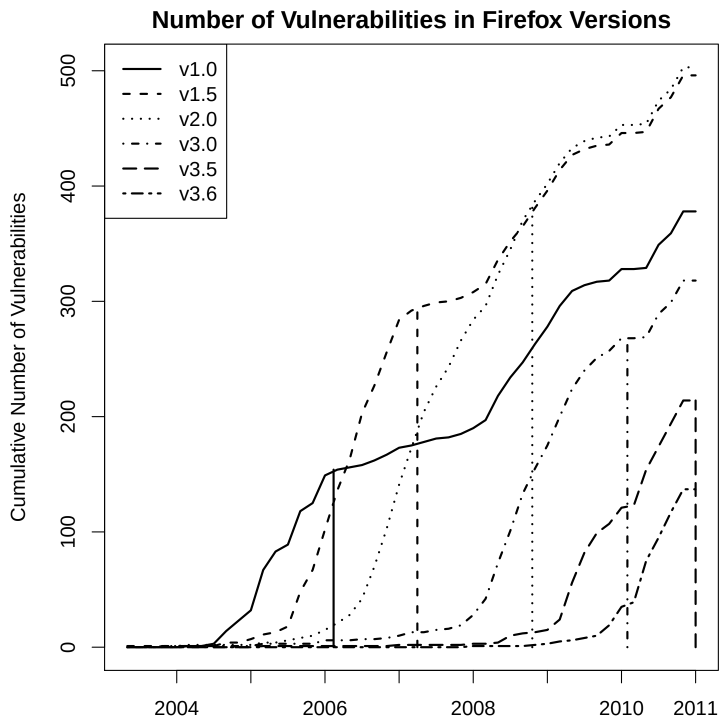
5.2 After-life Vulnerabilities and the Security Ecosystem

We looked at security advisories of Firefox and found 335 MFSAs, from MFSA-2005-008 to MFSA-2010-48. In order to find out in which version a vulnerability applies to, we look at the NVD entry for a particular vulnerability and take the earliest version for which the vulnerability is relevant. For example, MFSA 2008-60 describes a crash with memory corruption. This MFSA links to CVE 2008-5502, for which NVD asserts that versions v3.0 and v2.0 are vulnerable. The intuitive expectation (confirmed by the tests) is that the vulnerability was present already in v2.0 and that v3.0 inherited it from there.

Figure 5.4 exhibits the cumulative numbers of vulnerabilities in individual versions of Firefox. In the figure, we additionally mark the end-of-life for each version by a vertical line. As is apparent, the number continues to grow up even if the life time of a version is terminated. We call vulnerabilities discovered after the life time of a version as *after-life vulnerabilities.*

By the time of this observation, Firefox v3.5 and v3.6 are alive. Obviously we have no after-life vulnerabilities for them. However, for other versions, Figure 5.4 shows a significant amount of after-life vulnerabilities in the security landscape of individual versions of Firefox.

This phenomenon could be explained by the ecosystem of code evolution, as previously



Cumulative number of vulnerabilities for the various Firefox versions. End-of-life for a version is marked with vertical lines. As is apparent, the number continues to rise even past a version's end-of-life.

Figure 5.4: Vulnerabilities discovered in Firefox versions

presented in Figure 5.3. Even when a version is dead, their code base still survives for a very long time since the code base is usually inherited across versions, see Figure 5.2. Thus when a vulnerability is discovered in an alive version, *i.e.*, a version which is still being supported, it has some chances that this vulnerability falls into the code base of an older version, see also Figure 5.2 (right). As the result, the number of after-life vulnerabilities arises.

After-life vulnerabilities are usually discovered in alive versions, then found to affect also retro versions. In alive versions, these vulnerabilities are fixed and shipped to users through security patches. However, they are not fixed in dead versions. Consequently, any products relied on dead versions of Firefox would expose themselves to a major threat: they contain a lot public-but-non-fixed after-life vulnerabilities.

We further study the breakdown of cumulative vulnerabilities in each version to see the origin of vulnerabilities, *i.e.*, where vulnerabilities were firstly introduced and survived. Depend on versions that a vulnerability affects, it can be classified into following sets:

- *Inherited vulnerabilities* are ones spanning consecutive versions.

- *Foundational vulnerabilities* are inherited ones, but apply also for the very first version *e.g.,* v1.0.

- *Local vulnerabilities* are ones introduced in some versions, but fixed before the next version comes out.

- *Survive vulnerabilities* are one discovered in some versions, and still survive in the next versions.

- *Regressive vulnerabilities* are present in some versions, then they disappear to reappear again in later versions.

This classification is obviously not exclusive. In the set of vulnerabilities of version x, the inherited set $I(x)$ subsumes foundational set $F(x)$, and survive set of the immediate predecessor $S(x-1)$. Hence, if we categorize vulnerabilities of Firefox in general (do not consider versions), we have three complete disjoint sets: foundational, non-foundational inherited, and local vulnerabilities. Similarly, if we categorize vulnerabilities of each version individually, we have four disjoint sets: foundation, non-foundational inherited, survive, and local vulnerabilities. In the collected vulnerability data, we observed a single instance of regressive vulnerability, but it turned to be an input mistake which has been corrected later on by the data provider.

The definition of foundational vulnerability is weaker (and thus more general) than the one used by Ozment and Schechter [OS06]. We do not claim that there exists some code in version v1.0 that is also present in, say, v1.5 and v2.0 when a vulnerability is foundational. For us it is enough that the vulnerability applies to v1.0, v1.5 and v2.0. This is necessary because many vulnerabilities (in the order of 20-30%) are not fixed. For those vulnerabilities it is impossible, by looking at the CVS and Mercurial sources without extensive and bias-prone manual analysis, to identify the code fragment from which they originated.

Table 5.1 reports the number of vulnerabilities in Firefox depended on the versions they are discovered (columns), and the version they were first introduced (rows). For example, there were 99 vulnerabilities that were discovered during the lifetime of Firefox v3.0, which were introduced in Firefox v1.0. Since we have no regressions (see above), these 99 vulnerabilities also apply to all intermediate versions v1.5 and v2.0.

We can now easily categorize the vulnerabilities in the table according to the categories that interest us: inherited vulnerabilities are the numbers above the diagonal (they are carries over from some previous version); foundational vulnerabilities are those in the first row,

Table 5.1: Vulnerabilities in Firefox

Version at Introduction	Version at Discovery					
	v1.0	v1.5	v2.0	v3.0	v3.5	v3.6
v1.0	79	72	33	99	34	61
v1.5	—	109	88	0	0	0
v2.0	—	—	163	24	0	1
v3.0	—	—	—	64	30	5
v3.5	—	—	—	—	34	49
v3.6	—	—	—	—	—	21

Table 5.2: Vulnerabilities in individual versions of Firefox

(a) All vulnerabilities

Inherited from	Version					
	v1.0	v1.5	v2.0	v3.0	v3.5	v3.6
v1.0	378	299	227	194	95	61
v1.5	-	197	88	0	0	0
v2.0	-	-	188	25	1	1
v3.0	-	-	-	99	35	5
v3.5	-	-	-	-	83	49
v3.6	-	-	-	-	-	21
Total	378	496	503	318	214	137

(b) After-life vulnerabilities

Inherited from	Version			
	v1.0	v1.5	v2.0	v3.0
v1.0	228	203	126	50
v1.5	-	1	0	0
v2.0	-	-	1	0
v3.0	-	-	-	-
v3.5	-	-	-	-
v3.6	-	-	-	-
Total	228	204	127	50

excluding the first element (they are carries over from version v1.0); local vulnerabilities are those on the diagonal (they are fixed before the next major release and are not carried over).

Another interesting perspective is to look at vulnerabilities in individual versions. Table 5.2(a) reports the cumulative numbers of individual versions of Firefox, and their breakdown. These number could be derived from Table 5.1. For example, the cumulative number of vulnerabilities for a particular version, *e.g.*, v2.0, is the sum of cells (row, col) where $row \leq$ v2.0 and $col \geq$ v2.0, which is 503. For each version in the columns, numbers in the first row (except version v1.0) are foundational vulnerabilities, numbers in the diagonal are sum of local vulnerabilities and survive vulnerabilities, and others are non-foundational inherited ones. Table 5.2(b) is similar to Table 5.2(a), but only after-life vulnerabilities are counted.

According to Table 5.2, among the total vulnerabilities in individual versions, on average, 51% are inherited from the very first version – foundational vulnerabilities, 17% are inherited from other versions. Intuitively, inherited vulnerabilities (both foundational and non-foundational) are responsibility of the legacy code in each version. Hence, the contribution of legacy code to the (in)security of software (Firefox) is still a large portion. It is coherent to the large amount of legacy LoC in each version.

Substantially, about 40% of vulnerabilities have been discovered after the versions were out of support. These after-life vulnerabilities are mostly foundational, see Table 5.2(b). Considering the market share of Firefox, see Figure 5.3, there are a significant amount of exploitable vulnerabilities in the ecosystem of Firefox.

In short, the observation based on the collected data has reveal the following finding about the security landscape of Firefox.

> *"For each version of Firefox, foundational vulnerabilities take a significant amount among the total vulnerabilities. More than one-third of vulnerabilities are after-life i.e., discovered after a version were out of support, and most of them are foundational."*

5.3 Threats to Validity

Construct validity includes threats affecting the way we collect vulnerability data.

Bias in data collection. We apply the software infrastructure described in Chapter 4. As discussed, it might have some construction validity to the observation in this chapter. We inherit the mitigation described in Section 4.2 to reduce the bias in the collected data.

Bias in NVD. We determine the Firefox versions from which a vulnerability originated by looking at the earliest Firefox version to which the vulnerability applies, and we take that information from the "vulnerable versions" list in the NVD entry. If these entries are not reliable, we may have bias in the analysis. We have manually confirmed accuracy for few NVD entries, and an automatic large-scale calibration will be a part of future work (considering the time this observation were made). Indeed, we have done such calibration in Chapter 9 where we report the bias in NVD and revisit the findings in this observation.

Internal validity concerns the causal relationship between the collected data and the conclusion in the study.

Ignoring the severity. We deliberately ignore the severity of vulnerabilities in our study. Because current severity scoring system, CVSS, adopted by NVD and other ones (*e.g.*, qualitative assessment such as critical, moderate used in Microsoft Security Bulletin) have shown their limitation. In accordance to Bozorgi *et al.* [Boz10], these systems are “inherently ad-hoc in nature and lacking of documentation for some magic numbers in use". Moreover, in that work, Bozorgi *et al.* showed that there is no correlation between severity and exploitability of vulnerabilities.

External validity is the extent to which our conclusion could be generalized to other scenarios. The combination of multi-vendor databases (*e.g.,* NVD, Bugtraq) and software vendor's databases (*e.g.,* MFSA, Bugzilla) only works for products for which the vendor maintains a vulnerability database and is willing to publish it. Also, the source control log mining approach only works if the vendor grant community access to the source control, and developers commit changes that fix vulnerabilities in a consistent, meaningful fashion *i.e.,* independent vulnerabilities are fixed in different commits, each associated with a message that refers to a vulnerability identifier. These constraints eventually limit the application of the proposed approach.

Another facet of generality, which is also the limitation of this observation, is that whether the findings are valid to other browsers, or other categories of software such as operating system? We plan to overcome this limitation by extending the observation to different software in future.

5.4 Chapter Summary

First, for the *individual*, we have the obvious consequence that running after-life software exposes the user to significant risk, which should therefore be avoided. Also, we seem to discover vulnerabilities late, and this, together with low software evolution speeds, means that we will have to live with vulnerable software and exploits and will have to solve the problem on another level.

Second, for the *software ecosystem*, the finding that there are still significant numbers of people using after-life versions of Firefox means that old attacks will continue to work. This means that the penetrate-and-patch model of software security (*i.e.,* software-evolution-as-a-security-solution) might not be enough, and that systemic measures, such as multi-layer defenses, need to be considered to mitigate the problem.

These phenomena reveal that the problem of inherent vulnerabilities is merely a small part of the problem, and that the lack of maintenance of older versions leave software (Firefox) widely open to attacks. Security patch is not made available because it is not being deployed and because many users are slow at moving to newer version of software.

In terms of understanding the interplay of the evolution of vulnerabilities with the evolution of software we think that the jury is still out, we cannot in any way affirm that most vulnerabilities are due to foundational or anyhow past errors. We need to refine these findings by a careful analysis of the fraction of the code base for each version.

These results have been possible by looking at vulnerabilities in a different way. Other studies have studied a vulnerability's *past*, *i.e.,* once a vulnerability is known, we look at where it was introduced, who introduced it etc. In this observation, we look at a vulnerability's *future*, *i.e.,* we look at what happens to a vulnerability after it is introduced, and find that it survives in after-life versions even when it is fixed in the current release.

The observation made in this chapter relies on the vulnerability claims by NVD. This chapter assumes the data is all correctly provided. In Chapter 8, we present an automatic method to estimate the retro persistence of vulnerability claims by NVD. Chapter 9 discusses an experiment assessing the validity of vulnerability claims for Firefox and Chrome. The experiment results exposes that many vulnerability claims for older versions of Chrome and Firefox are not correct. Thus it might impact the observation of this chapter.

In the next chapter, we are going to present the observation on the traditional validation methodology for vulnerability discovery models. The observation has revealed some critical biases in the traditional methodology. Based on that, we have proposed a novel evaluation methodology which can substitute the traditional one.

Chapter 6

A Methodology to Evaluate Vulnerability Discovery Models

Vulnerability Discovery Models (VDMs) operate on known vulnerability data to estimate the total number of vulnerabilities that will be reported after software is released. This chapter presents an observation on the traditional validation methodology for VDMs. It discusses several issues which might bias the outcomes of validation experiments that follow the traditional methodology. Based on that, this chapter proposes an empirical methodology that systematically evaluates the performance of VDMs along two dimensions: quality and predictability. The proposed methodology tackles all identified issues of the traditional methodology.

Time-based vulnerability discovery models (VDMs) are parametric functions counting the number of cumulative vulnerabilities of a software at an arbitrary time t. For example, if $\Omega(t)$ is the cumulative number of vulnerabilities at time t, the function of the linear model (LN) is $\Omega(t) = At + B$ where A, B are two parameters of LN, which are calculated from the historical vulnerability data. Accurate models can be useful instruments for both software vendors and users to understand security trends, plan patching schedules, decide updates, and forecast security investments.

Figure 6.1 sketches a taxonomy of major VDMs. It includes Anderson's Thermodynamic (AT) model [And02], Rescorla's Quadratic (RQ) and Rescorla's Exponential (RE) models [Res05], Alhazmi & Malaiya's Logistic (AML) model [AM05b], AML for Multi-version (MVDM) model

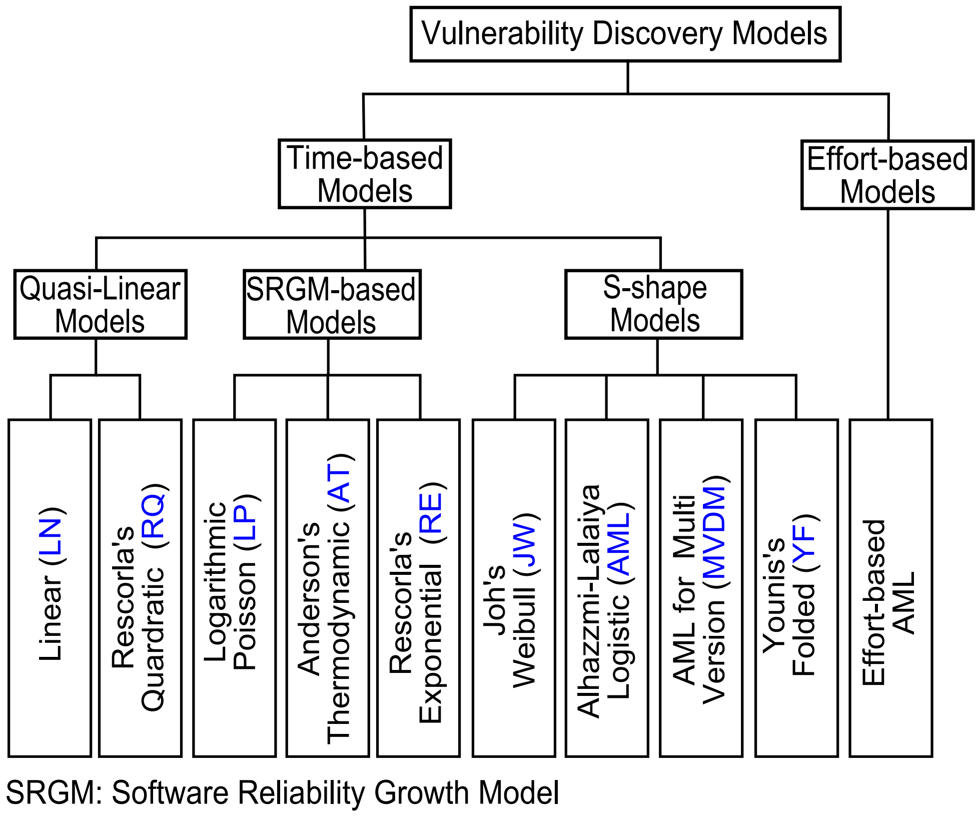

Vulnerability Discovery Models
Time-based Models
Effort-based Models
Quasi-Linear Models
SRGM-based Models
S-shape Models
Linear (LN)
Rescorla's Quardratic (RQ)
Logarithmic Poisson (LP)
Anderson's Thermodynamic (AT)
Rescorla's Exponential (RE)
Joh's Weibull (JW)
Alhazzmi-Lalaiya Logistic (AML)
AML for Multi Version (MVDM)
Younis's Folded (YF)
Effort-based AML
SRGM: Software Reliability Growth Model

Figure 6.1: Taxonomy of Vulnerability Discovery Models.

[Kim07], Weibull model (JW) [Joh08], and Folded model (YF) [You11]. Hereafter, we shortly refer to time-based VDM as VDM.

The *goodness-of-fit* (GoF) of these models, *i.e.,* how well a model could fit the numbers of discovered vulnerabilities, is normally evaluated in each paper on a specific vulnerability data set, except AML which has been validated for different types of applications (*i.e.,* operating systems [Alh05; AM08], browsers [Woo06a], web servers [AM06b; Woo11]). Yet, all of the validations so far have been done by the model authors, and there is no independent validation by researchers who are different than these very authors. Furthermore, the validation results of these studies might be biased by the following issues:

1. Past studies do not clearly define the notion of vulnerability. Indeed different definitions of vulnerability (*e.g.,* different databases such as NVD, versus MFSA) might lead to different counted numbers of vulnerabilities, and consequently, different conclusions.

2. All versions of a software are considered as a single entity. Though they belong to a

same product line, they are still different entities because they are different by a non-negligible amount of code. Considering them as a single entity might make the validation results imprecise.

3. A model has been usually considered as a good fit to a data set if its goodness-of-fit test returns *p-value* ≥ 0.05. This threshold is sound to reject a bad model, but it is overly optimistic to conclude whether a model is good.

4. The goodness-of-fit of the models is often evaluated at a single time point (of writing the paper). This could seriously impact the conclusion about the quality of a VDM because a VDM could obtain a good fit at a certain time point (*i.e.,* horizon), but could turn to be bad at another time point. For example, while fitting AML to Win2K vulnerabilities, the experiment in [Alh05] reported the significance level *p-value* $= 0.44$, which could be positive; whereas *p-value* $= 0.05$ in [Alh07], which is bad. Moreover, no study uses VDMs as a predictor, for example, to forecast data for the next quarter.

To deal with these issues, it is necessary to have a methodology that analyzes the performance of VDMs independently and systematically. In this chapter we propose a methodology that addresses these issues, and answers two questions concerning VDMs: *"Are VDMs adequate to capture the discovery process of vulnerabilities?"*, and *"which VDM is the best?"*.

The rest of this chapter is organized as follows. Section **??** presents terminology in this chapter. Section 6.1 discusses an observation on the traditional methodology for conducting validation experiments for VDMs in the literature. Section 6.3 summarizes the proposed methodology in a nut shell. Section 6.4 details the proposed methodology. Section 6.5 summarizes the chapter.

6.1 An Observation on the Traditional Validation Methodology

This section describes an observation on the traditional validation methodology for VDMs and past valuation experiments following that method. We separate the observation into two parts. First, we summarize the previous studies on VDMs and the methodology that is employed to perform the validation. Second, we summarize the actual results of the validation performed in past studies and discuss some critical issues.

6.1.1 The Traditional Methodology

Table 6.1 summarizes VDM validation studies. Each study is reported with its target VDMs and the classes of software applications used to conduct the experiment. The table also reports the validation methodology of the studies. VDMs have been validated in several software classes spanning from server applications, browsers, to operating systems. These studies shared a common validation methodology which fitted VDMs to a single time horizon of collected vulnerability data. They used χ^2 test to determine whether a VDM fits actual data. If the test returned *p-value* ≥ 0.05, they claimed the VDM to be a good fit to the data.

Thus, we employ the χ^2 test in our methodology because it yields comparable results between traditional single horizon analysis and ours (when the horizon is restricted to be unique). Furthermore, χ^2 test seems to be the most appropriate one among other goodness-of-fit tests, such as Kolmogorov-Smirnov (K-S) test, and the Anderson-Darling (A-D) test. The K-S test is an exact test; it, however, only applies to continuous distributions. An important assumption is that the parameters of the distribution cannot be estimated from the data. Hence, we cannot apply it to perform the goodness-of-fit test for a VDM. The A-D test is a modification of the K-S test that works for some distributions [NIS12a, Chap. 1] (*i.e.,* normal, log-normal, exponential, Weibull, extreme value type I, and logistic distribution), but some VDMs violate this assumption.

Moreover, many VDM classifications of past studies claimed that a VDM is a good fit to a data set when the χ^2 test returns *p-value* ≥ 0.05 because 0.05 is the significance level to rule out models that surely do not fit. However it does not mean the models are good. We avoid this pitfall by using the acceptance threshold of 0.80, and rejection threshold of 0.05. Otherwise, a VDM is inconclusive. We further discuss about these thresholds in Section 6.4.2. Additionally, we propose *inconclusiveness contribution* factor ω as a means to study the quality of inconclusive VDM in the quality analysis.

Some studies [AM05b; AM08] employed Akaike Information Criteria (AIC) [Aka85], which measures the relative quality of a statistical model for a given data set, to compare VDMs. However, AIC gives no information about the absolute quality. It thus cannot be used to determine the goodness-of-fit of VDM. Moreover, AIC varies with the number of free parameters of a VDM. Consequently, it might not be a good indicator to compare VDMs, because a model with more free parameters naturally grants an advantage in AIC. Therefore we do not use AIC, but rely on statistic tests to determine the goodness-of-fit and compare VDMs.

The predictability of VDMs were also discussed in some studies [AM06b; Woo11; You11] by exploiting two measures, namely Average Error (AE) and Average Bias (AB) [Mal92]. How-

Table 6.1: Summary of VDM validation studies.

Akaike Information Criteria (AIC) measures the relative quality of a statistical model for a given data set. Average Error (AE) and Average Bias (AB) measure the average ratios between the actual data and the generated model.
Acronym: *OS* = operating system

			Validation Method		
Study	Validated VDM	Software Class	Fit Model	GoF test	Predictability
Alhazmi *et al.*[Alh05]	AML	OS	1 horizon	χ^2 test	–
Alhazmi *et al.*[AM05b]	AML, AT, LP, RE, RQ	OS	1 horizon	χ^2 test, AIC	–
Alhazmi *et al.*[Alh07]	AML, LN	OS	1 horizon	χ^2 test	–
Alhazmi *et al.*[AM06b]	AML, LN	Web Server	1 horizon	χ^2 test	AE,AB
Alhazmi *et al.*[AM08]	AML, AT, LN, LP, RE, RQ	OS	1 horizon	χ^2 test, AIC	–
Woo *et al.*[Woo06b]	AML	OS, Web Server	1 horizon	χ^2 test	–
Woo *et al.*[Woo06a]	AML	Browser	1 horizon	χ^2 test	–
Woo *et al.*[Woo11]	AML	OS, Web Server	1 horizon	χ^2 test	AE,AB
Joh *et al.*[Joh08]	AML, JW	OS	1 horizon	χ^2 test	–
Kim *et al.*[Kim07]	AML, MVDM	DBMS, Web Server	1 horizon	χ^2 test	–
Younis *et al.*[You11]	AML, YF	Browser, OS, Web Server	1 horizon	χ^2 test	AE,AB
Rescorla [Res05]	RE, RQ	OS	1 horizon	unknown	–

ever the application of AE and AB in these studies was inappropriate, because these measures were calculated for time points before the largest time horizon of the data set used for fitting the VDMs. The authors used a VDM fitted to the data observed at time t_0, and measured its predictability at time $t_i < t_0$. In other words, this was not 'prediction' in the common sense.

We avoid the above pitfall by analyzing the predictability of VDMs in a natural way. Concretely, we fit a VDM to the data observed at time t_0, and use the fitted model to evaluate against data observed at time $t_j > t_0$.

6.1.2 The Validation Results of VDMs in Past Studies

Table 6.2 summarizes the validation results for VDMs. This table reports the *p-values* returned by the goodness-of-fit test between generated curves and actual data. In Table 6.2, *p-values* greater than or equal 0.80 (*i.e.,* good fit) are bold, *p-values* between 0.05 and 0.80 (*i.e.,* inconclusive-fit) are italic, otherwise it is a not-fit.

The AML model, inspired by the s-shape logistic model, is proposed by Alhazmi and Malaiya [AM05b]. The idea behind is to divide the discovery process into three phases: *learn-*

Table 6.2: Summary of VDM validation results (*p-values*) in the literature.

This table reports the returned *p-values* for the goodness-of-fit tests. The values are formatted to indicate the goodness-of-fit of the VDM, particularly: **blue,bold**-good fit; *italic*-inconclusive; red-not fit.

Model	Study	Year	Firefox	IE	IE 8	Mozilla	MySQL	FreeBSD 4.0	OSX 5	RH Fedora	RH Linux 6.0	RH Linux 6.2	RH Linux 7.0	RH Linux 7.1	RHEL 2.1	RHEL 3.0	Win 2K3	Win2K	Win7	Win95	Win98	WinNT 4.0	WinXP	Apache	Apache 1	Apache 2	IIS	IIS 4	IIS 5
AML	[Alh05]	2005																*0.44*		**1**	*0.74*	**0.92**	**0.96**						
	[AM05b]	2005										**1**								**1**			**0.92**						
	[Alh07]	2006										**1**		**0.99**				*0.05*		**1**	*0.21*	**0.92**	*0.32*						
	[AM06b]	2006																							**1**	**1**		**1**	**1**
	[Woo06b]	2006																			**1**	**1**		**1**			**1**		
	[Woo06a]	2006	*0.41*	0		**1**																							
	[Kim07]	2007					**0.99**																	**1**					
	[AM08]	2008								*0.43*		**1**								**1**			*0.15*						
	[Joh08]	2008									**0.81**	**0.85**			**0.83**	*0.66*	**0.96**						**0.94**						
	[Woo11]	2011																			**1**	*0.65*		**1**			**1**		
	[You11]	2011			*0.73*				**0.98**										*0.70*							**1**			
AT	[AM05b]*	2005										0								0			0						
	[AM08]*	2008								0		0								0			0						
JW	[Joh08]	2008									**0.80**	**0.85**			**0.81**	*0.64*	**0.97**						**0.94**						
LN	[Alh07]*	2006										**0.93**		0				**1**		0	**0.95**	0	*0.08*						
	[AM06b]*	2006																							0	**1**		0	*0.23*
	[AM08]*	2008								0		0								0			0						
LP	[AM05b]*	2005										**1**								0			**0.97**						
	[AM08]*	2008								0		0								0			0						
RE	[AM05b]*	2005										**0.93**								0			**0.96**						
	[Res05]	2005						*0.29*					*0.33*																
	[AM08]*	2008								0		0								0			0						
RQ	[AM05b]*	2005										**0.92**								0			**1**						
	[Res05]	2005						*0.17*					*0.17*									*0.59*							
	[AM08]*	2008								0		*0.26*								0			**0.97**						
YF	[You11]	2011			**0.98**				**0.94**										**0.97**							**1**			

*: the validation experiment is conducted by people who are not (co-)authors of the corresponding model.

ing phase, linear phase, and *saturation phase.* First, people need time to study the software, so they discover less vulnerabilities. Second, when they understand the software, they can discover more vulnerabilities. Finally, people lose interest in finding vulnerabilities when the software is out of date. So cumulative vulnerabilities tend to be stable. However, the observation in Chapter 5 showed that this idea might not hold as vulnerabilities found for the current version usually affect also earlier ones thus generating an increase of so-called "after-life" vulnerabilities[1]. Nonetheless, we still adopt their idea in the proposed methodology by dividing software life time into three periods: young, middle-age, and old.

The AML model has been validated in several applications spanning in various software classes, see Table 6.2, such as operating systems [Alh05; AM05b; Alh07; AM08], server applications [AM06b; Woo06b; Woo11], and browsers [Woo06a]. In most cases, AML was either inconclusive-fit or good-fit. Notably, the goodness-of-fit of AML was different for the same application across different studies. For instance, AML well fitted Win98 in [Woo06b; Woo11] ($p\text{-}value = 1$), but inconclusively fitted Win98 in [Alh05] ($p\text{-}value = 0.74$) and [Alh07] ($p\text{-}value = 0.21$). The difference between *p-values* in these experiments is non-negligible. Such difference can be explained by the validation methodology based on a single horizon. This is a clear evidence that goodness-of-fit of a model is changing overtime. Thus, fitting a model to a single time horizon is potentially misleading. We cope with this issue by analyzing the VDM goodness-of-fit during the entire life time of software.

Anderson [And02] proposed the AT model based on reliability growth models, but he did not evaluate it. Other studies [AM05b; AM08] showed that AT is not appropriate.

Rescorla [Res05] proposed RQ and RE models. He validated them on WinNT 4.0, Solaris 2.5.1, FreeBSD 4.0 and RedHat 7.0. In all cases, the goodness-of-fit of these models were inconclusive since their *p-value* ranged from 0.17 to 0.59. Rescorla also discussed many shortcomings of NVD, but his study heavily relied on it nonetheless. We partially address these shortcomings by taking into account other data sources.

6.2 Research Questions

In this chapter, we address the two following questions:

RQ3 *How to evaluate the performance of a VDM?*

RQ4 *How to compare between two or more VDMs?*

In order to satisfactorily answer the questions above, we must address the following issues that potentially affected the validity of previous studies.

Vulnerability counting issue. This issue affected the vulnerability data collection process in past studies. The issue has two folds: what counted as *one* vulnerability, and what considered as *one* vulnerable software.

[1] After-life vulnerabilities of a version are ones discovered after the date when this version is out of support, see also Chapter 5.

- In the first fold, a vulnerability could be either an advisory report by software vendors (*e.g.,* MFSA), or a security bug causing software to be exploited (*e.g.,* Mozilla Bugzilla), or an entry in third-party data sources (*e.g.,* an NVD entry, or CVE, alternatively). Some entries may be classified differently by different entities: a third-party database might report vulnerabilities, but the vendor security bulletin may not classify them as such. Consequently, the number of vulnerabilities could be widely different depending on the way of counting vulnerabilities, for instance, choosing different data sources. A VDM could perfectly fit counts in a data source, but poorly fit counts in another one.

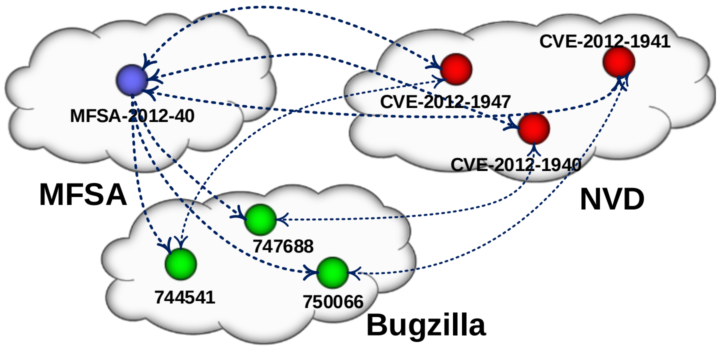
- In the second fold, some studies (*e.g.,* [Woo06a; Woo11]) considered all versions of software as a single entity, and counted vulnerabilities for it. Our previous study [Mas11] showed that each Firefox version has its own code base, which may differ by 30% or more from the immediately preceding one. The same applies to Chrome[2]. Another example, Joh *et al.* [Joh08], in their experiment, showed that AML and JW curves fitted for the 'single' Linux (*i.e.,* all versions of Linux as a single entity), and those fitted for individual Linux versions (*i.e.,* v6.0, v6.2) were utterly statistically different. Therefore, as time goes by, we can no longer claim that we are counting vulnerabilities of the same application.

Example 6.1 Figure 6.2(a) exemplifies the first fold of this issue, where a conceptual security flaw could be counted differently if different data sources were used. This flaw concerns the buffer overflow in Firefox v13.0. It is reported by: 1 entry in MFSA (MFSA-2012-40), 3 entries in Bugzilla (744541, 747688, and 750066), and 3 CVEs in NVD (CVE-2012-1947, CVE-2012-1940, and CVE-2012-1941). The cross references between these entries are illustrated as directional connections. How many vulnerabilities should we count in this case?

Figure 6.2(b) visualizes the second fold of this issue in a plot of the cumulative vulnerabilities of Firefox v1.0, Firefox v1.5, and Firefox v1.0-1.5 as a single entity. Clearly, the function of the "global" version should be different from the functions of the individual versions. ■

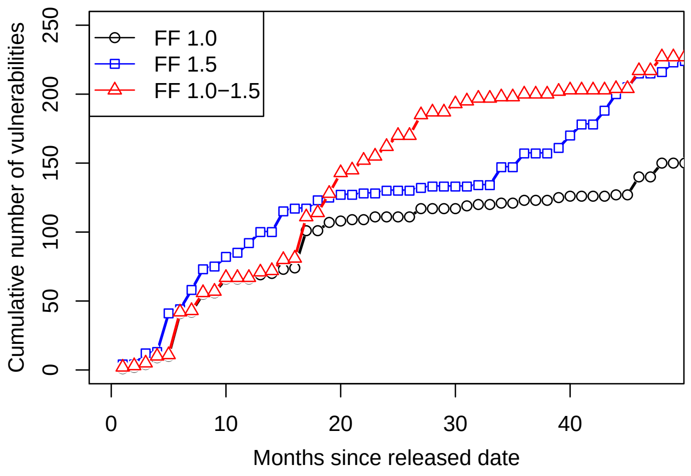
Table 7.3 later in the next chapter shows how the choice of the counting method has a massive impact on the results: by using the NVD alone, LN scores 45% of not-fit samples (third-worst), while the YF model makes a 55% of good fits (best of all). However, by counting the number of bugs correlated with number of NVD entries, *i.e.,* NVD.NBug, the roles are

[2] By looking at the source code of Chrome (`http://dev.chromium.org/Home`), we found that after one year the number of new components (*i.e.,* body and header C++ files) increases more than 100%.



The arrow-headed lines indicates the cross-references between entries.

(a) A conceptual security flaw in three data sources



This shows the cumulative vulnerabilities of Firefox v1.0, v1.5, and v1.0-v1.5 as a single entity. The "global" entity exhibits a trend that is not present in the "individual" versions.

(b) Trends between individual versions and their combination

Figure 6.2: The two folds of the vulnerability counting issue.

reversed: LN exhibits a 41% of good fits (second bests), while YF shows a disastrous 50% of not-fit samples (fourth worst).

Acceptance threshold issue. This issue affected the decision of past studies whether a model was a good fit, or a bad fit to a data set based on the result of the χ^2 test. Most of past studies concluded a model was a good fit if the χ^2 test returned *p-value* ≥ 0.05. However, 0.05 is the threshold to reject a surely bad model. Yet, there is a long stretch from concluding that a model is not surely a bad one to concluding that it is surely a good one.

Temporal goodness-of-fit issue. This issue impacted the ability of VDMs to explain history. Previous studies took a snapshot of vulnerability data, and fitted VDMs to this entire snapshot. This made a brittle claim of fitness. Moreover, it could explain historical data but told us nothing about future behavior. Yet, we are interested in the ability of VDMs to be a good “law of nature" that is valid across releases and time and to some predict extent the future.

Example 6.2 In Table 6.2, the *p-values* that AML fitted Win2K vulnerabilities in [Alh05; Alh07] were 0.44 and 0.05, respectively. While the former is inconclusive, the latter is at the border of rejection *i.e.,* not fit. This is explained because AML was fitted to data sets at two different time horizons in these experiments. ■

Comparison issue. This issue impacted the way past studies used to compare VDMs, where comparison was relied directly on the absolute *p-values* yielded by the goodness-of-fit test. The rule was: the higher *p-value*, the better model. However, the literature has shown that such *p-values* have been changing over time, see Table 6.2. As a result, we might obtain opposite conclusion if we compare VDMs at different time points.

6.3 Methodology Overview

We propose a methodology (see Table 6.3) to answer these questions. The methodology consists of data collection and analysis steps to empirically assess different aspects of VDMs. It addresses all above issues as follows:

- We address the *vulnerability counting issue* by considering different counting methods on different vulnerability data sources. Hence, the performances of VDMs are evaluated on average.

  Moreover, we evaluate VDMs on vulnerability data of individual releases of evolving applications, instead of considering all releases of an application as a single entity. The rationale for this choice is discussed later in Section 6.4.1.

- We address the *acceptance threshold issue* by employing the Type-II error threshold (*i.e.,* 0.80) which is an considered desirable threshold [McK05, Chap.8] for the power of the χ^2 test to decide whether an estimated model is a good fit. We also use the Type-I error threshold (*i.e.,* 0.05) to reject models since it is widely used in not only the literature, but also other disciplines.

- We mitigate the *temporal goodness-of-fit issue* by essentially analyzing the goodness-of-fit of VDMs monthly until the date of data collection, instead of taking an arbitrary time point in the lifetime of software. We also examine the ability of VDMs in predicting the future trend.

- We address the *comparison issue* by using statistical tests to compare VDMs based on their quality of fitting historical data and their predictability of future trends.

Table 6.3: Methodology overview.

Step 1 Acquire the vulnerability data	
DESC.	Identify the vulnerability data sources, and the way to count vulnerabilities. If possible, different vulnerability sources should be used to select the most robust one. Observed samples then can be extracted from collected vulnerability data.
INPUT	Vulnerability data sources.
OUTPUT	Set of observed samples.
CRITERIA	**CR1** *Collection of observed samples* • Vulnerabilities should be counted for individual releases (possibly by different sources). • Each observable sample should have at least 5 data points.
Step 2 Fit the VDM to observed samples	
DESC.	Estimate the parameters of the VDM formula to fit observed samples as much as possible. The χ^2 goodness-of-fit test is employed to assess the goodness-of-fit of the fitted model based on criteria CR2.
INPUT	Set of observed samples.
OUTPUT	Set of evaluated samples.

to be continued...

Table 6.3: Methodology overview (continued).

CRITERIA	**CR2** *The classification of the evaluated samples based on the p-value of a χ^2 test.* • **Good Fit**: *p-value* $\in [0.80, 1.0]$, a good evidence to accept the model. We have more than 80% chances of generating the observed sample. • **Not Fit**: *p-value* $\in [0, 0.05)$, a strong evidence to reject the model. It means less than 5% chances that the fitted model would generate the observed sample. • **Inconclusive Fit**: *p-value* $\in [0.05, 0.80)$, there is not enough evidence to neither reject nor accept the fitted model.
Step 3 Perform goodness-of-fit quality analysis	
DESC.	Analyze the goodness-of-fit quality of the fitted model by using the temporal quality metric which is the weighted ratio between fitted evaluated samples (both *Good Fit* and *Inconclusive Fit*) and total evaluated samples.
INPUT	Set of evaluated samples.
OUTPUT	Temporal quality metric.
CRITERIA	**CR3** *The rejection of a VDM.* A VDM is rejected if it has a temporal quality lower than 0.5 even by counting *Inconclusive Fits* samples as positive (with weight 0.5). Different periods of software lifetime could be considered: • 12 months (young software) • 36 months (middle-age software) • 72 months (old software)
Step 4 Perform predictability analysis	

to be continued...

Table 6.3: Methodology overview (continued).

DESC.	Analyze the predictability of the fitted model by using the predictability metric. Depending on different usage scenarios, we have different observation periods and time spans that the fitted model supposes to be able to predict. This is described in CR4.
INPUT	Set of evaluated samples.
OUTPUT	Predictability metric.
CRITERIA	**CR4** *The observation period and prediction time spans based on some possible usage scenarios.*

Scenario	Observation Period (months)	Prediction Time Span (months)
Short-term planning	6–24	3
Medium-term planning	6–24	6
Long-term planning	6–24	12

Step 5 Compare VDM

DESC.	Compare the quality of the VDM with other VDMs by comparing their temporal quality and predictability metrics.
INPUT	Temporal quality and predictability measurements of models in comparison.
OUTPUT	Ranks of models.
CRITERIA	**CR5** *The comparison between two VDM*

A VDM vdm_1 is better than a VDM vdm_2 if:

- either the predictability of vdm_1 is significantly greater than that of vdm_2,
- or there is no significant difference between the predictability of vdm_1 and vdm_2, but the temporal quality of vdm_1 is significantly greater than that of vdm_2.

The temporal quality and predictability should have their horizons and prediction time spans in accordance to criteria CR3 and CR4. Furthermore, a controlling procedure for multiple comparisons should be considered.

6.4 Methodology Details

This section discusses the details of our methodology to evaluate the performance of a VDM.

6.4.1 Step 1: Acquire the Vulnerability Data

The acquisition of vulnerability data consists of two sub steps: *Data set collection*, and *Data sample extraction*.

During *Data set collection*, we identify data sources for the study. The classification of data sources is presented in Table 3.2. For our purposes, the following features of a vulnerability are interesting and must be provided:

- *Unique ID* (R_{ID}): is the identifier of a vulnerability.
- *Discovery Date* (T_D): refers to the date when a vulnerability is reported to the database[3].
- *Affected Versions* (V_A): is a list of releases affected by a vulnerability.
- *Reference Links* (R_{REF}): is a list of links to other sources.

Not every feature is available from all data sources. To obtain missing features, we can use R_{ID} and R_{REF} to integrate data sources and extract the expected features from secondary data sources.

Example 6.3 Vulnerabilities of Firefox are reported in three data sources: NVD[4], MFSA, and Mozilla Bugzilla. Neither MFSA nor Bugzilla provides the *Affected Versions* feature, but NVD does. Each MFSA entry has links to NVD and Bugzilla. Therefore, we could to combine these data sources to obtain the missing data. ■

We address the *vulnerability counting issue* issue by taking into account different definitions of vulnerability. We collected different vulnerability data sets with respect to these definitions. We collected vulnerability data for individual releases. Table 6.4 shows different data sets in this work. They are combinations of data sources : third-party (*i.e.,* NVD), vendor advisory, and vendor bug tracker. The descriptions of these data sets for a *release r* are as follows:

[3]The actual discovery date might be significantly earlier.

[4]Other third party data sources (*e.g.,* OSVDB, Bugtraq, IBM XForce) also report Firefox's vulnerabilities, but most of them refer to NVD by the CVE-ID. Therefore, we consider NVD as a representative of third-party data sources.

Table 6.4: Formal definition of data sets.

Data set	Definition
NVD(r)	$\{\mathsf{nvd} \in \mathsf{NVD} \mid \mathsf{r} \in \mathsf{nvd}.V_A\}$
NVD.Bug(r)	$\{\mathsf{nvd} \in \mathsf{NVD} \mid \exists \mathsf{b} \in \mathsf{BUG} : \mathsf{r} \in \mathsf{nvd}.V_A \wedge \mathsf{b}.R_{ID} \in \mathsf{nvd}.R_{REF}\}$
NVD.Advice(r)	$\{\mathsf{nvd} \in \mathsf{NVD} \mid \exists \mathsf{a} \in \mathsf{ADV} : \mathsf{r} \in \mathsf{nvd}.V_A \wedge \mathsf{a}.R_{ID} \in \mathsf{nvd}.R_{REF}\}$
NVD.NBug(r)	$\{\mathsf{b} \in \mathsf{BUG} \mid \exists \mathsf{nvd} \in \mathsf{NVD} : \mathsf{r} \in \mathsf{nvd}.V_A \wedge \mathsf{b}.R_{ID} \in \mathsf{nvd}.R_{REF}\}$
Advice.NBug(r)	$\{\mathsf{b} \in \mathsf{BUG} \mid \exists \mathsf{a} \in \mathsf{ADV}, \exists \mathsf{nvd} \in \mathsf{NVD} : \mathsf{r} \in \mathsf{nvd}.V_A \wedge \mathsf{b}.R_{ID} \in \mathsf{a}.R_{REF} \wedge \mathsf{nvd}.R_{ID} \in \mathsf{a}.R_{REF} \wedge \mathsf{cluster}_{\mathsf{a}}(\mathsf{b}.R_{ID}, \mathsf{nvd}.R_{ID})\}$

Note: $\mathsf{nvd}.V_A, \mathsf{nvd}.R_{REF}$ denote the vulnerable releases and references of an entry nvd, respectively. $\mathsf{a}.R_{ID}, \mathsf{b}.R_{ID}, \mathsf{nvd}.R_{ID}$ denote the identifier of a, b, and nvd. $\mathsf{cluster}_{\mathsf{a}}(\mathsf{b}.R_{ID}, \mathsf{nvd}.R_{ID})$ is a predicate checking whether $\mathsf{b}.R_{ID}$ and $\mathsf{nvd}.R_{ID}$ are located next together in the advisory a.

- NVD(r): a set of CVEs claiming r is vulnerable.
- NVD.Bug(r): a set of CVEs confirmed by at least a vendor bug report, and claiming r is vulnerable.
- NVD.Advice(r): a set of CVEs confirmed by at least a vendor advisory, and claiming r is vulnerable. Notice that the advisory report might *not* mention r, but later releases.
- NVD.Nbug(r): a set of vendor bug reports confirmed by a CVE claiming r is vulnerable.
- Advice.NBug(r): a set of bug reports mentioned in a vendor advisory report, which also refers to at least a CVE that claims r is vulnerable.

We do *not* use the NVD alone in our studies. We will later show in Chapter 9 that it may contain significant errors to the point of tilting statistical conclusions.

For *Data sample extraction*, we extract observed samples from collected data sets. An *observed sample* is a time series of (monthly) cumulative vulnerabilities of a release. It starts from the first month since release to the end month, called *horizon*. A month is an appropriate granularity for sampling because week and day are too short intervals and are subject to random fluctuation, see also [Sch09a] for a discussion. Additionally, this granularity was used in the literature (*e.g.*, studies listed in Table 6.1).

Let R be the set of analyzed releases and DS be the set of data sets, an observed sample (denoted as os) is a time series (TS) defined as follows:

$$os = \textsc{ts}(r, ds, \tau) \tag{6.1}$$

where:

- $r \in R$ is a release in the evaluation;
- $ds \in DS$ is the data set where samples are extracted;
- $\tau \in \mathrm{T}_r = \left[\tau^r_{min}, \tau^r_{max}\right]$ is the horizon of the observed sample, in which T_r is the *horizon range of release* r.

In the horizon range of release r, the minimum value of horizon τ^r_{min} of r depends on the starting time of the first observed sample of r. Here we choose $\tau^r_{min} = 6$ for all releases so that all observed samples have enough data points for fitting all VDMs. The maximum value of horizon τ^r_{max} depends on how long the data collection period is for each release.

Example 6.4 IE v4.0 was released in September, 1997 [Wik12b]. The first month was October, 1997. The first observed sample of IE v4.0 is a time series of 6 numbers of cumulative vulnerabilities for the $1st, 2nd, \ldots, 6th$ months. Starting data collection on $01st$ July 2012, IE v4.0 would have been released for 182 months, yielding 177 observed samples. The maximum value of horizon ($\tau^{\mathsf{IEv4.0}}_{max}$) is 182. ■

6.4.2 Step 2: Fit a VDM to Observed Samples

We estimate the parameters of the VDM formula by a regression method so that the VDM curve fits an observed sample as much as possible. We denote the fitted curve (or fitted model) as:

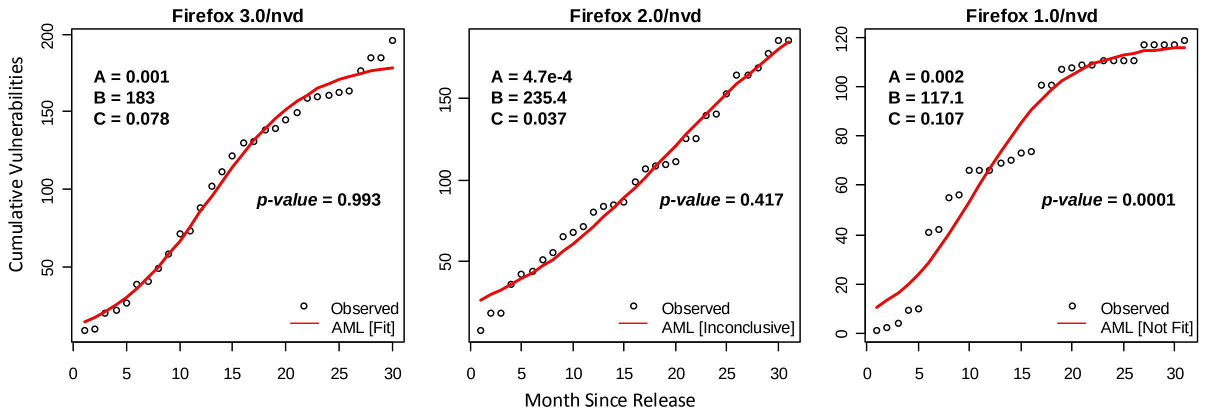
$$vdm_{\mathrm{TS}(r,ds,\tau)} \tag{6.2}$$

where vdm is the VDM being fitted; $os = \mathrm{TS}(r, ds, \tau)$ is an observed sample from which the vdm's parameters are estimated. (6.2) could be shortly written as vdm_{os}.

Example 6.5 Fitting the AML model to the NVD data set of Firefox v3.0 at the $30th$ month, *i.e.*, the observed sample $os = \mathrm{TS}(\mathsf{FF3.0}, \mathsf{NVD}, 30)$, generates the curve:

$$AML_{\mathrm{TS}(\mathsf{FF3.0},\mathsf{NVD},30)} = \frac{183}{183 \cdot 0.078 \cdot e^{-0.001 \cdot 183 \cdot t} + 1}$$

Figure 6.3 illustrates the plots of three curves $AML_{\mathrm{TS}(r,\mathsf{NVD},30)}$, where r is $\mathsf{FF3.0}, \mathsf{FF2.0}$, and $\mathsf{FF1.0}$. The X-axis shows months since release, and the Y-axis is the cumulative number of vulnerabilities. Circles represent observed vulnerabilities. Solid lines indicate fitted curves. ■



A,B,C are three parameters in the formula of the AML model: $\Omega(t) = \frac{B}{BCe^{-ABt}+1}$ (see also Table 7.2)

Figure 6.3: Fitting the AML model to the NVD data sets for Firefox v3.0, v2.0, and v1.0.

In Figure 6.3, the distances of the circles to the curve are used to estimate the goodness-of-fit of the model. To measure the goodness-of-fit, we employ Pearson's Chi-Square (χ^2) test as aforementioned in Section 6.1. In this test, we calculate the χ^2 statistic value of the curve by using the following formula:

$$\chi^2 = \sum_{t=1}^{\tau} \frac{(O_t - E_t)^2}{E_t} \tag{6.3}$$

where O_t is the observed cumulative number of vulnerabilities at time t (*i.e.,* t^{th} value of the observed sample); E_t denotes the expected cumulative number of vulnerabilities which is the value of the curve at time t. The χ^2 value is proportional to the differences between the observed values and the expected values. Hence, the larger χ^2, the smaller goodness-of-fit. If the χ^2 value is large enough, we can safely reject the model. In other words, the model statistically does not fit the observed data set. The χ^2 test requires all expected values be at least 5 to ensure the validity of the test [NIS12a, Chap. 1]. If there is any expected value less than 5, we need to increase the starting value of t in (6.3) until $E_t \geq 5$.

The conclusion whether a VDM curve statistically fits an observed sample relies on the *p-value* of the test, which is derived from χ^2 value and the degrees of freedom (*i.e.,* the number of months minus one). Semantically, the *p-value* is the probability that we falsely reject the *null hypothesis* when it is true (*i.e.,* error Type I: false positive). The null hypothesis used in past research paper is that *"the model fits the data."* [Alh07, page 225]. Therefore, if the *p-value* is less than the significance level α of 0.05, we can reject a VDM because there is less than 5% chances that this fitted model would generate the observed sample. This provides us a robust test to *discard* a model.

To accept a VDM, we exploit the power of the χ^2 test which is the probability of rejecting the null hypothesis when it is false. Normally, 'an 80% power is considered desirable' [McK05, Chap. 8]. Hence we *accept* a VDM if the *p-value* is greater than or equal to 0.80. We have more than 80% chances of generating the observed sample from the fitted curve. In other cases, we should neither accept nor reject the model (inconclusive fit).

The criteria CR2 in Table 6.3 summarizes the assessment the goodness-of-fit based on the *p-value* of the χ^2 test.

In the sequel, we use the term *evaluated sample* to denote the triplet composed by an observed sample, a fitted model, and the *p-value* of the χ^2 test.

Example 6.6 In Figure 6.3, the first plot shows the AML model with a *Good Fit* ($p\text{-}value = 0.993 > 0.80$), the second plot exhibits the AML model with an *Inconclusive Fit* ($0.05 < p\text{-}value = 0.417 < 0.80$), and the last one denotes the AML model with a *Not Fit* ($p\text{-}value = 0.0001 < 0.05$). To calculate the χ^2 test we refit the model each and every time. So we have 1,526 different parameters A, B and C for each good fit curve (see Figure 6.3). Notice how each set of parameters is widely different. If we used the same parameters for different versions, we would rarely obtain a good fit. ■

6.4.3 Step 3: Perform Goodness-of-Fit Quality Analysis

We introduce the *goodness-of-fit quality* (or *quality*, shortly) by measuring the overall number of *Good Fit*s and *Inconclusive Fit*s among different samples. Previous studies considered only one observed sample in their experiment, the one with the largest horizon.

Let $OS = \{\textsc{ts}(r, ds, \tau) | r \in R \wedge ds \in DS \wedge \tau \in \mathrm{T}_r\}$ be the set of observed samples, the *overall quality* of a model *vdm* is defined as the weighted ratio of the number of *Good Fit* and *Inconclusive Fit* evaluated samples over the total ones, as shown:

$$Q_\omega = \frac{|GES| + \omega \cdot |IES|}{|ES|} \tag{6.4}$$

where:

- $ES = \{\langle os, vdm_{os}, p\rangle | os \in OS\}$ is the set of evaluated samples generated by fitting *vdm* to observed samples;
- $GES = \{\langle os, vdm_{os}, p\rangle \in ES | p \geq 0.80\}$ is the set of *Good Fit* evaluated samples;
- $IES = \{\langle os, vdm_{os}, p\rangle \in ES | 0.05 \leq p < 0.80\}$ is the set of *Inconclusive Fit* evaluated samples;

- $\omega \in [0..1]$ is the *inconclusiveness contribution* factor denoting that an *Inconclusive Fit* is ω times less important than a *Good Fit*.

The overall quality metric ranges between 0 and 1. The quality of 0 indicates a completely inappropriate model, whereas the quality of 1 indicates a perfect one. This metric is a very optimistic measure as we are essentially “refitting" the model as more data become available. Hence, it is an upper bound value.

The factor ω denotes the contribution of an inconclusive fit to the overall quality. A skeptical analyst would expect $\omega = 0$, which means only *Good Fits* are meaningful. Meanwhile an optimistic analyst would set $\omega = 1$, which mean an *Inconclusive Fit* is as good as a *Good Fit*. The optimistic choice $\omega = 1$ has been adopted by the model proponents in their proposal while assessing the VDM quality (see Section 6.1).

The value of ω could be set based on either specific experiments, or an analysis on the average *p-value* ($\bar{p}$) of inconclusive cases. The idea of such analysis is that:

- If $\bar{p} \approx 0.05$, the VDM most likely does not fit the actual data, $\omega = 0$;
- if $\bar{p} \approx 0.80$, more likely the case that the VDM well fits the data, $\omega = 1$.

Therefore, we could approximate ω based on the average *p-value* as follows:

$$\omega \approx \frac{\bar{p} - 0.05}{0.80 - 0.05} \tag{6.5}$$

where $\bar{p}$ is the average *p-value* of inconclusive evaluated samples. We have analyzed about 6,100 inconclusive evaluated samples, the average *p-value*: $\bar{p} = 0.422$. According to (6.5), $\omega \approx 0.5$. It is consistent with the intuition that an *Inconclusive Fit* is as half-good as a *Good Fit*. The choice of $\omega = 0.5$ thus could be a good compromise.

Example 6.7 Among 3,895 evaluated samples of AML to IE, Firefox, Chrome, and Safari, AML has 1,526 *Good Fits*, 1,463 *Inconclusive Fits*. The overall quality of AML with different ω thus is:

$$\begin{aligned} Q_{\omega=0} &= \frac{1,526}{3,895} = 0.39 \\ Q_{\omega=1} &= \frac{1,526 + 1,463}{3,895} = 0.77 \\ Q_{\omega=0.5} &= \frac{1,526 + 0.5 \cdot 1,463}{3,895} = 0.58 \end{aligned}$$

■

The overall quality metric does not capture peak performance in time. A VDM could produce a lot of *Good Fits* evaluated samples for the first 6 months, but almost *Not Fits* at other horizons. Unfortunately, the metric did not address this phenomenon.

To avoid this unwanted effect, we introduce the *temporal quality* metric which represents the evolution of the overall quality over time. The temporal quality $Q_\omega(\tau)$ is the weighted ratio of the *Good Fit* and *Inconclusive Fit* evaluated samples over total ones at the particular horizon τ. The temporal quality is formulated as follows:

$$Q_\omega(\tau) = \frac{|GES(\tau)| + \omega \cdot |IES(\tau)|}{|ES(\tau)|} \tag{6.6}$$

where:

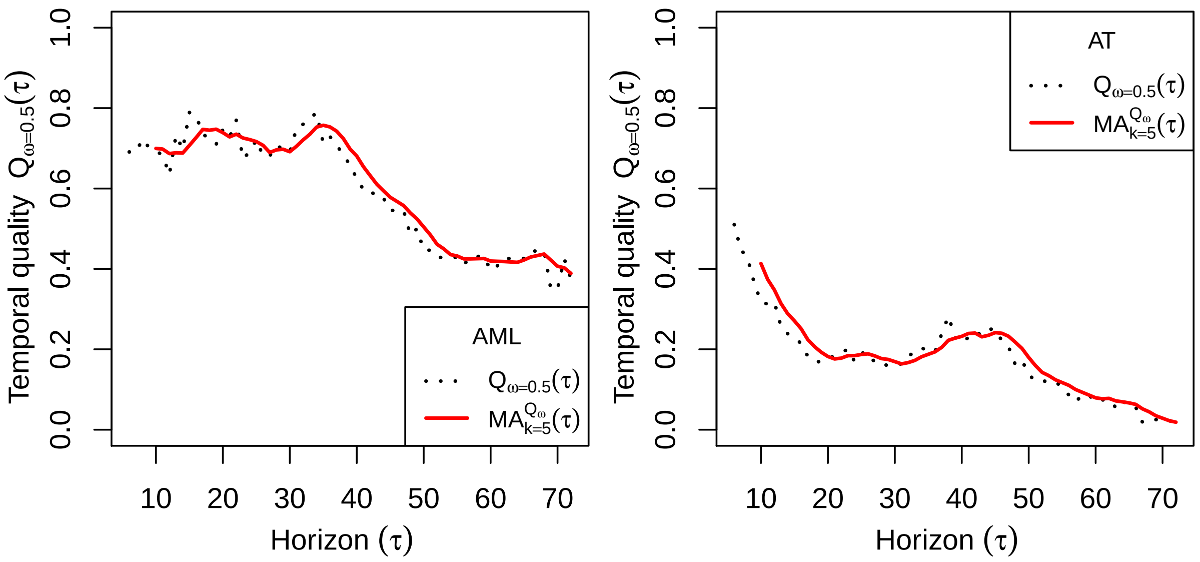
- $\tau \in \mathrm{T}$ is the horizon that we observe samples, in which $\mathrm{T} \subseteq \bigcup_{r\in R} \mathrm{T}_r$ is the subset of the union of the horizon ranges of all releases r in evaluation;
- $ES(\tau) = \left\{\langle os, vdm_{os}, p\rangle \,|\, os \in OS(\tau)\right\}$ is the set of evaluated samples at the horizon τ; where $OS(\tau)$ is the set of observed samples at the horizon τ of all releases;
- $GES(\tau) \subseteq ES(\tau)$ is the set of *Good Fit* evaluated samples at the horizon τ;
- $IES(\tau) \subseteq ES(\tau)$ is the set of *Inconclusive Fit* evaluated samples at the horizon τ;
- ω is the same as for the overall quality Q_ω.

To study the trend of the temporal quality $Q_\omega(\tau)$, we use the *moving average* which is commonly used in time series analysis to smooth out short-term fluctuations and highlight longer-term trends. Intuitively each point in the moving average is the average of some adjacent points in the original series. The moving average is defined as follows:

$$MA_k^{Q_\omega}(\tau) = \frac{1}{k}\sum_{i=1}^{k} Q_\omega(\tau - i + 1) \tag{6.7}$$

where k is the *window size*. The choice of k changes the spike-smoothening effect: the higher k, the smoother the spikes. Additionally, k should be an odd number so that variations in the mean are aligned with variations in the data rather than being shifted in time.

Example 6.8 Figure 6.4 depicts the moving average for the temporal quality of AML and AT models. In this example, we choose a window size $k = 5$ because the minimum horizon is six ($\tau^r_{min} = 6$), so k should be less than this horizon ($k < \tau^r_{min}$); and $k = 3$ is too small to smooth out the spikes. ■



Dotted lines are the temporal quality with $\omega = 0.5$, solid lines are the moving average of the temporal quality with the window size $k = 5$.

Figure 6.4: Moving average of the temporal quality of sample AML and AT models.

6.4.4 Step 4: Perform Predictability Analysis

The predictability of a VDM measures the capability of predicting future trends of vulnerabilities. This essentially makes a VDM applicable in practice. The calculation of the predictability of a VDM has two phases, *learning phase* and *prediction phase*. In the learning phase, we fit a VDM to an observed sample at a certain horizon. In the prediction phase, we evaluate the qualities of the fitted model on observed samples in future horizons.

We extend (6.6) to calculate the prediction quality. Let $vdm_{\text{TS}(r,ds,\tau)}$ be a fitted model at horizon τ. The prediction quality of this model in the next δ months (after τ) is calculated as follows:

$$Q^*_\omega(\tau,\delta) = \frac{|GES^*(\tau,\delta)| + \omega \cdot |IES^*(\tau,\delta)|}{|ES^*(\tau,\delta)|} \tag{6.8}$$

where:

- $ES^*(\tau,\delta) = \left\{\left\langle \text{TS}(r,ds,\tau+\delta), vdm_{\text{TS}(r,ds,\tau)}, p\right\rangle\right\}$ is the set of evaluated samples at the horizon $\tau+\delta$ in which we evaluate the quality of the model fitted at horizon τ ($vdm_{\text{TS}(r,ds,\tau)}$) on observed samples at the future horizon $\tau+\delta$. We refer to $ES^*(\tau,\delta)$ as set of evaluated samples of prediction;

- $GES^*(\tau,\delta) \subseteq ES^*(\tau,\delta)$ is the set of *Good Fit* evaluated samples of prediction at the horizon $\tau+\delta$;

- $IES^*(\tau,\delta) \subseteq ES^*(\tau,\delta)$ is the set of *Inconclusive Fit* evaluated samples of prediction at the horizon $\tau+\delta$.

- ω is the same as for the overall quality Q_ω.

Example 6.9 Figure 6.5 illustrates the prediction qualities of two models AML and AT starting from the horizon of $12th$ month ($\tau = 12$, left) and $24th$ month ($\tau = 24$, right), and predicting the value for next 12 months ($\delta = 0\ldots12$). White circles are prediction qualities of AML, and red (gray) circles are those of AT. ■

In planning, the idea of 3-6-12-24 month rolling plan which has been widely adopted in many fields such as banking, clinical trials, and economic planning. The basic idea is to anticipate things in next 3, 6, 12. We report the predictability of VDMs in next 3, 6, and 12 months, but not in next 24 months because all VDMs do not perform well. For example, considering that a new version is shipped at least every quarter, we could envisage the following sample scenarios:

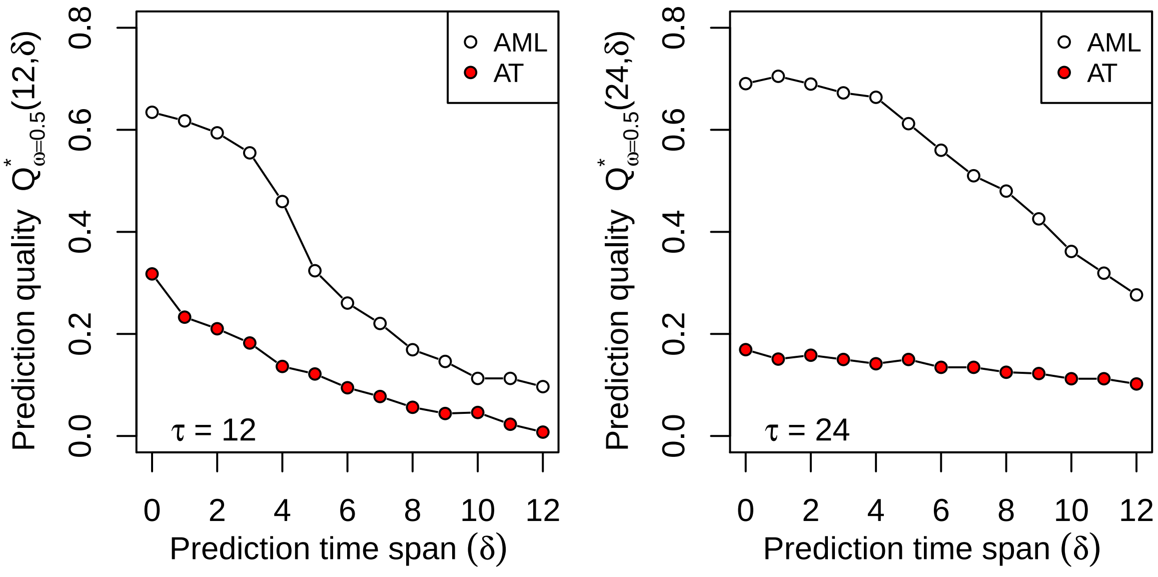
- *Short-term planning* (3 months): we are looking for the ability to predict the trend in next quarter, *i.e.,* 3 months, to plan the short-term activities such as allocating resources for fixing vulnerabilities.

- *Medium-term planning* (6 months): we are looking on what is going in next 6 months for mid-term decisions such as whether to keep the current system or to go over the hassle of updating it.

- *Long-term planning* (12 months): we would like to predict a realistic expectation for vulnerability reports in the next one year to plan the long-term activities.

We should assess the predictability of a VDM not only along the prediction time span, but also along the horizon to ensure that the VDM is able to consistently predict the vulnerability trend in an expected period. To facilitate such assessment we introduce the *predictability* metric which is the average of prediction qualities at a certain horizon.

The predictability of the curve vdm_{os} at the horizon τ in a time span of Δ months is defined as the average of the prediction quality of vdm_{os} at the horizon τ and its Δ consecutive



Picture describes how good each model is in predicting the future after having fed data of the first τ months.

Figure 6.5: The prediction qualities of AML and AT at fixed horizons $\tau = 12$ and 24 to some variable prediction time spans.

horizons $\tau+1, \tau+2, ..., \tau+\Delta$, as follows:

$$Predict_{\omega}(\tau,\Delta) = \sqrt[\Delta+1]{\prod_{\delta=0}^{\Delta} Q^*_{\omega}(\tau,\delta)} \tag{6.9}$$

where Δ is the prediction time span.

In (6.9), we use the geometric mean instead of the arithmetic mean because the temporal quality is a normalized measure. The arithmetic mean of ratios might produce a meaningless result, whereas the geometric mean behaves correctly [FW86].

6.4.5 Step 5: Compare VDMs

This section addresses the research question RQ4 concerning the comparison between VDMs based on quality and predictability.

VDMs only make sense if they could predict the future trend of vulnerabilities. Hence a VDM which perfectly fits the history data, but badly estimates the future trend even in a short period, is utterly useless: *a better model is the one that better forecasts the future.*

The comparison between two models vdm_1 and vdm_2 is done as follows. Let ρ_1, ρ_2 be the predictability of vdm_1 and vdm_2, respectively.

$$\begin{aligned}\rho_1 &= \{Predict_{\omega=0.5}(\tau,\Delta) | \tau = 6..\tau_{max}, vdm_1\} \\ \rho_2 &= \{Predict_{\omega=0.5}(\tau,\Delta) | \tau = 6..\tau_{max}, vdm_2\}\end{aligned} \tag{6.10}$$

where the prediction time span Δ could follow the criteria CR4; $\tau_{max} = \min(72, \max_{r \in R} \tau^r_{max})$. We employ the one-sided Wilcoxon rank-sum test to compare ρ_1, ρ_2. If the returned *p-value* is less than the significance level $\alpha = 0.05$, the predictability of vdm_1 is stochastically greater than that of vdm_2. It also means that vdm_1 is better than vdm_2. If *p-value* $\geq 1 - \alpha$, we conclude the opposite *i.e.,* vdm_2 is better than vdm_1. Otherwise we have not enough evidence either way.

If the previous comparison is inconclusive, we repeat the comparison using the value of temporal quality of the VDMs instead of predictability. We just replace $Q_{\omega=0.5}(\tau)$ for $Predict_{\omega=0.5}(\tau, \Delta)$ in the equation (6.10), and repeat the above activities.

When we compare models *i.e.,* we run several hypothesis tests, we should pay attention on the familywise error rate which is the probability of making one or more type I errors. To avoid such problem, we apply an appropriate controlling procedure such as the Bonferroni correction: the significance level by which we conclude a model is better than another one is divided by the number of tests performed.

Example 6.10 When we compare one model against other seven models, the Bonferroni-corrected significance level is: $\alpha = {}^{0.05}/_{7} \approx 0.007$. ■

The above comparison activities are summarized in the criteria CR5 (see Table 6.3).

6.5 Chapter Summary

This chapter has discussed an observation on the traditional validation methodology for VDMs in the literature. The observations has revealed several issues in that methodology. These issues might bias the outcomes of any validation experiments which follow the traditional methodology. Based on that observation, this chapter has proposed an empirical methodology for conducting validation experiments for VDMs. The methodology consisted of five steps which include two quantitative analyses: *quality analysis* and *predictability analysis*. In each step, we proposed criteria as base lines to help analysts during the evaluation of VDMs. Some of criteria however are not fixed, but could be change to match the custom need of different usage scenarios of VDMs.

In the next chapter, we will describe an experiment to evaluate the performance of several existing VDMs. The experiment follows the methodology described in this chapter. By the experiment in the next chapter, we aim to test the validation methodology in this chapter.

CHAPTER 7

AN EVALUATION OF EXISTING VULNERABILITY DISCOVERY MODELS

The previous chapter has proposed an empirical methodology to evaluate the performance of VDMs. This chapter applies this method to conduct a validation experiment to evaluate the performance of several existing VDMs. The experiment assesses these VDMs in different usage scenarios in order to 1) study whether existing VDMs are applicable in real (or close-to-real) world settings, and 2) understand which is the superior VDM in which usage scenario. The results show that some models should be rejected outright, while some others might be adequate to capture the discovery process of vulnerabilities. Furthermore, among considered usage scenarios, the simplest linear model is the most appropriate choice in terms of both quality and predictability when a browser version is young. Otherwise, logistics-based models are better choices.

THIS chapter applies the methodology proposed in the previous chapter to evaluate analyze to which extent existing VDMs could be employed in different usage scenarios that have been previously discussed in Chapter 6. The following VDMs are evaluated in the experiment described in this chapter: AML, AT, JW, LN, LP, RE, RQ, and YF.

As apparent from Table 6.2, researchers often chose operating systems as target applications to validated VDMs, but paid little attention to other software classes, especially web browsers. Moreover the discussion in Chapter 4 shows that web browsers are one of the most important class of internet applications. Web browsers are one of the top-ten products which have much vulnerabilities recently. Additionally, operating systems, another top-ten products, have been validated several times in the past (Table 6.1). Thus, in this validation experiment, we validate VDMs on web browsers.

The rest of this chapter is organized as follows. Section 7.1 presents the research questions of this chapter. Section 7.2 describes the experiment setup. Section 7.3 reports and discusses the outcomes of the experiment. Finally, Section 7.4 discusses the difference of results obtained by the traditional validation methodology and the one described in Chapter 6. Section 7.5 discusses the threats to validity. Section 7.6 summarizes the chapter.

7.1 Research Questions

This chapter focuses on the following research questions:

RQ6 *Is the proposed VDM evaluation methodology effective in evaluating VDMs?*

RQ7 *Among existing VDMs, which one is the best?*

We answer the above questions by conducting a *quality analysis* and a *predictability analysis* (see also Section 6.4.3 and Section 6.4.4) that follow the guidelines in the previous chapter to evaluate the performance of VDMs, and to compare VDMs. While performing these analyses, we set the *inconclusiveness factor* ω to 0.5 which could be considered as a good compromise for inconclusive cases of goodness-of-fit (see the discussion why we choose this value in Section 6.4.3). We use this setting to justify the applicability of a VDM in this experiment, as well as to compare VDMs. Furthermore, the quality and predictability metrics might be uniformly distributed from 0 to 1, where 0 indicates an completely inappropriate model while 1 means a perfectly fitted one. Hence we choose the mid point value of 0.5 as a base line for the assessment of the applicability and the predictability. In other words, we expect an appropriate (or adequate) VDM should have its quality and predictability significantly greater than 0.5 *i.e.,* above the average.

7.2 Experimental Setup

This section describes the software infrastructure and the descriptive statistics of observable samples. The data sources of vulnerabilities are described in Table 4.1. We employ the software infrastructure discussed in Section 4.1 to acquire vulnerability data for browsers.

7.2.1 The Software Infrastructure

Figure 7.1 illustrates the software infrastructure for the experiment. In this figure, rectangles denote the scripts. Arrows illustrate the direction of data flows. The infrastructure consists of three scripts as follows:

- *Data Resample script.* This script takes the browsers' vulnerability data (see Section 4.1) for sampling observed data samples. The outcome of this script is a collection of observed data samples representing for six data sets as described in Table 6.4. The observed data samples are then piped to the *VDM Model Fitting* script.
- *VDM Model Fitting script.* This script takes observed data samples and performs model fitting for all data samples to all VDMs. The output is a collection of evaluated samples which are routed to the latter processor. The output of the script is a collection of evaluated data samples.
- *VDM Quality/Predictability Analysis script.* This script takes the generated evaluated samples and executes the quality, predictability analysis (see Step 3, Step 4). It also executes the VDMs comparison (Step 5).

The schemas of the observed data samples and evaluated samples are described as follows:

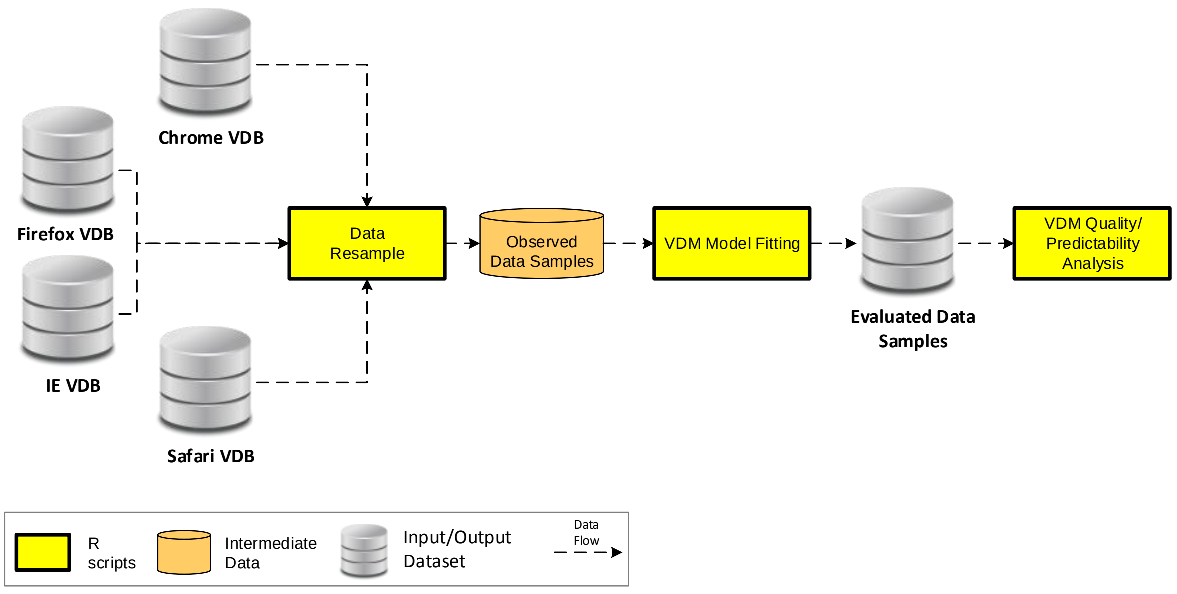


Figure 7.1: The software infrastructure of the experiment.

$$\begin{aligned}
\textit{Observed Data Samples} &= (\mathsf{dataset},\ \mathsf{browser},\ \mathsf{version},\ \mathsf{horizon},\ \mathsf{dataPoints}) \\
\textit{Evaluated Data Samples} &= (\mathsf{vdmModel},\ \mathsf{dataset},\ \mathsf{browser},\ \mathsf{version},\ \mathsf{horizon},\ \mathsf{p\text{-}value})
\end{aligned}$$

The feature dataset determines the way data were sampled; horizon, measured by months since the release date of the corresponding version, is the time point when data is sampled; dataPoints is a time series of monthly cumulative vulnerabilities since the first month to the observed horizon; vdmModel is the estimated model of a particular VDM to an observed data sample represented by browser, version, and horizon; $\mathsf{p}-\mathsf{value}$ is the returned *p-value* by the χ^2 test for the goodness-of-fit of the estimated model to the observed data sample.

7.2.2 Collected Vulnerability Data Sets

Table 7.1 reports the descriptive statistics of observed samples in five collected data sets (see Table 6.4). In the table, we use dashes (–) to denote the unavailability of some data sets for some browsers due to the lack of data sources (see Table 4.1). The latest time horizon for these data set is $30th$ June 2012. It means vulnerabilities reported after the date are not in consideration. In total, we have collected $4,507$ observed samples for 30 major releases of browsers, *i.e.,* Chrome v1.0–v12.0, Firefox v1.0–v5.0, IE v4.0–v9.0, and Safari v1.0–v5.0.

Notably, the above collected data sets are not independent each others, for instance NVD.Bug and NVD.Advice are sub sets of NVD. They represent for different ways of counting vulnerabilities from the NVD data source. In our experiment we treat these data sets equally and fit them all to VDMs to avoid the *vulnerability definition bias* (Section 6.2). This might have the accumulative effect on the quality and predictability analysis.

However, this accumulative effect might be negligible because the later Table 7.3 reporting the statistics of evaluated samples shows an evidence that the responses of VDMs to these

Table 7.1: Descriptive statistics of observed data samples

Column names: med. - median, μ - mean, σ - standard deviation. Dash (–) means data set is not available due to missing data sources.

Browser	Releases	NVD				NVD.Bug				NVD.Advice				NVD.NBug				Advice.NBug				All Data Sets			
		Total	med.	μ	σ	Total	med.	μ	σ	Total	med.	μ	σ	Total	med.	μ	σ	Total	med.	μ	σ	Total	med.	μ	σ
Firefox	8	378	*42*	*47*	*30*	378	*42*	*47*	*30*	378	*42*	*47*	*30*	378	*42*	*47*	*30*	378	*42*	*47*	*30*	1,890	*210*	*236*	*148*
Chrome	12	281	*20*	*23*	*10*	281	*20*	*23*	*10*	–	–	–	–	281	*20*	*23*	*10*	–	–	–	–	843	*62*	*70*	*29*
IE	5	573	*130*	*115*	*59*	–	–	–	–	573	*130*	*115*	*59*	–	–	–	–	–	–	–	–	1,146	*260*	*229*	*118*
Safari	5	314	*60*	*63*	*35*	–	–	–	–	314	*60*	*63*	*35*	–	–	–	–	–	–	–	–	628	*120*	*126*	*69*
Total	30	1,546	*36*	*52*	*44*	659	*27*	*33*	*23*	1,265	*64*	*70*	*48*	659	*27*	*33*	*23*	378	*42*	*47*	*30*	4,507	*104*	*150*	*118*

Table 7.2: The VDMs in evaluation and their equation.

VDMs are listed in the alphabetical order. The meaning of the VDMs' parameters are referred to their original work.

Model	*Equation*
Alhazmi-Malaiya Logistic (AML) [Alh05]	$\Omega(t) = \frac{B}{BCe^{-ABt}+1}$
Anderson Thermodynamic (AT) [And02]	$\Omega(t) = \frac{k}{\gamma}\ln(t) + C$
Joh Weibull (JW) [Joh08]	$\Omega(t) = \gamma(1 - e^{-\left(\frac{t}{\beta}\right)^{\alpha}})$
Linear (LN)	$\Omega(t) = At + B$
Logarithmic Poisson (LP) [MO84]	$\Omega(t) = \beta_0 \ln(1 + \beta_1 t)$
Rescorla Exponential (RE) [Res05]	$\Omega(t) = N(1 - e^{-\lambda t})$
Rescorla Quadratic (RQ) [Res05]	$\Omega(t) = \frac{At^2}{2} + Bt$
Younis Folded (YF) [You11]	$\Omega(t) = \frac{\gamma}{2}\left[\mathrm{erf}\left(\frac{t-\tau}{\sqrt{2}\sigma}\right) + \mathrm{erf}\left(\frac{t+\tau}{\sqrt{2}\sigma}\right)\right]$

Note: *erf()* is the error function, $\mathrm{erf}(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}\,dt$

data sets are very different.

7.3 An Assessment on Existing VDMs

We apply the methodology to assess the performance of existing VDMs (see also Table 7.2). The experiment evaluates these VDMs on 30 releases of the four popular web browsers: IE, Firefox, Chrome, and Safari. Here, only the formulae of these models are provided. More detail discussion about these models as well as the meaning of their parameters are referred to their corresponding original work.

In this assessment, we consider 8 out of 10 VDMs listed in the taxonomy (see Figure 6.1). Two models MVDM and Effort-based AML (AML-E) are excluded because: *1)* MVDM requires additional data concerning source code analysis, *i.e.*, the ratio of share code between versions, which is only available for Chrome and Firefox; *2)* AML-E uses a different approach that attempts to use test-effort as the main factor instead of calendar time, which are not comparable to other models.

Table 7.3: The number of evaluated samples.

Column names: G.F - Good Fit, I.F - Inconclusive Fit, N.F - Not Fit.

Model	NVD				NVD.Bug				NVD.Advice				NVD.NBug				Advice.NBug				All Data Sets			
	Total	G.F	I.F	N.F	Total	G.F	I.F	N.F	Total	G.F	I.F	N.F	Total	G.F	I.F	N.F	Total	G.F	I.F	N.F	Total	G.F	I.F	N.F
AML	1,375	***43%***	*32%*	*24%*	559	*30%*	***48%***	*22%*	1,064	***49%***	*24%*	*27%*	559	***77%***	*12%*	*10%*	338	***62%***	*13%*	*25%*	3,895	***49%***	*28%*	*23%*
AT	1,378	*8%*	*18%*	***74%***	559	*10%*	*15%*	***75%***	1,157	*9%*	*17%*	***74%***	559	*8%*	*15%*	***77%***	338	*5%*	*38%*	***57%***	3,991	*8%*	*19%*	***73%***
JW	1,344	*39%*	*18%*	***44%***	547	*28%*	*30%*	***42%***	1,019	***64%***	*10%*	*26%*	551	*40%*	*14%*	***46%***	336	***60%***	*21%*	*19%*	3,797	***46%***	*17%*	*37%*
LN	1,378	*36%*	*19%*	***45%***	559	*20%*	*31%*	***49%***	1,157	*41%*	*16%*	***43%***	559	***41%***	*23%*	*36%*	338	*40%*	*15%*	***45%***	3,991	*36%*	*20%*	***44%***
LP	1,377	*42%*	*14%*	***43%***	559	*19%*	*34%*	***46%***	1,069	***46%***	*13%*	*41%*	559	*28%*	*20%*	***52%***	338	*33%*	***46%***	*20%*	3,902	*37%*	*20%*	***42%***
RE	1,378	*41%*	*14%*	***44%***	559	*20%*	*34%*	***46%***	1,069	***46%***	*13%*	*41%*	559	*13%*	*27%*	***60%***	338	*17%*	*30%*	***52%***	3,903	*33%*	*20%*	***47%***
RQ	1,378	*29%*	*20%*	***51%***	559	*24%*	*34%*	***43%***	1,157	***50%***	*10%*	*39%*	559	*14%*	*13%*	***74%***	338	*4%*	*2%*	***94%***	3,991	*30%*	*16%*	***53%***
YF	1,358	***55%***	*20%*	*25%*	551	***54%***	*29%*	*17%*	966	***71%***	*11%*	*19%*	558	*28%*	*22%*	***50%***	338	*14%*	*7%*	***78%***	3,771	***51%***	*18%*	*31%*
Total	10,966	*37%*	*19%*	***44%***	4,452	*26%*	*32%*	***43%***	8,658	***46%***	*14%*	*40%*	4,463	*31%*	*18%*	***51%***	2,702	*30%*	*22%*	***49%***	31,241	*36%*	*20%*	***44%***

We follow Step 2 to fit the above VDMs to collected observed samples. The model fitting relies on the function `nls()` of R [R D11]. The model fitting took approximately 82 minutes on a dual-core 2.73GHz Windows machine with 6GB of RAM yielding 31,241 curves in total. Notably, during the model fitting, `nls()` is unable to fit some models in some observed samples. Hence the number of generated curves are less than the number of observed samples multiplied by the number of VDMs.

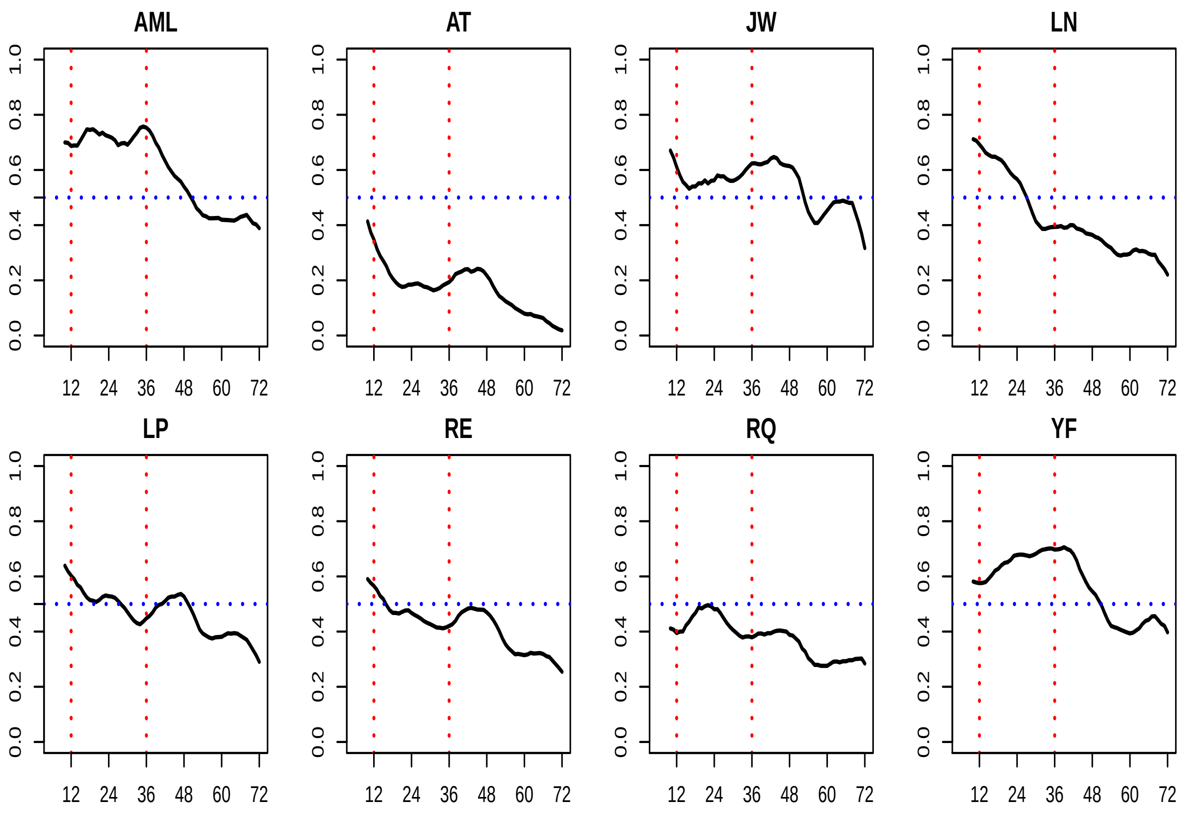
Table 7.3 reports the number of evaluated samples for each VDM in each data set. We also report the percentage of *Good Fit*, *Inconclusive Fit*, and *Not Fit* in each data set. Apparently, AML and YF obtain more *Good Fits* than other models, in relative percentage of the number of evaluated samples in each data set. Additionally, VDMs obtain more *Good Fits* in NVD.Advice than other data sets.

Subsequently, we perform the analysis on the quality and the predictability of VDMs according to Step 3 and Step 4. We also execute Step 5 to compare VDMs.

7.3.1 Goodness-of-Fit Analysis for VDMs

The analysis is conducted on all evaluated samples based on all collected data sets. The inconclusiveness contribution factor ω is set to 0.5 as described in CR3. As discussed, we reuse the three-phase idea from the AML model to divide the life time of a browser into three periods: *young* – when a browser is released for 12 months or less; *middle-age* – released for 13 – 36 months; and *old* – released more than 36 months.

Figure 7.2 exhibits the moving average (windows size $k = 5$) of the temporal quality $Q_\omega(\tau)$. We cut $Q_\omega(\tau)$ at horizon 72 though we have more data for some systems (*e.g.,* IE v4, FF v1.0):



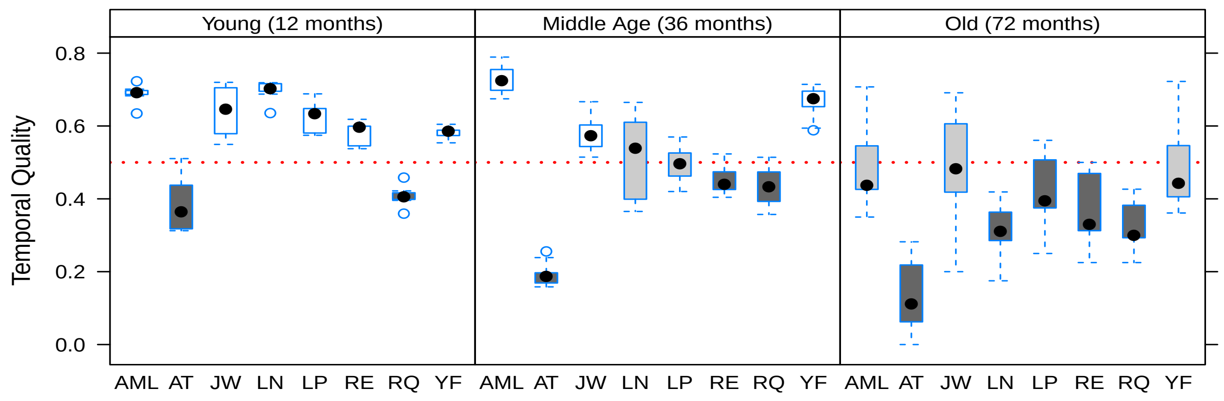
The X-axis is the number of months since release (*i.e.*, horizon τ). The Y-axis is the value of temporal quality. The solid lines are the moving average of $Q_{\omega=0.5}(\tau)$ with window size $k = 5$. The dotted horizontal line at 0.5 is the base line to assess VDM. Vertical lines are the marks of the horizons of $12th$ and $36th$ month.

Figure 7.2: The trend of temporal quality $Q_{\omega=0.5}(\tau)$ of the VDMs in first 72 months.

the vulnerability data reported for versions released after 6 years might be not reliable, and might overfit the VDMs. The dotted vertical lines marks horizons 12 and 36 corresponding to browser age periods. The dotted horizon line at 0.5 is used as a base line to assess VDMs.

Figure 7.2 shows a clear evidence that both AT and RQ should be rejected since their temporal qualities always sink below the base line. Other models may be adequate when browsers are young. AML and LN look better than other models in this respect.

In the middle-age period, the AML model is still relatively good. JW and YF improve when approaching month $36th$ though JW get worse after month $12th$. The quality of both LN and LP worsen after month $12th$, and sink below the base line when approaching month $36th$. RE is almost below the base line after month $15th$. Hence, in the middle-age period, AML, JW, and YF models may turn to be adequate; LN and LP are deteriorating but might be still considered adequate; whereas RE should clearly be rejected.



A horizonal line at value of 0.5 is used as the base line to justify temporal quality. Box plots are coloured with respect to the comparison between the corresponding distribution and the base line: white - significantly above the base line, gray - no statistical difference, dark gray - significantly below the base line (*i.e.,* rejected).

Figure 7.3: The temporal quality distribution of each VDM in different periods of software lifetime.

When browsers are old (36+ months), AML, JW, and YF deteriorate and dip below the base line since month 48*th* (approx.), while others collapse since month 36*th*.

Figure 7.3 summarizes the distribution of VDM temporal quality in three periods: *young* (before month 12*th*), *middle-age* (month 13*th*-36*th*), and *old* (month 37*th*-72*nd*). The red horizontal line at 0.5 is the base line. We color these box plots according to the comparison between the corresponding distribution and the base line as follows:

- white: significantly greater than the base line;
- dark gray: significantly less than the base line (we should reject the models);
- gray: not statistically different from the base line.

The box plots clearly confirm our observation in Figure 7.2. Both AT and RE models are all significantly below the base line. AML, JW, and YF modes are significantly above the base line when browsers are young and middle age, and not statistically different from the base line when browsers are old. LN and LP models are also significantly good when browsers are young, but are deteriorating in the middle-age period, and dip below the base line for old browsers.

In summary, our quality analysis shows that:

- AT and RQ models should be rejected.

- All other models may be adequate when browser is young. Only s-shape models (*i.e.,* AML, YW, YF) might be adequate when browsers are middle-age.
- No model is good enough when the browsers are too old.

7.3.2 Predictability Analysis for VDMs

From the previous quality analysis, AT and RQ models are low quality. Hence, we exclude these models from the predictability analysis. Furthermore, since no model is good when browsers are too old, we analyze the predictability of these models only for the first 36 months since the release of a browser. This period is still a large time if we consider that most recent releases live less than a year [Chr12; Wik12a; Wik12b; Wik12c].

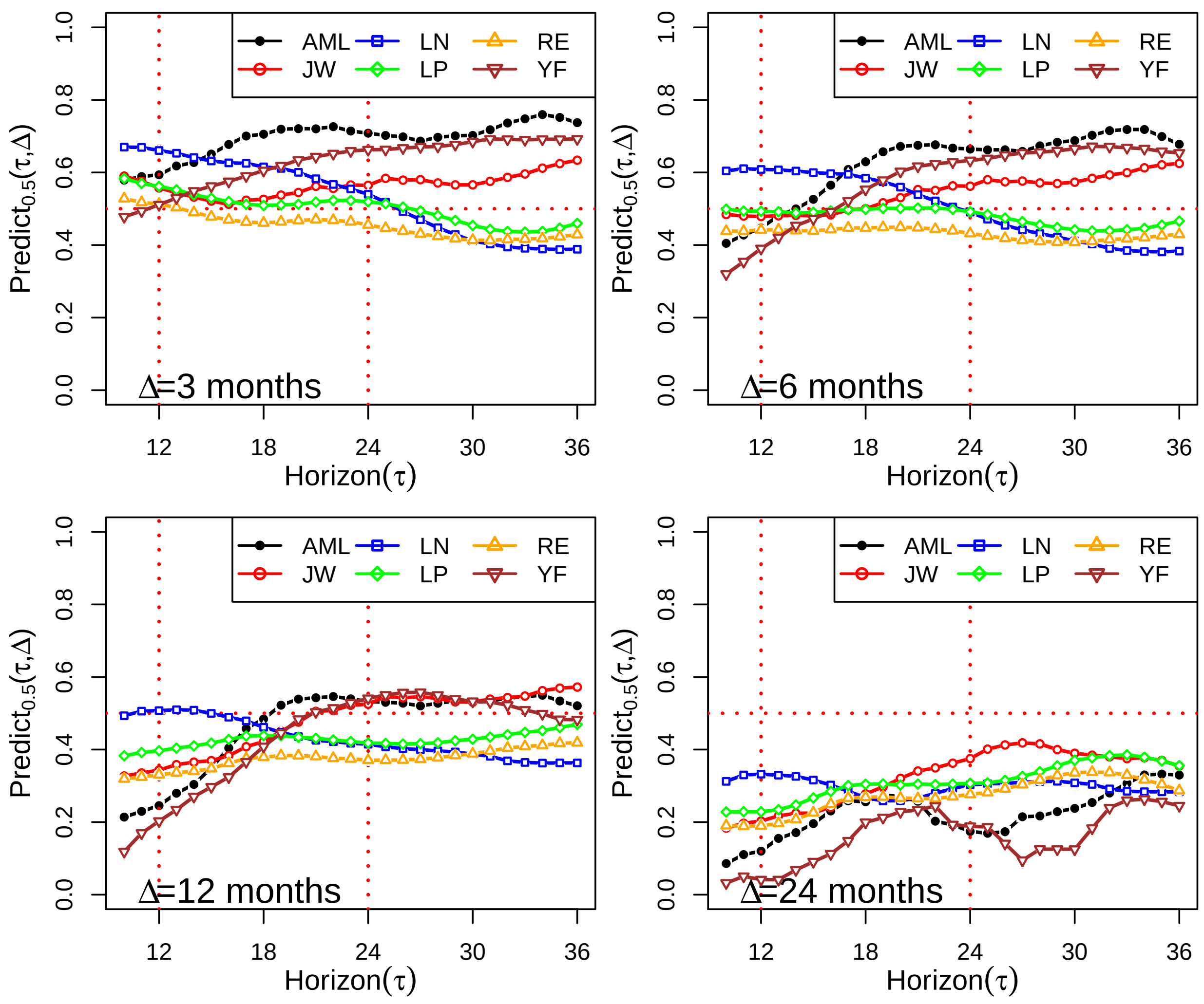
Predictability is a bi-dimensional function as it takes the horizon of data collection for fitting and the prediction time. Figure 6.5 shows a graph where the horizon is fixed at 12 and 24 while the prediction time varies and the ability to predict invariably decreases as we move further into the future.

In Figure 7.4 we keep the prediction time fixed and let the fitting horizon vary: our purpose is to understand which is the best model for a given time horizon. As we can see from the picture, the predictability lines go down (model is good at the beginning bug deteriorates with software ages) as well as up (model is more appropriate for older software).

Figure 7.4 reports the moving average (windows size equals 5) for the trends of VDMs' predictability along horizons in different prediction time spans. The horizonal line at 0.5 is the base line to assess the predictability of VDMs (as same as the temporal quality of VDMs).

When the prediction time span is short ($\Delta = 3$ months, top-left corner), the predictability of LN, AML, JW, and LP models is above the base line for young software (12 months). When software is approaching month $24th$, though decreasing the predictability of LN is still above the base line, but goes below the base line after month $24th$. The LP model is no different with the base line before month $24th$, but then also goes below the base line. In contrast, the predictability of AML, YF and JW are improving with age. They are all above the base line until the end of the study period (month $36th$. Therefore, only s-shape models (AML, YF, and JW) may be adequate for middle-age software.

For the medium prediction time span of 6 months, only the LN model may be adequate (above the base line) when software is young, but becomes inadequate (below the base line) after month $24th$. S-shape models are inadequate for young software, but are improving quickly as software ages. They become adequate after month $18th$ and keep this performance until the end of the study period.

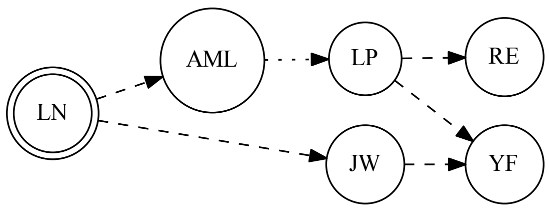


A horizonal line at value of 0.5 is the base line to assess the predictability.

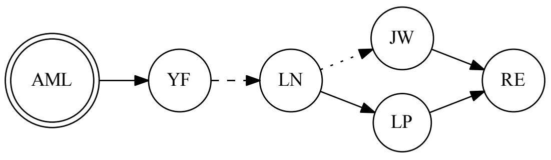
Figure 7.4: The predictability of VDMs in different prediction time spans (Δ).

When the prediction time span is long (*i.e.*, 12 months), LN is approximately around the base line, while all other models sink below it for young browsers. In other words, no model could be adequate for young browsers in this prediction time span. After month $18th$, the AML model goes above the base line, and after month $24th$, all s-shape models are above the base line.

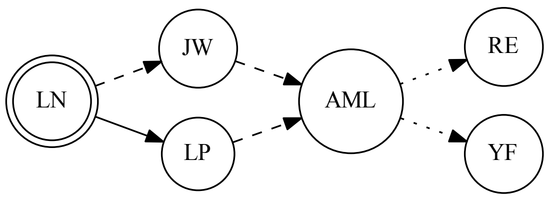
When the prediction time span is very long (*i.e.*, 24 months) no model is good enough as all models sink below the base line.



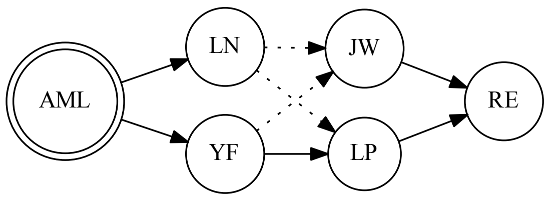
(a) Young releases, short-term prediction (τ = 6..12, Δ = 3)



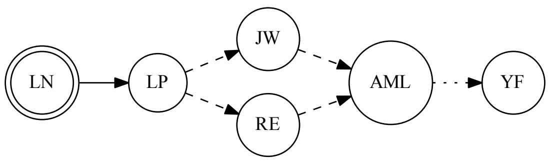
(b) Middle-age releases, short-term prediction (τ = 12..24, Δ = 03)



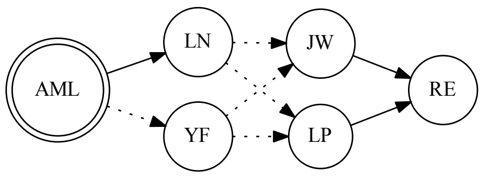
(c) Young releases, medium-term prediction (τ = 6..12, Δ = 6)



(d) Middle-age releases, medium-term prediction (τ = 12..24, Δ = 6)



(e) Young releases, long-term prediction (τ = 6..12, Δ = 12)



(f) Middle-age releases, long-term prediction (τ = 12..24, Δ = 12)

A directed connection from two nodes determines that the source model is better than the target one with respect to their predictability (dashed line), or their quality (dotted line), or both (solid line). A double cirlce marks the best model. RQ and AT are not shown as they are the worst models.

Figure 7.5: The comparison results among VDMs in some usage scenarios.

7.3.3 Comparison of VDMs

The comparison between VDMs follows Step 5. Instead of reporting tables of *p-value*s, we visualize the comparison results in terms of directed graphs where nodes represent models, and connections represent the order relationship between models.

Figure 7.5 summarizes the comparison results between models in different settings of horizons (τ) and prediction time spans (Δ). A directed connection from two models determines that the source model is better than the target model in terms of either predictability, or quality, or both. The connection line-style is as follows:

- *Solid line*: the predictability and quality of the source is significantly better than the

Table 7.4: Suggested models for different usage scenarios.

Observation Period (month)	Prediction Time Span (month)		Best Model	$2nd$ Best Model(s)
6 – 12	3	(short-term)	LN	AML, JW
6 – 12	6	(medium-term)	LN	JW, LP
6 – 12	12	(long-term)	LN	LP
13 – 24	3	(short-term)	AML	YF
13 – 24	6	(medium-term)	AML	YF, LN
13 – 24	12	(long-term)	AML	YF, LN

target's.

- *Dashed line*: the predictability of the source is significantly better than the target.
- *Dotted line*: the quality of the source is significantly better than the target.

By the word *significantly*, we means the *p-value* of the corresponding one-sided Wilcoxon rank-sum test is less than the significance level. We apply the Bonferroni correction to control the multi comparison problem, hence the significance level is: $\alpha = 0.05/5 = 0.01$.

Based on Figure 7.5, Table 7.4 suggests model(s) for different usage scenarios described in CR4 (see Table 6.3).

In short, *when browsers are young, the LN model is the most appropriate choice. This is because the vulnerability discovery process is linear. When browsers are approaching middle-age, the AML model becomes superior.*

7.4 Discussion

This section compares our methodology to the traditional validation method described in Section 6.1. For the traditional methodology: VDMs are fitted to the NVD data set at the largest horizon. In other words, we use following observed samples to evaluate VDMs:

$$OS_{\mathsf{NVD}} = \left\{\textsc{ts}(r, \mathsf{NVD}, \tau^{r}_{max}) | r \in R\right\}$$

where R is the set of all releases mentioned in Section 7.2.2.

The fitting results are reported in Table 7.5. To improve readability, we report the categorized goodness-of-fit based on the *p-value* (see CR2) instead of the raw *p-value*s. In this

Table 7.5: A potentially misleading results of overfitting VDMs in the largest horizon of browser releases, using NVD data sets

The goodness of fit of a VDM is based on *p-value* in the χ^2 test. *p-value* < 0.05: not fit (×), *p-value* ≥ 0.80: good fit (✓), and inconclusive fit (blank) otherwise. It is calculated over the entire lifetime.

	Firefox								**Chrome**												**IE**					**Safari**				
	1	1.5	2	3	3.5	3.6	4	5	1	2	3	4	5	6	7	8	9	10	11	12	4	5	6	7	8	1	2	3	4	5
AML	×	×		×	✓				✓		×				×		✓			×	✓		×		✓	×				✓
AT	×	×	×	×	×	×			×	×	×	×	×	×	×	×	×	×	×		×	×	×	×	×	×	×	×	×	
JW	×	×	✓	✓	✓	✓	✓		×	×	×	×			✓	✓					×	✓	×	✓		×	×	×	×	×
LN	×	×		×			✓		×	×	×	×								×	×	×	×	✓		×	×	×	×	
LP	×	×	✓	✓	✓	✓	✓		×	×	×	×	×				×				×	✓	×	×	✓	×	×	×	×	
RE	×	×	✓	✓	✓	✓	✓		×	×	×	×	×				×				×	✓	×	×	✓	×	×	×	×	
RQ	×	×	×	×	×		✓		×	×	×					×	×	×	×	×	×	×	×	×	✓	×	×	×	×	×
YF	×	×	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		×				✓	✓	✓	×	✓	×	×	×	×	

table, we use a check mark (✓), a blank, and a cross (×) to respectively indicate a *Good Fit*, an *Inconclusive Fit*, and a *Not Fit*. Cells are shaded accordingly to improve the visualization effect. Notably, as in the literature, an *Inconclusive Fit* is equivalent to a *Good Fit*, *i.e., inconclusiveness contribution* factor $\omega = 1$.

The table shows that two models AT and RQ have a large number of *Not Fits* entries (90% and 70% respectively); whereas other models have less than 50% *Not Fits* entries. Yet only the YF model has more than 50% *Good Fits* entries. We observe that this is a very large time interval and some systems have long gone into retirement. For example, FF v2.0 vulnerabilities are no longer sought by researchers. They are a byproduct of research on later versions.

From Table 7.5, we might conclude: *(1)* AML and YF are the "best" model (YF is slightly better than AML); *(2)* AT and RQ are the "worst"; and *(3)* other models are approximately equal.

With reference to Table 7.6, the conclusions obtained by the traditional methodology are clearly less informative than those by the proposed methodology. They both agree that AT and RQ are the worst. However, our methodology provides statistical evidences about the superior performance of LN and AML in *different* periods of browser life time, whereas the traditional one does not. Our methodology therefore supports for selection of VDMs better than the traditional one.

An interesting issue is whether we need the full complexity of the methodology and could attain the same insight by a reduced number of steps. As an example, we could have stopped the analysis at Step 2, after the production of Table 7.3. However, this table could not also distinguish between AML and YF. Moreover, it obfuscates the advantages of LN. Hence, in order to obtain a sound evidence we really need to consider the subsequent steps that analyze temporal quality and predictability.

In conclusion, *our proposed methodology is better than the traditional one by providing more sound evidences about the performance of VDMs in different usage scenarios along the software life time.*

7.5 Threats to Validity

Construct validity includes threats affecting the way we collect vulnerability data and the way we generate VDM curves with respect to the collected data. Following threats in this category are identified:

Bias in data collection. Similar to the observation in Chapter 5, we also apply the software infrastructure described in Chapter 4. As discussed, it might have some construction validity to the observation in this chapter. We inherit the mitigation described in Section 4.2 to reduce the bias in the collected data.

Bias in bug-affects-version identification. We do not completely known which bugs affect which versions. We assume that a bug affects all versions mentioned in its linked NVD entry. This might overestimate the number of bugs in each version. To mitigate this, we estimate the latest release that a bug might impact, and filter all vulnerable releases after this latest. Such estimation is done by the technique discussed in [Sli05; NM13c]. The potential errors in NVD discussed in [NM13c] only affect the retrospective fitness of models over the long term so only valuations after 36 months might be affected.

Bias in NVD. We determine the browser versions affected by a vulnerability by looking at the “vulnerable versions” list in the NVD entry. If these entries are not reliable, we may have bias in the analysis. We have manually confirmed accuracy for few NVD entries. As also discussed in Section 5.3, an automatic large-scale calibration should be done. Indeed, we have done such calibration in Chapter 9 where we report the bias in NVD, but we have not yet revisited the findings in this experiment. This would be a part of future work.

Error in curve fitting. We fitted VDMs on data by using the Nonlinear Least-Square technique implemented in R [R D11] (`nls()` function). This might not produce the most optimal solution and may impact the goodness-of-fit of VDMs. To mitigate this issue, we additionally employed a commercial tool *i.e.,* CurveExpert Pro[1] to cross check the goodness-of-fit in many cases. The results have shown that there is no difference between R and CurveExpert.

Internal validity concerns the causal relationship between the collected data and the conclusion in the study. Our conclusions are based on statistical tests. These tests have their own assumptions. Choosing tests whose assumptions are violated might end up with wrong conclusions. To reduce the risk we carefully analyzed the assumptions of the tests to make sure no unwarranted assumption was present. We did not apply any tests with normality assumptions since the distribution of vulnerabilities is not normal.

External validity is the extent to which our conclusion could be generalized to other scenarios. Our experiment is based on the vulnerability data of some major releases of the four most popular browsers covering almost all market shares. Therefore we can be quite confident about our conclusion for browsers in general. However, it does not mean that our conclusion is valid for other types of application such as operating systems. Such validity requires extra experiments.

7.6 Chapter Summary

This chapter has presented an experiment to validate the empirical performance of VDMs. The experiment followed the methodology described in Chapter 6 to assess eight VDM (*i.e.,* AML, AT, LN, JW, LP, RE, RQ, and YF) on 30 major releases of four web browsers: IE, Firefox, Chrome, and Safari. The outcomes of experiment, which are summarized in Table 7.6, have revealed that:

- AT and RQ models should be rejected since their quality is not good enough.
- For young software, the quality of all other models may be adequate. Only the predictability of LN is good enough for short (*i.e.,* 3 months and medium (*i.e.,* 6 months) prediction time spans, other models however is not good enough for latter time span.
- For middle-age software, only s-shape models (*i.e.,* AML, JW, and YF) may be adequate in terms of both quality and predictability.

[1]`http://www.curveexpert.net/`, site visited on 16 Sep, 2011

Table 7.6: Performance summary of VDMs.

Model	Performance
AT, RQ	should be rejected due to low quality.
LN	is *the best model* for first 12 months$^{(*)}$.
AML	is *the best model* for 13th to 36th month $^{(*)}$.
RE, LP	may be adequate for first 12 months $^{(**)}$.
JW, YF	may be adequate for 13th to 36th month$^{(*)}$.

$^{(*)}$: in terms of quality and predictability for next 3/6/12 months.
$^{(**)}$: in terms of quality and predictability for next 3 months.

- For old software, no model is good enough.
- No model is good enough for predicting vulnerabilities for a very long period (*i.e.,* 24 months).

In conclusion, *for young releases of browsers (*6 – 12 *months old) it is better to use a linear model to estimate the vulnerabilities in the next* 3 – 6 *months. For middle age browsers (*12 – 24 *months) it is better to use an s-shape logistic model.*

In the next chapter, we are going to address potential bias in NVD's *vulnerable versions* data feature by proposing a method that can identify code evidence for a vulnerability claim – a claim that a version is vulnerable to a vulnerability. Also we test the proposed method and assess the bias of vulnerability claims by NVD for Chrome and Firefox in the subsequent chapter.

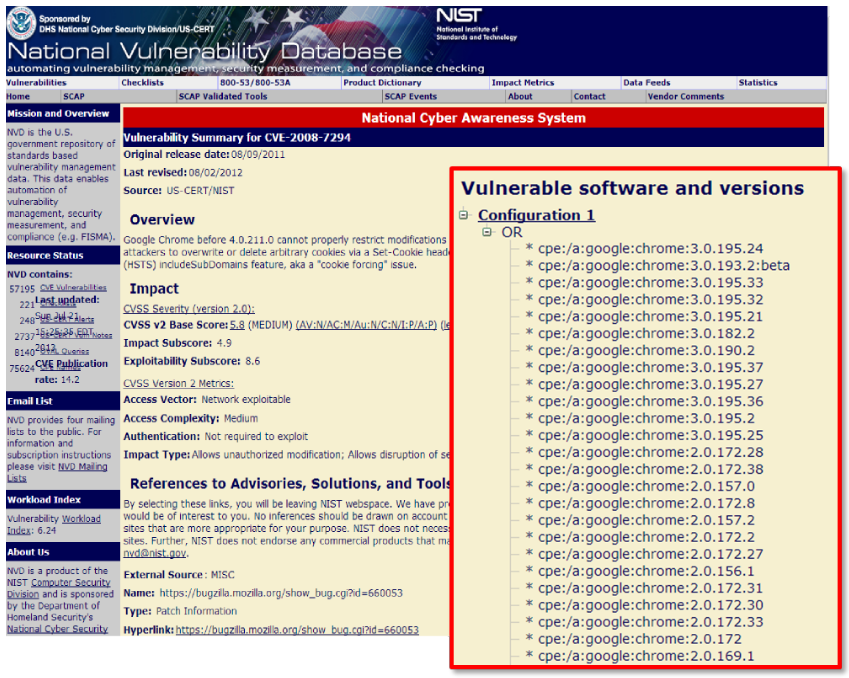
CHAPTER 8

AN EMPIRICAL METHOD TO ASSESS THE VULNERABILITIES RETRO PERSISTENCE

This chapter describes an automated method that could identify evidences for the existence of vulnerabilities in retro software versions. The method takes a list of vulnerabilities plus their corresponding security bugs, and looks for the evidences in the code base of retro versions that are claimed to be vulnerable to these vulnerabilities. Based on that, we could determine whether a vulnerability claim is spurious or not. The method could be useful while evaluating the bias to the count-of-vulnerability-based assessment of software compliance, or while evaluating the bias to scientific studies that are built upon the information that which versions are affected by which vulnerabilities.

FOUNDATIONAL vulnerability analysis is usually based on a data feature called *'vulnerable software and versions'* (or *vulnerable versions*, shortly) of each CVE. This feature specifies versions of particular applications that are vulnerable to the vulnerability described in the entry. Figure 8.1 illustrates this feature of CVE-2008-7294 which lists all Chrome versions before v3.0.195.24. It means this CVE affects Chrome v3.0 and all retrospective versions.

According to our analysis on foundational vulnerabilities, Chrome v2–v12 are rife with foundational vulnerabilities, approximately 99.5%; whereas this number in Firefox v1.5–v12.0 is around 75%. A *foundational vulnerability* [OS06] is one that was introduced in the very


Sponsored by
DHS National Cyber Security Division/US-CERT

National Vulnerability Database
automating vulnerability management, security measurement, and compliance checking

Vulnerabilities | Checklists | 800-53/800-53A | Product Dictionary | Impact Metrics | Data Feeds | Statistics
Home | SCAP | SCAP Validated Tools | SCAP Events | About | Contact | Vendor Comments

Mission and Overview

NVD is the U.S. government repository of standards based vulnerability management data. This data enables automation of vulnerability management, security measurement, and compliance (e.g. FISMA).

Resource Status

NVD contains:

57195 CVE Vulnerabilities
221 Checklists
248 US-CERT Alerts
2737 US-CERT Vuln Notes
8140 OVAL Queries
75624 CPE Names

Last updated: Sun Jul 21 15:25:35 EDT 2013

CVE Publication rate: 14.2

Email List

NVD provides four mailing lists to the public. For information and subscription instructions please visit NVD Mailing Lists

Workload Index

Vulnerability Workload Index: 6.24

About Us

NVD is a product of the NIST Computer Security Division and is sponsored by the Department of Homeland Security's National Cyber Security

National Cyber Awareness System

Vulnerability Summary for CVE-2008-7294

Original release date: 08/09/2011

Last revised: 08/02/2012

Source: US-CERT/NIST

Overview

Google Chrome before 4.0.211.0 cannot properly restrict modifications
attackers to overwrite or delete arbitrary cookies via a Set-Cookie head
(HSTS) includeSubDomains feature, aka a "cookie forcing" issue.

Impact

CVSS Severity (version 2.0):

CVSS v2 Base Score: 5.8 (MEDIUM) (AV:N/AC:M/Au:N/C:N/I:P/A:P) (le

Impact Subscore: 4.9

Exploitability Subscore: 8.6

CVSS Version 2 Metrics:

Access Vector: Network exploitable

Access Complexity: Medium

Authentication: Not required to exploit

Impact Type: Allows unauthorized modification; Allows disruption of se

References to Advisories, Solutions, and Tools

By selecting these links, you will be leaving NIST webspace. We have pr
would be of interest to you. No inferences should be drawn on account
sites that are more appropriate for your purpose. NIST does not neces
sites. Further, NIST does not endorse any commercial products that ma
nvd@nist.gov.

External Source: MISC

Name: https://bugzilla.mozilla.org/show_bug.cgi?id=660053

Type: Patch Information

Hyperlink: https://bugzilla.mozilla.org/show_bug.cgi?id=660053

Vulnerable software and versions

Configuration 1
OR
* cpe:/a:google:chrome:3.0.195.24
* cpe:/a:google:chrome:3.0.193.2:beta
* cpe:/a:google:chrome:3.0.195.33
* cpe:/a:google:chrome:3.0.195.32
* cpe:/a:google:chrome:3.0.195.21
* cpe:/a:google:chrome:3.0.182.2
* cpe:/a:google:chrome:3.0.190.2
* cpe:/a:google:chrome:3.0.195.37
* cpe:/a:google:chrome:3.0.195.27
* cpe:/a:google:chrome:3.0.195.36
* cpe:/a:google:chrome:3.0.195.2
* cpe:/a:google:chrome:3.0.195.25
* cpe:/a:google:chrome:2.0.172.28
* cpe:/a:google:chrome:2.0.172.38
* cpe:/a:google:chrome:2.0.157.0
* cpe:/a:google:chrome:2.0.172.8
* cpe:/a:google:chrome:2.0.157.2
* cpe:/a:google:chrome:2.0.172.2
* cpe:/a:google:chrome:2.0.172.27
* cpe:/a:google:chrome:2.0.156.1
* cpe:/a:google:chrome:2.0.172.31
* cpe:/a:google:chrome:2.0.172.30
* cpe:/a:google:chrome:2.0.172.33
* cpe:/a:google:chrome:2.0.172
* cpe:/a:google:chrome:2.0.169.1

Figure 8.1: The *vulnerable software and versions* feature of the CVE-2008-7294.

first version of a software (*i.e.,* v1.0), but survived and is discovered later in newer versions. In theory, foundational vulnerabilities have higher chance to be exploited than others because they are exposed to attack longer than others. By finding these vulnerabilities in v1.0, attackers could use them to exploit recent versions (say, v18) at the release date. As the result, foundational vulnerabilities are a source for zero-day exploits. A PCI DSS assessor would then be right in claiming that Chrome v4 should lead to the security problem.

We however have noted an abnormality in the Chrome vulnerability data reported by NVD. It seems that Chrome developers introduced lots of vulnerabilities in the initial version, but almost no vulnerability was introduced in subsequent versions. This could be true if the subsequent versions contained only bug fixes and few functional improvements (*i.e.,* few code changes). In contrast, the study on the evolution of Chrome code base (`src.chromium.org`) has revealed that the number of source components[1] of Chrome v12 is approximately as double as those of Chrome v4, *i.e.,* about 100% new components has been introduced in Chrome v12 since v4. This was such a huge change. Therefore, a possible explanation for the abnormality is that: either yet more vulnerabilities in these Chrome versions have not been detected, or there is a problem in the vulnerability data of Chrome, or

[1]A component is a C++ source file plus its (optional) header file.

both.

According to an archive document[2], the information reported in this feature is *"obtained from various public and private sources. Much of this information is obtained (with permission) from CERT, Security Focus and ISS/X-Force"*. However, our private communications with NIST, host of NVD, and software vendors, have revealed a "paradox": NIST claimed vulnerable versions were taken from software vendors [NIS12b]; whereas, software vendors claimed they did not know about this information [Moz11].

This ambiguity might result the over-counting of (foundational) vulnerabilities in older versions of Chrome, Firefox and other software. This severely impacts not only academic community *e.g.,* [Res05; OS06; You11; Mas11; NM12c], but also industrial companies. For instance, your products which embeds an old version of browser might lose compliance with PCI DSS due to a large number of unfixed vulnerabilities. Then you might either update to new version, or pay a fine, or be kicked out of the market. Unfortunately, these options are all expensive.

This motivates our work that empirically validates the reliability of the NVD assessment on the status of being vulnerable of retro software versions.

The rest of this chapter is organized as follows. Section 8.1 describes our research questions. Section 8.2 details our proposed validation method. Section 8.3 briefly discusses related studies in the field. Section 8.4 summarizes the chapter.

8.1 Research Questions

In this chapter, we address the following research question:

RQ5 *How to estimate the validity of a vulnerability claim to a retro version of software?*

A *vulnerability claim* is a statement by a data source that a particular software version is vulnerable to a particular CVE. Figure 8.1 shows an example of the claims listed in an NVD entry. A vulnerability claim to a software version is technically equivalent to a vulnerability of this version. Thereby in this chapter, we shortly refer to vulnerability claim as *vulnerability*. Also, we denote a vulnerability claim which is not correct as *spurious vulnerability claims*.

To understand whether a vulnerability claim is spurious *i.e.,* answering RQ5, a straightforward way is to reproduce the malicious or undesirable behavior in the corresponding

[2]This page is removed, but can be accessed by URL `http://web.archive.org/web/20021201184650/http://icat.nist.gov/icat_documentation.htm`

software version. This is only possible for a few vulnerabilities for which a proof of concept exploit exists, *e.g.,* in metasploit (`www.metasploit.com`), and it can be used for automated verification. This setup has been used for exploit kit verification [All13a] which only included few hundred vulnerabilities. For large scale verification of NVD claims such strategies is not feasible. At first NVD does not reveal enough detail information to carry out the exploits; second, a manual verification of thousands of vulnerabilities is simply unfeasible. We therefore need an automated approach to claim verification.

We propose a method that automatically identifies the code evidence of a vulnerability in the code base of a particular version. From this evidence, we could estimate the correctness of a vulnerability claim. The detail of the proposed method is elaborated further in Section 8.2.

8.2 The Method to Identify Code Evidence for Vulnerability Claims

The proposed method builds upon the work by Sliwerski *et al.* [Sli05], who attempted to detect source lines of code that are responsible for general programming bugs. Though vulnerabilities are also programming bugs, they have specific features. The major difference is that vulnerabilities are mostly discovered after a software has been shipped to customers. Thus, vulnerabilities affect not only software vendors themselves, but *e.g.,* in case of browsers, millions of users worldwide. Successful exploits of vulnerabilities therefore might cause million-dollar loss. This results in major differences between the proposed method and [Sli05] as follows:

1. The proposed method could accept false positives (*i.e.,* a version is claimed to be vulnerable, while it is not), but try to avoid false negatives (*i.e.,* a version is claimed to be clean, while it is vulnerable) as much as possible. In contrast, the approach by [Sli05] tried to minimize false positives.

2. The proposed method focuses on the question: *“which versions are truly affected by which vulnerability claims?"*, which was not the concern of the approach by [Sli05]. Therefore, they could not answer this question.

Table 8.1 summarizes the proposed method. The method takes available vulnerability data sources as a starting point. The output of each step is piped to its consecutive step. The

Table 8.1: Overview of the proposed validation method.

INPUT	All available vulnerability data sources	
STEP 1	*Acquire vulnerability data*	Acquire vulnerabilities and their responsible security bugs from vulnerability data sources.
STEP 2	*Locate bug-fix commits*	Locate the lines of code responsible for vulnerabilities by employing a repository mining approach.
STEP 3	*Identify vulnerable code footprints*	Determine the LoCs that are modified to fix the vulnerability. We call these LoCs *vulnerable code footprint.*
STEP 4	*Determine evidence for vulnerability claims*	Scan through the code base of every software version for the vulnerable code footprints.
OUTPUT	Vulnerability claims and their affected versions with evidence	

output of the final step, which is also the method outcome, is a list of vulnerabilities with their affected versions associated with code evidences.

In order to identify a version of the software where a vulnerability actually exists for sure, we rely on the consistency of the development process by software manufactures. In particular, we make use of the following assumptions:

ASS8.1 *The developers either mention bug ID(s) responsible for a vulnerability in the description of the commit that contains the bug fix, or mention the commit ID that fixes the bug in the bug's report.*

ASS8.2 *A bug-fix commit is for a single bug.*

ASS8.3 *A vulnerability claim about a software version is **evidence-supported** if either there exists at least a vulnerable code-footprint for this vulnerability in the code base of this version, or the vulnerability gets fixed by only adding new lines of code. Otherwise, a vulnerability claim is spurious.*

By making the above assumptions, we might face a number of threats to validity. Antoniol *et al.* [Ant08] and Bird *et al.* [Bir09] discussed two potential biases corresponding to **ASS8.1**: first, developers do not mention bug ID(s) in a bug-fix commit; second, developers mention bug ID(s) in a non-bug-fix commit. Bird *et al.* [Bir09] also pointed that the latter bias is negligible, while the former does exist.

The second assumption **ASS8.2** is important because if a bug-fix commit contains changes for fixing multiple bugs (*i.e., multiple-bug-fix commit*), we cannot distinguish the lines of code (LoCs) that were touched to fix which bugs. Consequently we might end up with a result that vulnerability claims corresponding to these bugs are valid in the same versions of software, which is not necessary true. Therefore if the number of multiple-bug-fix commit is too high, this will rise threat biasing the outcome of the proposed method.

Concern **ASS8.3**, it is not necessarily true that the changed LoCs are the vulnerable ones, albeit they might have helped to remove the vulnerability. For example, a vulnerability that could lead to SQL injection attack could be fixed by inserting a sanitizer around a user's input in another module. We will then consider all versions where this sanitiser is missing as vulnerable. This is not necessary true; for example previous versions might have used another model for input and the latter model had proper input sanitizer. This is acceptable in this context because we are trying to minimize false negatives, while accepting false positives.

Occasionally we could not find evidence neither in favor nor against a vulnerability claim. This could happen because either the corresponding CVE does not have any responsible security bug due to the incompleteness of the data source, or the bug-fix commit of the responsible bug cannot be located due to the incompleteness of the method.

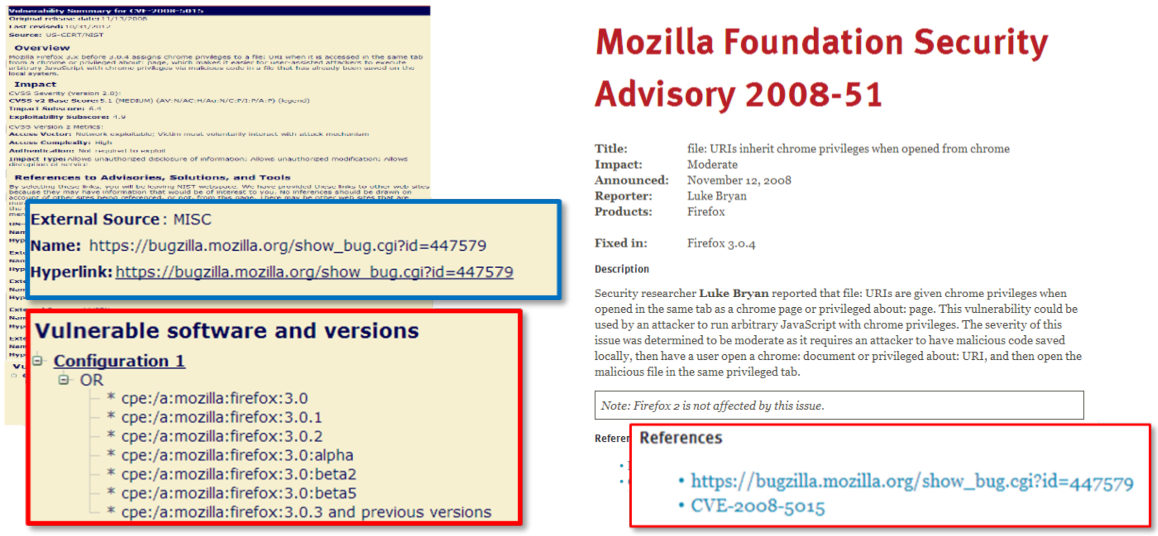
Hereafter, we elaborate the steps of the proposed method.

8.2.1 Step 1: Acquire Vulnerability Data

For validation purposes, we need to obtain security bugs responsible for CVEs, from which we can establish traces from CVEs to the code base. A CVE entry provides a general description of a vulnerability. Such description usually contains less technical information, and emphasize more about the impact of a vulnerability so that it could be understandable by most users. A security bug, in the other side, provides a more technical data for software developer to fix the bug.

There are two official ways to obtain corresponding security bugs of a CVE. First, each CVE might have references to its corresponding security bugs. These references are reported in the *references* feature of a CVE. Second, the official security advisories by software manufacture might report CVE and its corresponding security bugs.

Example 8.1 Figure 8.2(a) shows an example where the corresponding security bug of `CVE-2008-5015` is reported as in its *references* feature. In this example, it is a URL to a security bug report 447579 of Firefox. For Firefox, bug report hyperlinks usually have two forms: `https:`



Vulnerability Summary for CVE-2008-5015
Original release date: 11/13/2008
Last revised: 10/31/2012
Source: US-CERT/NIST

Overview
Mozilla Firefox 3.x before 3.0.4 assigns chrome privileges to a file: URI when it is accessed in the same tab from a chrome or privileged about: page, which makes it easier for user-assisted attackers to execute arbitrary JavaScript with chrome privileges via malicious code in a file that has already been saved on the local system.

Impact
CVSS Severity (version 2.0):
CVSS v2 Base Score: 5.1 (MEDIUM) (AV:N/AC:H/Au:N/C:P/I:P/A:P) (legend)
Impact Subscore: 6.4
Exploitability Subscore: 4.9
CVSS Version 2 Metrics:
Access Vector: Network exploitable; Victim must voluntarily interact with attack mechanism
Access Complexity: High
Authentication: Not required to exploit
Impact Type: Allows unauthorized disclosure of information; Allows unauthorized modification; Allows disruption of service

References to Advisories, Solutions, and Tools
By selecting these links, you will be leaving NIST webspace. We have provided these links to other web sites because they may have information that would be of interest to you. No inferences should be drawn on account of other sites being referenced, or not, from this page. There may be other web sites that are

External Source : MISC
Name: https://bugzilla.mozilla.org/show_bug.cgi?id=447579
Hyperlink: https://bugzilla.mozilla.org/show_bug.cgi?id=447579

Vulnerable software and versions
Configuration 1
OR
* cpe:/a:mozilla:firefox:3.0
* cpe:/a:mozilla:firefox:3.0.1
* cpe:/a:mozilla:firefox:3.0.2
* cpe:/a:mozilla:firefox:3.0:alpha
* cpe:/a:mozilla:firefox:3.0:beta2
* cpe:/a:mozilla:firefox:3.0:beta5
* cpe:/a:mozilla:firefox:3.0.3 and previous versions

Mozilla Foundation Security Advisory 2008-51

Title:	file: URIs inherit chrome privileges when opened from chrome
Impact:	Moderate
Announced:	November 12, 2008
Reporter:	Luke Bryan
Products:	Firefox
Fixed in:	Firefox 3.0.4

Description

Security researcher **Luke Bryan** reported that file: URIs are given chrome privileges when opened in the same tab as a chrome page or privileged about: page. This vulnerability could be used by an attacker to run arbitrary JavaScript with chrome privileges. The severity of this issue was determined to be moderate as it requires an attacker to have malicious code saved locally, then have a user open a chrome: document or privileged about: URI, and then open the malicious file in the same privileged tab.

Note: Firefox 2 is not affected by this issue.

References
- https://bugzilla.mozilla.org/show_bug.cgi?id=447579
- CVE-2008-5015

(a) Report detail for CVE-2008-5015 (b) Report detail for MFSA-2008-51

Figure 8.2: Selected features from a CVE (a), and from an MFSA report (b).

`//bugzilla.mozilla.org/show_bug.cgi?id=`n (for single bug), or `https://bugzilla.mozilla.org/bug_list.cgi?=`n,n (for bug list). For Chrome, the hyperlink to a bug report is usually `http://code.google.com/p/chromium/issues/detail?id=`n. In these hyperlinks, n is an integer number indicating the bug ID. ∎

Example 8.2 Figure 8.2(b) illustrates an example where CVE and its corresponding security bug are reported by vendor advisory reports, *e.g.*, MFSA for Firefox. The figure shows a snapshot of an MFSA entry: MFSA-2008-51. The *References* section of this entry reports two hyperlinks: one for a security bug (`https://bugzilla.mozilla.org/show_bug.cgi?id=447579`), and another one for a CVE entry (CVE-2008-5015). So we heuristically assume that this security bug is responsible for that CVE. ∎

8.2.2 Step 2: Locate Bug-Fix Commits

This step takes the list of vulnerabilities and their corresponding security bug identifier determined in the previous step to locate their corresponding bug-fix commits in the code base. A *bug-fix commit* is a commit entry in the code base repository that contains changes to fix a (security) bug. There are two popular techniques to locate bug-fix commits: *repository mining* and *bug-report mining*.

Figure 8.3: Bug-fix commits of Chrome (a) and Firefox (b).

In each commit, the commit ID (*i.e.*, revision ID), changed files, and fixed bug ID are highlighted.

```
r41106 | inferno@chromium.org | 2010-03-10 02:03:43 +0100
(Wed, 10 Mar 2010) | 10 lines
Changed paths:
   M /branches/249/src/chrome/browser/views/login_view.cc
Merge 40708 - This patch fixes [... text truncated for saving space]
BUG=36772
TEST=Try a hostname url longer than 42 chars to see that
it wraps correctly and wraps to the next line.
```

(a) A Chrome bug-fix commit

```
changeset: 127761:88cee54b26e0
author: Justin Lebar <justin.lebar@gmail.com>
date: 2013-01-07 09:44 +0100
files: +|-|*dom/ipc/ProcessPriorityManager.cpp
desc: Bug 827217 - Fix null-pointer crash with webgl.can-
lose-context-in-foreground=false.
```

(b) A Firefox bug-fix commit

- The *repository mining* technique was introduced by Sliwerski *et al.* [Sli05] and adopted by many other studies in the literature *e.g.*, [Neu07; Shi11]. This technique parses commit logs of the code base repository for the security bug IDs according to predefined patterns. In our case, the commit logs mentioning security bug ID(s) are bug-fix commits.

- The *bug-report mining* technique, adopted by Chowdhury and Zulkernine [CZ11], parses a security bug report for bug-fix information. Such information includes changed locations in code base, which could be referred to as either links to bug-fix commits, or links to particular revision of changed source files. In the latter case, we assume the revision of changed source files is bug-fix commit.

Example 8.3 In Chrome, a bug-fix commit refers to bug IDs by the patterns `BUG=n(,n)` or `BUG=http://crbug.com/n`, where *n* is the bug ID. In Firefox, bug IDs usually follow keywords such as *bug*. Figure 8.3 exemplifies two bug-fix commits: one for Chrome, and another one for Firefox. In each bug-fix commit, we highlight interesting information including the revision ID of the bug-fix commit, the list of changed source files, and the bug ID fixed by the commit. ■

These two techniques are complement each other since the advantage of a technique is the disadvantage of the other. The *repository mining* technique requires access to commit logs which might not be publicly available. It could locate bug-fixes for undisclosed bug reports – the *advantage*. However it might skip bug-fixes which do not mention explicitly the security bug IDs (*e.g.,* when merging from external repositories) – the *disadvantage*. On the other hand, the *bug-report mining* technique could parse the bug report the bug-fixes even if the bug IDs were not mentioned in these bug-fixes – the *advantage*. But it could not locate bug-fixes for undisclosed bug reports, though these bug-fixes explicitly mention the bug IDs – the *disadvantage*.

Example 8.4 For instance, bug-fixes for the WebKit module[3] in Chrome usually do not contain the bug IDs because they are merged from another repository. ■

With reference to **ASS8.2**, after identifying bug-fixes we should investigate the distribution of number of bugs fixed per bug-fix commit to understand the potential impact of multiple-bug-fix commits.

8.2.3 Step 3: Identify Vulnerable Code Footprints

This step takes bug-fix commits and annotates source files in the commits to determine vulnerable code footprints. A *vulnerable code footprint* is a piece of code which is changed (or removed) in order to fix a security bug. The intuition to identify such vulnerable code footprints is to compare the revision where a security bug is fixed (*i.e.,* bug-fix commit) to its immediate parent revision. Pieces of code that appear in the parent revision but not in the bug-fixed revision are considered vulnerable code footprints.

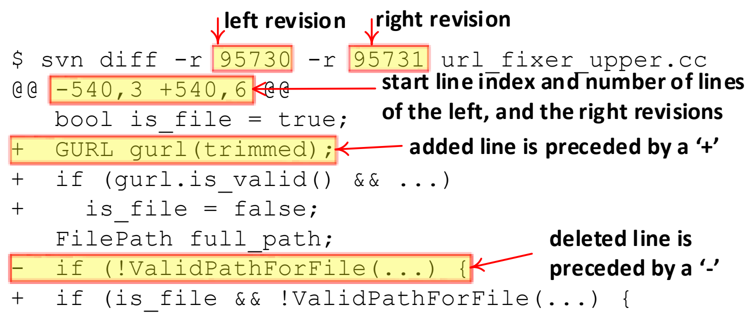
Let r_{fix} be the revision ID of a bug-fix commit. We compare every file f changed in this revision to its immediate parent revision[4]. We employ the `diff` command supported by the repository to do the comparison. By parsing the comparison output, we can identify the vulnerable code footprints. We ignore formatting changes such as empty lines, or lines which contain only punctuation marks. Such changes occur frequently in all source files, and therefore they do not characterize the changes to fix security bugs.

Example 8.5 Figure 8.4(a) illustrates an excerpt of the comparison between revision $r95730$ and $r95731$ of file `url_fixer_upper.cc` by using `diff` command. The command produces

[3]The module used by Chrome to render HTML pages

[4]In an SVN repository, the immediate parent of the revision r_{fix} is $r_{fix} - 1$. In some other repository such as Mercurial, the immediate parent is determined by performing the command `parent`

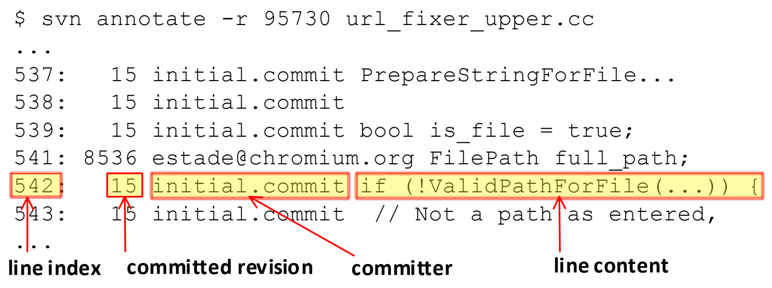
Figure 8.4: Excerpts of the output of `diff` (a), and of the output of `annotate` (b).



```
$ svn diff -r 95730 -r 95731 url_fixer_upper.cc
@@ -540,3 +540,6 @@
   bool is_file = true;
+  GURL gurl(trimmed);
+  if (gurl.is_valid() && ...)
+    is_file = false;
   FilePath full_path;
-  if (!ValidPathForFile(...) {
+  if (is_file && !ValidPathForFile(...) {
```

left revision
right revision
start line index and number of lines of the left, and the right revisions
added line is preceded by a '+'
deleted line is preceded by a '-'

(a) An excerpt of `diff`



```
$ svn annotate -r 95730 url_fixer_upper.cc
...
537:   15 initial.commit PrepareStringForFile...
538:   15 initial.commit
539:   15 initial.commit bool is_file = true;
541: 8536 estade@chromium.org FilePath full_path;
542:   15 initial.commit if (!ValidPathForFile(...)) {
543:   15 initial.commit  // Not a path as entered,
...
```

(b) An excerpt of `annotate`

an output in Unify Diff format where changes are organized in hunks. A hunk begins with a header which is surrounded by double-at signs (@@), contains the start line index and number of lines. Added lines, deleted lines, and unchanged lines are respectively preceded by a plus sign, a minus sign, and a space character. The vulnerable code footprint is deleted lines *e.g.,* in this excerpt, which is line #542. ■

Next, we identify the origin of vulnerable code footprints *i.e.,* the revision where the potential bad code is introduced. Such origins are achieved by annotating the source file f at immediate parent revision of the bug-fix commit. In an annotation of a source file, every individual line is annotated with meta-information such as the origin revision, the committed time, and the author. The annotation is done by the `annotate` command of the repository

Example 8.6 Figure 8.4(b) presents an excerpt of the annotation of file `url_fixer_upper.cc` at the immediate parent revision of the bug-fix commit, *i.e.,* revision 95730. According to this excerpt, the origin revision of vulnerable code footprint #542 in Example 8.5 is 15. ■

Table 8.2: The execution of the method on few Chrome vulnerabilities.

CVE	Reported Versions	Bug ID	Bug-fix Commits	Footprint	Versions w/ Evidence
2011-2822	v1–v13	72492	url_fixer_upper.cc[1] (r95731)	$\langle r15, 542\rangle$	v1–v13
2011-4080	v1–v8	68115	media_bench.cc[2] (r70413)	$\langle r26072, 352\rangle$, $\langle r53193, 353\rangle$	v3–v8
2012-1521	v1–v18	117110	–	–	–

[1]: `chrome/browser/net/url_fixer_upper.cc` [2]: `media/tools/media_bench/media_bench.cc`

8.2.4 Step 4: Determine Vulnerability Evidences

This step scans through the code base of all version claimed to be vulnerable for the existence of vulnerable code footprints. Such existence is the supported evidence for the claimed that a version is actually vulnerable to a vulnerability. A special case is present when a CVE was fixed by only adding new code. In this case, no vulnerable code footprint is detected. In this scenario, we assume conservatively that all original LoCs of the file where a vulnerability is fixed are all vulnerable code footprints. If a version contains the file, then it is vulnerable. This solution does not introduce false negatives, but may let false positives survive. Indeed notice that the version has been already claimed to be vulnerable. For a compliance perspective, this is acceptable albeit maybe costly.

Example 8.7 Table 8.2 shows a few validation examples of Chrome vulnerability claims. CVE-2011-2822 is reported to affect Chrome v1 up to v13. Its responsible bug is 72492. In Step 2, by scanning the log, the bug-fix commit is revision r95731 of file `url_fixer_upper.cc`. In Step 3, we diff revision r95730 and r95731 of this file (see Figure 8.4(a)). The vulnerable code footprint is determined as {#542}. Then we annotate r95730 of the file to get the revision of the code footprint, which is $\{r15\}$ (see Figure 8.4(b)). In Step 4, we scan for this line in the code base of all versions, and found it in v1 to v13. Finally, we identify the vulnerable versions for this vulnerability, which are v1–v13. ∎

Example 8.8 This example illustrates a case where the rule *"version X and its previous versions are vulnerable"* was applied. The description CVE-2012-4185 said:

> *"Buffer overflow in the nsCharTraits::length function in **Mozilla Firefox before 16.0**, Firefox ESR 10.x before 10.0.8, Thunderbird before 16.0, Thunderbird ESR*

10.x before 10.0.8, and SeaMonkey before 2.13 allows remote attackers to execute arbitrary code or cause a denial of service (heap memory corruption) via unspecified vectors."

By applying the above strategy, all versions from v1.0 – v15.0 are claimed as vulnerable to this vulnerabilities. The corresponding bug for this CVE is 785753. This bug indicated that it was a global-buffer-overflow in the `nsCharTraits::length` function. This bug was fixed by changing the file `netwerk/base/src/nsUnicharStreamLoader.cpp` as follows.

```
     if (NS_FAILED(rv)) {
-      NS_ASSERTION(0 < capacity - haveRead,
-                   "Decoder returned an error but filled the output buffer! "
-                   "Should not happen.");
+      if (haveRead >= capacity) {
+        // Make room for writing the 0xFFFD below (bug 785753).
+        if (!self->mBuffer.SetCapacity(haveRead + 1, fallible_t())) {
+          return NS_ERROR_OUT_OF_MEMORY;
+        }
+      }
       self->mBuffer.BeginWriting()[haveRead++] = 0xFFFD;
       ++consumed;
```

The plus (+) determines newly added lines, and the minus (-) indicates deleted lines. In this case, the vulnerability's cause might be the lack of a conditional check for a circumstance that the Firefox developers did not think it would happen. It was fixed by adding the missing check. We traced the original revision of the deleted line and found that it was introduced since the revision 70061, and stayed there until revision 108991. We scanned through the code based of Firefox v15 and downward for deleted lines. We could only found these deleted lines in Firefox v6 to v15. Clearly, we could not say this vulnerability affects also Firefox v1.0 to v5.0 as claimed by this NVD entry. ■

8.3 Related Work

Sliwerski *et al.* [Sli05] proposed a technique that automatically locates fix-inducing changes. This technique first locates changes for bug fixes in the commit log, then determines earlier changes at these locations. These earlier changes are considered as the cause of the later fixes, and are called fix-inducing. This technique has been employed in several studies

[Sli05; Zim07] to construct bug-fix data sets. However, none of these studies mention how to address bug fixes which earlier changes could not be determined. These bug fixes were ignored and became a source of bias in their work.

Bird *et al.* [Bir09] conducted a study the level bias of techniques to locate bug fixes in code base. The authors have gathered a data set linking bugs and fixes in code base for five open source projects, and manual checked for the biases in their data set. They have found strong evidence of systematic bias in bug-fixes in their data set. Such bias might be also existed in other bug-fix data set, and could be a critical problem to any study relied on such biased data.

Antoniol *et al.* [Ant08] showed another kind of bias that the bug-fixes data set might suffer from. Many issues reported in many tracking system are not actual bug reports, but feature or improvement requests. Therefore, this might lead to inaccurate bug counts. However, such bias rarely happens for security bug reports. Furthermore, Nguyen *et al.* [Ngu10], in an empirical study about bug-fix data sets, showed that the bias in linking bugs and fixes is the symptom of the software development process, not the issue of the used technique. Additionally, the linking bias has a stronger effect than the *bug-report-is-not-a-bug* bias.

Meneely *et al.* [Men13] studied the properties of so-called vulnerability-contributing commits (VCC) which are similar to the commits containing vulnerability code footprints in this chapter. Meneely *et al.* applied the similar method to identify security bug-fix commits, but then they follow an ad-hoc approach to identify VCC. Thus, the identification of VCC for 68 vulnerabilities of Apache HTTP server took them hundreds of man-hours over six months. Here, we have to deal with thousands of vulnerabilities.

8.4 Chapter Summary

This chapter presented a method to identify code evidence for vulnerability claims. The method was inspired by the work of Sliwerski *et al.* [Sli05]. Sliwerski *et al.* [Sli05] aimed to identify to code inducing fixes for bugs in general, meanwhile the proposed method focused on the evidence of the present of vulnerabilities. Such objectives resulted in the significant difference between the two methods: the method by Sliwerski *et al.* [Sli05] tried to reduce false positives, while the proposed method aimed to reduce false negatives, and could accept false positives.

The method took a list of vulnerabilities and their corresponding security bugs as input. Then it traced the commits in the source code repository for the commits that fixed security bugs. From these commits, it determined the so-called vulnerable code footprints which are changed LoCs to fix security bugs. Then it traced for the origin revision where vulnerable code footprints were introduced. Finally it scanned the code base of individual versions to determine the vulnerable status of these versions.

In the next chapter, we are going to check the effectiveness of the proposed method in the sense that whether it can assess the vulnerabilities claims by NVD for Chrome and Firefox. We also conduct experiments to see whether there is any bias in NVD vulnerability claims, and how the potential bias might impact the conclusion of scientific studies relying on them.

CHAPTER 9

AN EMPIRICAL ASSESSMENT FOR THE RETRO PERSISTENCE OF VULNERABILITY CLAIMS BY NVD

This chapter applies the assessment method for the retro persistence of vulnerabilities described in Chapter 8 to empirically assess the vulnerability claims by NVD for 33 major versions of Chrome and Firefox. We used the proposed method to validate the folk knowledge that when inserting data in NVD, analysts apply overly a conservative rule "version X and its previous versions are vulnerable". The experiment results have shown that more than 30% of vulnerability claims to each of these versions are spurious. As a result, many scientific studies claiming that vulnerabilities tend to be foundational were not in reality due to the NVD marking scheme.

WE in this chapter present an experiment to study whether the proposed assessment method for the retro persistence of vulnerabilities actually works or not. The experiment analyzes vulnerability claims by NVD for 33 major versions of Chrome and Firefox. We aim to validate the folk knowledge that when making vulnerability claims for each NVD entry, the NVD analysts apply overly a conservative rule *"version X and its previous versions are vulnerable."*.

The rest of this chapter is organized as follows. Section 9.1 describes the chapter's research questions. Section 9.2 shows the analysis on the collected data for Chrome and Firefox. Section 9.3 reviews the impact of spurious vulnerability claims to two vulnerability studies. Section 9.4 presents potential threats to validity and how they are addressed. Section 9.5 summarizes this chapter.

9.1 Research Questions

In this chapter, we consider the following research questions:

RQ8 *Is the proposed assessment method effective in assessing the retro persistence of vulnerabilities?*

RQ9 *To what extend are vulnerability claims by NVD trustworthy?*

RQ10 *To what extend does the bias in vulnerability claims by NVD (if any) impact conclusions of a vulnerability analysis?*

To study the effectiveness of the proposed assessment method *i.e.,* answering RQ8, we apply the proposed method to conduct an experiment assessing the number of spurious vulnerability claims for 18 major versions of Chrome (*i.e.,* v1.0–v18), and 15 major versions of Firefox (*i.e.,* v1.0–v12.0). We measure the ability to assess the majority of vulnerability claims of Chrome and Firefox. If the method could be able to assess at least two third of vulnerability claims, it will be an evidence for the effectiveness of the proposed method.

We answer RQ9 by measuring the ratio of spurious vulnerability claims, which is hereafter referred to as *error rate*. In many analyses, a small error rate could be acceptable, but other analyses might be biased. Suppose that we have two vulnerability samples X and Y (for example, foundational vulnerabilities in Chrome and Firefox), we want to test whether the outputs of a function f (*e.g.,* mean, rank, standard error, or so) on X and Y are significantly different. The statistical test is basically a *diff* function measuring the chance that $f(X)$ is different from $f(Y)$. Traditionally the significance level is 0.05 which means that if $\mathit{diff}(f(X), f(Y))$ is greater than 0.95, we could conclude a significant difference. However, if X contains more than 5% of errors, we are measuring $\mathit{diff}(f(X-0.05), f(Y))$. If the errors are not uniformly distributed, the errors might impact the output of f. Consequently, the evaluation of true *diff* might have passed from *lower than* 5% to *greater than* 5%. As the result, the conclusion might not be statistically significant. From an industry perspective a greater error rate that might introduces a notion of reasonable doubt to a compliance assessment.

We further examine the systematic characteristic of the spurious vulnerability claims along the life time of each version – *version age* (*i.e.,* the number of months since the release of particular versions). Industry-wise the presence of a systematic bias might lead to systematic deployment of over restrictive security measures or to the unwarranted preference of a software over another.

We conduct another experiment to address RQ10. The experiment explores the effect of spurious vulnerability claims to the validity of the studies on foundational vulnerabilities in order to revisit the finding that the majority of vulnerabilities are foundational[OS06]. We analyze the difference in the conclusions made in two different settings. The first setting uses all vulnerabilities claimed by NVD. The second setting also uses vulnerabilities claimed by NVD, but excludes all spurious ones.

9.2 The Assessing Experiment of Vulnerability Claims

We apply the proposed method to validate the trustworthiness of vulnerability claims by NVD on Chrome and Firefox (answer for RQ9). For Firefox we obtain bug-fix commits by using the repository mining technique because it discovered bug-fix commits for almost security bugs. For Chrome, we also use the repository mining technique for undisclosed security bugs reports, and the bug-report mining technique for security bugs fixed in imported projects (*e.g.,* WebKit). These security bugs, as discussed, cannot be located by mining the repository because their bug IDs were not mentioned in the bug-fix commits.

The implementation scripts of the method take approximately 14 days (*i.e.,* 336 hours) on a 2 x quad-core 2.83GHz Linux machine with 4GB of RAM to assess approximately 9,800 vulnerability claims for Chrome and Firefox. However it is still dramatically more efficient than an ad-hoc approach adopted by Meneely *et al.* [Men13], which took six months to evaluate 68 vulnerabilities.

Hereafter, we present the software infrastructure for the experiment, and some statistics of the experiment, as well as our analysis on the spurious vulnerability claims for these two browsers.

9.2.1 The Software Infrastructure

Figure 9.1 presents the software infrastructure for the experiment that assesses the retro persistence of Chrome and Firefox vulnerabilities. The body of this infrastructure consists of the following scripts:

- *Commit Log Parser.* This script takes the commit logs of the source code repositories of browsers, and vulnerability data of Chrome and Firefox (*i.e., Chrome VDB* and *Firefox*

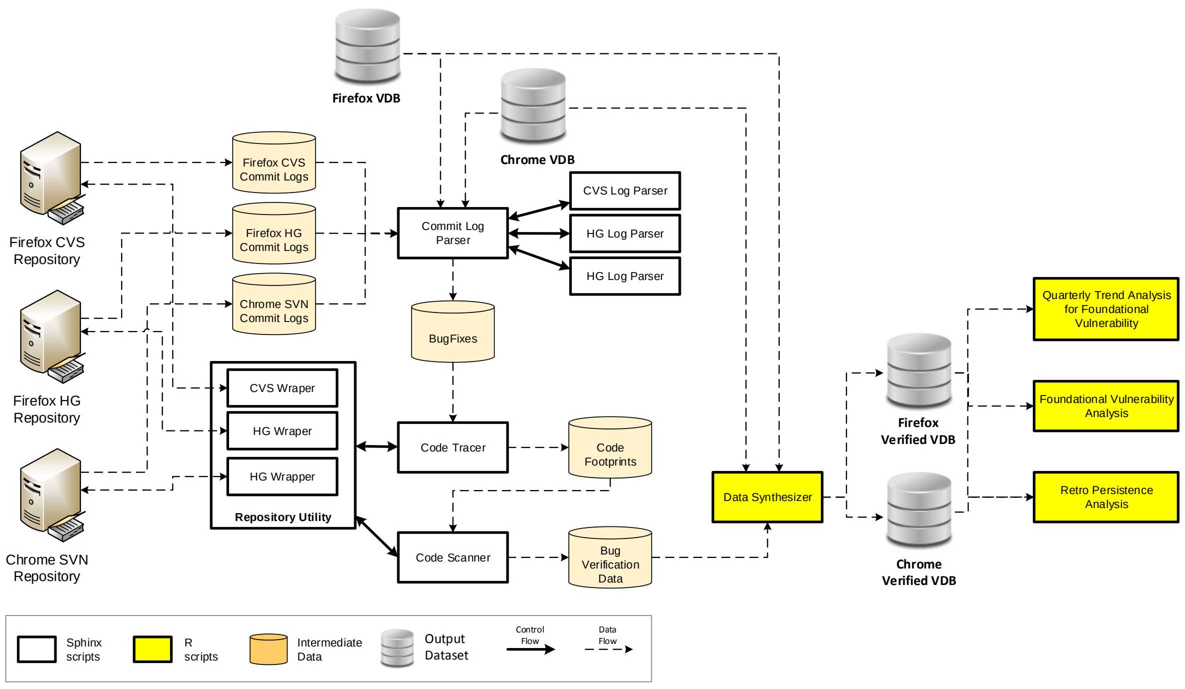


Figure 9.1: The software infrastructure for assessing the vulnerabilities retro persistence.

VDB, see Section 4.1) as inputs to produce the *BugFixes* data set. Because the repository of Firefox was migrated from CVS to HG since version v3.5, we have three different kinds of commit logs: *Firefox CVS Commit Logs*, *Firefox HG Commit Logs*, *Chrome SVN Commit Logs*. These commit logs are text files. Thus, this script relies on particular parsing script for each type of commit logs (*i.e.*, *CVS Log Parser*, *HG Log Parser*, and *SVN Log Parser*). The *BugFixes* data set maintains the links between security bugs to particular source components that were touch to fix it.

- *Code Tracer*. This script consumes the *BugFixes* data set to produce the *Code Footprint* data set, which maintains the links between a security bug to particular LoCs that potentially contribute to the existence of this bug. For this purpose, this script looks for the original version of modified LoCs of source components in *BugFixes*. This is done thank to the repository servers via the *Repository Utility* scripts.

- *Code Scanner*. This script scans LoCs in *Code Footprint* in the code bases of all versions of Chrome and Firefox to determine the earliest version affected by a security bug. This is also done with the aid of repository servers via the *Repository Utility* scripts. The outcome of this script is the *Bug Verification Data* data set.

- *Data Synthesizer.* This script aggregates data from Chrome and Firefox vulnerabilities plus the *Bug Verification Data* data set to produce *Firefox Verified VDB*, and *Chrome Verified VDB* data sets. These data sets are basically the same as *Firefox VDB*, and *Chrome VDB* plus extra information about the earliest version affected by each vulnerability. The aggregated data sets are then consumed by analysis scripts to produce desired outputs for answering research questions.

The schemas of the data sets mentioned in Figure 9.1 are as follows:

BugFixes	= (bugID, browser, repository, fixedCommit, component)
Code Footprint	= (bugID, browser, repository, originalCommit, component, LoC)
Bug Verification Data	= (bugID, browser, component, version, LoC)
Firefox Verified VDB	= (bugID, bugDate, mfsaID, mfsaDate, cveID, cveDate, minAffectedVersion, maxAffectedVersion, estimatedMinVersion)
Chrome Verified VDB	= (bugID, bugDate, cveID, cveDate, minAffectedVersion, maxAffectedVersion, estimatedMinVersion)

9.2.2 Descriptive Statistics

Table 9.1 presents the numbers of CVEs affecting Chrome and Firefox by April 2013. Particularly, there are 768 CVEs affecting Chrome, and 876 CVEs affecting Firefox. Out of those, 728 Chrome CVEs (94.8%), and 730 Firefox CVEs (83.3%) have at least one responsible security bug. These CVEs make a total of 9,800 vulnerability claims to 18 major versions of Chrome (v1–v18), and 15 major versions of Firefox (v1.0–v12.0).

The detailed outcomes of the experiment for vulnerability claims in individual versions of Chrome and Firefox are reported in Table 9.2, Table 9.3, respectively. On average, each version of Chrome has about 309 vulnerability claims. Of these, approximately 28.6% are unverifiable, and 35.9% are found spurious by our method. The average number of vulnera-

Table 9.1: Descriptive statistics for vulnerabilities of Chrome and Firefox

	Number of CVEs			Total
	verifiable	w/o resp. bugs	w/o bug-fix	
Chrome	554 (72.1%)	40(5.2%)	174(22.7%)	**768**
Firefox	681 (77.7%)	146(16.7%)	49(5.6%)	**876**

Table 9.2: Descriptive statistics of vulnerability claims of Chrome.

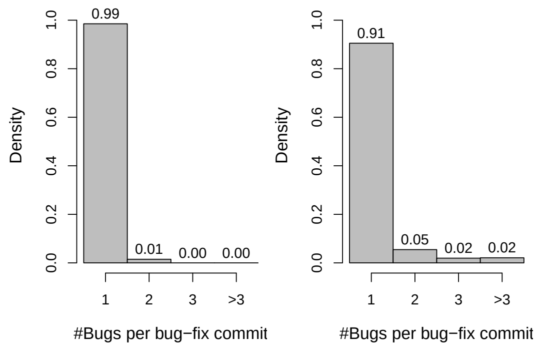
		Unverifiable		Verifiable	
Release	Total	w/o resp. bug	w/o bug-fix	w/ evidence	spurious
Chrome v1	526	5.9%	22.1%	34.8%	37.3%
Chrome v2	512	3.9%	22.7%	36.1%	37.3%
Chrome v3	504	3.6%	22.8%	38.7%	34.9%
Chrome v4	498	3.4%	22.5%	43.0%	31.1%
Chrome v5	455	1.1%	22.2%	38.9%	37.8%
Chrome v6	405	1.2%	24.0%	43.0%	31.9%
Chrome v7	391	1.3%	24.6%	42.2%	32.0%
Chrome v8	371	1.3%	24.5%	43.7%	30.5%
Chrome v9	337	1.5%	26.4%	42.7%	29.4%
Chrome v10	304	1.3%	28.0%	40.1%	30.6%
Chrome v11	273	1.8%	26.0%	38.1%	34.1%
Chrome v12	239	2.1%	25.5%	38.1%	34.3%
Chrome v13	217	1.8%	25.3%	36.9%	35.9%
Chrome v14	177	2.3%	22.6%	32.2%	42.9%
Chrome v15	121	4.1%	24.8%	38.0%	33.1%
Chrome v16	112	3.6%	25.0%	26.8%	44.6%
Chrome v17	88	4.5%	27.3%	20.5%	47.7%
Chrome v18	35	5.7%	48.6%	5.7%	40.0%
Mean(std.dev)	**309** (155)	**2.8%** (1.5%)	**25.8%** (5.8%)	**35.5%** (9.3%)	**35.9%**(5.1%)

bility claims per each version of Firefox is slightly less than Chrome, about 283. Comparing to Chrome, vulnerability claims per each Firefox version are less unverifiable (10.3%), and slightly less spurious (31.5%).

As suggested in Step 2 (see Section 8.2.4), we investigate the distribution of fixed bugs per bug-fix commit to understand the unwanted effect of multiple-bug-fix commits that potentially biases the experiment outcomes. Figure 9.2 shows these distributions for Chrome (left) and Firefox (right). In almost all cases for Chrome and in over 90% for Firefox, a bug-fix commit only contain fixes for one bug. Clearly developers of both Chrome and Firefox are really focused on fixing security bugs; they fix each security bug individually, and commit the bug-fix to the repository when a bug is fixed. This consistent behavior makes the unwanted

Table 9.3: Descriptive statistics of vulnerability claims of Firefox.

		Unverifiable		Verifiable	
Release	Total	w/o resp. bug	w/o bug-fix	w/ evidence	spurious
Firefox v1.0	454	12.3%	6.2%	32.6%	48.9%
Firefox v1.5	461	12.6%	6.3%	38.8%	42.3%
Firefox v2.0	469	7.0%	5.5%	45.6%	41.8%
Firefox v3.0	388	4.6%	6.4%	45.1%	43.8%
Firefox v3.5	336	3.0%	6.5%	53.0%	37.5%
Firefox v3.6	310	2.9%	7.4%	52.3%	37.4%
Firefox v4.0	253	0.8%	8.3%	62.8%	28.1%
Firefox v5.0	230	0.0%	8.3%	67.4%	24.3%
Firefox v6.0	220	0.0%	7.7%	68.2%	24.1%
Firefox v7.0	210	0.0%	7.6%	68.1%	24.3%
Firefox v8.0	203	0.5%	7.9%	66.5%	25.1%
Firefox v9.0	196	0.0%	7.7%	66.8%	25.5%
Firefox v10.0	176	0.0%	8.0%	67.0%	25.0%
Firefox v11.0	175	0.0%	8.0%	70.3%	21.7%
Firefox v12.0	165	0.0%	8.5%	69.7%	21.8%
Mean(std.dev)	**283** (108)	**2.9%** (4.3%)	**7.4%** (0.9%)	**58.3%** (12.2%)	**31.4%** (9.0%)

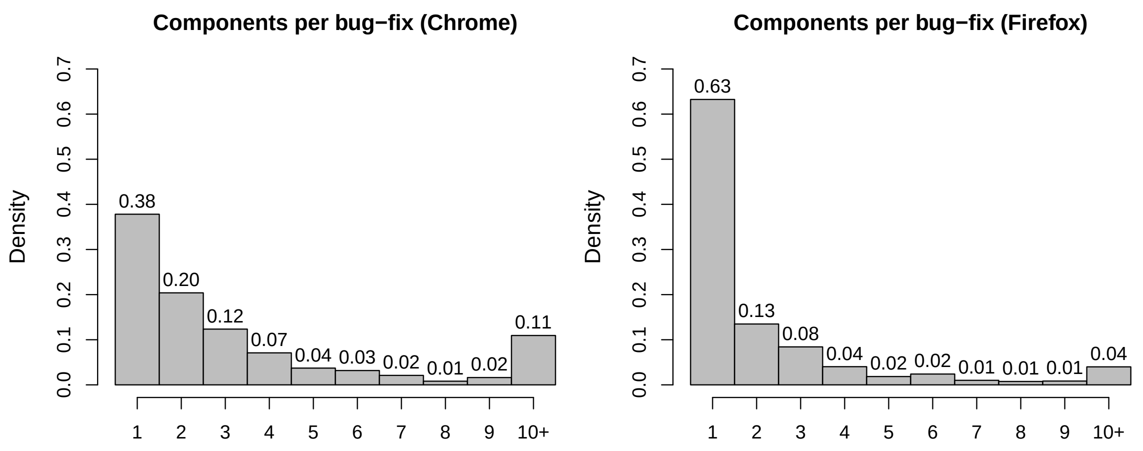


(a) Chrome (b) Firefox

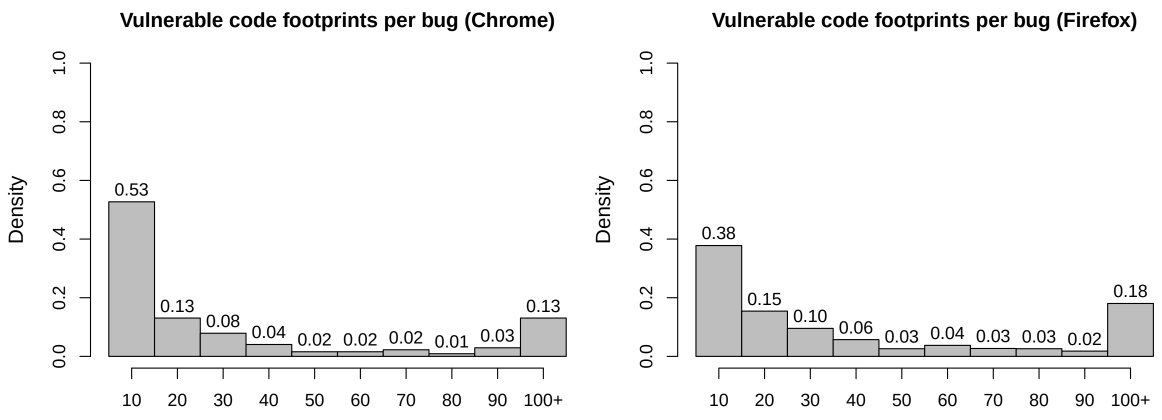
Figure 9.2: The number of bugs per bug-fix commit in Chrome (a) and in Firefox (b).

effect of multiple-bug-fix commit negligible in our experiment.

We further investigate the complexity of a security bug-fix commit in two aspects: the



(a) Number of components per bug-fix commit



(b) Number of vulnerable code footprints per bug-fix commit

Figure 9.3: The complexity of bug-fix commits by number of source components (a) and by number of vulnerable code footprints (b).

number of source components touched to fix a bug, and the number of vulnerable code foot prints. The intuition behind this investigation is that a less complex bug-fix commit will generate less bias in the experiment outcome.

Figure 9.3(a) reports the distributions of source components touched per bug-fix commit for Chrome (left) and Firefox (right). In Chrome, 77% of the cases a security bug gets fixed by touching at most four components, and 38% are fixed by touching only one component. Meanwhile, in Firefox, 76% are fixed by touching at most two components, and up to 63% of the cases are fixed by touching one component. Moreover, in terms of touched components, the number of complicated security bugs which require touching over ten components is about 11% in Chrome, and only 4% in Firefox. In short, bug-fix commits touching one component take the largest portion in both Chrome and Firefox. They are majority in Firefox, but are not in Chrome nonetheless.

Figure 9.3(b) exhibits the histograms of vulnerable code footprints per bug-fix commit for Chrome (left) and Firefox (right). In Chrome, 78% security bugs have up to 40 vulnerable code footprints, of those 53% have up to 10 footprints. In Firefox, 76% security bugs have up to 60 footprints, 10-footprint (or less) security bugs are only 38%. Here we can see an opposite observation between Chrome and Firefox, 10-footprint security bugs are majority in Chrome, but are not in Firefox, although they also take the largest portions in the distributions of both Chrome and Firefox.

On average, for two-third of Chrome security bugs, each has 15.26 vulnerable code footprints, and gets fixed by touching 1.84 components. Those numbers for Firefox are 21.18 and 1.17. Apparently, security bugs are local phenomena, which might help to reduce the potential bias in the proposed method.

9.2.3 The Analysis on the Spurious Vulnerability Claims

Table 9.2 and Table 9.3 show a non-negligible amount of unverifiable vulnerability claims for both Chrome and Firefox, approximately 28.6% and 10.3% respectively. The error rate measured by the ratio of the spurious vulnerability claims to the total ones in each analyzed version could be significantly worse. At best all, these unverifiable vulnerability claims are not spurious. The measured error rate is therefore the lower bound of the actual value. In the sequel, we define two error rates: *optimistic error rate* (OER) and *pessimistic error rate* (PER).

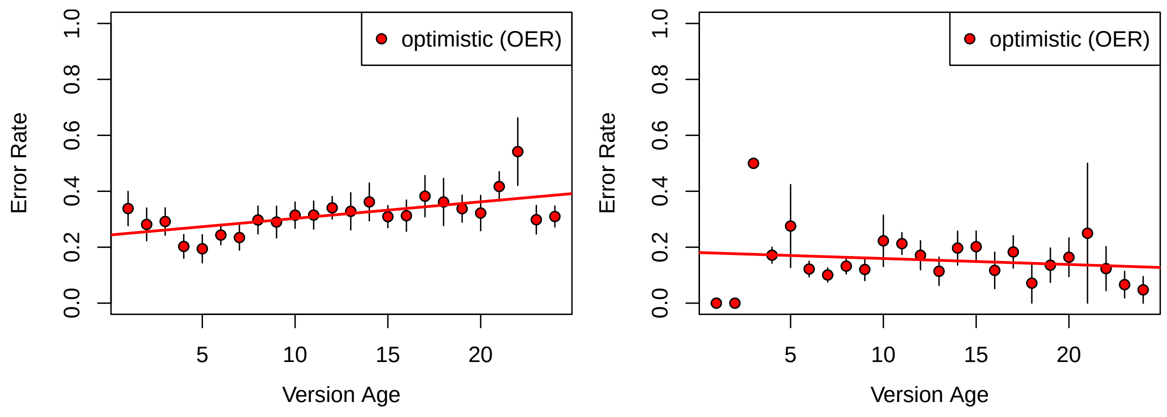
$$OER(v) = \frac{|spurious(v)|}{|vulnerabilities(v)|} \tag{9.1}$$

$$PER(v) = \frac{|spurious(v)| + |unverifiable(v)|}{|vulnerabilities(v)|} \tag{9.2}$$

where v is a version; $|spurious(v)|, |unverifiable(v)|$, and $|vulnerabilities(v)|$ are the number of spurious, unverifiable, and total vulnerabilities of v.

From (9.2) and (9.1), it is clearly that the PER is always greater than the OER. Thus the OER is the lower bound of the actual error rate. If the OER is bad, the actual error rate and the PER are even worse.

We study the systematicness of the error rates. The study period covers first 36 months of each version because the version life cycle (*i.e.,* interval between two consecutive major



(a) Chrome (b) Firefox

Version age is the number of months since the release of a particular version. A red (dark) circle is the average OER of all versions in their particular age. The bars are the standard errors.

Figure 9.4: The average error rates (with error bars) of Chrome (a) and Firefox (b) along the lifetime of individual versions.

versions) is quite short for recent versions of Firefox [Wik13] and all versions of Chromes [Chr13].

Figure 9.4 illustrates the evolution of the OER along the version age *i.e.*, the number of months since the release date of individual versions. The circles in the figure indicate the mean values; and the vertical bars determine the standard errors. The lines the linear model showing the global trends.

For Chrome, Figure 9.4(a) exhibits a growing trend of OER along the development of version age. The magnitude of the mean OER is mostly around 0.2 to 0.4. The error bars are quite small in most of the cases, which means there are less variant among OER of individual versions. It means the number of spurious vulnerability claims in analyzed Chrome versions are remarkable. This phenomenon is consistent during the version life time.

The story of Firefox illustrated in Figure 9.4(b) develops in a different direction: the global trend of OER is slightly going down as long as the versions are in the market. The magnitude of the mean OER is smaller, mostly from 0 to 0.2 with few outlines. The small error bars in most cases also indicate the small variance of OER of individual Firefox versions.

Clearly the vulnerability claims of Firefox are more reliable than those of Chrome since the ratio of spurious vulnerability claims for Firefox is smaller than Chrome's. Moreover, the error rate of Firefox tends to decrease overtime, whereas the error rate of Chrome tends to move up.

These inconsistent behaviors between two competing browsers could be potentially explained by the process that vulnerability claims are done. According to the private communication with NVD, the NVD analysis team do not perform any tests to determine which versions are affected by which CVEs. The vulnerability claims are derived from the CVE description by MITRE (`www.mitre.org`), release notes by software vendors, and additional data by third-party security researchers. Therefore, to ensure completeness, all versions before a version X are claimed vulnerable to a CVE if its description says something like: *"version X and before"* or *"X and 'previous' versions"*. Apparently, in this case the NVD analysis team received more detailed information for Firefox than for Chrome.

In summary, the experiment has provided evidences for the non-negligible error in the vulnerability claims made by NVD to retrospective versions of Chrome and Firefox. This is potentially the result of an unreliable process of making vulnerability claims. This evidence therefore recommends a careful revision of scientific studies and, especially, any compliance assessments that are relied upon such vulnerability claims.

9.3 The Impact of Spurious Vulnerability Claims

The previous analysis in Section 9.2.3 has shown a significant amount of spurious vulnerability claims do exist. This section investigates the potential impact of spurious vulnerability claims (RQ10) to scientific analyses based on such data. For this purpose, we examine two studies about *the majority of foundational vulnerabilities* and *the trend of foundational vulnerabilities.*

9.3.1 The Majority of Foundational Vulnerabilities

A foundational vulnerability is a vulnerability which is introduced in the very first version (*i.e.,* v1.0), but continues to survive in next versions. In this section we revisit the claim on the majority of foundational vulnerabilities: *"Foundational vulnerabilities are the majority in each version of both Chrome and Firefox"*. The claim could be formulated into the following hypothesis.

H9.1$_{A+}$ *More than* 50% *of vulnerabilities of a version are foundational.*

The subscript $A+$ indicates **H9.1**$_{A+}$ is an alternative hypothesis. It means that if the returned *p-value* of a statistic test is less than the significant level 0.05, we could reject the null hypothesis and accept the alternative one.

After a long evolution progress, modern versions of software might be completely different from the initial one. Obviously, foundational vulnerabilities should not be found in these modern versions. Thus, the claim about the majority of foundational vulnerabilities is eventually false. Therefore we relax the concept of foundation vulnerability to *inherited vulnerability*, see also Section 5.2. An *inherited vulnerability* of a version X is a vulnerability affecting X and its preceding versions. The claim about the majority of foundational vulnerabilities is relaxed to the claim about the majority of inherited vulnerabilities, which is *"Inherited vulnerabilities are the majority"*. Similarly, we test the following hypothesis:

H9.2$_{A+}$ *More than* 50% *of vulnerabilities in a version X also exist in version X-1.*

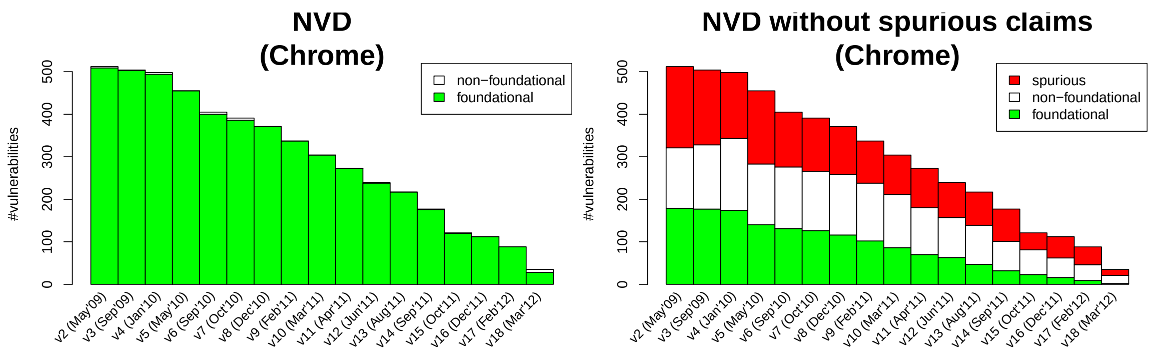
H9.3$_{A+}$ *More than* 50% *of vulnerabilities in a version X also exist in version Y which is older than X at least 6 month.*

The hypothesis **H9.2**$_{A+}$ follows exactly the definition of inherited vulnerabilities. Meanwhile, the hypothesis **H9.3**$_{A+}$ considers the short-cycle release policy where software vendors try to ship a new version in a relative short period (*e.g.,* less than 2 months per version). Due to this policy, two consecutive versions might not have enough significant difference in their code base. We assume that two versions which are different at least 6 month would have significant changes in their code base.

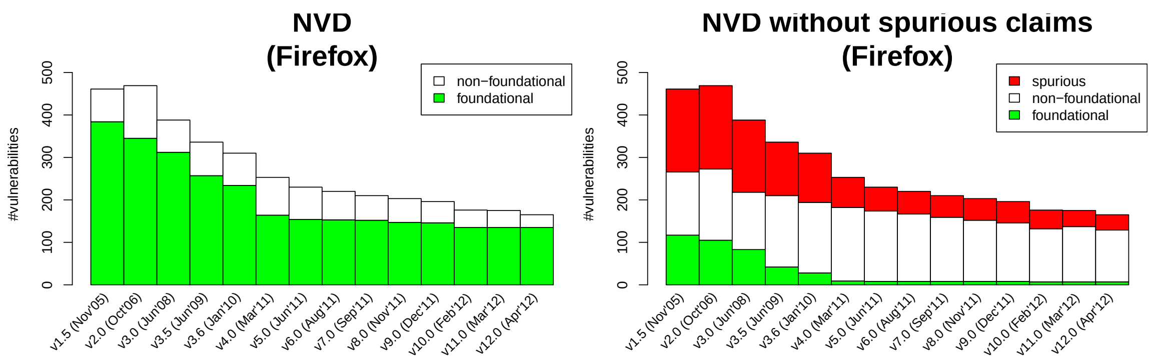
We test these hypotheses in two data sets: one for all vulnerability claims by NVD, and another one for vulnerability claims excluding ones which are found spurious by the proposed method. To the brevity, we shortly refer to the former as *NVD* data set, and refer to the latter as *Verified NVD* data set.

We could use either one-sided t-test or one-sided Wilcoxon signed-rank test. The former tests on the mean, but requires the ratios to be normally distributed. The latter does not requires normality, but tests on the median instead. Therefore, we first check the normality of the ratios by the Saphiro-Wilk test. If the normality test returns *p-value* greater than 0.05, the ratios are normally distributed. Then we will use t-test to check the hypothesis. Otherwise, we will use Wilcoxon signed-rank test.

Figure 9.5 reports the distributions of foundational vulnerability claims for Chrome (a) and Firefox (a), reported by both NVD (left) and Verified NVD (right) data sets. Clearly, in these versions, foundational vulnerability claims are dominant, approximately 99% and 75% per each version in Chrome and Firefox, respectively. The most remarkable difference between two data sets is that the amount of vulnerability claims (both foundational and non-foundational) in the Verified NVD data set is dramatically lower than the NVD data set. This



(a) Chrome foundational vulnerabilities



(b) Firefox foundational vulnerabilities

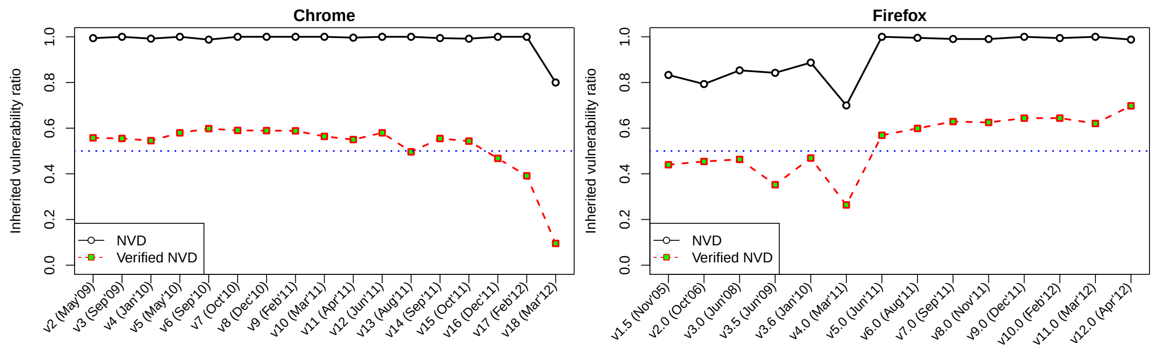
The dates in the X axis are the release dates.

Figure 9.5: Foundational vulnerabilities by NVD: all vulnerability claims (left) and spurious vulnerability claims excluded (right).

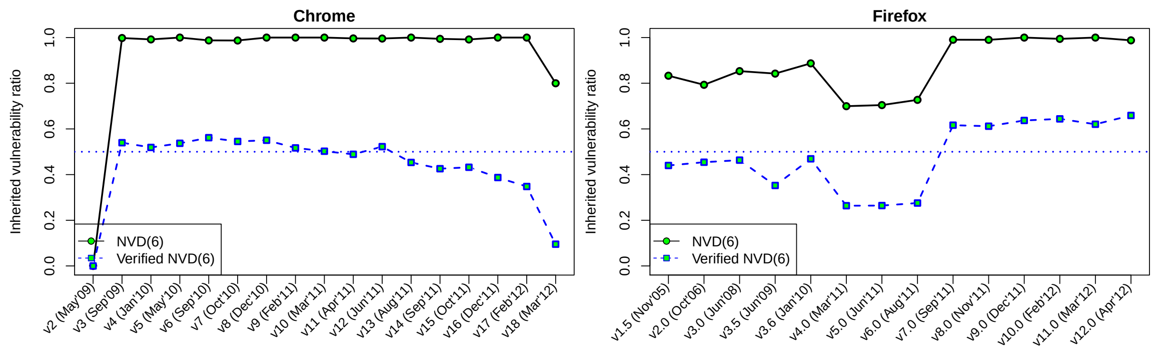
is because of the high number of spurious vulnerability claims found in each version, see Table **??**. From the figure, foundational vulnerabilities are no longer dominant, especially for Firefox v4.0 and onward.

Figure 9.6 reports the ratios of inherited vulnerabilities in individual versions of Chrome and Firefox. In Figure 9.6(a), we count the inherited vulnerabilities of a version X from all its preceded versions, see **H9.2**$_{A+}$. Meanwhile, in Figure 9.6(b), we only count inherited vulnerabilities from preceded versions which are at least 6 month older, see **H9.3**$_{A+}$. In this figure, circles and squares denote the ratios of inherited vulnerabilities counted from NVD and Verified NVD data sets, respectively.

From Figure 9.6 we can observed a similar phenomenon in the foundational vulnerabilities. In NVD data set, inherited vulnerabilities are dominant in both ways of counting.



(a) Inherited vulnerabilities from preceded versions



(b) Inherited vulnerabilities from preceded versions which are at least 6 month older

Figure 9.6: The ratios of inherited vulnerabilities in Chrome and Firefox.

However, they might be no longer dominant in Verified NVD data set. There is a weird data point in Chrome's: the number of inherited vulnerabilities in Figure 9.6(b) is 0. It is because the interval between Chrome v1.0 and v2.0 was less than 6 months. By applying the counting method described in **H9.3**$_{A+}$, Chrome v2.0 does not have any inherited vulnerabilities.

We run the Shapiro-normality test on vulnerabilities data. Sometimes, it rejects the null hypothesis (*i.e.,* data is not normality, $p\text{-}value = 0.07 \cdot 10^{-6}$ – Chrome, NVD), sometime it does not (*i.e.,* data is normality, $p\text{-}value = 0.95$ – Firefox, NVD). Therefore, we use Wilcoxon signed-rank test to check the hypotheses. The outcomes of the hypothesis tests are reported in Table 9.4. Notice that the reported *p-values* are for rejecting the null hypothesis. Therefore, if $p\text{-}value < 0.05$, we accept the alternative hypothesis, and reject it otherwise.

Table 9.4 shows that if we rely on the NVD data set, all the hypotheses are accepted with strong evidences (*i.e., p-values* are almost zero). However, if we use the Verified NVD data set, which is NVD data set excluded the spurious vulnerability claims, we obtain the opposite conclusions in most cases. It is therefore an evidence for the significant impact of spurious

Table 9.4: The Wilcoxon signed-rank test results for the majority of foundational and inherited vulnerabilities.

Numbers in parentheses are *p-values* returned by the Wilcoxon signed-rank test for the corresponding hypothesis. If *p-value* < 0.05, the null hypothesis is rejected, it means we accept the alternative hypothesis. Otherwise, we reject the alternative hypothesis.

	Hypothesis	NVD		Verified NVD	
		Chrome	Firefox	Chrome	Firefox
H9.1$_{A+}$	More than 50% of vulnerabilities of a version are foundational	Accept ($0.01 \cdot 10^{-2}$)	Accept ($0.06 \cdot 10^{-3}$)	Reject (1.00)	Reject (1.00)
H9.2$_{A+}$	More than 50% of vulnerabilities in a version X also exist in version X-1	Accept ($0.01 \cdot 10^{-2}$)	Accept ($0.05 \cdot 10^{-2}$)	Accept (0.03)	Reject (0.16)
H9.3$_{A+}$	More than 50% of vulnerabilities in a version X also exist in version Y which is older than X at least 6 month	Accept ($0.01 \cdot 10^{-1}$)	Accept ($0.05 \cdot 10^{-2}$)	Reject (0.85)	Reject (0.67)

vulnerability claims to the study on the majority of foundational/inherited vulnerabilities. Many foundational/inherited vulnerabilities do not really exist. They are a phenomenon which can be better explained by the policy *"version X and previous versions are vulnerable"* as discussed above.

9.3.2 The Trend of Foundational Vulnerability Discovery

In this study, we replicate the experiment described by Ozment and Schechter [OS06] to study the existence and direction of trend in the discovery of foundational vulnerabilities. We employ Laplace test for trend [NIS12a, Chap. 8] which was also used in [OS06] to search for a trend quarterly during the browser age.

The Laplace test computes the Laplace factor which compares the centroid of the observed discovery times with the mid-point of the observation period. This factor approximates the standardized normal random variable (*e.g.*, *z*-score). The following formula shows how the Laplace factor z is computed.

$$z = \frac{\sqrt{12n}\sum_{i=1}^{n}\left(t_i - \frac{T}{2}\right)}{n \cdot T} \tag{9.3}$$

where n is the number of foundational vulnerabilities discovered within the observation period T; t_i is the interval (*e.g.,* in days) between the discovery time of the i-th vulnerability and the beginning time of the observation period. The interpretation of the Laplace factor z is as follows:

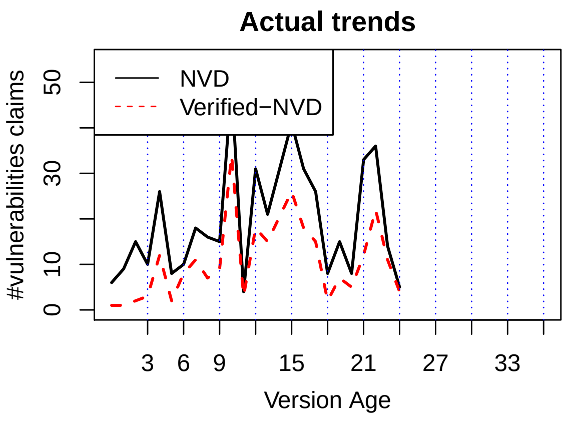
- $z > 1.96$: there is a significant upward trend in the period T with 95% confidence.
- $z < -1.96$: there is a significant downward trend in the period T with 95% confidence.
- $-1.96 \leq z \leq 1.96$: there is either an upward trend ($z > 0$) or a downward trend ($z < 0$) in the data, but the trend is not significant. Statistically speaking, we conclude there is no trend in the observation period.

When the Laplace test indicates a significant trend (either increasing or decreasing trend) in a certain time period, we call it an *event*. In a certain period, an event could be detected in both data sets, *i.e.,* NVD and Verified NVD, by the Laplace test. Sometimes, an event could only be detected in only one data set. We refer to the former as *common event*, and the latter as *inconsistent event*.

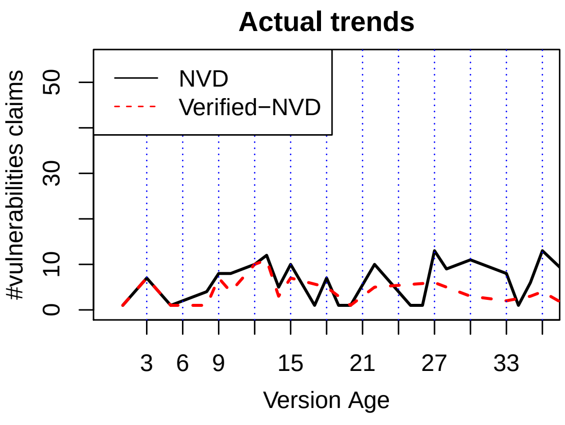
We want to determine whether spurious vulnerability claims have a significant impact on the trends of foundation vulnerability discovery. For this purpose, we first perform the Laplace test for quarterly trends of foundational vulnerabilities discovery along the age of individual versions in two data sets: NVD and Verified NVD. Then, for each version, we count the number of inconsistent events. If the numbers of inconsistent events in all versions are significantly different from 0, we could conclude a significant impact of spurious vulnerability claims on the foundational vulnerability trends. In other words, we test the following null hypothesis:

H9.4$_0$ *The mean of inconsistent events in all individual versions is not significantly different from 0.*

We run the experiment on versions of Chrome and Firefox. In the experiment, we measure the interval t_i of the i-th vulnerability by the number of days. However the published dates of NVD are a poor approximation for the discovery dates of vulnerabilities [Res05; Ozm05]. It is because when the NVD security team receive the vulnerability reports, they usually wait for software vendors to fix the vulnerabilities before announcing the NVD entries. Therefore, we approximate the discovery dates of vulnerabilities by the dates when the bug reports corresponding to vulnerabilities were filed. By doing so, we assume that if a



(a) Chrome v5



(b) Firefox v3.0

NVD: all vulnerability claims (with spurious ones); Verified NVD: vulnerability claims without spurious ones.

Figure 9.7: The actual discovery trends of foundational vulnerabilities.

Table 9.5: Number of events (*i.e.,* significant quarterly trends)

		Inconsistent Event		
Browser	Common Event	Only NVD	Only Verified NVD	Total
Chrome (v2–v18)	23 (61%)	5 (13%)	10 (26%)	38 (100%)
Firefox (v1.5–v12.0)	5 (18%)	22 (78%)	1 (4%)	28 (100%)
Total	28 (42%)	27 (41%)	11 (17%)	66 (100%)

vulnerability is discovered by a white-hat researcher, he/she will notify (direct or indirectly) software vendors as soon as possible. Then a bug report will be filed. For vulnerabilities discovered by black-hat, we have no glue about the actual discovery dates.

Figure 9.7 reports the actual trends of foundational vulnerabilities for both Chrome (v5), exemplified in Figure 9.7(a), and Firefox (v3.0), exemplified Figure 9.7(b). In this figure, the solid line presents the trend reported by NVD, and dashed line indicates trend reported by Verified NVD. For Chrome, the NVD trend and Verified NVD trend have similar shape, but different from the magnitude. Meanwhile, for Firefox, these trends are clearly different in both shape and magnitude.

We run the Laplace test for quarterly trends of foundation vulnerabilities of Chrome and Firefox. Figure 9.8 reports the Laplace factors for Chrome v5.0. The figure shows the different

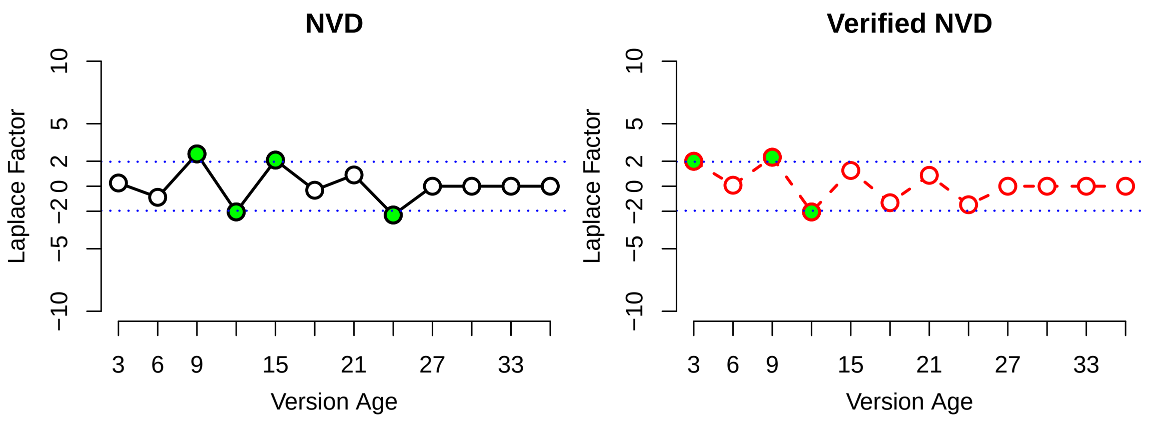


Figure 9.8: The Laplace test for quarterly trends in Chrome v5 foundation vulnerabilities.

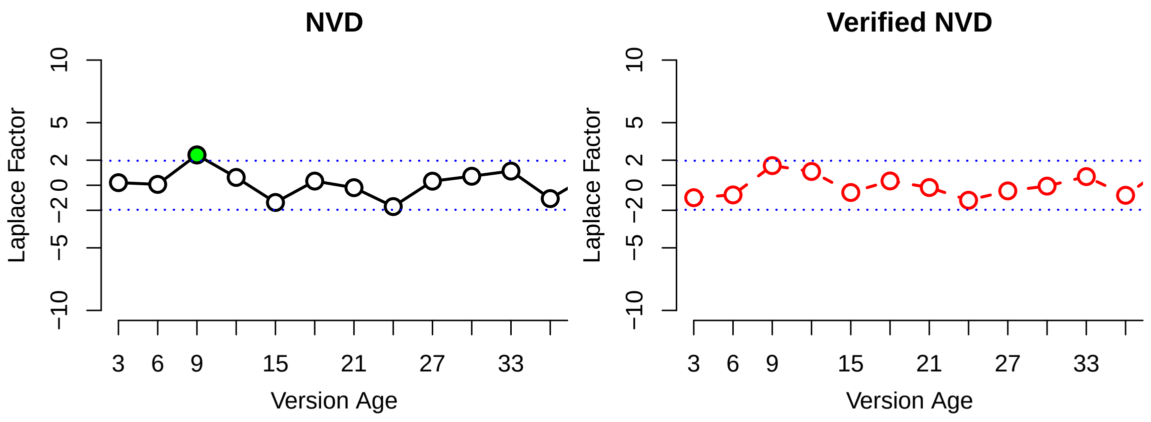


Figure 9.9: The Laplace test for quarterly trends in Firefox v3.0 foundation vulnerabilities.

outcomes of Laplace test by including or excluding spurious vulnerability claims (*i.e.*, NVD and Verified NVD data sets, respectively). Before month 12*th*, NVD reports two significant increasing trends; Verified NVD reports one extra significant increasing trend, which will be missed if we look at NVD. In contrast, after month 12*th*, NVD reports other two significant trends, which do not appear in Verified NVD.

The Laplace factors for Firefox is reported in Figure 9.9. This figure also remarks the difference of the Laplace outcomes between NVD and Verified NVD. The former reports a significant trend during the life time of Firefox v3.0. This trend however disappear in the latter data set. The complete Laplace tests for quarterly trend for Chrome and Firefox could be found in the Appendix A.1, Figure A.1–A.2.

Table 9.5 summarizes the number of events identified by the Laplace test. This table re-

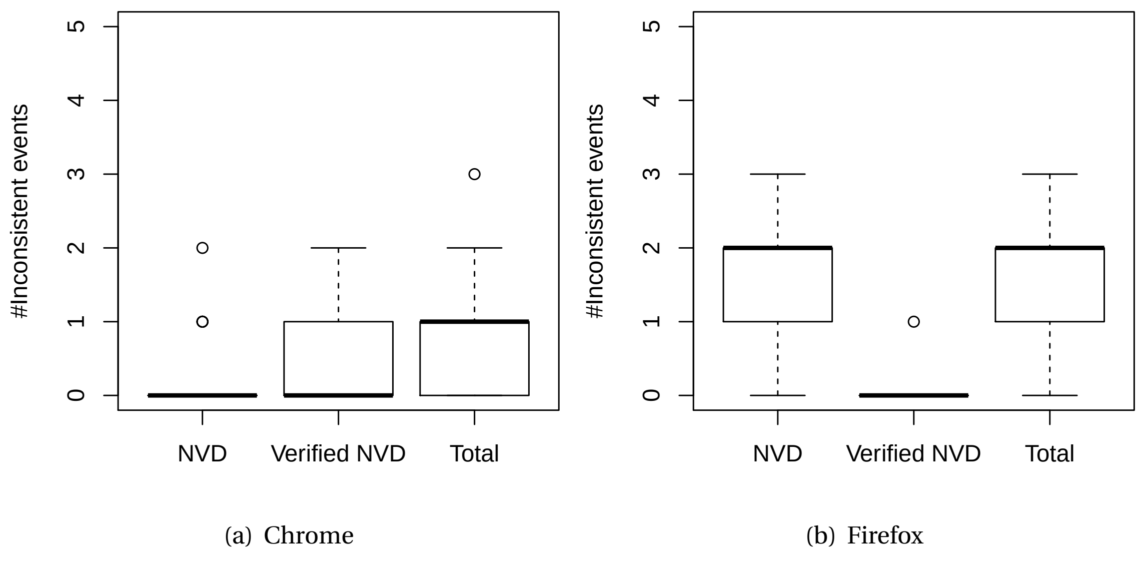


Figure 9.10: The distribution of inconsistent events in NVD and Verified NVD.

ports the total number of common events (the second column), the number of inconsistent events including events observed only in NVD (the third column), and events observed only in Verified NVD (the forth column) in all analyzed versions of Chrome and Firefox. The table shows that for Chrome, there are a lot of common events between two data sets (26 events – 59%). This could be explained by the similarity of shape between the actual trends for Chrome in both data sets (see Figure 9.7(a)). However, we can still observed the difference between to data sets by looking at the number of inconsistent events (18 inconsistent events – 41%). This difference is sharpen in the case of Firefox, the number of common events is small (7 events – 20%), while the numbers of inconsistent event is large (28 inconsistent events – 80%).

The breakdown distributions of inconsistent events in individual versions of Chrome and Firefox are illustrated in Figure 9.10. Interested readers are referred to Appendix A.1, Table A.1–A.2 for absolute numbers of the distributions.

We additionally run statistic test to see whether the numbers of inconsistent events in individual versions of Chrome and Firefox are different from zero, see **H9.4**$_0$. The Shapiro-Wilk normality test rejects the null hypothesis for both Chrome (p-$value = 0.005$) and Firefox (p-$value = 0.006$). It means these distributions are not normal. Thus we rely on Wilcoxon singed-rank test to check **H9.4**$_0$. The outcome of the Wilcoxon test also rejects **H9.4**$_0$ for both Chrome (p-$value = 0.003$) and Firefox (p-$value = 0.001$). This means that the numbers of inconsistent events are significantly greater than 0. In other words, it is an evidence for the significant impact of spurious vulnerability claims on the analysis about the quarterly trends of foundational vulnerability discovery.

9.4 Threats to Validity

Construct validity includes threats affecting the approach by means of which we collect and verify vulnerabilities. Threats in this category come from the assumptions as follows.

Bias in vulnerability data set. We apply the software infrastructure described in Chapter 4. Thus the study in this chapter has a number of validity threats described in Section 4.2. We also apply the mitigation procedures in Section 4.2 to minimize the threats.

Biases in bug-fix commit data. As outlined previously, there are two potential biases on bug-fix commit data [Bir09]: the developers do not mention the bug ID in a bug-fix commit; and the developers mention a bug ID in a non-bug-fix commit. To evaluate the impact of the latter bias, we performed a qualitative analysis on some bug-fix commits and found that all are actually bug fixes. This confirms the finding in [Bir09] for this type of bias. As for the former bias, we check the completeness of the bug-fix commits for vulnerabilities. As discussed, about one fourth of vulnerabilities are unverifiable (see also Table 9.1). We optimistically assumed that these vulnerabilities are not spurious. Therefore, our conclusions are the lower bound of the real errors.

Bias in the validation method. The method assumption **ASS8.3** is apparently syntactical and might not cover all the cases of bug fixes since it is extremely hard to automatically understand the root cause of vulnerabilities. Therefore, the method classifies a NVD-reported vulnerability of a particular version as correct while it may be a false-positive. Again it only makes our conclusion lower bound of the real error, thus it make our case stronger.

Bias in the method implementation. It is possible that the implementation of the validation method has some bugs, causing bias in the identification of vulnerability evidences. To minimize such problem, we employ multi-round test-and-fix approach where we ran the program on some vulnerabilities, then we manually checked the output, and fixed found bugs. We repeated this until no bug was found. Finally, we randomly checked the output again to ensure there was no mistake.

Internal validity concerns the causal relationship between the collected data and the conclusion. Our conclusions are based on statistical tests. These tests have their own assumptions which may be violated by the data. To reduce the risk we carefully analyzed the assumptions of the tests: for instance, we did not apply any tests with normality assumption since the distribution of vulnerabilities is not normal.

External validity is the extent to which our conclusion could be generalized to other applications. We tested the proposed method on browser but we did not use in any way this information. The method could be used and the experiment could be replicated on different software.

9.5 Chapter Summary

This chapter described an experiment applying the assessment method described in Chapter 8 to assess the retro persistence validity of vulnerability claims by NVD for Firefox and Chrome. The experiment has assessed 1,235 out of 1,644 CVEs (∼ 75%) in 33 versions of Chrome and Firefox. The assessment took approximately 14 days. It is an evidence that the proposed method is not only effective (*i.e.,* majority of vulnerabilities have been assessed), but also efficient (*i.e.,* in comparison with 6 months for 68 vulnerabilities by using an ad-hoc method [Men13]).

The experiment results have pointed out that about 30% of vulnerabilities claims by NVD for Chrome and Firefox are spurious. It is also an evidence for the overdose of the rule *"version X and its previous versions are vulnerable"* while marking which versions are vulnerable to which vulnerabilities. In other words, retro versions of Chrome and Firefox have less vulnerabilities than they were reported.

We further have conducted other experiments to see to what extend spurious vulnerability claims impact scientific vulnerability studies. In these experiments, we have revisited the observation about the majority of foundational vulnerabilities in Chapter 5. By eliminating all spurious vulnerabilities, we found that foundational vulnerabilities are no longer the majority in security landscape of individual versions of Chrome and Firefox. We even relaxed the constraint to see whether inherited vulnerabilities are the majority. Again, we found only a weak evidence that it is the case, but probably it is due to the short-cycle release policy currently adopted by software vendors. In another experiment analyzing the quarterly trends of foundational vulnerabilities by using Laplace test, we have also noticed a significant different between the reported trends by using the data with and without the spurious vulnerability claims. These experiments have presented evidences that spurious vulnerability claims did significantly impact the outcomes of scientific vulnerability studies.

In the next chapter, we are going to describe the observation on the correlation between dependency metrics and the vulnerable status of source components.

CHAPTER 10

Conclusion

This chapter summarizes the observations, findings, as well as invented artifacts presented in previous chapters of the dissertation. Based on that, the chapter also discusses future research directions that could be leveraged by the outcomes of this dissertation.

FROM the objective of the dissertation is to independently and systematically validate an empirical models concerning vulnerabilities, we have presented several observations and artifacts serving for the objectives. This chapter summarizes the key points of such observations and artifacts (Section 10.1), and discusses potential future research based on the results of this dissertation (Section 10.2).

10.1 Summary of Contributions

Inspiring by the following key observations in the literature: an inadequate amount of discussion about the quality of data source in empirical experiments on vulnerabilities, and critical issues in the traditional validation methodology for VDMs, as well as the lack of independent evaluation for proposed VDMs, we have conducted several activities and experiments aiming at filling the observed gaps. Here are the main contributions of the dissertation.

A systematic survey on the usage of vulnerability data sources. We have conducted a survey about empirical vulnerability studies in past eight years from 2005 to 2012. The survey included 59 publications, which were referred to as *primary studies*, in international workshops, conferences/symposium, and journals. The survey focused on the usage of vulnerability data sources in the past. Concretely, it addressed the following research questions:

RQ1 *Which are the popular data sources for vulnerability studies?*

RQ2 *Which data sources and features are used for which studies?*

To find out the answers, the survey has presented a qualitative analysis the data usage in 59 collected primary studies. The analysis showed that third-party data sources were preferred more than other data sources in conducting empirical vulnerability studies. Among several data sources, NVD was the most popular one, which was used in approximately 62% of primary studies across different research topics. Among features of data sources, Affected Versions (V_A) and Announced Date (T_A) are the most frequently used features in the collected primary studies.

An empirical methodology for the evaluation of the performance of VDMs. The observation on past studies in the field of VDM has pointed several critical biases in the traditional methodology, which were widely adopted in the literature, to evaluate the performance of VDMs. These biases included: *vulnerability definition bias* – which concerned the way vulnerability was understood and counted, *multi-version software bias* – which concerned the consideration of all versions of evolving software as a single entity, *acceptance threshold bias* – which concerned how VDMs were either accepted or rejected while fitting on a data set, and *overfitting bias* – which concerned the way VDMs were used in predicting future vulnerability trends.

These biases have impacted the outcomes of past evaluation experiments. Hence, we have worked out on an empirical methodology that took into consideration all above issues to address the two fundamental research questions in the field:

RQ3 *How to evaluate the performance of a VDM?*

RQ4 *How to compare between two or more VDMs?*

The methodology proposed two quantitative metrics: *temporal goodness-of-fit quality*, and *predictability*. The former indicates how well a VDM could fit existing vulnerability data. The latter determines how well a VDM could predict the future trends of vulnerabilities. The methodology included a sequence of fully-discussed steps, which consisted of criteria and justification in each step, that took input exactly as same as the input of the traditional evaluation methodology to produce more informative and precise outputs than the traditional methodology. Additionally, the proposed methodology enabled a statistic-powered comparison between VDMs, which are undoubtedly better than the traditional one. The effectiveness of the proposed methodology has been evaluated in an evaluation experiments on several versions of mainstream web browsers.

An evaluation and comparison on the empirical performance of existing VDMs. As an effort to evaluate the effectiveness of the proposed methodology to evaluate VDM performance, we have conducted an evaluation experiment on thirty versions of mainstream web browsers: Chrome, Firefox, Internet Explorer, and Safari. The experiment considered eight VDMs: AML, AT, LN, JW, LP, RE RQ, and YF. The experiment focused on the following research questions:

RQ6 *Is the proposed VDM evaluation methodology effective in evaluating VDMs?*

RQ7 *Among existing VDMs, which one is the best?*

By *effective* we meant the methodology could be able to evaluate VDMs and produce desired results. The experiment has showed that AT and RQ model should not be used due to their consistently low quality along the browser lifetime. Other models might be adequate. Interestingly, for young versions of browsers (no more than 12 months since the release date) the simplest model – the LN model – was the best in terms of quality and predictability. For middle age browsers (12 – 36 months), the AML model became the winner.

An empirical method for the assessment of vulnerabilities retro persistence. We proposed an empirical method to identify code evidence for vulnerability claims. By this method, we aimed to answer the following research question:

RQ5 *How to estimate the validity of a vulnerability claim to a retro version of software?*

The proposed method took a list of vulnerabilities and their corresponding security bugs as input. Then it traced the commits in the source code repository for the commits that fixed security bugs. From these commits, it determined the so-called vulnerable code footprints which are changed LoCs to fix security bugs. Then it traced for the origin revision where vulnerable code footprints were introduced. Finally it scanned the code base of individual versions to determine the vulnerable status of these versions. The outcome of the proposed method will provide a better insight about the security landscape of retro versions of software.

An assessment on the bias of vulnerability claims by NVD for Chrome and Firefox. We have conducted an experiment applying the assessment method described in Chapter 8. The experiment assessed the retro persistence validity of vulnerability claims by NVD for Firefox and Chrome. The purposes of the experiment are to answer the following research questions:

RQ8 *Is the proposed assessment method effective in assessing the retro persistence of vulnerabilities?*

RQ9 *To what extend are vulnerability claims by NVD trustworthy?*

RQ10 *To what extend does the bias in vulnerability claims by NVD (if any) impact conclusions of a vulnerability analysis?*

Similar to evaluation experiment for VDMs, by the word *"effective"*, we wanted to know whether the proposed assessment method is able to assess the majority of vulnerabilities. The experiment has assessed the retro persistence of more than 75% (1,235 out of 1,644 CVEs) vulnerabilities in 33 versions of Chrome and Firefox in approximately 14 days. It is an evidence that the proposed method is not only effective (*i.e.,* majority of vulnerabilities have been assessed), but also efficient (*i.e.,* in comparison with 6 months for 68 vulnerabilities by using an ad-hoc method [Men13]).

The experiment results have pointed out that about 30% of vulnerabilities claims by NVD for Chrome and Firefox are spurious. It is also an evidence for the overdose of the rule *"version X and all of its previous versions are vulnerable"* while marking which versions are vulnerable to which vulnerabilities. In other words, retro versions of Chrome and Firefox have less vulnerabilities as they were reported.

We further have conducted other experiments to see to what extend spurious vulnerability claims impact scientific vulnerability studies. In these experiments, we have revisited the observation about the majority of foundational vulnerabilities in Chapter 5. By eliminating all spurious vulnerabilities, we found that foundational vulnerabilities are no longer the majority in security landscape of individual versions of Chrome and Firefox. We even relaxed the constraint to see whether inherited vulnerabilities are the majority. Again, we found only a weak evidence that it is the case, but probably it is due to the short-cycle release policy current adopted by software vendors. In another experiment analyzing the quarterly trends of foundational vulnerabilities by using Laplace test, we have also noticed a significant different between the reported trends by using the data with and without the spurious vulnerability claims. These experiments have presented evidences that spurious vulnerability claims did significantly impact the outcomes of scientific vulnerability studies.

10.2 Limitation and Future Directions

Based on the limits of the presented experiments (*i.e.,* threats to validity), and the observation on past work, this section discusses the limitations as well as future directions of research as follows.

10.2.1 The Need of Experiment Replication

An obvious limitation to the dissertation is that all experiments in this dissertation are conducted on the vulnerability data of web browsers, but not other kinds of software applications. Though we have discussed why we target web browsers in the experiments – see Chapter 4, it still rises an external threat to the validity, which has been discussed at the end of each experiment presented in the dissertation, see Section 5.3, Section 7.5, Section 9.4. However, this threat is unavoidable not only in this dissertation, but also in other empirical studies. Therefore, one of a future work is to replicate the experiments in other kinds of applications such as operating systems, server applications, database management systems.

10.2.2 The Need of a Maturity Model for Vulnerability Data

An empirical study of vulnerabilities usually consists of following common steps: security researchers raise hypothesis, acquire necessary vulnerability data, test their hypothesis, and report the result. In this process, the quality of data source strongly affect the quality of the study. This has been confirmed in the experiment testing the impact of spurious vulnerability claims to the outcomes of an analysis, see Section 9.3. Therefore, it is necessary to have a model to qualitatively or quantitatively assess the quality of a data set, as well as the reliability of an experiment based upon a data set.

The conversations between me and other researchers agreed that such model is not only important for empirical vulnerability studies, but also to other empirical experiments which are based upon a data set. However, we have also agreed that it is impossible to have a silver-bullet solution to qualify the quality of data set in a general sense. Hence, a maturity model which takes into account particular characteristics of vulnerability studies, and focuses only on vulnerability studies will make sense.

We have conducted a preliminary study in this direction, and have proposed a model where we could evaluate the maturity of data set along different dimensions, such as the coverage of data samples in terms of volume and time, the representation of data source, as well as the documentation of the data collection by the data source provider. Obviously, the result is still very preliminary and needs more effort to be accomplished.

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APPENDIX A

Appendix

A.1 Details of Laplace Test for Quarterly Trends of Foundational Vulnerabilities

This section presents the complete output of the Laplace test of quarterly trends for foundational vulnerability discovery in Chrome, see Figure A.1, and in Firefox, see Figure A.2. These figures are organized as a table of plots where each browser version occupies a row. The first column is a plot describing the actual trends of vulnerability discovery along version age. In this plot, the solid line represents the trend of all vulnerability claims by NVD – the NVD data set, and the dashed line represents the similar trend, but excluding spurious vulnerability claims identified by the proposed method – the Verified NVD data set. The plots in the two last columns illustrate the Laplace factors z, see (9.3), for quarterly trends in NVD and Verified NVD data sets, respectively.

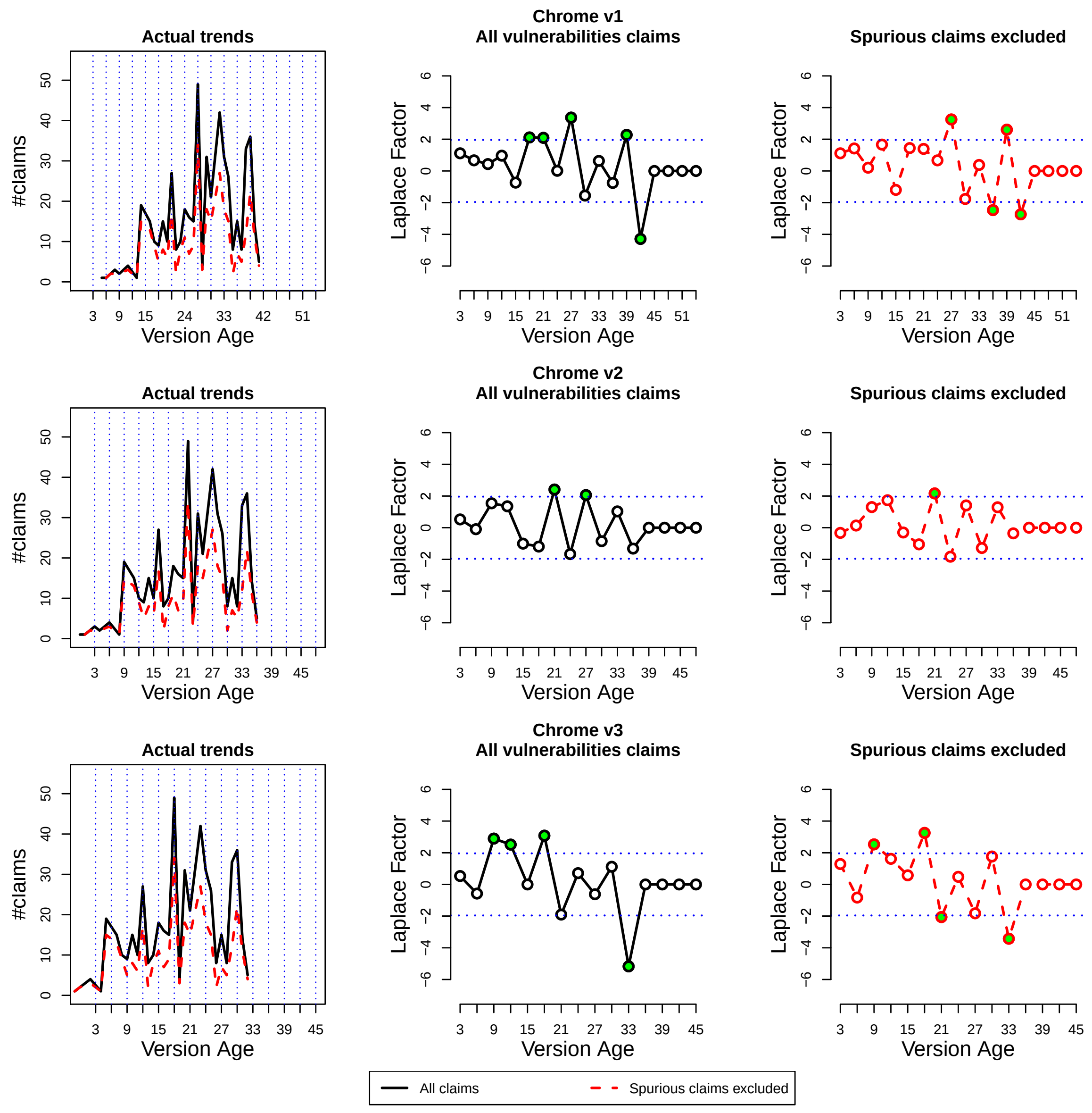

Figure A.1: Laplace test for trend in quarterly foundational vulnerability discovery for Chrome

(to be continued in next page)

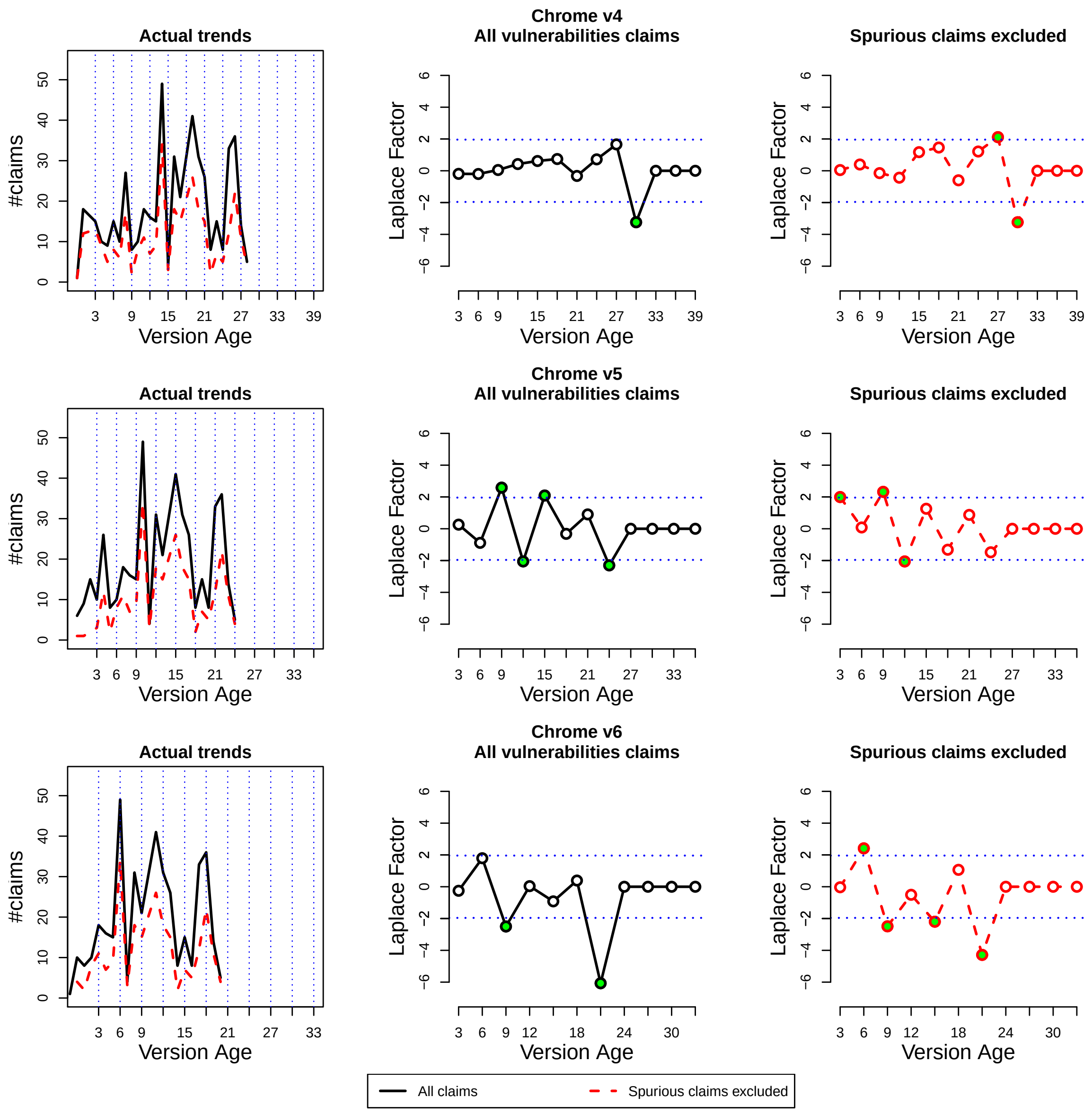

Figure A.1: Laplace test for trend in quarterly foundational vulnerability discovery for Chrome (to be continued in next page)

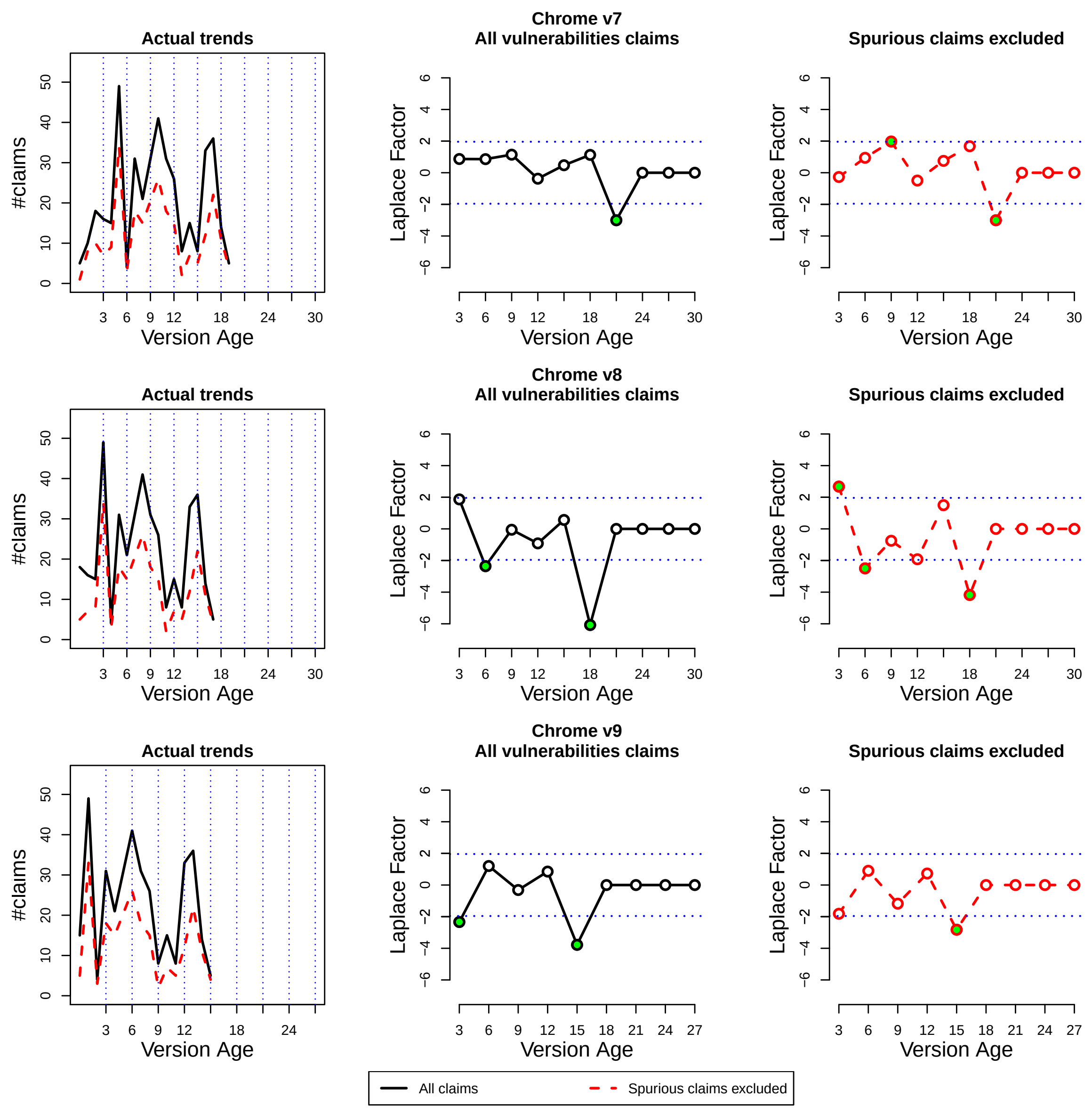

Figure A.1: Laplace test for trend in quarterly foundational vulnerability discovery for Chrome (to be continued in next page)

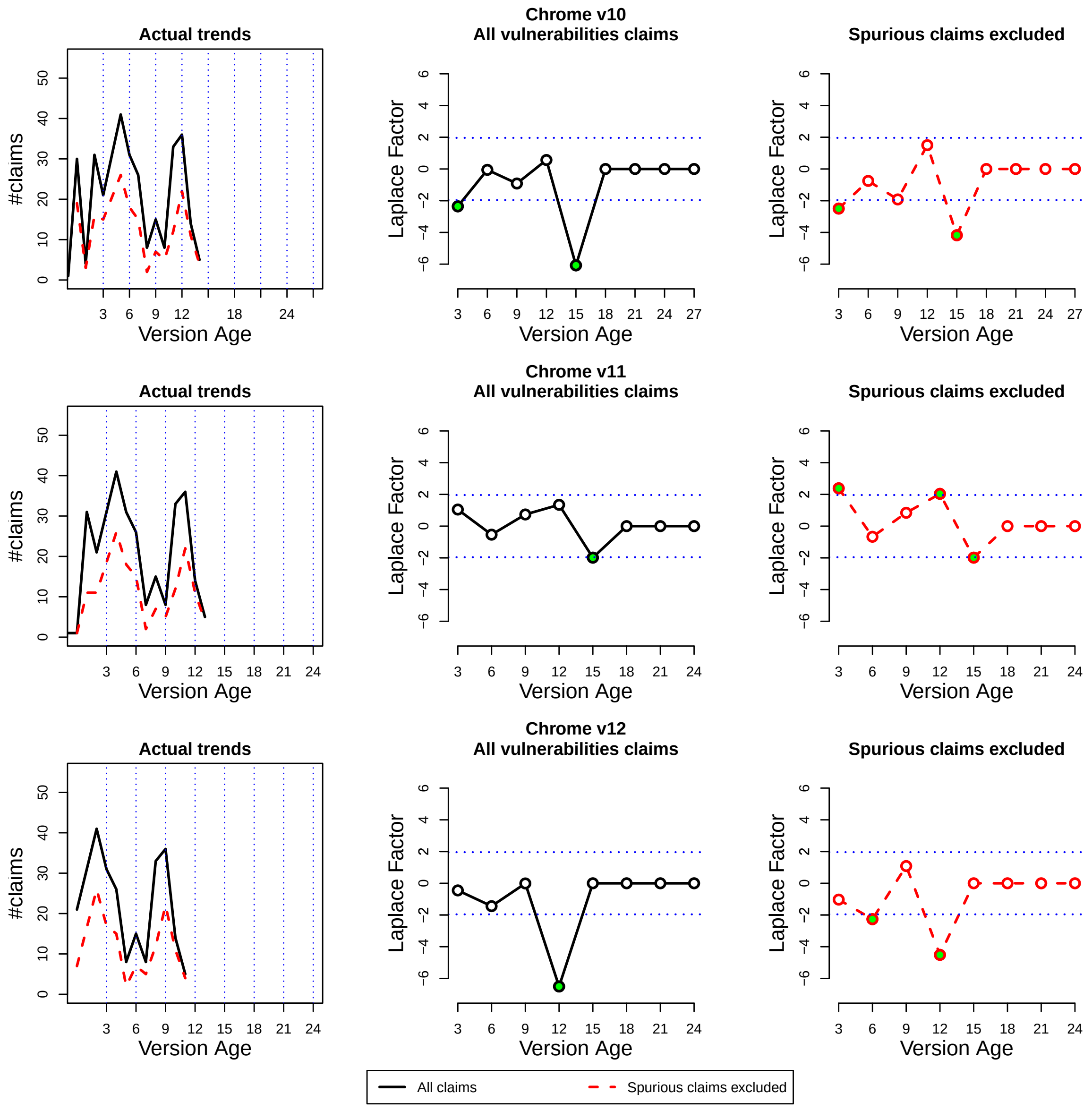

Figure A.1: Laplace test for trend in quarterly foundational vulnerability discovery for Chrome (to be continued in next page)

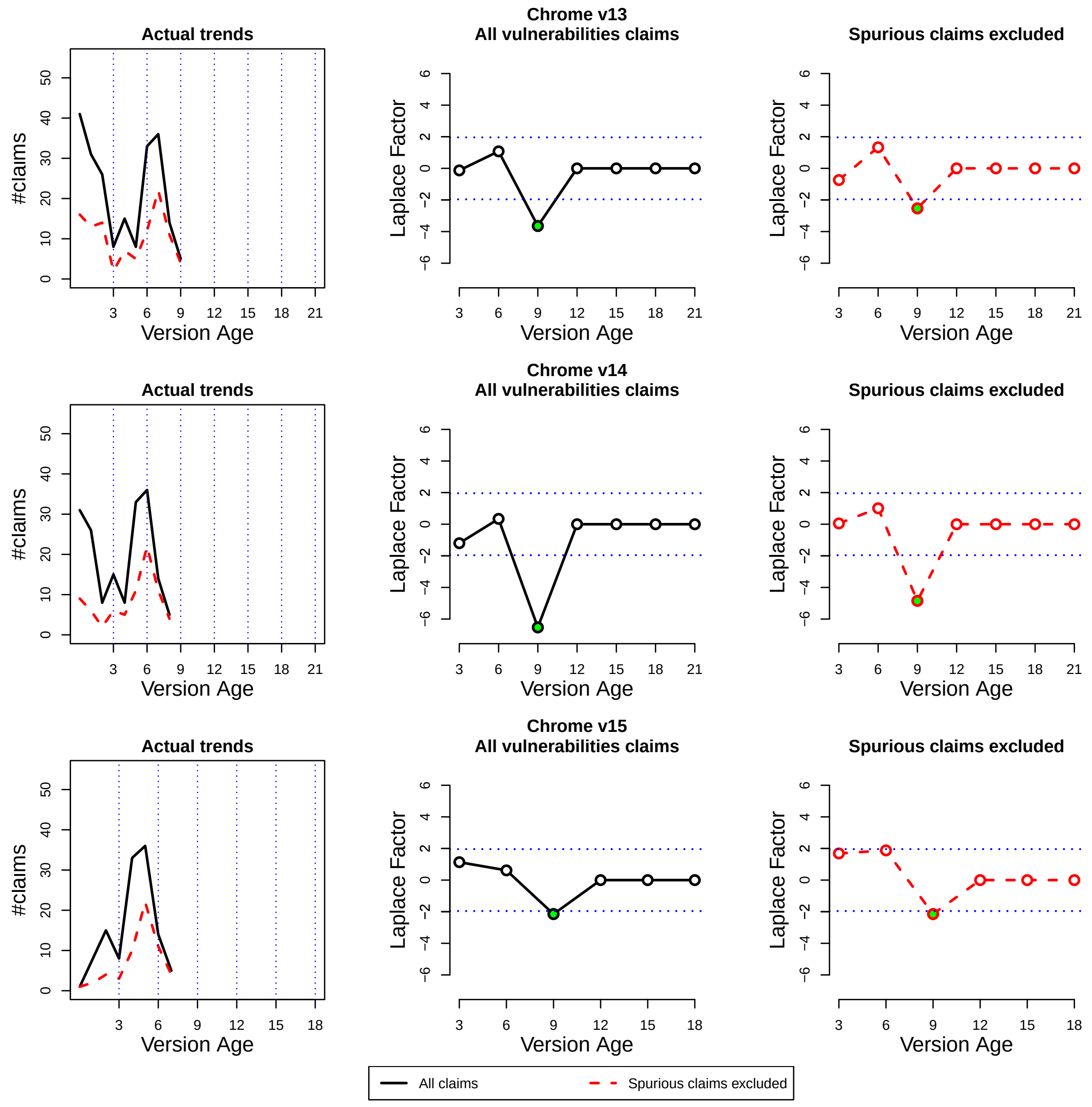

Figure A.1: Laplace test for trend in quarterly foundational vulnerability discovery for Chrome (to be continued in next page)

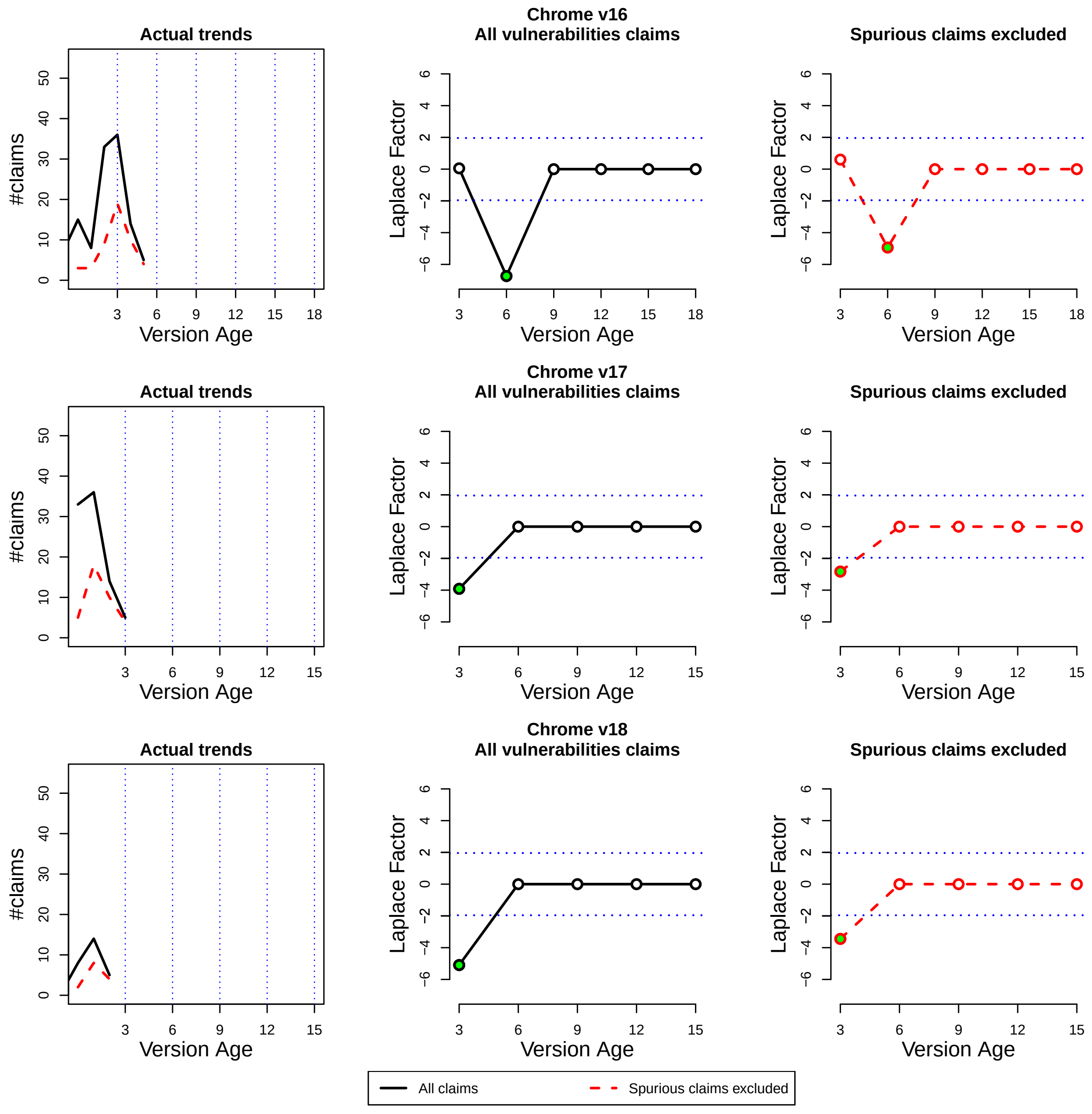

Figure A.1: Laplace test for trend in quarterly foundational vulnerability discovery for Chrome (continued from previous pages)

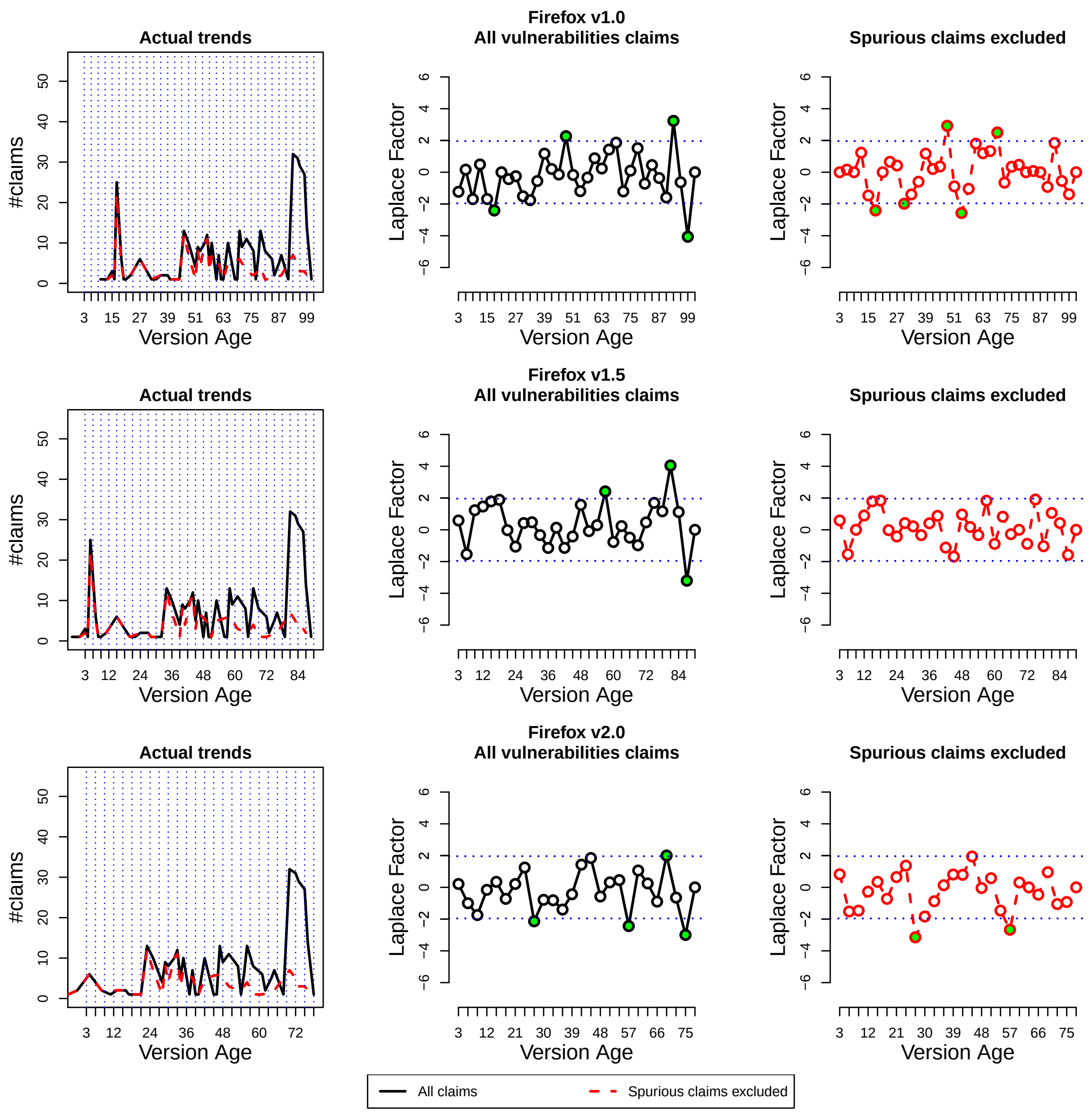

Figure A.2: Laplace test for trend in quarterly foundational vulnerability discovery for Firefox

(to be continued in next page)

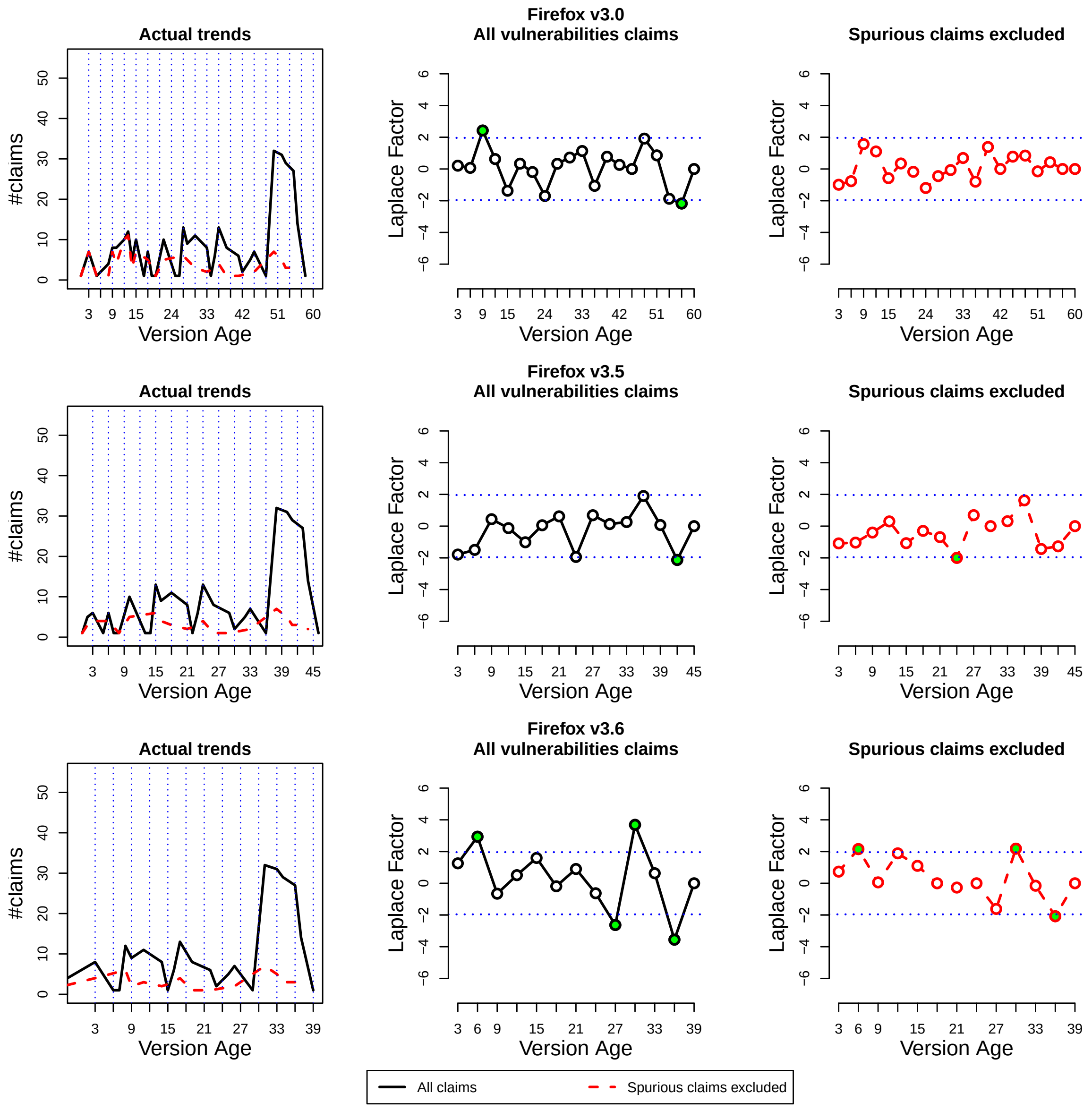

Figure A.2: Laplace test for trend in quarterly foundational vulnerability discovery for Firefox (to be continued in next page)

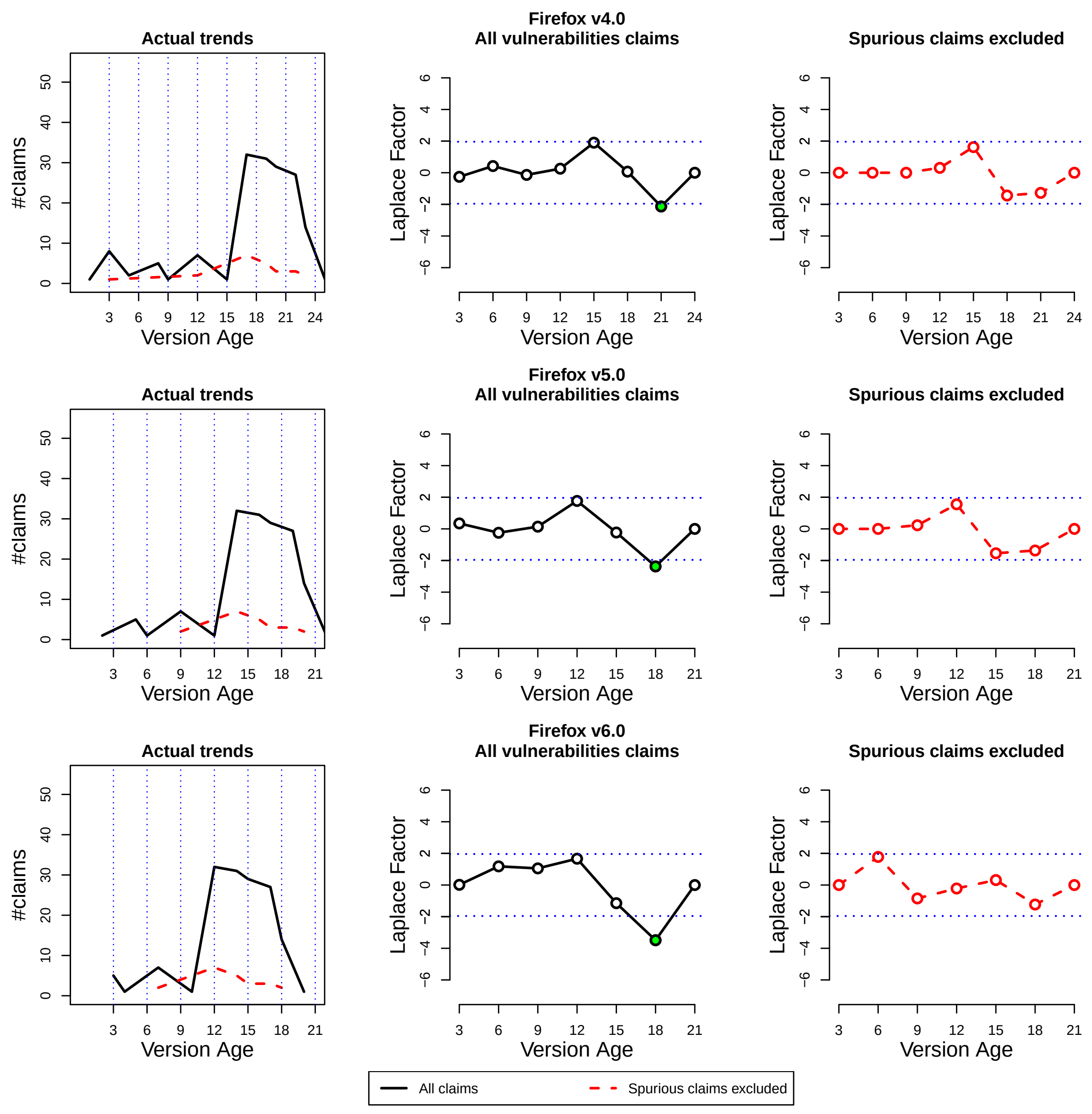

Figure A.2: Laplace test for trend in quarterly foundational vulnerability discovery for Firefox (to be continued in next page)

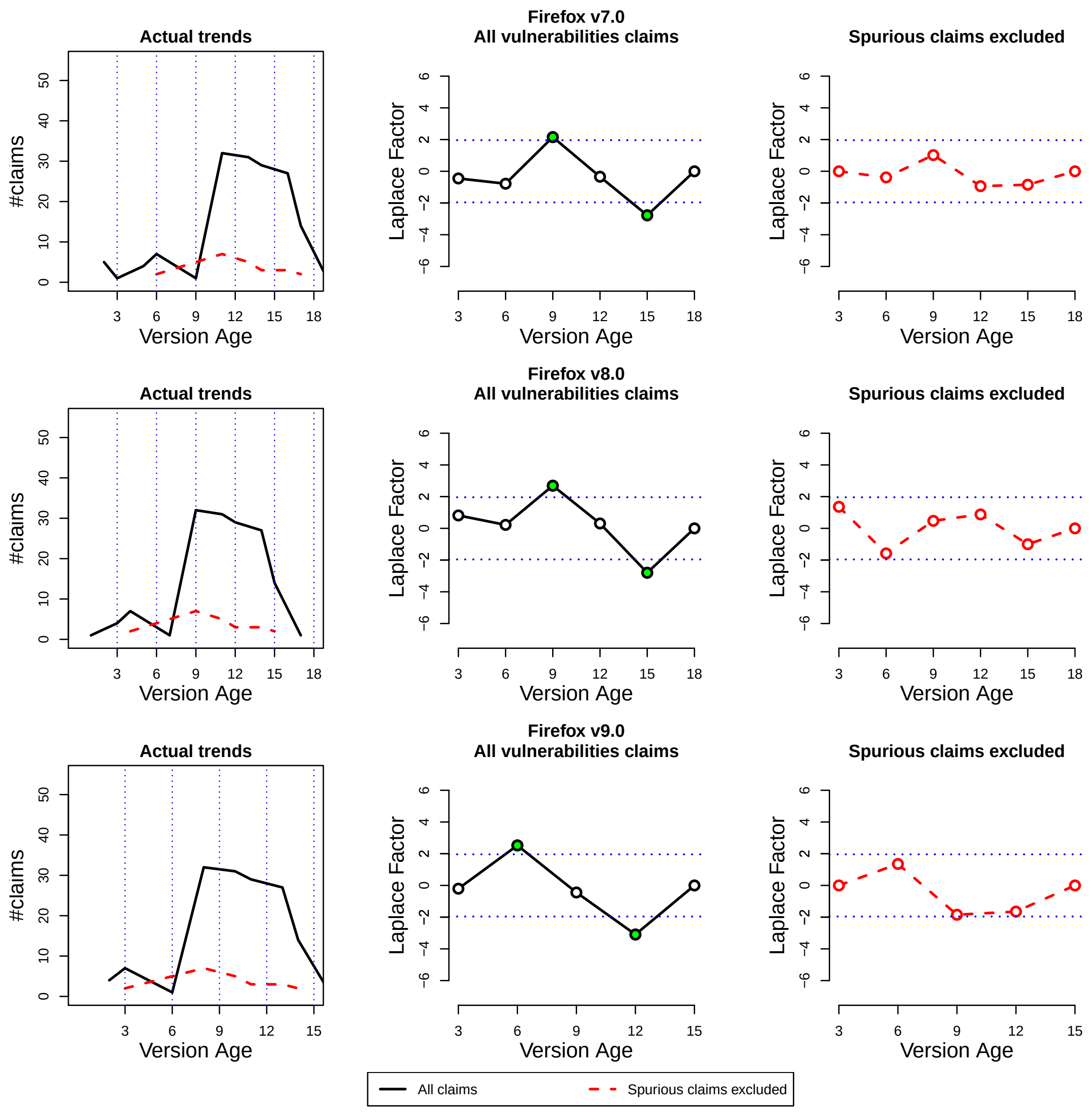

Figure A.2: Laplace test for trend in quarterly foundational vulnerability discovery for Firefox (to be continued in next page)

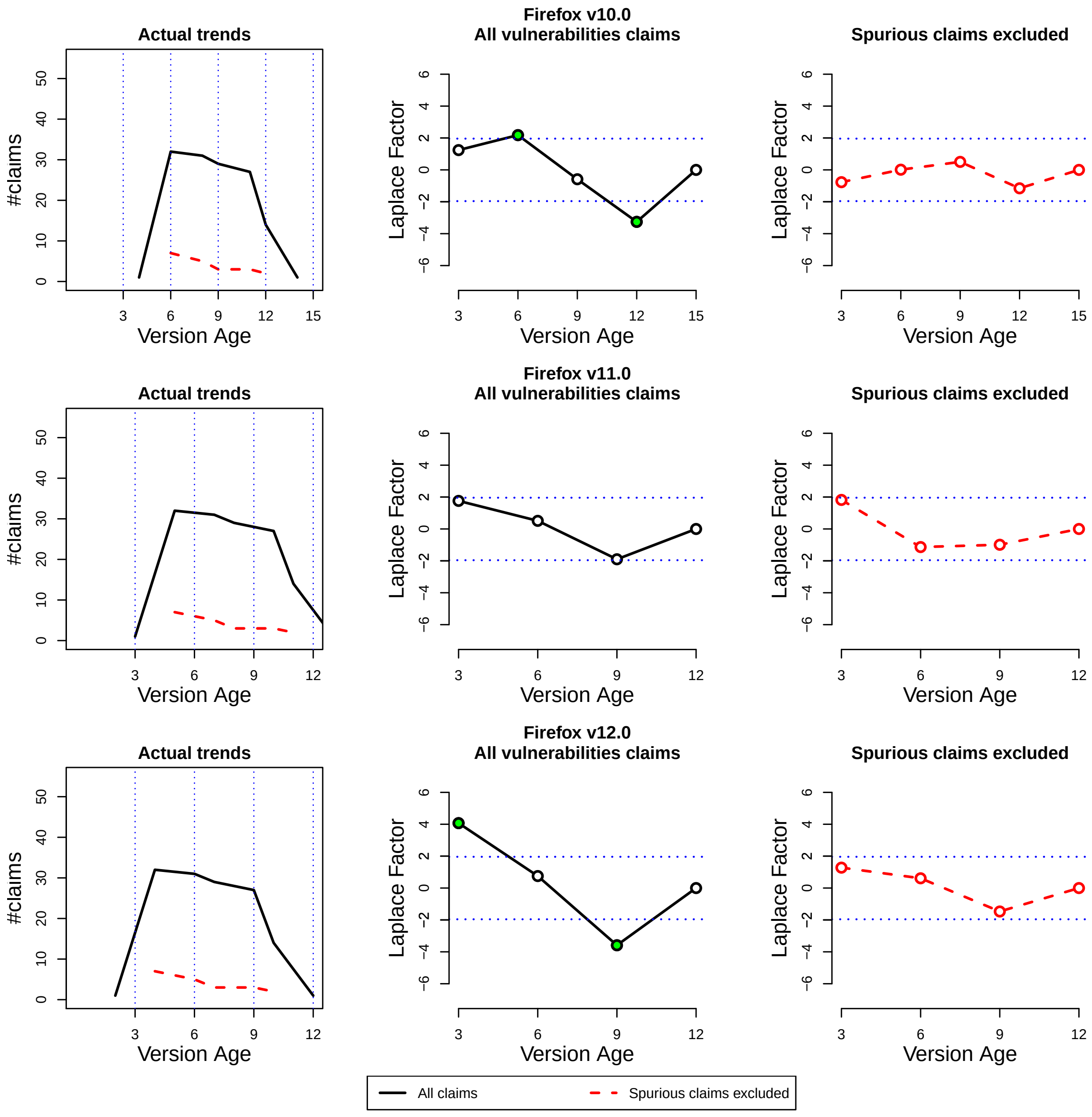

Figure A.2: Laplace test for trend in quarterly foundational vulnerability discovery for Firefox (continued from previous pages)

Table A.1: Inconsistent events in Laplace test for quarterly trends in Chrome.

Numbers in the second and third columns are the version ages (in month) when the Laplace factors indicate significant trends.

	Inconsistent Events		
Release	NVD data set	Verified NVD data set	Count
Chrome v1	18, 21	36	3
Chrome v2	27	–	1
Chrome v3	12	21	2
Chrome v4	–	27	1
Chrome v5	15, 24	3	3
Chrome v6		6, 15	2
Chrome v7	–	9	1
Chrome v8	–	3	1
Chrome v9	3	–	1
Chrome v10	–	–	0
Chrome v11	–	3, 12	2
Chrome v12	–	6	1
Chrome v13	–	–	0
Chrome v14	–	–	0
Chrome v15	–	–	0
Chrome v16	–	–	0
Chrome v17	–	–	0
Chrome v18	–	–	0

Table A.2: Inconsistent events in Laplace test for quarterly trends in Firefox.

Numbers in the second and third columns are the version ages (in month) when the Laplace factors indicate significant trends.

	Inconsistent Events		
Release	NVD data set	Verified NVD data set	Count
Firefox v1.0	93, 99	30, 54, 69	5
Firefox v1.5	57, 81, 87	–	3
Firefox v2.0	69, 75	–	2
Firefox v3.0	9, 57	–	2
Firefox v3.5	42	24	2
Firefox v3.6	27	–	1
Firefox v4.0	21	–	1
Firefox v5.0	18	–	1
Firefox v6.0	18	–	1
Firefox v7.0	9, 15	–	2
Firefox v8.0	9, 15	–	2
Firefox v9.0	6, 12	–	2
Firefox v10.0	6, 12	–	2
Firefox v11.0	–	–	0
Firefox v12.0	3, 9	–	2