A ground-truth dataset of real security patches

Sofia Reis
INESC-ID & IST/ULisbon, Portugal
sofia.o.reis@tecnico.ulisboa.pt

Rui Abreu
INESC-ID & FEUP, Portugal
rui@computer.org

Abstract

Training machine learning approaches for vulnerability identification and producing reliable tools to assist developers in implementing quality software—free of vulnerabilities—is challenging due to the lack of large datasets and real data. Researchers have been looking at these issues and building datasets. However, these datasets usually miss natural language artifacts and programming language diversity. We scrapped the entire CVE details database for GitHub references and augmented the data with 3 security-related datasets. We used the data to create a ground-truth dataset of natural language artifacts (such as commit messages, commits comments, and summaries), meta-data and code changes. Our dataset integrates a total of 8057 security-relevant commits—the equivalent to 5942 security patches—from 1339 different projects spanning 146 different types of vulnerabilities and 20 languages. A dataset of 110k non-security-related commits is also provided. Data and scripts are all available on GitHub. Data is stored in a .CSV file. Codebases can be downloaded using our scripts. Our dataset is a valuable asset to answer research questions on different topics such as the identification of security-relevant information using NLP models; software engineering and security best practices; and, vulnerability detection and patching; and, security program analysis.

1 Introduction

Research surrounding security patches understanding (11), identification (12, 14, 19, 20, 8, 7, 4, 9, 21) and automated repair (8, 13) are hot topics in software security. However, empirically validating and reproducing these approaches is challenging due to the lack of widely accepted and easy-to-use databases of real vulnerabilities (10).

Accessing this kind of data is not an easy task for several reasons: 1) many security patches are not publicly available; 2) developers do not use MITRE’s convention (e.g., CVE-2017-4971) to identify vulnerabilities in commit messages; 3) commit messages are poorly written and do not provide enough/any information. Previous research has shown that it is possible to find more vulnerability-fixing commits either using keywords on commits messages (17, 16) or training and applying machine learning algorithms (21, 17, 18).

With our data, we aim to provide a ground-truth dataset—real security patches previously validated by experts—capable of supporting research using natural language, code changes, and codebases. We scrapped the Common Vulnerabilities Exposures (CVE) Details database (1) for references to GitHub commits, i.e., code changes used to patch CVEs. For each CVE, we collected CVE ID, CWE ID, Vulnerability Type, CVE Severity Score, Summaries and GitHub references. We augmented this data with other 3 datasets that also contain vulnerabilities and the URL links to security patches: Secbench (17, 16), Pontas et al. (15) and Big-Vul (5). We crossed the data from datasets with the descriptive data obtained from CVE Details to complete the information regarding each CVE. After merging and cleaning the data (e.g., remove duplicates and links for branches already commits ahead.

of the patch version), we collected the metadata of each GitHub commit: message commit, author, date, comments, files, code changes and commit parents.

Our dataset integrates a total of 8057 security-relevant commits—the equivalent to 5942 security patches—from 1339 different projects spanning 146 different types of vulnerabilities (CWEs) and 20 languages. We provide natural language artifacts and code changes. Codebases can be pulled/downloaded using our scripts. For machine learning purposes, we also provide a dataset of 110161 security-unrelated commits. The negative dataset can be extended or even built from scratch with our scripts. Our dataset is a valuable asset to answer research questions on different topics such as detection of security-relevant information; commits classification; software engineering and security best practices; understand security patches, their impact, and risks; vulnerability detection and patching; and generic security program analysis.

Why is our dataset important? Our dataset is different from previous work in the following points:

Secbench (2017) ([17][16]) is a dataset of 676 single-commit security patches—the patch and vulnerable version are available for each case. Patches span 51 different classes (CWEs) and 18 languages. Data was collected by crawling 113 different open-source projects and applying regular expressions on commit messages to detect vulnerabilities fixes (e.g., fix xss). Our dataset integrates more security patches, natural language artifacts, code changes and a negative dataset for machine learning purposes.

VulnIoss (2018) ([6]) provides results of code metrics and release data of 17738 software vulnerabilities. We do not use this dataset because they do not provide commit id/sha(s). Our dataset instead provides commit data, code changes, and natural language artifacts.

Pontas et al. (2019) ([15]) is a manually curated dataset of 624 Java vulnerabilities. The authors tracked the CVE updates and mapped the CVE IDs manually to the code versions on GitHub. The dataset only provides the commit IDs, projects, and CVE IDs. We provide a dataset with more programming languages and more features regarding the CVEs, commits, and code changes.

Big-Vul (2020) ([5]) is a dataset of the code changes and CVE summaries for 3755 vulnerabilities in C/C++. Authors scrapped the CVE Details database and searched the resulting CVE entries on open-source repositories to map the respective codebases. We scrapped the CVE Details database as well and found more 2224 security-relevant commits. Our dataset also provides cases for other programming languages and natural language artifacts.

The contributions of our work are the following ones:

Ground-truth Dataset: We organized, cleaned and extended previous research work by producing a larger dataset of vulnerabilities—validated by experts—with new features: files extension and programming languages. The dataset contains the details of each CVE, code changes information and natural language artifacts (CVEs summaries, commits messages and commits comments).

Toolset: Both the dataset and tools implemented to scrape, clean, and manipulate the data are available in the GitHub repository ([2]).

2 Data Collection

Our dataset was built using the following methodology:

(1) CVE Details Scraping: We scraped the entire CVE Details ([1]) website by year. For each year, we obtained the entire list of published CVEs and scraped the webpage of each CVE in the list. We saved all the data provided on the webpage. However, we only integrate the following features; CVE ID, CWE ID, CVE Severity, Summary and GitHub references. We filtered the results to only entries with links/references to GitHub. References not pointing for specific versions of the repository were removed (e.g., https://github.com/branch_x_x) because we were not able to ensure that the branch was still on the patch version. The scripts are available in the scraper/ folder.

(2) Fusing Existing Datasets: We fused 3 datasets of security patches with the CVEs obtained in the previous step (CVE Details Scraping): Secbench ([17][16]), Pontas et al. ([15]) and Big-Vul ([5]). Table [1] shows the initial distribution of commits and patches of each dataset and their license. After fusing the data, duplicates and entries for other source code hosting websites were removed. We
crossed the fused data with the CVE details data to complete the CVE entries with CWEs and summaries. The scripts are available in the scripts/ folder.

Table 1: Distribution of commits before and after phase (2)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Before (2)</th>
<th>After (2)</th>
<th>License</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Commits</td>
<td>Patches</td>
<td>Commits</td>
</tr>
<tr>
<td>CVE details</td>
<td>4529</td>
<td>4183</td>
<td>2224</td>
</tr>
<tr>
<td>(1) Secbench</td>
<td>676</td>
<td>676</td>
<td>659</td>
</tr>
<tr>
<td>(17) Pontas et al.</td>
<td>1282</td>
<td>624</td>
<td>1127</td>
</tr>
<tr>
<td>Big-Vul (5)</td>
<td>4529</td>
<td>3755</td>
<td>4047</td>
</tr>
</tbody>
</table>

(3) Extracting Meta-Data: We used the GitHub API to retrieve the meta-data of each commit: message, author, date, changed files, comments, and parents. Each comment has an author, date, and body text. Each file has a path, number of additions, number of deletions, number of changes, and status. We built a script to add 2 features to the dataset: extension of the files and programming languages. We inferred programming languages from the extension files.

(4) Generate Negative Dataset: We used the GitHub API to retrieve 50 random security-unrelated commits per project of the positive dataset. We cleaned the commits using security-related keywords such as “secur”, “patch”, “cve”, “vuln”, “attack”. This dataset integrates only two columns: commit link and commit message. The scripts are available in the negative/ folder.

Table 2: Description of the positive data collected (security patches)

<table>
<thead>
<tr>
<th>CVE Details</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>cve_id</td>
<td>The common vulnerabilities and exposures identifier.</td>
</tr>
<tr>
<td>project</td>
<td>GitHub project name.</td>
</tr>
<tr>
<td>sha</td>
<td>Commit key or identifier of the version in the project repository.</td>
</tr>
<tr>
<td>cwe_id</td>
<td>The common weakness enumeration identifier.</td>
</tr>
<tr>
<td>score</td>
<td>Severity score of the vulnerability.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Code Changes</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>files</td>
<td>Set of files changed by the patch. Information schema: path, additions, deletions, changes, status.</td>
</tr>
<tr>
<td>language</td>
<td>Programming Language.</td>
</tr>
<tr>
<td>github</td>
<td>Commit link.</td>
</tr>
<tr>
<td>parents</td>
<td>Commit keys for previous software version.</td>
</tr>
<tr>
<td>date</td>
<td>Date of the changes.</td>
</tr>
<tr>
<td>author</td>
<td>Author of the changes.</td>
</tr>
<tr>
<td>ext_files</td>
<td>Extension of the files.</td>
</tr>
<tr>
<td>lang</td>
<td>Programming Language.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Natural Language Artifact</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>summary</td>
<td>Summary of the vulnerability.</td>
</tr>
<tr>
<td>message</td>
<td>Commit message.</td>
</tr>
<tr>
<td>comments</td>
<td>Comments set. Information schema: author, date and body.</td>
</tr>
</tbody>
</table>

3 Dataset Description

In total, we collected 8057 security-relevant commits—the equivalent to 5942 security patches—from 1339 different projects spanning 146 different types of vulnerabilities (CWEs) and 20 languages. The dataset integrates 16 different columns of data for each commit. Table 2 describes in more detail each feature of the dataset. We provide scripts to retrieve the CVE Details data (scraper folder); to fuse, clean and manipulate the data (scripts folder); to augment data by adding features such as the extension files and the programming language in which the commits were implemented the data (scripts/add_features.py script); and, scripts to generate the negative dataset, i.e., the dataset.
Figure 1: Distribution of commits per programming language. The top-3 of most prevalent programming languages are C/C++ (3944 commits), Java (1369 commits) and PHP (1350 commits).

Figure 1 shows the number of commits implemented in each language for the 20 languages available in our dataset. The top-3 of most prevalent programming languages are C/C++ (3944 commits), Java (1369 commits) and PHP (1350 commits). Security-relevant commits are less prevalent amongst Erlang (3), Lua (5) and Vala (3)—less than 15 commits were obtained per language.

Figure 2 shows the amount of commits distributed by the top-20 of vulnerabilities (CWEs). Our dataset comprises commits to patch 146 different types of CWEs. The most common commits patch vulnerabilities such as the CWE-79: Improper Neutralization of Input during Web (870 commits), CWE-20: Improper Input Validation (712 commits), CWE-119: Improper Restriction of Operations within the Bound of a Memory Buffer (705 commits), CWE-200: Exposure of Sensitive Information to an Unauthorized Actor (419 commits), CWE-125: Out-of-bounds Read (380 commits). These represent 38.1% of the entire dataset.

Figure 3 shows the number of commits used to patch software vulnerabilities per year. The security-relevant commits of this dataset were published from 1999 until 2021. The number of security-relevant commits between 2016 and 2019 are the most predominant ones.

Table 3: Files and code changes descriptive data

<table>
<thead>
<tr>
<th>Files</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Code files</td>
<td>26032</td>
<td>76.87%</td>
</tr>
<tr>
<td>Test files</td>
<td>6770</td>
<td>19.99%</td>
</tr>
<tr>
<td>Changelogs/News</td>
<td>933</td>
<td>2.75%</td>
</tr>
<tr>
<td>Readme</td>
<td>131</td>
<td>0.39%</td>
</tr>
<tr>
<td>Total of Files</td>
<td>33866</td>
<td>100%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Code Churn</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Additions (+++)</td>
<td>1113450</td>
<td>74.60%</td>
</tr>
<tr>
<td>Deletions (- - -)</td>
<td>379203</td>
<td>25.40%</td>
</tr>
<tr>
<td>Total of Changes</td>
<td>1492653</td>
<td>100%</td>
</tr>
</tbody>
</table>
Figure 2: Distribution of commits for the top-20 of vulnerabilities (CWEs). The dataset comprises commits to patch 146 different types of CWEs.

Figure 3: Distribution of commits per year (from 1999 to 2021). The number of commits between 2016 and 2019 are the most predominant ones.
Table 3 shows the distribution of files and code changes of the positive dataset. A total of 8057 security-related commits were performed across 33866 different files: 76.87% are code files, 19.99% are test files, 2.75% are changelogs and news files; and, 0.39% are readme files. To patch the total of 5942 security patches integrated into this dataset, 1113450 lines of code were added, and 379203 lines of code were deleted. In total, more than 1M of changes were performed.

Figure 4 shows wordclouds for the different natural language artifacts: CVE summaries (Figure 4a), messages (Figure 4b) and comments (Figure 4c). Each wordcloud shows the importance of the words used in our artifacts. CVE summaries are brief explanations of vulnerabilities and possible attacks—words such as “attacker”, “remote”, “service”, “allows” and “user” are the most common. While security-relevant commit messages usually describe an action such as fixing a vulnerability. Figure 4b supports this by showing words such as “fix”, “issue”, “review”, and “change”. Comments are usually performed by developers, project contributors or users asking for information on the vulnerability/code. The most important words are “issue”, “commit”, “CVE” “thank” and “github”.

Overall, wordclouds reflect the natural language artifacts goals.

A dataset of security-unrelated commits (negative dataset) was generated from the projects integrated in the dataset of security patches. For each project in the positive dataset, we collected 50 random commits. Non-security related keywords were leveraged to clean the dataset. In total, we selected 110161 random non-security related commits from the projects in the positive dataset. Each entry of the negative dataset represents a non-security-related commit. For each commit, the dataset integrates 1) the github link for the code changes and 2) the commit message of the change.

Both datasets are available on our GitHub repository in the comma-separated values (CSV) format (dataset folder). Scripts to download the codebases of the commits are provided. The jupyter notebooks used to report this analysis are also available.

4 Future research and Improvements

One of the issues in the field of security program analysis is the lack of easy-to-use, well-organized and diverse datasets of security patches. Our dataset provides a larger dataset considering commits for 20 programming languages, 146 types of vulnerabilities and 3 different types of artifacts: meta-data, natural language data and codebases. This dataset can be used in several vulnerability related research topics such as:

Identification and classification of security-relevant commits. This is a recent hot topic in the software engineering field. Machine learning models to identify and classify automatically this kind of commits are being created (21;18). These models aim to fasten software releases and notify developers when new vulnerabilities are reported. Our natural language artifacts can be used to train deep learning approaches based on text mining and natural language processing to detect this type of commits.

Vulnerability detection and patching. Over the past 2 decades, a lot of research as been developed in the vulnerability detection field (12;14;19;20;3;4;9;21). More recently, research in vulnerability patching has emerged (8;13). However, many of these techniques are not well tested
due to the lack of code samples and do not cover some types of vulnerabilities. Deep learning approaches have a huge potential to tackle the later issue, but due to the lack of data to well train and test the models, these approaches do not succeed. We provide a large dataset of real data capable of boosting research in these fields.

**Understand the impact and risks of security patches.** Researchers performed a large scale empirical study to understand security patches characteristics (11). However, there is a low understanding on the impact and risks of security patches on software. Our scripts allow the user to download the codebases of the commits, previous commit(s), and the diff between both. With code-centric information, researchers can better understand security patches and their features. New neural networks can be trained with this data to detect and patch vulnerabilities. This kind of data can also be used to create models using software properties to predict the risk of patches on companies and software development.

**Explore if the best practices of software engineering and security are being used.** Code evolves and teams change. Assessing the quality of commits and reports may be crucial to make development easier for everyone. Our natural language artifacts can be used to explore if best practices are being used. Code changes data can also be leveraged to better understand if the best practices of development are being used.

5 Limitations and Challenges

Our dataset integrates security patches without a CVE assigned. Thus, we were not able to get the CVE Details meta-data for these cases: 10% of the rows are missing descriptive data, e.g., the vulnerability identifier (CVE ID), summary, type of vulnerability (CWE ID), and score. In other hand, our methodology to infer the programming language from the extension files involved in the commits failed on classifying less than 5% of the entire dataset. Thus, some commits might not have a programming language associated. Both issues will be improved/addressed in the future.

6 Conclusions

We fused 4 different security-related data sources and created a ground-truth dataset of natural language artifacts, meta-data, and code changes. Our dataset integrates a total of 8057 security-relevant commits—the equivalent to 5942 security patches—from 1339 different projects spanning 146 different types of vulnerabilities and 20 languages. In addition, this dataset provides a negative dataset of 110k non-security-related commits. Data and scripts are available on GitHub. Data is stored in a .CSV file and codebases can be download using our scripts. Our goal is to extend this dataset in the future by crossing the entire CVEs list with github information. An interactive website to navigate the data is under development. Our dataset is a valuable asset to answer research questions on different topics such as the identification of security-relevant commits; software engineering and security best practices; understand security patches, their impact, and risks; and, vulnerability detection and patching.

7 Acknowledgments

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References


Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]. Check Section 5.
   (c) Did you discuss any potential negative societal impacts of your work? [No]. All the vulnerabilities in this dataset were already fixed. Therefore, we argue that there is no negative societal impact.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes].

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [No]. We do not include any theoretical results.
   (b) Did you include complete proofs of all theoretical results? [No]. We do not include any theoretical results.

3. If you ran experiments (e.g. for benchmarks)...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes]. All the data and scripts are available here https://github.com/TQRG/security-patches-dataset.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]. We specify the difference between positive and negative data and how both datasets were collected.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No]. We only performed scraping experiments.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [No].

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]. We cite the creators of the datasets we leveraged in Section 1.
   (b) Did you mention the license of the assets? [Yes]. The license is provided in table 1.
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes]. We provide the code changes information and natural language artifacts to each of the patches.
   (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [Yes]. All the datasets are open-source and available for research.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes]. We provide the GitHub usernames of the authors of the security patches and comments. However, all of this information is already available publicly.

5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [No]. We did not use human subjects in this work.
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [No]. We did not use human subjects in this work.
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [No]. We did not use human subjects in this work.