Simplification of Training Data for Cross-Project Defect Prediction

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Abstract—Cross-project defect prediction (CPDP) plays an important role in estimating the most likely defect-prone software components, especially for new or inactive projects. To the best of our knowledge, few prior studies can give us very explicit guidelines on how to select suitable training data from a large number of public software repositories. In this paper, we proposed a training data simplification method for practical CPDP in consideration of release time, level of granularity and filtering strategy of data sets. Based on an empirical study on 32 releases of 10 open-source projects, we elaborately compared the prediction performance of different defect predictors built with five well-known classifiers under the condition of simplifying training data at different levels of granularity and with two famous filters. The results indicate that using the riTDS method with Peter filter, the prediction model based on Naïve Bayes can achieve fairly good performance. In addition, we also provided quantitative evidence on the selection of a suitable filter in terms of a new index.

Keywords—cross-project defect prediction, training data simplification, software quality, data mining, transfer learning

I. INTRODUCTION

Software defect prediction is a research field that seeks effective methods for predicting the defect-proneness in a given software component. These methods help software engineers allocate limited resources to those components that are most likely to contain defects in testing and maintenance activities. Early studies on this field usually trained defect predictors from the data of historical releases in the same project and predicted defects in the upcoming releases, or reported the results of cross-validation on the same data set [1]. This is referred to as Within-Project Defect Prediction (WPDP). Zimmermann et al. [2] stated that defect prediction performs well within projects as long as there is a sufficient amount of data available to train prediction models. However, the major problem is that such an assumption does not always hold in practice, especially for newly-created or inactive software projects.

Fortunately, there are many on-line public defect data sets from other projects available to be training data sets (TDSs), such as PROMISE1 and NASA2. Thus, some researchers have been inspired to overcome the aforementioned problem by means of Cross-Project Defect Prediction (CPDP) [1, 2, 5, 9–11, 14]. In general, CPDP is the art of using the data from other projects to predict software defects in the target project. Until now, CPDP models have been proven to be feasible by many previous studies [1, 9]. On the other hand, He et al. found that the overall performance of CPDP was drastically improved with suitable training data [1], while Turhan et al. also affirmed that using a complete TDS would lead to excessive false alarms [11]. That is, the quality rather than the quantity of a TDS is more likely to affect the outcomes of CPDP to some extent.

There is no doubt that defect data sets available on the Internet will become more and more, along with the popularity of open-source software. The construction of a suitable TDS of quality gathered from a large number of public software repositories is still a challenge for CPDP [14]. To the best of our knowledge, there are two primary ways to investigate the issue. On one hand, many researchers attempted to reduce data dimensions using feature selection techniques, and numerous studies have validated that a reduced feature subset can improve the performance and efficiency of defect prediction [13, 28]. On the other hand, few researchers began to try to simplify a TDS by reducing data volumes [1, 5], so as to exclude irrelevant training data and retain those most suitable ones. Although the results of these methods seem very promising, most of them are time-consuming and impractical for software engineers when dealing with a growing number of defect data sets.

In addition, despite the feasibility and promising performance of CPDP, none of existing CPDP models takes the actual release time of TDSs and test data sets into consideration. For example, in [1], the authors selected three releases (i.e., Camel-1.6, Jedit-3.2 and Xalan-2.5) as the most suitable training set for the target release Ant-1.6. According to the information collected from archive.apache.org, the release time of Ant-1.6 is actually earlier than that of Camel-1.6 (see Table I). In other words, they used a TDS that includes the data generated in the future to predict the current test data, implying that the method is not suitable for practical software development, because it is impossible to gather such data at the time of the test. Moreover, the same problem also exists in other representative studies [2, 5, 12, 14] within this field.

Considering the importance of defect prediction in software
development and maintenance, we should pursue practical CPDP models and the related engineering guiding principles, rather than the methods that can only achieve high prediction accuracy or other performance measures; furthermore, TDS simplification on data volumes is the key to accomplishing the vision when the data from other projects available on the Internet is ever-increasing. Hence, the goal of this study is to propose a practical method to simplify a large amount of training data for CPDP, and to provide an empirical analysis on the performance of our method in terms of different levels of granularity and filtering strategies. On the other hand, previous studies [5, 11] just verified the performance of these filtering strategies for CPDP, but they did not offer any practical guidelines for the decision-making on which granularity, strategy and classifier should be preferably selected in a specific scenario. In this paper, we also want to seek useful guiding principles to assist software engineers in building suitable defect predictors. In order to achieve the above goals, we focus mainly on exploring the following research questions:

RQ1: Which level of granularity for TDS simplification performs better: release or instance?

RQ2: Which prediction model built in our context is more likely to be suitable for CPDP?

RQ3: Which strategy for TDS simplification should be preferable in a specific scenario?

The contribution of our work is threefold. First, the release time of training data and test data overlooked by previous studies is considered in the process of candidate TDS selection, which is an important step towards understanding and building practical CPDP models. Second, our findings provide an important insight into the guidelines that determine a proper level of granularity for TDS simplification and the most suitable prediction model. Third, we offer quantitative evidence on the selection of a suitable filtering strategy for simplifying candidate TDS in terms of the defect-proneness ratio of training data to test data (abbreviated to DPR). We believe that the results of our study could be a stepping stone for current and future approaches to practical CPDP, as well as a new attempt to software engineering data simplification with transfer learning techniques in the era of Big Data.

The rest of this paper is organized as follows. Section II is a review of related work. In Section III, we introduce the methods for TDS simplification in detail, and in Section IV we evaluate our experiments with a case study based on 10 open-source projects. Section V and Section VI present and discuss our findings and the threats to validity, respectively. Finally, we conclude this paper and present an agenda for future work in Section VII.

II. RELATED WORK

A. Cross-Project Defect Prediction

Since sometimes it is difficult for WPDP to collect sufficient historical data, CPDP is currently popular within the field of defect prediction. To the best of our knowledge, the earliest study on CPDP was performed by Briand et al. [10], who applied the prediction model built on Xpose to Jwritter. The authors validated that such a model performed better than the random model and outperformed it in terms of class size. However, Zimmermann et al. [2] conducted a large-scale experiment on data vs. domain vs. process, and found that CPDP was not always successful (21/622 predictions). They also found that CPDP was not symmetrical between Firefox and IE, known as the most used web browsers. Similar results are reported in [21–23].

Turhan et al. [11] analyzed the performance of CPDP based on 10 projects collected from the PROMISE repository. They proposed a nearest-neighbor filtering technique to filter out the irrelevant cross-project data. Moreover, they investigated the case where prediction models were constructed from a mix of within- and cross-project data, and concluded that when there was limited project historical data (e.g., 10% of historical data), such mixed project predictions were viable, as they performed as well as within-project prediction models [12].

Rahman et al. [9] conducted a cost-sensitive analysis on the efficacy of CPDP based on 38 releases of nine large Apache Software Foundation (ASF) projects. Their findings revealed that the cost-sensitive cross-project prediction performance was not worse than the within-project prediction performance, and was substantially better than the random prediction performance. Peters et al. [5] introduced a new filter to realize cross-company learning compared with the state-of-the-art Burak filter [11]. The results showed that their approach could build 64% more useful predictors than both within-company and cross-company approaches based on the Burak filter, and demonstrated that cross-company defect prediction was able to be applied very early in a project’s lifecycle.

He et al. [1] conducted three experiments on the same data sets used in this study, to test and verify the idea that training data from other projects can provide acceptable prediction results. They further proposed an approach to automatically selecting suitable training data for those projects without local historical data. Towards training data selection for CPDP, Herbold [14] proposed several useful strategies according to 44 data sets from 14 open-source projects. The results demonstrated that their selection strategies improved the achieved success rate of CPDP significantly, but the quality of the results was still unable to match with WPDP.

The review reveals that previous studies focused mainly on the feasibility of CPDP and the selection of suitable training data at a single level of granularity of data. However, relatively little attention has been paid to empirically exploring the impact of TDS simplification in terms of different levels of granularity on prediction performance. Moreover, little is known about the decision on the proper choice among the existing strategies for TDS simplification.

B. Defect Prediction with Transfer Learning

Transfer learning techniques have attracted more and more attention in machine learning and data mining over the last several years [19], and the successful applications include
software effort estimation [20], text classification [24], name-entity recognition [25], natural language processing [26] and email spam filtering [27]. Recently, CPDP was also deemed as a transfer learning problem. The problem setting of CPDP is related to the adaptation setting in transfer learning for building a classifier in the target project using the training data from those relevant source projects. So far, transfer learning techniques have been proven to be appropriate for CPDP in practice [17].

In order to harness cross-company defect datasets, Ma et al. [18] utilized the transfer learning method to build faster and highly effective prediction models. They proposed a novel algorithm that uses the information of all the suitable features in training data, known as Transfer Naive Bayes (TNB), and the experimental result indicated that TNB was more accurate in terms of AUC (the area under the receiver operating characteristic curve) and less time-consuming than those benchmark methods.

Nam et al. [17] applied the transfer learning method, called TCA (Transfer Component Analysis), to finding a latent feature space for the data of both training and test projects by minimizing the distance between the data distributions while preserving the original data properties. After learning the latent space, in terms of six characteristics, i.e., mean, median, min, max, standard deviation and the number of instances, the data of the training and test projects will be mapped onto it to reduce the data distribution difference. The experimental results for eight open-source projects indicated that their method significantly improved CPDP performance.

In general, although the above studies improve the performance of CPDP, they are time-consuming in that their experiments are conducted at the level of instance (file). In this study, to overcome the data distribution difference between source and target projects, we also adopted the TCA method, which was applied to the releases available from different projects first.

### III. Methodology

According to [19], transfer learning is defined as follows: Given a source project $P_S$ and a target project $P_T$, transfer learning aims to improve the learning of the target prediction in $P_T$ using the knowledge extracted from $P_S$, where $P_T \neq P_S$. Assuming that source and target projects have the same set of features, they may differ in feature distribution characteristics. The goal of our method is to learn a model from the selected source projects (training data) and apply the learned model to a target project (test data). Based on transfer learning techniques, in the following paragraphs, we present a TDS simplification method for practical CPDP, shown in Fig. 1. Specifically, unlike previous studies, we introduce two levels of granularity and two types of filtering strategies for TDS simplification based on characteristic vectors and feature vectors.

#### A. Release-level Simplification: rTDS

A TDS is often comprised of many releases from different projects. The coarse-grained simplification of such a TDS is based on the idea of calculating the distance between candidate training data and test data in terms of the distribution characteristics. In our method, an instance can be represented as $X_i = \{f_{i1}, f_{i2}, \ldots, f_{in}\}$, where $f_{ij}$ is the $j$th feature value of instance $X_i$ and $n$ is the number of features. For each feature, we can further obtain its distribution characteristics in a data set, e.g., the mean value, which can be written as $C_{mean} = \{mean_{f1}, mean_{f2}, \ldots, mean_{fn}\}$. Thus, the characteristic vector of a data set can be formulated as $V = \{C_1, C_2, \ldots, C_m\}$, where $m$ is the number of characteristic elements of a data set. Note that, in our study a data set is a release of a software project. The TDS simplification at the level of granularity of release is referred to as $rTDS$.

Based on the characteristic vectors, we use the Euclidean distance as a filtering criteria to select the “proper” training data. Concretely, we choose the $k$ most similar releases using the $k$-nearest neighbor algorithm. Algorithm 1 formalizes this simplification process. Note that, $|R^*|$ represents the number of releases in the candidate TDS, and $relArray$ and $distArray$ are used to temporarily store the releases selected from the candidate TDS and the distances between every pair of releases, respectively.

#### Algorithm 1 Release-level TDS Simplification

**Input:**
- candidate releases $R_{cand}$
- target release $R_{target}$
- number of desired releases $k$
- $relArray$, $distArray \leftarrow \emptyset$, $i = 0$

**for each** $r \in |R_{cand}|$ **do**

$d \leftarrow distance(V(r), V(R_{target}))$

**if** $i < k$ **then**

$relArray[i] \leftarrow r$; $distArray[i] \leftarrow d$; $i++$

**else**

$ascendingsort(relArray, distArray)$

**if** $distArray[k - 1] > d$ **then**

$relArray[k - 1] \leftarrow r$; $distArray[k - 1] \leftarrow d$

**end if**

**end if**

**end for**

**return** $relArray$

#### B. Instance-level Simplification: iTDS

If we employ a complete TDS—an aggregate of multiple data sets—to build a defect predictor, the result will contain excessive false alarms [11]. Therefore, compared with the $rTDS$, the fine-grained simplification of a TDS should be conducted based on the similarity of instances (files) between training data and target data, which is referred to as $iTDS$.

Following the same experimental setting described in the previous section, for each release, its instance can be represented as $X_i = \{f_{i1}, f_{i2}, \ldots, f_{in}\}$. Unlike the $rTDS$, we directly calculate the Euclidean distance between training instances and target instances, and return the $k$ nearest training instances.
as the eventual TDS. Algorithm 2 formalizes this method. Note that, $|I^*|$ represents the number of instances in a release, and $instArray$ and $distArray$ are used to temporarily store the selected instances and the distances between every pair of instances, respectively.

**Algorithm 2** Instance-level TDS Simplification

**Input:**
- candidate instances $I^{\text{cand}}$;
- target instances $I^{\text{target}}$;
- number of desired instances $k$;
- $instArray$, $distArray$ ← $\emptyset$, $l = 0$;

**for** each $i \in |I^{\text{target}}|$ **do**
  **for** each $j \in |I^{\text{cand}}|$ **do**
    $d \leftarrow \text{distance}(X_i, X_j)$;
    **if** $l < k$ **then**
      $instArray[i][l] \leftarrow j$; $distArray[i][l] \leftarrow d$; $l += 1$;
    **else**
      $\text{min} = \text{min}(distArray)$;
      **if** $\text{min}[k - 1] > d$ **then**
        $instArray[i][k - 1] \leftarrow j$;
        $distArray[i][k - 1] \leftarrow d$;
      **end if**
    **end if**
  **end if**
**end for**
**return** $instArray[i]$;

**end for**

**C. Strategy for TDS simplification: riTDS**

As mentioned in Section I, there are a large number of online public defect data sets available to be candidate training data, and it is time-consuming to completely calculate the distances between every pair of instances by Algorithm 2. However, using Algorithm 1 alone may cause excessive false alarms. Thus, we propose a compromise strategy called riTDS, which obtains the candidate $rTDS$ first and then simplifies it by the method like iTDS. This strategy can be interpreted as a combination of the aforementioned two cases. In other words, first of all we can select the $k$ nearest releases instead of using all available releases as the candidate training data (i.e., $rTDS$). Subsequently, we further simplify the candidate $rTDS$ at the level of granularity of instance.

There are two types of the state-of-the-art strategies for instance-level TDS simplification according to the choice of reference data. One is driven by test data and returns the $k$ nearest TDS instances for each test instance, but the other is just the opposite and returns the $k$ nearest test instances for each TDS instance. To the best of our knowledge, Burak filter [11] and Peter filter [5] are the two typical representatives respectively. For more details of their implementation, please refer to the related literature. Note that, our primary goal in this section is to find some helpful guidelines for software engineers to definitely discriminate the application contexts of each strategy, instead of improving the performance of these existing filters. Algorithm 3 formalizes the implementation of this new strategy.

**Algorithm 3** A novel strategy for TDS simplification

**Input:**
- candidate releases $TDS^{\text{cand}}$;
- target release $S^{\text{target}}$;
- number of desired releases and instances $k1, k2$;
- $rTDS$, $riTDS$ ← $\emptyset$;
- $rTDS \leftarrow \text{Algorithm1}(TDS^{\text{cand}}, S^{\text{target}}, k1)$
  **if** strategy $\leftarrow \text{Burak filter}$ **then**
    $riTDS \leftarrow \text{Burak}_riTDS(rTDS, S^{\text{target}}, k2)$;
  **else**
    $riTDS \leftarrow \text{Peter}_riTDS(rTDS, S^{\text{target}}, k2)$;
  **end if**
**return** $riTDS$;

**IV. CASE STUDY**

**A. Data Setup**

In contrast to previous studies, we extracted the experimental datasets from the PROMISE repository according to their release time to make the settings look more realistic, and any releases without explicit release time were excluded. Detailed information on the 32 releases of 10 open-source projects is listed in Table I. Each instance in these data sets represents a class (.java) file and consists of 20 software metrics and a binary label for the defect proneness. A list with all 20 metrics used in this study as well as their descriptions is provided by Jureczko et al. [3].

For our experiments, we need to select a target data set and its appropriate TDS. Each release in the 32 releases in chronological order was selected to be the target data set once, i.e., we repeated our approach for 32 different cross-project defect predictions. With regard to our primary objective, we set...
up an initial TDS for CPDP, which excludes any releases from the target project. For example, for Jedit-4.0, the latest release Jedit-3.2 cannot be included in its initial TDS. Therefore, in fact, we just need to repeat our approach for 28 releases because the first four data sets are from the same project and will not suitable for CPDP in our context. This example for the data setup was visualized in Fig. 2.

### B. Prediction Models and Performance Measures

In this study, prediction models were built with five well-known classification algorithms—namely, J48, Logistic Regression (LR), Naïve Bayes (NB), Support Vector Machine (SVM) and Random Forest (RF)—used in prior studies. All classifiers were implemented in Weka. For our experiments, we used the default parameter settings for different classifiers specified in Weka unless otherwise specified.

In addition, we used a binary classification technique to predict classes that are likely to contain defects. A binary classifier can make two possible errors: false positive (FP) and false negative (FN). Besides, a correctly classified defective class is a true positive (TP) and a correctly classified non-defective class is a true negative (TN). The prediction models and performance measures used in our experiments are summarized in Table II.

<table>
<thead>
<tr>
<th>Projects</th>
<th>#Classes</th>
<th>%Defect-proneness</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Xerces-init</td>
<td>162</td>
<td>48%</td>
<td>2000/02/29</td>
</tr>
<tr>
<td>Xerces-1.2</td>
<td>440</td>
<td>16%</td>
<td>2000/09/01</td>
</tr>
<tr>
<td>Xerces-1.3</td>
<td>453</td>
<td>15%</td>
<td>2001/01/31</td>
</tr>
<tr>
<td>Xerces-1.4</td>
<td>588</td>
<td>74%</td>
<td>2001/05/22</td>
</tr>
<tr>
<td>Jedit-3.2</td>
<td>272</td>
<td>33%</td>
<td>2001/08/29</td>
</tr>
<tr>
<td>Jedit-4.0</td>
<td>306</td>
<td>25%</td>
<td>2002/04/12</td>
</tr>
<tr>
<td>Xalan-2.4</td>
<td>723</td>
<td>15%</td>
<td>2002/09/03</td>
</tr>
<tr>
<td>Xalan-2.5</td>
<td>803</td>
<td>48%</td>
<td>2003/04/14</td>
</tr>
<tr>
<td>Ant-1.5</td>
<td>293</td>
<td>11%</td>
<td>2003/08/12</td>
</tr>
<tr>
<td>Poi-1.5</td>
<td>237</td>
<td>59%</td>
<td>2003/08/27</td>
</tr>
<tr>
<td>Ant-1.6</td>
<td>351</td>
<td>26%</td>
<td>2003/12/18</td>
</tr>
<tr>
<td>Poi-2.0</td>
<td>314</td>
<td>12%</td>
<td>2004/01/26</td>
</tr>
<tr>
<td>Xalan-2.6</td>
<td>885</td>
<td>46%</td>
<td>2004/02/29</td>
</tr>
<tr>
<td>Poi-2.5</td>
<td>385</td>
<td>64%</td>
<td>2004/03/02</td>
</tr>
<tr>
<td>Ivy-1.1</td>
<td>111</td>
<td>57%</td>
<td>2005/06/13</td>
</tr>
<tr>
<td>Lucene-2.0</td>
<td>195</td>
<td>47%</td>
<td>2006/05/26</td>
</tr>
<tr>
<td>Ivy-1.4</td>
<td>241</td>
<td>7%</td>
<td>2006/10/09</td>
</tr>
<tr>
<td>Ant-1.7</td>
<td>745</td>
<td>22%</td>
<td>2006/12/13</td>
</tr>
<tr>
<td>Velocity-1.4</td>
<td>196</td>
<td>75%</td>
<td>2007/01/27</td>
</tr>
<tr>
<td>Velocity-1.5</td>
<td>214</td>
<td>66%</td>
<td>2007/03/13</td>
</tr>
<tr>
<td>Poi-3.0</td>
<td>442</td>
<td>64%</td>
<td>2007/05/18</td>
</tr>
<tr>
<td>Synapse-1.0</td>
<td>157</td>
<td>10%</td>
<td>2007/06/08</td>
</tr>
<tr>
<td>Lucene-2.2</td>
<td>247</td>
<td>58%</td>
<td>2007/06/19</td>
</tr>
<tr>
<td>Camel-1.0</td>
<td>339</td>
<td>4%</td>
<td>2007/07/02</td>
</tr>
<tr>
<td>Camel-1.2</td>
<td>608</td>
<td>36%</td>
<td>2007/10/16</td>
</tr>
<tr>
<td>Synapse-1.1</td>
<td>222</td>
<td>27%</td>
<td>2007/11/12</td>
</tr>
<tr>
<td>Synapse-1.2</td>
<td>256</td>
<td>34%</td>
<td>2008/06/09</td>
</tr>
<tr>
<td>Camel-1.4</td>
<td>872</td>
<td>17%</td>
<td>2008/07/22</td>
</tr>
<tr>
<td>Lucene-2.4</td>
<td>340</td>
<td>60%</td>
<td>2008/10/10</td>
</tr>
<tr>
<td>Velocity-1.6</td>
<td>220</td>
<td>35%</td>
<td>2012/08/12</td>
</tr>
<tr>
<td>Ivy-2.0</td>
<td>352</td>
<td>11%</td>
<td>2009/01/20</td>
</tr>
<tr>
<td>Camel-1.6</td>
<td>965</td>
<td>19%</td>
<td>2009/02/17</td>
</tr>
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</table>

### TABLE II: The measures and models used in our experiments

<table>
<thead>
<tr>
<th>Performance Measure</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>( \frac{TP + TN}{TP + TN + FP + FN} )</td>
</tr>
<tr>
<td>Recall ( pd )</td>
<td>( \frac{TP}{TP + FN} )</td>
</tr>
<tr>
<td>Precision ( prec )</td>
<td>( \frac{TP}{TP + FP} )</td>
</tr>
<tr>
<td>F-measure</td>
<td>( \frac{2 \times prec \times recall}{prec + recall} )</td>
</tr>
<tr>
<td>G-measure</td>
<td>( \frac{2 \times prec \times recall}{prec + recall + \frac{1}{2} \times (1 - prec \times recall)} )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Classifiers</th>
</tr>
</thead>
<tbody>
<tr>
<td>J48 Decision Tree</td>
</tr>
<tr>
<td>Logistic Regression</td>
</tr>
<tr>
<td>Naïve Bayes</td>
</tr>
<tr>
<td>Support Vector Machine</td>
</tr>
<tr>
<td>Random Forest</td>
</tr>
</tbody>
</table>

### C. Results

We organize our results according to the three research questions proposed in Section I. Because the dimension of the characteristic vectors in the \( riTDS \) depends on the numbers of involved features and characteristics, in this study we used only two primary characteristics as used in [14]: mean value and standard deviation. These two characteristics are frequently used to reasonably reflect the distribution of feature values. To answer the question \( RQ3 \), we introduce a balance index, which is used to seek an optimal trade-off point \( \rho \) to support the decision-making process between training set-driven filter and test set-driven filter in the \( riTDS \). Assuming that \( Prec_i \) is the precision of using filter \( i \) with a specific \( \rho \). The balance between two filters \( i \) and \( j \) is defined as follows:

\[
balance = \frac{2 \times Prec_i \times Prec_j}{Prec_i + Prec_j}.
\]**
and 0.459 respectively, whereas their corresponding \( pf \) values are 0.128 and 0.144 respectively. Additionally, the overall changing trends of the four measures achieved by the iTDS method are more stable. That is, the performance of instance-level TDS simplification is more reliable according to the results achieved by the five typical learning algorithms.

Regarding the stable trend, we further investigated the actual size of the TDS used to train defect predictors. As expected, Fig. 4 indicates that the rising size of a TDS does not improve the prediction performance significantly, because the results do not change significantly with an obvious linear growth of the average ratio. In Fig. 3, the measures of prediction performance begin to become stable when \( k \) equals 4, where the average ratios of the number of used releases and instances to their totals are 33.7% and 20.6%, respectively. In other words, the quality rather than the quantity of the training data is a crucial factor that affects the performance of CPDP. This is one of our primary motivations to simplify the training data in this study.

The first value on the x-axis \((k = 0)\) in Fig. 3(a) represents the result obtained by a prior method [1] without considering the release time. Clearly, the measure values of the prior method are higher than those of our approach at the level of release. The most likely explanation is that the previous method selects the nearest releases from all available releases, whereas the iTDS only selects the nearest releases before the test time, that is, its initial TDS is a subset of the previous method’s. Despite this, we still believe that the actual results of our approach are more valuable than those ideal results with regard to software engineering practices.

The fine-grained method of TDS simplification performs better and the size of simplified TDS can be reduced up to 79.4% off compared to the original size.

**RQ2:** Which prediction model built in our context is more likely to be suitable for CPDP?

Fig. 3 also shows that Naïve Bayes yields the best performance among all classifiers because of the greatest accuracy and the lowest probability of false alarms. Although other prediction models, built with J48, Logistic Regression and Random Forest, present impressive \( f \)-measure values, all of them have a fairly high probability of false alarms. Furthermore, this advantage of Naïve Bayes becomes more significant with an increase of \( k \) value. Our results further validate the statement that simple modeling techniques tend to perform well [15].

Interestingly, whichever level of granularity we select, the SVM shows the worst performance. There is an obvious gap between the SVM and other prediction models in question in terms of \( f \)-measure and \( g \)-measure, especially when using the iTDS method. In literature [14], the author weighted the instances of training data, thus leading to a remarkable improvement by the SVM. In this study, the reason why we
Fig. 3: Results of our experiments on the performance of different prediction models. The figure shows the mean (accuracy, \( pf \), \( f\)-measure and \( g\)-measure) values calculated among the 28 CPDP cases with J48, Logistic Regression, Naïve Bayes, SVM and Random Forest, based on release-level and instance-level simplification, respectively. The first value on the x-axis (\( k = 0 \)) in Fig.3(a) represents the result obtained by a previous method proposed by He et al. [1].

The performance of the predictor built with Naïve Bayes is the best for CPDP in our context.

**RQ3:** Which strategy for TDS simplification should be preferable in a specific scenario?

Predictably, the \( iTDS \) method is time-consuming and impractical enough to determine the proper training data when the available training data is abundant. Thus, we compared the \( rTDS \) method with the \( iTDS \) method on \( f\)-measure and \( g\)-measure, as shown in Table III. The results show that Peter filter outperforms Burak filter, and Burak filter appears to be not as good as the \( iTDS \) in most cases. It is worthwhile to note that the value of parameter \( k2 \) for each test instance in Algorithm 3 is set to 10, because it was also used in the prior studies [5, 11].

In addition, Fig. 5 shows the results of both filtering strategies for CPDP with the best defect predictor (i.e., Naïve Bayes) drawn from RQ2. For each \( k \), \#(\( \Delta f > 0 \)) for a given filter represents the number of releases whose \( f\)-measure values calculated with this filter are larger. That is, for the \( i \)th release, if \( f^b_{burak} > f^b_{peter} \), \#(\( \Delta f > 0 \)) of Burak filter is incremented by 1, otherwise the number of Peter filter increases by 1. The definition of \#(\( \Delta g > 0 \)) is similar to that of \#(\( \Delta f > 0 \)). The results highlight that Peter filter does outperform Burak filter, indicated by a clear majority of higher bars with diagonal stripes, although two exceptions exist in Fig. 5(b). Furthermore, the results show that this superiority reaches its peak when \( k = 7 \), which indicates that a proper number of the nearest neighbors is also very important for prediction performance.

we also collected the experimental results for each target release to investigate the relationship between the choice of filtering strategies and the primary characteristic of releases. Fig. 6(a) shows the total number of times that Peter filter performs better than Burak filter in terms of \( f\)-measure and \( g\)-measure for each target release, when \( k \) ranges from 1 to 10. If a release is located above the dotted line, the probability of a preference for Peter filter is over 50%. Otherwise, Burak filter should be preferable. For example, there are four target releases whose \#Times values are ten for both measures, i.e., 4(Xalan-2.4), 7(Ant-1.6), 11(Ivy-1.1) and 14(Ant-1.7). They should be given a high priority to choosing Peter filter because of their maximum values. Conversely, Burak filter appears to be more suitable for the target releases 10, 16 and 23 (i.e., Poi-2.5, Velocity-1.5 and Synapse-1.2). According to the distribution of \#Times, we find that Peter filter tends to be suitable for those releases with high DPR values (see Fig. 6(b)), because the median DPRs for the group \#Times ≥ 5 are 1.67 and 1.71 in terms of \( f\)-measure and \( g\)-measure respectively, which are almost twice as much as those of the group \#Times < 5.

However, it is very clear that the above evidence only shows an overall trend towards using training data to guide the process of TDS simplification, but it cannot yet effectively help us make a reasonable decision on the choice of an appropriate filtering strategy. Therefore, we gathered the 280 \((10 \times 28 = 280)\) results obtained in Fig. 5, and they were divided into Peter group and Burak group according to

did not take the weight into account is that we focus primarily on understanding the differences between the methods of TDS simplification from the perspective of granularity, (i.e., \( rTDS \) vs. \( iTDS \)). Hence, we used the same data processing method for all classifiers under discussion, without considering specific optimization for any ones.
TABLE III: The change rate (%) of $f$-measure and $g$-measure of the riTDS with Naïve Bayes

<table>
<thead>
<tr>
<th>riTDS</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>iTDS</td>
<td>0.371</td>
<td>0.364</td>
<td>0.355</td>
<td>0.353</td>
<td>0.354</td>
<td>0.356</td>
<td>0.355</td>
<td>0.354</td>
<td>0.350</td>
<td>0.348</td>
</tr>
<tr>
<td>riTDS-Burak</td>
<td>+1.5</td>
<td>+8.9</td>
<td>+3.4</td>
<td>-0.9</td>
<td>-3.3</td>
<td>-3.8</td>
<td>-1.9</td>
<td>-3.8</td>
<td>-0.3</td>
<td></td>
</tr>
<tr>
<td>riTDS-Peter</td>
<td>+0.2</td>
<td>+4.7</td>
<td>+4.1</td>
<td>+0.3</td>
<td>0.0</td>
<td>+3.2</td>
<td>+5.1</td>
<td>+7.0</td>
<td>+6.9</td>
<td>+13.5</td>
</tr>
</tbody>
</table>

- The number of the measure ($\#(\Delta > 0)$) is calculated among the 28 CPDP cases with Naïve Bayes.

![Fig. 5](image1.png)

**Fig. 5:** A comparison between Burak filter and Peter filter in terms of $\Delta f$ and $\Delta g$.

- The result shows that the balance values reach their peaks when $\rho = 1.34$ (left) and $\rho = 1.38$ (right) in Fig. 7. That is, we can employ these two values as the corresponding thresholds to determine the eventual choice of filtering strategy in terms of $f$-measure and $g$-measure, respectively. For example, with respect to $f$-measure, Peter filter should be recommended if the DPR value of a target release is greater than 1.34, otherwise Burak filter should be preferable.

![Fig. 6](image2.png)

**Fig. 6:** (a) The total number of times that Peter filter performs better than Burak filter for each target release in terms of $f$-measure and $g$-measure (some nodes are overlapping), and the dotted line represents the probability of randomly selecting a filter; (b) The standardized boxplot of the distribution of DPR according to the $\#Times$.

![Fig. 6](image3.png)

**Fig. 6:** (a) The total number of times that Peter filter performs better than Burak filter for each target release in terms of $f$-measure and $g$-measure (some nodes are overlapping), and the dotted line represents the probability of randomly selecting a filter; (b) The standardized boxplot of the distribution of DPR according to the $\#Times$.

- The riTDS method with training set-driven filter can achieve fairly good prediction performance, and the selection of a proper filtering strategy depends on the reasonable threshold of DPR.

V. DISCUSSION

**RQ1:** A large amount of training data may not lead to a high prediction performance of CPDP, implying the necessity of simplifying training data. However, none of the existing
methods takes the release time of training data and test data into consideration, which is a key factor for building real and practical CPDP models. As we consider such a factor, our experimental results show that the prediction performance based on the instance-level TDS simplification is better and more stable, indicating that the TDS simplification at the fine-grained level of granularity can obtain high-quality training data, though it is more time-consuming than the release-level method. Furthermore, there is an obvious decrease on the probability of false alarms with an increase of $k$ value, especially when using a Na"ive Bayes classifier, because more representative instances are involved in the selected TDS.

**RQ2:** As we know, Na"ive Bayes is a robust machine learning algorithm for supervised software defect prediction problems in both WPDP and CPDP. Interestingly, the result is completely consistent with the conclusions drawn in the literature [15, 16], that is, Na"ive Bayes outperforms the other typical classifiers within our CPDP context. It is worthwhile to note that different prediction models were built based on these classifiers without specific optimization, because in this study we focused primarily on the levels of granularity and filtering strategies for TDS simplification. However, the differences between different prediction models on prediction performance indicate that simple classifiers, such as Na"ive Bayes, can be preferable for training data of quality.

**RQ3:** As an alternative strategy, the training data-driven filter for TDS simplification is better than the test data-driven filter, which is consistent with the findings obtained in [5]. However, the authors did not analyze the specific application scenarios for each filter. We filled the gap in terms of a balance index based on DPR and found that using training data to guide TDS simplification not only performs better as a whole, but also is more suitable for those projects with a high DPR. Note that, in order to make the right decision between Burak filter and Peter filter according to the value of balance, we seek the optimal trade-off point through gradually changing the value of $\rho$ with an increment of 0.1.

**VI. Threats to Validity**

In this study, although we obtained several interesting findings according to the three research questions proposed in Section I, there still exist some potential threats to the validity of our work.

Threats to **construct validity** are primarily related to the data sets we used. All of the data sets were collected by Jureczko and Madeyski [3] and Jureczko and Spinellis [4] with the support of two existing tools (BugInfo and Ckjm). These data sets have been validated and applied to several prior studies, though there may exist errors in the process of defect identification. Therefore, we believe that our results are credible and can be reproduced. Note that, we did not apply data normalization before building defect predictors, and the impact of different normalization methods on prediction performance will be discussed in an extended version of this paper.

Threats to **internal validity** are mainly related to various learning algorithm settings in our study. For our experiments, although the $k$-nearest neighbor algorithm (KNN) was selected as the basic selection algorithm, we are aware that our results would change if we use a different method. However, to the best of our knowledge, both KNN and its variants were successfully applied to TDS simplification in several prior studies [5, 14]. Moreover, we did not implement specific optimization for any classifiers in question when building different prediction models, because the goal of this experiment is not to improve the performance of a given classifier.

Threats to **external validity** could be related to the generality of the results to other on-line public data sets used for defect prediction, such as NASA and Mozilla. The data sets used in our experiments are chosen from a small subset of all projects in the PROMISE repository, and it is possible that we casually selected these data sets that have better (or worse) than average CPDP performance, implying that some of our findings (e.g., the threshold of $\rho$ calculated with Na"ive Bayes) might not be generalizable to other data sets.

**VII. Conclusion**

TDS simplification, which filters out irrelevant training data, plays an important role in building better CPDP models. This study reports an empirical study aiming at investigating a practical CPDP model and the impact of the level of granularity and filtering strategy on TDS simplification, when considering the actual release time of each data set. The study
has been conducted on 32 releases of 10 open-source projects in the PROMISE repository and consists of (1) a comparison between release-level and instance-level TDS simplification; (2) a selection of the best prediction model in our context; and (3) an assessment of specific application scenarios for the state-of-the-art filtering strategies for TDS simplification.

The results indicate that the fine-grained method (instance-level) captures better f-measure and g-measure values than the coarse-grained one, and the advantage becomes more significant with an increase of the size of selected data sets. In addition, our results also show that Naive Bayes is more suitable for building predictors for CPDP with simplified training data. Finally, with regard to the actual context, the suitable for building predictors for CPDP with simplified data sets.

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