The Impact of Release-based Training on Software Vulnerability Prediction Models

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ABSTRACT

Software vulnerability prediction models have been an object of study for several years. The ability to predict which portions of code are more prone to contain vulnerabilities leads to focus testing efforts, potentially increasing code quality and reducing security threats [4]. Most of the proposed models have been evaluated with cross-validation, which consists in splitting the dataset in k equal-sized folds and computing the average performance obtained in k rounds of validation, in such a way that each fold is part of the training set k - 1 times and composes the test set once. However, in a real-case scenario, one is interested in training the model by using information related to prior releases of software, and obtaining predictions on the current version to be released. So there is a gap between the performance observed in research studies and those that would be obtained in a real environment. We want to start working to bridge this gap, by following the indications given by Jimenez et al. [2]. To ensure robust scientific findings, they solicited the community to employ the experimental and empirical methodology they proposed, which takes into account the time constraints of the real-world context. Seizing this suggestion, we start taking small steps in this direction, by performing a preliminary study on Walden et al.'s dataset [3]. We aim to analyze how differently vulnerability prediction models would perform if evaluated with a release-based approach rather than with cross-validation. Our initial findings reflect Jimenez et al.'s considerations, so we propose to continue following their track with deeper investigation.

INTRODUCTION

Nowadays, our society runs on software: from financial transactions to health treatments, we rely on software systems. The current pandemic has even increased our dependency on software, leading the whole world population to interact with software for every social and emergency need. Nevertheless, all that glitters is not gold: the security risks associated with the presence of vulnerabilities are extreme. As an example, let consider the *WannaCry* ransomware attack, which exploited a vulnerability of the Windows operating system to infect more than 230,000 computers across over 150 countries during a single day, and caused total damages in the range of hundreds of millions USD [5]. Vulnerability exploits are hence a serious threat to software systems, so it is crucial to release code that has been checked to contain no vulnerabilities. As summarized by Ghaffarian et al. [1], several approaches for vulnerability discovery have been proposed: the most promising seem to be those based on Machine Learning prediction models. These approaches are based on the fact that models can learn from known vulnerabilities, and then predict whether an unseen portion of code is likely to contain vulnerabilities. Such prediction models could be extremely useful in a software production environment, where one would be interested in training a model using vulnerability data discovered in the previous releases of the application, and make predictions on new code to be released, in order to concentrate testing effort only on those portions of source code predicted to be probably vulnerable. Unfortunately, as pointed out by Jimenez et al. [2], most studies do not investigate the performance of models trained with a release-based approach, but use cross-validation instead. While this validation can provide initial indications on the accuracy of prediction models, in a real-case scenario vulnerability data become available following time constraints, i.e., developers discover vulnerabilities only after releasing the software. Hence, a more realistic validation methodology would provide insights into the suitability of vulnerability prediction models in practice. The methodology suggested by Jimenez et al. consists in validating the model at a certain time *t*, using in the training phase only the information that is available at *t*, i.e, vulnerabilities already discovered and reported before *t*. Along with a release-by-release validation approach, this ensures that researchers operate as closely as possible to reality.
We want to seize this suggestion, by performing a replication of their study using a different dataset, i.e., Walden et al.'s PHP vulnerability dataset [3]. In this paper we present a preliminary investigation to start working in this direction.

OBJECTIVES

Our preliminary study consists in taking small steps from the traditional cross-validation approach towards the realistic one suggested by Jimenez et al. [2]. For our research we use the Walden et al.'s PHP vulnerability dataset [3], which has been published by the authors along with an investigation [4] about how the Random Forest classifier performs when trained using two different approaches: one based on code metrics and the other based on textual tokens. Both in the original work and in all those using the same dataset, the proposed models are evaluated by using cross-validation. In order to eventually veer towards the realistic methodology, we initially try to understand how a release-based approach would impact the models' performance.
We hence formulate the following research questions, that we discuss about in this paper:
RQ1: *What is the performance of vulnerability prediction models trained using a release-based approach when compared to models trained using cross-validation?*
RQ2: *Which modelling approach is more sensitive to the use of a different validation method?*
After this preliminary study, we aim to further work and follow Jimenez et al.'s indications to perform a deeper investigation on the real-world validation methodology.

	Cross-validation	Release-based
Precision	0.95	0.07
Recall	0.74	0.39
Inspection rate	0.39	0.05
F1-score	0.82	0.12
MCC	0.72	0.15

Table 1: Performance of the Software metrics approach.

	Cross-validation	Release-based
Precision	0.97	0.18
Recall	0.84	0.79
Inspection rate	0.43	0.04
F1-score	0.90	0.29
MCC	0.82	0.36

Table 2: Performance of the Text mining approach.

METHODOLOGY

We perform our research by taking as a baseline the Walden et al.'s work [4], in which the authors compared the performance of the Random Forest classifier when trained using two different sets of features: one based on code metrics and the other based on textual tokens. The authors collected a dataset [3] of 223 vulnerabilities extracted from several versions of three popular applications, i.e. PHPMyAdmin, Moodle and Drupal. In this preliminary study, we only use the vulnerability data of PHPMyAdmin, which comprises 75 vulnerabilities found in 95 releases of the application, between 2.0.0 and 4.0.9. Since the dataset is highly unbalanced, i.e., the number of vulnerable files is much smaller than the number of neutral files, we apply undersampling as a data balancing technique. Undersampling consists in removing instances of neutral files, i.e., the majority class, in order to retain the same number as vulnerable files, i.e., the minority class. We first replicate the original study by Walden et al., by performing 3-fold cross-validation to evaluate the models' performance. The dataset is split into 3 equally large folds and 3 rounds are executed. For each round, 2 folds are used for training and the other one is used for testing: each fold is part of the training set twice and composes the test set once. Afterwards, we apply a release-based training approach to analyze the differences in the performance. Our release-based training approach consists in training the model on files from prior releases and testing it on later releases. We base the evaluation on the confusion matrix, which summarizes the predictions provided by the model, and consider the most popular performance indicators, i.e., Precision, Recall, F1-score and Matthews Correlation Coefficient (MCC). We also measure Inspection Rate as defined by Walden et al. [4], which indicates the amount of source code files that developers need to check and correct before release.

INITIAL FINDINGS

As a summary of our initial findings, we report in this document Tables 1 and 2, which show the performance of the Random Forest classifier in different experiments. For the release-based approach, we indicate the results of the experiment in which we considered 85 releases in the training set, i.e. from 2.2.0 to 3.5.8, and 10 releases in the testing set, i.e. from 4.0.0 to 4.0.9.

We can answer **RQ1** by analyzing the difference between columns of a same table. By just looking at Matthews Correlation Coefficient, which summarizes the models effectiveness, we can see that the overall performance drops drastically when applying a release-based approach. This finding is consistent with Jimenez et al.'s observations [2], which reveal the unsuitability of cross-validated models in the real-case scenario.

In order to answer **RQ2**, we inspect the differences between the two tables. The approach based on software metrics seems to be the most sensitive to the modification of the validation method. However, the performance obtained by the text mining approach are not reasonable to use the model in practice.

FUTURE WORK

In the future we plan to continue our research in this direction, by following Jimenez et al.'s suggestions [2]. We first want to perform deeper investigation on the release-by-release validation approach. This consists in considering the average performance obtained in several experiments, executed with an incremental methodology: in the first experiment, the model is trained on the first release and is evaluated on the second release; then, in the second experiment, the model is trained on the first and second release and is evaluated on the third release; and so on. We also plan to consider the time-aware approach described by Jimenez et al. [2], by modifying the vulnerabilities' presence in the different releases of the dataset, basing on the time at which they have been discovered and reported by the developers. In this way we will obtain a new dataset that will be more similar to the base knowledge owned by the developers in a real-world scenario. We will then be able to evaluate how vulnerability prediction models would actually perform in reality.

REPLICATION

We provide the replication package for our study[1]. It contains the preprocessed data that we used for training and testing, along with Python scripts to run the experiments.

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