Iterative versus Exhaustive Data Selection for Cross Project Defect Prediction: An Extended Replication Study

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Received: date / Accepted: date

Abstract Context: The effectiveness of data selection approaches in improving the performance of cross project defect prediction (CPDP) has been shown in multiple previous studies. Beside that, replication studies play an important role in the support of any valid study. Repeating a study using the same or different subjects can lead to better understandings of the nature of the problem.

Objective: We use an iterative dataset selection (IDS) approach to generate training datasets and evaluate them on a set of randomly created validation datasets in the context of CPDP while considering a higher range of flexibility which makes the approach more feasible in practice.

Method: We replicate an earlier study and present some insights into the achieved results while pointing out some of the shortcomings of the original study. Using the lessons learned, we propose to use an alternative training/validation dataset generation approaches which not only is more feasible in practice, but also achieves slightly better performances. We compare the results of our experiments to those from scenarios A, B, C and D from the original study.

Results: Our experiments reveal that IDS is heavily recall based. The average recall performance for all test sets is 0.933 which is significantly higher than that from the replicated method. This in turn comes with a loss in precision. IDS has the lowest precision among the compared scenarios that use Decision Table learner. IDS however, achieves comparable or better F-measure performances. IDS achieves higher mean, median and min F-measure values while being more stable generally, in comparison with the replicated method.

Conclusions: We conclude that datasets obtained from iterative/search-based approaches is a promising way to tackle CPDP. Especially, the performance increase in terms of both time and performance encourages further investigation.
of our approach. However, the performance of IDS is based on high recall in the expense of a loss in precision. Using different optimization goals as well as incorporating feature selection techniques are possible future directions to investigate.

**Keywords** Cross Project Defect Prediction · Search Based Optimization · Training Data Selection · Replication

1 Introduction

Applying defect prediction in practice has been a challenge. The lack of and the difficulty of collecting and organizing defect related data is one of the reasons why companies do not consider using defect prediction in practice [22] and it is usually limited to research studies [9]. Cross Project Defect Prediction (CPDP) comes to the rescue in such circumstances as it is an affordable solution for the companies that look for minimal effort of data collection. Additionally, the use of CPDP is justified, since the change of practices in software development over time affects the relevance of collected local data, because the existing practices might not be representative anymore [15,9]. On the other hand, the key premise of CPDP is learning and applying, from and to, different sets of projects [26,22]. Hence, in presence of relevant data from other projects including open source ecosystems, CPDP can result in practical applications because even a tiny decrease in the bug rates can lead to significant financial savings in terms of quality assurance costs [22], as opposed to exponential growth in repair costs and damages [22] as a result of failure to discover bugs in a timely manner.

Despite the discussed benefits, cross project defect prediction approaches might have certain drawbacks and limitations. The first of such issues is the fact the most of the proposed approaches in the literature have fairly average effectiveness performances and they are not still powerful enough to outperform within project counterparts. As pointed out in [9], this is true even though the proposed approaches are usually far more complicated than their within project benchmarks. The other problem that arises in the context of CPDP, especially in light of their complexity and runtime requirements, is their applicability and chances of being used in practice. Finding a suitable dataset with similar defect distribution characteristics as the test set is likely to increase the performance of prediction models [21].

We replicate a study by He et al. [6] which addresses data selection for cross project defect prediction. The design of the experiments as well as the performed analyses are of particular interest in the replication. Using the lessons learned, we will present a dataset selection approach called Iterative Data Selection (IDS) as an alternative to the method from the original study. IDS works by assigning a “fitness” value to each generated dataset which is used during the selection and filtering processes of the approach. IDS is equipped with an additional control step to prevent low quality datasets from being accepted. Similar to the proposed approach in the original study, we present multiple candidate training datasets for each test set, if available. Additionally, by tweaking the proposed method, we have the ability to guarantee producing datasets for each test set, unlike the proposed method in the original study. Beside performing additional analyses, the replicated approach from the original study is also used as a benchmark for IDS. While we
are not solving the above concerns entirely, we propose steps in their direction, while evaluating and validating certain design decisions by earlier studies through replication.

2 Related Work

Studies in the area of cross project defect prediction, do not always agree in their conclusions. The systematic literature review by Hosseini et al [9], presents detailed discussions of the state of the art CPDP approaches with a specific focus on data approaches used in the literature. We describe the most relevant studies to our work next.

Turhan et al. [22] observed that CPDP under-performs WPDP. They also found that despite its good probability of detection rates, CPDP causes excessive false alarms. To overcome this problem, they proposed NN-Filter to select the most relevant training data instances from a pool of cross project datasets. Even though this method lowered the false alarm rates dramatically, its performance was still worse than WPDP.

Zimmermann et al. [26] tested the CPDP approach for 622 pairs of 28 datasets from 12 projects (open source and commercial) and found only 21 pairs (3.4%) that match their performance criteria (precision, recall and accuracy, all greater than 0.75). This means that the predictions will fail in most cases if training data is not selected carefully. They also found that CPDP is not symmetrical as data from Firefox can predict Internet Explorer defects, but the opposite does not hold. They argued that characteristics of data and process are crucial factors for CPDP.

He et al. [6] proposed to use the distributional characteristics (median, mean, variance, standard deviation, skewness, quantiles, etc.) for training dataset selection. They conclude that in the best cases cross project data may provide acceptable prediction results. They also state that training data from the same project does not always lead to better predictions and carefully selected cross project data may provide better prediction results than within-project (WP) data. They also found that data distributional characteristics are informative for training data selection.

Herbold [7] proposed distance-based strategies for the selection of training data based on distributional characteristics of the available data. They presented two strategies based on EM (Expectation Maximization) clustering and NN (Nearest Neighbor) algorithm with distributional characteristics as the decision strategy. They evaluated the strategies in a large case study with 44 versions of 14 software projects and they observed that i) weights can be used to successfully deal with biased data and ii) the training data selection provides a significant improvement in the success rate and recall of defect detection. However, their overall success rate was still too low for the practical application of CPDP.

Turhan et al. [23] evaluated the effects of mixed project data on predictions. They tested whether mixed WP and CP data improves the prediction performances. They performed their experiments on 73 versions of 41 projects using Naïve Bayes classifier. They concluded that the mixed project data would significantly improve the performance of the defect predictors.

Zhang et al. [25] created a universal defect prediction model from a large pool of 1,385 projects with the aim of relieving the need to build prediction models for
individual projects. They approached the problem of variations in the distributions by clustering and rank transformation using the similarities among the projects. Based on their results, their model obtained prediction performance comparable to the WP models when applied to five external projects and performed similarly among projects with different context factors.

Ryu et al. [20] presented a Hybrid Instance Selection with the Nearest Neighbor (HISNN) method using a hybrid classification to address the class imbalance for CPDP. Their approach used a combination of the Nearest Neighbour algorithm with Hamming distance and Naïve Bayes to address the instance selection problem.

Instance selection and data quality are investigated by Hosseini et al. [10,12,8]. The proposed model called GIS, approaches the instance selection problem using a search based method based on genetic algorithm and tries to build evolving training datasets while utilizing NN-Filter in the dataset evaluation process. The model also, takes steps toward addressing the data quality issues in the defect datasets.

This paper is organized as follows: The next section describes the original and replication studies. Data sets, Learning algorithms, different scenarios and procedures of performing the experiments in different scenarios will be presented in this section. The results and comparisons of the replication study is presented in section 4. Section 5 presents the motivations, details and results of our proposed approach. We follow the results section by a discussion about the proposed approach. Section 6 describes the threads to validity of our study. Finally, the last section concludes the paper and a summary of the findings as well as future works are discussed.

3 Research Methodology

The details of the experiments from the original study are presented in this section including the utilized research methodology, experiments, datasets and tools. The lessons learned from replicating this study would be used as the motivation for our proposed approach.

3.1 IDS vs the replicated method

Considering the different existing approaches in the literature, our proposed approach is different from the replicated method (and the rest of the studies generally) in the following ways.

− IDS uses a search based method to identify and filter acceptable and irrelevant/useless datasets respectively (as opposed to generating every combination up to a certain number and filtering them).
− IDS eliminates the need for additional generated datasets for meta learning (using data distributional characteristics, proposed in the original study).
− IDS can potentially generate a set of candidate datasets for any test set due to its wider coverage and certain control mechanisms in the approach.
− Practical implementation and applicability of the approach are considered which are important taking into account the higher speed of search versus
Scen-A | CP | Collects the results from a large number of predictions comprised of all combinations of one, two and three releases from other projects as training data (160,586 total combinations).

Scen-B | WP | 5-fold cross validation. The test sets are split randomly into 5 parts and each part is predicted with the data from the other four parts.

Scen-C | WP | Other (not necessarily previous) releases. Training datasets are constructed by combining the data from the other releases of the same project. The authors did not consider the chronological order of the releases in the projects, i.e. data from later release(s) of a project are used to predict earlier releases.

Scen-D | CP | Meta learner. The predictions from Scen-A combined with the extracted distributional characteristics of their corresponding training datasets are used to generate a meta-learner (using a decision tree) to predict the usefulness of other candidate datasets.

Table 1 Caption

exhaustive dataset generation, and wider range of coverage (any arbitrary number of datasets as training data) of the dataset space as well as effectiveness performance.

3.2 On the importance of replication studies

The discussed related work, as well as recent SLRs [5,9] show a growing trend toward studies in within and cross project defect prediction topics. While not specific to defect prediction and CPDP, studies in different areas including the aforementioned two, are not frequently replicated to assess their validity and generalizability and are usually treated as facts. One potential reason for this problem is the generally less value given to replication studies, one might say that rarely anyone is interested in inventing/validating the same object/concept again. But this is the source of the misconception. Replication studies are far more valuable and different from just doing the same procedures. The advantages include validating the interpretations from different viewpoints, catch potential experiment and design flaws, and more importantly, extract the lessons learned, some of which might have been neglected in original studies for one reason or another.

3.3 Description of the Original Study

We begin this section by providing the details of the replicated study [6] which involves investigating the usability of exhaustive dataset generation and meta-learning for cross project defect prediction.

To answer their research questions, He et al. conducted a set of predictions in multiple scenarios. The name of the scenarios, their types (within or cross project) and their description are presented in Table 1.

The main proposed method in the original study builds a meta-learner on top of the cross project prediction results from the Decision Table (DT) learner. For that purpose, an instance called train-test-result (TTR) is generated for each prediction from DT learner of Scen-A, which consists of the following three parts:
Fig. 1 An example dataset and its corresponding TTR instance

- The distributional characteristics of the training set (320 new features = 20 features × 16 characteristics).

- The distributional characteristics of the test set (320 new features = 20 features × 16 characteristics).

- The prediction result from the model created on training dataset and evaluated on the test dataset (successful (yes=1) or unsuccessful (no=0)).

The mentioned distributional characteristics consist of 16 statistical indicators, shown in Table 2. Using this method, 320 new features are generated for the 20 available features in each dataset (training and test datasets), i.e. (16 characteristics) × (20 features), resulting in a 641 attributes vector for each cross project prediction from Scen-A. Figure [1] illustrates the TTR part for a dataset (train or test).
### Table 2 List of the used data distributional characteristics

| Variable | Description |
|----------|-------------|
| **Central Tendency** | |
| Mean | Arithmetic mean or central value of a discrete set of numbers: specifically, the sum of the values divided by the number of values |
| Mode | The value that appears most often in a set of data |
| Median | The number separating the higher half of a data sample, a population, or a probability distribution |
| Harmonic Mean | The reciprocal of the arithmetic mean of the reciprocals of the data values (only for data that are measured absolutely on a strictly positive scale). |
| **Dispersion** | |
| Minimum | The lowest value in a population |
| Maximum | The highest value in a population |
| Range | The difference between the largest and smallest values |
| Variation Ratio | The proportion of cases which are not the mode |
| First Quartile | The value cutting off 25% lowest cases in a population |
| Third Quartile | The value cutting off 25% highest cases in a population |
| Interquartile Range | The difference between the first and third quartiles |
| Variance | The arithmetic mean of the squared deviation of the Mean to values of cases in a population |
| Standard Deviation | The square root of the Variance |
| Coefficient of Variation | The ratio of the Standard Deviation to the Mean |
| **Shape** | |
| Skewness | A measure of the asymmetry of the probability distribution |
| Kurtosis | A measure of the tailedness of the probability distribution |

#### 3.4 Datasets and Features

For these experiments, 34 releases of 10 open source Java projects from the PROMISE repository were used. These data sets were collected by Jureczko, Madeyski and Spinellis [13,14]. The List of the data sets is presented in Table 4. Each data set contains a number of instances corresponding to the classes in the release. Each instance has 20 features including static code metrics, object oriented and LOC metrics. The list of these metrics is shown in Table 3.

#### 3.5 Models and Evaluation

Five learners namely Naïve Bayes (NB), Decision Tree (C4.5), Decision Table (DT), Support Vector Machine (SVM) and Logistic Regression (LR) were used to construct the prediction models. The original study [2] contains brief description of these learners. None of the learners use hyper-parameter tuning in neither of the original study nor this replication.
Table 3 List of the metrics in each data set

| Variable | Description |
|----------|-------------|
| **CK suite (6)** | |
| WMC | Weighted Methods per Class |
| DIT | Depth of Inheritance Tree |
| LCOM | Lack of Cohesion in Methods |
| RFC | Response for a Class |
| CBO | Coupling between Object classes |
| NOC | Number of Children |
| **Martins metric (2)** | |
| CA | Afferent Couplings |
| CE | Efferent Couplings |
| **QMOOM suite (5)** | |
| DAM | Data Access Metric |
| NPM | Number of Public Methods |
| MFA | Measure of Functional Abstraction |
| CAM | Cohesion Among Methods |
| MOA | Measure Of Aggregation |
| **Extended CK suite (4)** | |
| IC | Inheritance Coupling |
| CBM | Coupling Between Methods |
| AMC | Average Method Complexity |
| LCOM3 | Normalized version of LCOM |
| **McCabe’s CC (2)** | |
| MAX CC | Max values of methods in the same class |
| AVG CC | Mean values of methods in the same class |
| LOC | Lines Of Code |

To assess the performance of the models, three indicators are used: Precision, Recall and F-measure. These indicators are calculated by comparing the outcome of the prediction model and the actual label of the data instances.

The original study demanded recall greater than 0.70 and precision greater than 0.50 for the predictions to be marked as successful/acceptable. Such thresholds were selected, as in practice, achieving higher values of these measures especially in light of the experiments by Zimmerman et al. [26], are proven empirically to be very difficult. The F-measure values are the basis of assessment to determine the superiority of a prediction over others.

3.6 Changes in the replication

The procedures of the original study are followed for most parts. Five learners are used for constructing the prediction models. For implementation purposes, NB, SVM, C4.5 and LR from Scikit-Learn[^1] version 0.16.1 library and Python 3.4 were used. This is the case for the final decision trees, used in Scen-D as well. Since DT learner was not present in Scikit-Learn 0.16.1 and further, the results of the DT learner were the main focus of the original study, WEKA[^2] version 3.6.13 was

[^1]: http://scikit-learn.org
[^2]: http://www.cs.waikato.ac.nz/ml/weka/
Table 4 data sets used in the study

| Release   | #classes | #DP | DP(%) | #LOC  |
|-----------|----------|-----|-------|-------|
| ant-1.3   | 125      | 20  | 0.160 | 37699 |
| ant-1.4   | 178      | 40  | 0.225 | 54195 |
| ant-1.5   | 293      | 32  | 0.109 | 87047 |
| ant-1.6   | 351      | 92  | 0.262 | 113234|
| ant-1.7   | 745      | 166 | 0.223 | 208653|
| camel-1.0 | 339      | 13  | 0.038 | 33721 |
| camel-1.2 | 608      | 216 | 0.355 | 66302 |
| camel-1.4 | 872      | 145 | 0.166 | 98080 |
| camel-1.6 | 905      | 188 | 0.195 | 113055|
| ivy-1.1   | 111      | 63  | 0.568 | 27292 |
| ivy-1.4   | 241      | 16  | 0.066 | 59286 |
| ivy-2.0   | 352      | 40  | 0.114 | 87769 |
| jedit-3.2 | 272      | 90  | 0.331 | 128886|
| jedit-4.0 | 306      | 75  | 0.245 | 144803|
| lucene-2.0| 195      | 91  | 0.467 | 50596 |
| lucene-2.2| 247      | 144 | 0.583 | 63571 |
| lucene-2.4| 340      | 203 | 0.597 | 102859|
| poi-1.5   | 237      | 141 | 0.595 | 55428 |
| poi-2.0   | 314      | 37  | 0.118 | 93171 |
| poi-2.5   | 385      | 248 | 0.644 | 119731|
| poi-3.0   | 442      | 281 | 0.636 | 129327|
| synapse-1.0| 157     | 16  | 0.102 | 28806 |
| synapse-1.1| 222     | 60  | 0.270 | 42302 |
| synapse-1.2| 256     | 86  | 0.336 | 53500 |
| velocity-1.4| 196   | 147 | 0.750 | 51713 |
| velocity-1.5| 214   | 172 | 0.814 | 54111 |
| velocity-1.6| 229   | 78  | 0.341 | 57012 |
| xalan-2.4 | 723      | 110 | 0.152 | 225088|
| xalan-2.5 | 803      | 387 | 0.482 | 304860|
| xalan-2.6 | 885      | 411 | 0.464 | 411737|
| xerces-init| 162    | 77  | 0.475 | 90718 |
| xerces-1.2| 440      | 71  | 0.161 | 159254|
| xerces-1.3| 453      | 69  | 0.152 | 167095|
| xerces-1.4| 588      | 437 | 0.743 | 141180|

the library of choice for it. A replication package is available online for further validation and verification.[3]

One major issue that we address in the presented results of the original study is the fact that the authors performed cross validation on the generated TTR dataset. We argue in later sections that this is not a valid assessment scheme. In Scen-B, we perform stratified cross validation as the details of this benchmark are not clearly specified in the original study. Stratification is the process of re-arranging the data as to ensure each fold is a good representative of the whole data. This approach is generally a better scheme, both in terms of bias and variance in comparison with the regular non-stratified cross-validation. Also, it is advised to repeat the cross validation process for a number of rounds ($M \times (Nfolds)$) due to the use of randomness in stratification and fold generation ($M=10$ in this study).

To measure the performance difference across the benchmarks, Mann-Whitney U tests are used. This test is a non-parametric test which is suitable for samples

[3] https://github.com/rebvar/IDS
Table 5 Average performances of the learners-Best cases vs. all predictions

| Learner | Mean Best training data sets | All data sets | Learner | Mean Best training data sets | All data sets |
|---------|------------------------------|---------------|---------|------------------------------|---------------|
| A-(Recall) | DT 0.709, C4.5 0.520, NB 0.672, LR 0.736, SVM 0.931 | DT 0.709, C4.5 0.520, NB 0.672, LR 0.736, SVM 0.931 | A-(F) | DT 0.583, C4.5 0.547, NB 0.553, LR 0.521, SVM 0.421 | DT 0.583, C4.5 0.547, NB 0.553, LR 0.521, SVM 0.421 |
| A-(Precision) | DT 0.313, C4.5 0.416, NB 0.318, LR 0.321, SVM 0.167 | DT 0.313, C4.5 0.416, NB 0.318, LR 0.321, SVM 0.167 |
| A-(F) | DT 0.631, C4.5 0.593, NB 0.592, LR 0.624, SVM 0.544 | DT 0.631, C4.5 0.593, NB 0.592, LR 0.624, SVM 0.544 |
| A-#Success | DT 10, C4.5 17, NB 10, LR 15, SVM 12 | DT 10, C4.5 17, NB 10, LR 15, SVM 12 |
| A-#TestSets | DT 15, C4.5 17, NB 10, LR 15, SVM 12 | DT 15, C4.5 17, NB 10, LR 15, SVM 12 |
| A-#Predictions | DT 34 for each learner, C4.5 3281 for each learner | DT 34 for each learner, C4.5 3281 for each learner |
| B-(Recall) | DT 0.421, C4.5 0.372, NB 0.593, LR 0.565, SVM 0.543 | DT 0.421, C4.5 0.372, NB 0.593, LR 0.565, SVM 0.543 |
| B-(Precision) | DT 0.421, C4.5 0.372, NB 0.593, LR 0.565, SVM 0.543 | DT 0.421, C4.5 0.372, NB 0.593, LR 0.565, SVM 0.543 |
| B-(F) | DT 0.421, C4.5 0.372, NB 0.593, LR 0.565, SVM 0.543 | DT 0.421, C4.5 0.372, NB 0.593, LR 0.565, SVM 0.543 |
| B-#Success | DT 9, C4.5 9, NB 1, LR 1, SVM 1 | DT 9, C4.5 9, NB 1, LR 1, SVM 1 |
| B-#TestSets | DT 9, C4.5 9, NB 1, LR 1, SVM 1 | DT 9, C4.5 9, NB 1, LR 1, SVM 1 |
| B-#Predictions | DT 34 for each learner, C4.5 340 for each learner | DT 34 for each learner, C4.5 340 for each learner |
| C-(Recall) | DT 0.593, C4.5 0.365, NB 0.455, LR 0.533, SVM 0.458 | DT 0.593, C4.5 0.365, NB 0.455, LR 0.533, SVM 0.458 |
| C-(Precision) | DT 0.505, C4.5 0.557, NB 0.569, LR 0.630, SVM 0.525 | DT 0.505, C4.5 0.557, NB 0.569, LR 0.630, SVM 0.525 |
| C-(F) | DT 0.505, C4.5 0.557, NB 0.569, LR 0.630, SVM 0.525 | DT 0.505, C4.5 0.557, NB 0.569, LR 0.630, SVM 0.525 |
| C-#Success | DT 8, C4.5 3, NB 1, LR 6, SVM 9 | DT 8, C4.5 3, NB 1, LR 6, SVM 9 |
| C-#TestSets | DT 8, C4.5 3, NB 1, LR 6, SVM 9 | DT 8, C4.5 3, NB 1, LR 6, SVM 9 |
| C-#Predictions | DT 34 for each learner, C4.5 206 for each learner | DT 34 for each learner, C4.5 206 for each learner |

with unequal sizes while eliminating the need for the normality assumption of the parametric t-test alternative. The Mann-Whitney U tests are performed using the R statistical software[^4]. To measure the magnitude of the differences, Cliff’s $d$[^17] is used. Cliff’s delta is a measure of how often values in one distribution are larger than the values in a second distribution. This measure is preferable to parametric counterparts, since it does not require any assumptions about the shape or spread of the distributions. Cliff’s $d$ can be calculated as

$$d = \frac{\#(x_i > x_j) - \#(x_i < x_j)}{m \times n}$$

where the two distributions are of sizes $n$ and $m$ with items $x_i$ and $x_j$, respectively, and $\#$ is defined as the number of times.

The original study uses t-tests as a statistical test of choice. However, the normality assumption required for t-test is satisfied only in six out of 510 results (5 learners × 34 datasets × 3 scenarios) using statistical tests. Additional inspection of the plots generated for the results showed clear deviations from normal distribution.

Since multiple comparisons increase the chance of a unlikely events, the likelihood of incorrectly rejecting a null hypothesis, i.e. making a Type I error increases. We adjust the significance level of individual tests according to the Bonferroni correction method when performing multiple comparisons. Therefore, the $p-value$ for each individual test should be less than $\alpha/#Tests$. Insignificant overall differences are expected when the sum of the obtained p-values over the learners exceeds

[^4]: [https://www.r-project.org](https://www.r-project.org)
\( \alpha = 0.05 \) (the overall significance level in this study). The performance difference can also be considered insignificant if equal number of individual tests (one or two) favor a scenario and one or three cases show insignificant differences respectively. In other cases, the majority voting is used to select the better scenario. We use these corrections when performing scenario-learner tests for scenarios A, B and C and the five utilized learners.

Finally, the outcome of different scenarios are depicted through violin plots. The violin plots are similar to box plots, but they also show the distribution of the utilized data as well. The average values of the best case results for each learner-scenario combination were presented in the original study. This values were used in the process of selecting the most suitable learner and data.

4 Results

Table 5 presents a summary of the results from Scenarios A, B and C. The best average achieved results per scenario per learner are shown in the left side of this table. These best values are selected based on the F-measure values, i.e. the highest F-measure value is selected per dataset as the best result. The right part of the table, summarizes the achieved results for all predictions for scenarios A, B and C.

For each scenario S, the row “S-#Predictions” represents the number of all predictions for which the average F-measure, precision and recall values are reported for each learner. In the case of best datasets (left side), this number is equal to 34 (one best prediction for each test set). On the right side, this value is equal to the total number of predictions in each scenario. The number of successful predictions and the number of test set these successful predictions belong to, are presented in “S-#Success” and “S-#Test” sets rows, respectively. The values on these two rows for the best cases are equal as only one best prediction is selected for each test set.

Even though the achieved results are similar to the results from the original study, they are not exactly the same. This is understandable to some extent for four of the learners that are implemented in Python and Scikit-Learn due to their probable implementation differences with those in WEKA, but the results of the decision table learner which are performed using WEKA show differences. Take the number of successful predictions of decision table as an example. The replicated experiments reveal 3,281 successful predictions which is important considering the large difference in comparison with the obtained results from the original study (3,965). The difference between best and all results is the highest for Scen-A. The higher best averages of Scen-A, well motivates the investigation of dataset filtration and identification, which is targeted by the original study and this replication. This table further shows the possible high number of irrelevant cross project datasets.

While SVM provides the highest number of successful predictions (7,484), the number of test datasets which these predictions belong to (13) are less than those for decision table (20), henceforth, decision table was justifiably selected to be used as the basis for Sce-D.

The achieved results of all predictions from scenarios A, B and C are illustrated in Figure 2. As illustrated, for Scen-A, all learners except SVM achieve
Fig. 2 F-measure results for Scen-A (top), Scen-B (middle), Scen-C (bottom)

similar overall prediction performances in terms of F-measure. Among these four, C4.5 achieve the highest F-measure value followed by NB, LR and DT. Despite the higher overall F-measure values for C4.5 and LR and the higher number of overall successful predictions in case of LR, they fail to predict as many individual datasets as DT does. The overall performances of LR and DT however are very similar as shown in the plots. Surprisingly, SVM with the highest number of successful predictions seems to be the least successful in terms of average performance measures and the number of individual predicted datasets. It provide the lowest average and median precision, recall and F-measure values in comparison with its counterparts. Assessing the results shows that most of the successful predictions by SVM are focused on specific datasets. For example for ivy-1.1, SVM finds 959 training sets in a set of 4,991 total predictions. He et al. asserted that SVM has a recall oriented behaviour. This behaviour is not clear from any of the plots or the statistical indicators.

According to Figure 2, the learners in Scen-B show different performances. The overall performances of C4.5 and LR seem to be better than the other learners.
In terms of number of predicted test sets, SVM and LR both are able to predict ten out of 34 test sets, successfully. NB on the other hand only has one successful prediction (velocity-1.4 with recall = 0.891, precision = 0.845 and F-measure = 0.868). Furthermore, SVM achieve 0 performances for recall, precision and F-measures in multiple cases and has the lowest means of recall, precision and F-measure values while having the highest number of test sets predicted along with LR.

Similar to the observations in the original study, Scen-C seems to provide less promising outcomes. NB, similar to its performance in Scen-B is the most stable learner and achieves the highest average F-measure for all predictions. The same inferior performances by SVM in terms of average recall precision and F-measure values are depicted in the plot for Scen-C as well. NB has only one successful prediction in this scenario as well (velocity-1.5 with recall = 0.887, precision = 0.656 and F-measure = 0.754). Also in the case of the best learners, the ratio of successful predictions is higher in both of scenarios B and C in comparison with Scen-A.

Table 6 presents the statistical tests for the comparisons of scenario A, B and C. We not only compared the scenarios as a whole, but also investigated the performance differences between individual learners across Scen-A and WPDP scenarios (B and C). As such, we perform five test for each scenario, one per each learner. Similar results are presented for Scen-D and IDS, in the next sections. Due to having many tests, effect sizes are not presented when comparing scenarios A, B and C.

The test results demonstrate that Scen-A is under-performing both WP scenarios (B and C), shown via the down and up arrows for significant and dashes for
non significant differences. Scen-B has the best performance as it achieves significantly better recall, precision and F-measure values in 14, 12 and 20 cases. Scen-A wins in only one recall case and the rest of the tests show a similar performance between scenarios A and B. Similarly Scen-C has a superior performance in comparison with Scen-A, even though the winning margin is not as good as that of Scen-B.

Summaries of the conducted tests per learners are presented in Table 7. In both set of comparisons the best cases for Scen-A are achieved by DT. The results presented in this table are consistent with the overall results presented in Table 6. These tests are conducted at the significance level of $\alpha = 0.01$. 

| Test Set   | A vs B |         |         | A vs C |         |         |
|------------|--------|---------|---------|--------|---------|---------|
| ant-1.3    | ↑↑↑/↑  | -↓↓/↓  | ↑↓/↑    | ↑↑↑/↑  | -↓↓/↓  | ↑↓/↑    |
| ant-1.4    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| ant-1.5    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| ant-1.6    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| ant-1.7    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| camel-1.0  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| camel-1.2  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| camel-1.4  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| camel-1.6  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| ivy-1.1    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| ivy-1.4    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| lucene-1.0  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| lucene-2.0  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| poi-1.5    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| poi-2.0    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| poi-2.5    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| poi-3.0    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| synapse-1.0| ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| synapse-1.2| ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| velocity-1.4| ↑↓/↑  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| velocity-1.5| ↑↓/↑  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| velocity-1.6| ↑↓/↑  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| xalan-2.4  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| xalan-2.5  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| xalan-2.6  | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| xerces-1.2 | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| xerces-1.3 | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |
| xerces-1.4 | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    | ↑↓/↑    |

|     | 1    | 0    | 0    | 1    | 0    | 0    |
|-----|------|------|------|------|------|------|
| Better | 0    | 0    | 0    | 29   | 21   | 28   |
| Equal | 20   | 23   | 16   | 29   | 31   | 28   |
| Worse | 13   | 11   | 18   | 4    | 3    | 6    |
Table 7 Learner based Comparisons of Differences using Based on Mann-Whitney U tests at $\alpha = 0.01$

| Learner | Status | A vs B Recall | Precision | F | A vs C Recall | Precision | F |
|---------|--------|---------------|-----------|---|---------------|-----------|---|
| DT      | Better | 11            | 7         | 10| 4             | 2         | 3 |
|         | Equal  | 8             | 10        | 3 | 26            | 25        | 23|
|         | Worse  | 15            | 17        | 21| 4             | 7         | 8 |
|         |        |               |           |   |               |           |   |
| C4.5    | Better | 6             | 1         | 2 | 5             | 0         | 2 |
|         | Equal  | 11            | 6         | 3 | 25            | 21        | 20|
|         | Worse  | 17            | 27        | 29| 4             | 13        | 12|
|         |        |               |           |   |               |           |   |
| NB      | Better | 7             | 5         | 4 | 0             | 1         | 0 |
|         | Equal  | 6             | 15        | 9 | 23            | 28        | 22|
|         | Worse  | 23            | 14        | 21| 11            | 5         | 12|
|         |        |               |           |   |               |           |   |
| LR      | Better | 6             | 3         | 3 | 5             | 2         | 3 |
|         | Equal  | 11            | 9         | 11| 22            | 24        | 24|
|         | Worse  | 17            | 22        | 20| 6             | 8         | 6 |
|         |        |               |           |   |               |           |   |
| SVM     | Better | 1             | 1         | 1 | 0             | 0         | 0 |
|         | Equal  | 13            | 12        | 13| 21            | 18        | 19|
|         | Worse  | 20            | 21        | 20| 15            | 16        | 15|

4.0.1 Scenario D

None of the described methods (scenarios A, B and C) use any strategy for dataset selection. This scenario aims at filtering irrelevant/useless datasets and finding the suitable datasets for prediction. While combining data sets exhaustively, may reveal good potential training datasets, the odds of detecting them in practice are low, taking into account the high number of generated candidates in Scen-A. Consider the DT results as an example. In four cases, the number of successful predictions for the test sets (ant-1.3, ant-1.7, jedit-4.0 and velocity-1.6) are tiny in comparison with the total number of predictions performed. It means that even though there exists some successful predictions for these test sets, finding them could be very unlikely. He et al. suggested to use the distributional characteristics of the datasets in data selection arguing that such characteristics reflect the properties of their related datasets. We discussed earlier that the results of the original study are based on performing cross validation on the generated TTR instances from all predictions of DT learner. Clearly, in a true cross project approach, TTR instances containing the characteristics of a certain dataset DS as either training or test parts should not be used. The reason for this claim is the fact that the labels of the test sets must not be used during training process. Identifying successful predictions is possible after calculating the performance measures which require the labels for the test data. This limits the number of predictions that are allowed to be used when training the final decision tree(s). For example, when predicting ant-1.3, the TTR instances containing ant-1.3 characteristics as either train or the test should not be used because it requires knowing the outcome of the predictions involving them. This is the case for other versions of the same project, e.g. other versions of Ant for any version of Ant.

Therefore, instead of conducting cross validation with a single decision tree and using all TTR instances, we build a tree for each project, guaranteeing that no information of any releases of the test dataset are present during the training process using the TTR instances.
Table 8 Performance of individual decision trees trained on the TTR instances from DT learner from Scen-A

| Project  | Recall | Precision | F   |
|----------|--------|-----------|-----|
| Ant      | 0.025  | 0.005     | 0.008 |
| Camel    | 0.000  | 0.000     | 0.000 |
| Ivy      | 0.469  | 0.941     | 0.626 |
| JEdit    | 0.030  | 0.030     | 0.030 |
| Lucene   | 0.548  | 0.785     | 0.646 |
| PoI      | 0.038  | 0.141     | 0.060 |
| Synapse  | 0.182  | 0.007     | 0.013 |
| Velocity | 0.925  | 0.449     | 0.604 |
| Xalan    | 0.050  | 0.007     | 0.013 |
| Xerces   | 0.310  | 0.018     | 0.033 |

4.1 Results of Scen-D

The 34 datasets considered in this study belong to 10 projects. No dataset in a project P is allowed to take part in training process when the goal is to predict a dataset in P. So, for 10 projects, 10 decision trees are required. The performance of these trees in terms of precision, recall and F-measure values are summarized in Table 8.

The performances achieved by “ivy”, “lucence” and “velocity” trees are high while the rest show weak results. Overall, the 10 trees detected a sum of 880 out of 3,281 total successful cross project predictions. They however, failed to detect the other 2,401 successful predictions while causing fairly high rate of false positives. In total, 3,949 failed predictions were detected as successful (nearly 4.5 times higher than the number of correctly detected successful predictions). Importantly, another 153,356 predictions were also correctly detected as not successful. Based on the detection rates, the overall recall, precision and F-measure values of detecting successful predictions are 0.268, 0.182 and 0.217 respectively for the defined criteria of the original study.

The average recall, precision and F-measure values of the detected datasets from Scen-D are presented in Table 9. The overall values are presented in terms of weighted average for both original and replicated studies (the overall values in the original are presented as average of averages, not weighted averages). We report the results in this fashion because, as will be described in later sections, our proposed approach is flexible toward dataset selection, which is based on control and acceptance and rejection criteria.

The results of the replicated experiments appear on the left side of the table whereas the original results are shown on the right side. The middle three columns labeled “#Train Sets”, “#Success” and “#All Success” are the number of predictions that the tree predicts (detects) as successful, the number of successful predictions that are correctly detected and the total number of successful predictions in the exhaustive experiments from Scen-A, respectively. For example, in case of ant-1.3, the tree predicts that 151 out of 4,089 total cross project predictions on ant-1.3 (not having ant releases as training or test sets) from Scen-A to be successful. We know from the results of the Decision Table learner in Scen-A that only five of all predictions on ant-1.3 were actually successful. Of those five,
Table 9 Average Precision, Recall and F-measure values and Success rates for each test set from the generated decision trees. Original and Replication Results

| Test Set  | Recall | Precision | F-measure | #Train Sets | #Success | #All Success | Recall | Precision | F-measure | #Train Sets |
|-----------|--------|-----------|-----------|-------------|----------|--------------|--------|-----------|-----------|-------------|
| ant-1.3   | 0.849  | 0.243     | 0.369     | 154         | 1        | 5            | 0.901  | 0.231     | 0.365     | 98          |
| ant-1.4   | 0.613  | 0.26      | 0.361     | 112         | 0        | 0            | -      | -         | -         | 0           |
| ant-1.5   | 0.766  | 0.17      | 0.262     | 68          | 0        | 0            | -      | -         | -         | 0           |
| ant-1.6   | 0.79   | 0.395     | 0.514     | 161         | 2        | 115          | -      | -         | -         | 0           |
| ant-1.7   | 0.794  | 0.339     | 0.464     | 155         | 0        | 1            | -      | -         | -         | 0           |
| camel-1.0 | 0.082  | 0.053     | 0.096     | 22          | 0        | 0            | -      | -         | -         | 0           |
| camel-1.2 | 0.565  | 0.387     | 0.443     | 21          | 0        | 0            | -      | -         | -         | 0           |
| camel-1.4 | 0.341  | 0.199     | 0.229     | 2           | 0        | 0            | -      | -         | -         | 0           |
| camel-1.6 | 0.365  | 0.194     | 0.227     | 2           | 0        | 0            | -      | -         | -         | 0           |
| ivy-1.1   | 0.877  | 0.597     | 0.707     | 186         | 176      | 375          | 0.815  | 0.621     | 0.695     | 131         |
| ivy-1.4   | 0.812  | 0.612     | 0.715     | 185         | 0        | 0            | 0.721  | 0.512     | 0.614     | 17          |
| ivy-2.0   | -      | -         | -         | 0           | 0        | 0            | -      | -         | -         | 0           |
| jedit-3.2 | 0.779  | 0.415     | 0.535     | 67          | 4        | 132          | 0.672  | 0.343     | 0.451     | 22          |
| jedit-4.0 | 0.786  | 0.346     | 0.474     | 66          | 0        | 2            | 0.727  | 0.276     | 0.397     | 22          |
| lucene-2.0| 0.871  | 0.505     | 0.636     | 147         | 77       | 192          | 0.748  | 0.509     | 0.599     | 92          |
| lucene-2.2| 0.838  | 0.604     | 0.698     | 141         | 154      | 208          | 0.715  | 0.600     | 0.649     | 72          |
| lucene-2.4| 0.837  | 0.668     | 0.707     | 148         | 136      | 233          | -      | -         | -         | 0           |
| poi-1.5   | 0.639  | 0.692     | 0.635     | 33          | 15       | 454          | 0.707  | 0.698     | 0.698     | 4           |
| poi-2.0   | 0.688  | 0.153     | 0.242     | 39          | 0        | 0            | 0.77   | 0.154     | 0.254     | 4           |
| poi-2.5   | 0.63   | 0.724     | 0.651     | 37          | 17       | 463          | 0.717  | 0.742     | 0.725     | 4           |
| poi-3.0   | 0.27   | 0.816     | 0.557     | 295         | 25       | 576          | 0.621  | 0.844     | 0.704     | 12          |
| synapse-1.0| 0.89   | 0.13      | 0.222     | 362         | 0        | 0            | 0.925  | 0.127     | 0.223     | 39          |
| synapse-1.1| 0.665  | 0.38      | 0.466     | 143         | 0        | 0            | 0.807  | 0.332     | 0.468     | 37          |
| synapse-1.2| 0.587  | 0.538     | 0.539     | 91          | 4        | 22           | 0.839  | 0.429     | 0.564     | 37          |
| velocity-1.4| 0.738  | 0.762     | 0.739     | 204         | 132      | 142          | -      | -         | -         | 0           |
| velocity-1.5| 0.763  | 0.699     | 0.719     | 202         | 137      | 147          | -      | -         | -         | 0           |
| velocity-1.6| 0.813  | 0.385     | 0.513     | 198         | 2        | 4            | -      | -         | -         | 0           |
| xalan-2.4 | 0.815  | 0.248     | 0.322     | 377         | 0        | 0            | 0.815  | 0.234     | 0.363     | 20          |
| xalan-2.5 | 0.27   | 0.592     | 0.341     | 280         | 0        | 109          | 0.568  | 0.551     | 0.555     | 20          |
| xalan-2.6 | 0.318  | 0.603     | 0.379     | 400         | 9        | 72           | 0.548  | 0.512     | 0.526     | 20          |
| xerces-1.2| 0.443  | 0.175     | 0.245     | 139         | 0        | 0            | 0.44   | 0.176     | 0.243     | 167         |
| xerces-1.3| 0.635  | 0.246     | 0.347     | 141         | 0        | 0            | 0.625  | 0.242     | 0.338     | 167         |
| xerces-1.4| 0.392  | 0.892     | 0.535     | 155         | 0        | 12           | 0.498  | 0.896     | 0.636     | 21          |
| xerces-init| 0.404  | 0.496     | 0.464     | 137         | 9        | 17           | 0.569  | 0.481     | 0.516     | 59          |
| Average   | 0.633  | 0.456     | 0.445     | 4289        | 860      | 3281         | 0.689  | 0.376     | 0.451     | 1082        |

The tree detects one and fails to detect the other four while predicting 150 more predictions, incorrectly as successful (false positives).

The tree in the original study does not detect any successful predictions for some of the datasets such as ant-1.4. Therefore, the performance values are missing from the presented results. This occurs only in one case in the new decision trees (only for ivy-2.0) whereas it is the case for 11 datasets in the original study. We argue that one main reason for this behaviour is the fact that some test set information are used (as part of training or test data) when performing cross-validation using the approach taken by the original study.
Table 10 Results of the Mann-Whitney U tests comparing the prediction in scenario A, B, C and D

| Test Set       | Recall | Prec. | F    | Recall | Prec. | F    | Recall | Prec. | F    |
|----------------|--------|-------|------|--------|-------|------|--------|-------|------|
| ant-1.0        | (0.69) | (0.45) | (0.15) | (0.99) | (0.11) | (0.99) | (0.91) | (0.71) | (0.68) |
| ant-1.4        | (0.70) | (0.03) | (0.59) | (1.00) | (1.00) | (1.00) | (1.00) | (0.09) | (0.92) |
| ant-1.5        | (0.68) | (0.42) | (0.01) | (0.97) | (0.07) | (0.79) | (0.77) | (0.84) | (0.71) |
| ant-1.7        | (0.71) | (0.49) | (0.09) | (0.95) | (0.09) | (0.68) | (0.98) | (0.70) | (0.90) |
| camel-1.0      | (0.66) | (0.22) | (0.04) | (1.00) | (1.00) | (1.00) | (0.93) | (0.71) | (0.62) |
| camel-1.2      | (0.74) | (0.29) | (0.74) | (1.00) | (0.71) | (1.00) | (0.99) | (0.43) | (0.99) |
| camel-1.4      | (0.10) | (0.88) | (0.30) | (1.00) | (1.00) | (1.00) | (0.57) | (0.71) | (0.14) |
| camel-1.6      | (0.18) | (0.77) | (0.02) | (0.00) | (1.00) | (0.00) | (0.71) | (0.43) | (0.71) |
| ivy-1.1        | (0.94) | (0.83) | (0.29) | (0.89) | (0.96) | (0.55) | (1.00) | (0.33) | (1.00) |
| ivy-1.4        | (0.85) | (0.82) | (0.57) | (1.00) | (1.00) | (1.00) | (0.58) | (0.58) | (0.58) |
| jedit-3.2      | (0.81) | (0.48) | (0.61) | (0.82) | (1.00) | (0.46) | (0.97) | (1.00) | (0.58) |
| jedit-4.0      | (0.82) | (0.56) | (0.31) | (0.97) | (1.00) | (0.15) | (0.80) | (1.00) | (0.97) |
| lucene-2.0      | (0.96) | (0.73) | (0.91) | (0.99) | (1.00) | (0.62) | (0.66) | (0.84) | (0.30) |
| lucene-2.2      | (0.96) | (0.75) | (0.95) | (0.20) | (0.96) | (0.55) | (0.91) | (0.33) | (0.86) |
| lucene-2.4      | (0.96) | (0.78) | (0.95) | (0.26) | (0.96) | (0.95) | (0.85) | (0.99) | (0.54) |
| poi-1.5        | (0.72) | (0.39) | (0.71) | (0.27) | (0.52) | (0.82) | (0.89) | (0.70) | (0.27) |
| poi-2.0        | (0.74) | (0.47) | (0.04) | (1.00) | (1.00) | (1.00) | (0.12) | (0.32) | (0.32) |
| poi-2.5        | (0.69) | (0.17) | (0.67) | (0.62) | (1.00) | (0.95) | (0.36) | (0.23) | (0.21) |
| poi-3.0        | (0.02) | (0.09) | (0.01) | (0.92) | (0.15) | (0.97) | (0.51) | (0.02) | (0.50) |
| synapse-1.0    | (0.76) | (0.37) | (0.24) | (1.00) | (1.00) | (1.00) | (0.85) | (0.95) | (0.92) |
| synapse-1.1    | (0.97) | (0.12) | (0.83) | (0.85) | (1.00) | (0.74) | (0.58) | (0.29) | (0.54) |
| synapse-1.2    | (0.57) | (0.06) | (0.70) | (0.63) | (0.30) | (0.47) | (0.99) | (0.96) | (0.99) |
| velocity-1.4    | (0.94) | (0.29) | (0.94) | (0.89) | (0.94) | (1.00) | (0.76) | (0.11) | (0.79) |
| velocity-1.5    | (0.95) | (0.55) | (0.94) | (0.00) | (0.81) | (0.55) | (0.29) | (0.31) | (0.31) |
| velocity-1.6    | (0.95) | (0.74) | (0.86) | (1.00) | (0.98) | (0.97) | (0.47) | (0.06) | (0.28) |
| xalan-2.3      | (0.45) | (0.39) | (0.39) | (0.99) | (0.99) | (0.96) | (0.38) | (0.29) | (0.79) |
| xalan-2.5      | (0.05) | (0.14) | (0.04) | (1.00) | (0.24) | (1.00) | (0.16) | (0.60) | (0.20) |
| xalan-2.6      | (0.14) | (0.06) | (0.14) | (0.80) | (0.77) | (0.99) | (0.18) | (0.59) | (0.28) |
| xerces-1.3     | (0.84) | (0.56) | (0.38) | (1.00) | (1.00) | (1.00) | (0.06) | (0.13) | (0.66) |
| xerces-1.3     | (0.86) | (0.53) | (0.39) | (1.00) | (1.00) | (0.91) | (0.12) | (0.25) | (0.65) |
| xerces-1.4     | (0.19) | (0.37) | (0.19) | (1.00) | (0.54) | (1.00) | (0.95) | (0.43) | (0.98) |
| xerces-init    | (0.92) | (0.51) | (0.75) | (0.80) | (0.99) | (1.00) | (0.42) | (0.18) | (0.82) |

Better: 28  3  23  21  4  14  15  0  11  
Equal: 5  7  9  5  5  3  17  21  16  
Worse: 0  25  1  7  24  16  1  12  6

For datasets such as camel-1.0, despite the number of actual predictions to be zero, the tree detects 22 (unsuccessful) predictions as successful. The mean values of evaluation measures for ivy-1.1, lucene-2.0, lucene-2.2, lucene-2.4, velocity-1.4 and velocity-1.5 satisfy the acceptance criteria. Despite that, no training datasets are detected for three of them, i.e. lucene-2.4, velocity-1.4, velocity-1.5 in the original study.

To further investigate the effectiveness of the method, Scen-D is compared with scenarios A, B and C through statistical tests. Table 10 presents the test results and computed effect sizes for these comparisons per scenario pair (D vs. X) per dataset. Since Scen-D is based only on DT learner, the results of the other scenarios are also only for DT. For brevity, only the effect sizes are presented in terms of actual numbers and the p-values are reported as down and up arrows.
when a significant difference is observed and a dash when the difference between
the compared counterparts is insignificant (at $\alpha = 0.05$).

According to the presented tests, Scen-D, effectively eliminates many non useful
predictions with a focus on recall. Specifically, Scen-D outperforms Scen-A in 28,
3 and 23 cases with recall, precision and F-measure respectively. Scen-A is better
in only one case according to the tests for the F-measure values and achieves equal
performance in 9 cases. The loss in precision in favor of recall is also evident from
the comparisons between Scen-D and Scen-B. We observed earlier in Table 7 that
Scen-A achieves its best performance from the DT results with 11, 8 and 10 wins
for recall, precision and F-measure values. These values are increased with Scen-
D to 21, 4 and 14 confirming the recall based nature of Scen-D. However, the
performance from Scen-B is still better in 16 cases and the two scenarios perform
statistically equal in 3 cases.

Scen-D outperforms Scen-C in terms of recall and F-measure. specifically, Scen-
D is the winner in 17 and 11 cases for recall and F-measure respectively. It however,
ever outperforms Scen-C in terms of precision while achieving equal performances
in recall : 15, precision : 17 and F-measure : 16 cases.

The overall results reveal higher recall and lower precision performances for
Scen-D and improvement in F-measure performances, which is based on the elimi-
nation of a large proportion of non useful datasets/predictions from Scen-A. These
findings are consistent with earlier studies such as that by Turhan et al. [22].

A depiction of the overall performance values achieved from Scen-D are shown
in Figure 3.

4.2 Discussion

The selection strategy in Scen-D, which is based on the distributional characteris-
tics of the datasets, clearly improves the predicting power (F-measure and Recall)
by filtering irrelevant datasets. These improvements were represented in terms
of statistical tests and effect sizes. Despite these improvements, the replication
shows lower performance results in comparison with the original study. Further,
the replication reveals that datasets can be found for almost all test sets (except for
ivy-2.0), unlike the original study which there are no identified training datasets
for 11 test sets. Please also note that, there are identified training datasets for
ivy-2.0 in the original study’s results. The first encountered problem in the design
of the original study’s experiments was the issue of using cross-validation to assess
the performance, which is not correct due to the use of test set labels information
in the predictions. This correct design however, shows different results in many
cases, especially, considering the number of datasets for which groups of prediction
are detected in the replication which the design from the original study failed to
detect. Having said these, the experiment reveal the difficulty of predicting some
of the datasets, based on the small number of predictions that are detected.

According to the results from Scen-A, we observed that some training datasets
have significantly higher predicting power. Table 11 shows the best training data
set for each individual learner. The basis of selecting a data set as the best training
data set is the number of test data sets it predicts. When there are multiple training
data sets with the same number of predicted test data sets, their average F-measure
value is used to select the best set. Please note that selecting the best approach
Table 11 Best training data sets in terms of the number of predicted test sets (successful predictions).

| Learner | Training set            | # predicts | List of the Predicted Test Sets                                                                 |
|---------|-------------------------|------------|-------------------------------------------------------------------------------------------------|
| C4.5    | synapse-1.0, synapse-1.2, xerces-1.4 | 9          | ivy-1.1, lucene-2.0, lucene-2.2, lucene-2.4, poi-1.5, poi-2.5, poi-3.0, velocity-1.4, velocity-2.5 |
| DT      | synapse-1.0, synapse-1.2, xerces-1.4 | 10         | ivy-1.1, lucene-2.0, lucene-2.2, lucene-2.4, poi-1.5, poi-2.5, poi-3.0, velocity-1.4, velocity-1.5, xalan-2.5 |
| NB      | xerces-1.4              | 8          | lucene-2.0, lucene-2.2, lucene-2.4, poi-1.5, poi-2.5, poi-3.0, xalan-2.5, xalan-2.6             |
| SVM     | ant-1.4, jedit-3.2, xerces-1.4 | 11         | ivy-1.1, lucene-2.0, lucene-2.2, lucene-2.4, poi-1.5, poi-2.5, poi-3.0, velocity-1.4, velocity-1.5, xalan-2.5, xalan-2.6 |
| LR      | velocity-1.5            | 9          | ivy-1.1, lucene-2.0, lucene-2.2, lucene-2.4, poi-1.5, poi-2.5, poi-3.0, xalan-2.5, xalan-2.6    |

Based on F-measure values, might lead to “best” datasets which might not be “acceptable” based on the defined criteria (e.g. recall $\geq 0.7$ and precision $\geq 0.5$ in the original paper). Such a case exists for example for ant-1.6 which the highest F-measure value does not lead to a prediction with recall $\geq 0.7$ and precision $\geq 0.5$ while there are 112 such successful predictions with lower F-measure values.

We observed earlier that with SVM only 13 test sets were predicted successfully. Of those 13 data sets, 11 of them could be predicted only by one training data set. This means that by only having three training data sets we can have acceptable results comparable to the results of all combinations of one, two and three training data sets eliminating the need to perform exhaustive training data generation. SVM has the highest number of test sets predicted by only one training data set followed by DT with ten predicted datasets. Notice that in the cases of LR and NB, the best training dataset is an individual original training dataset, not a combination of multiple sets. The xerces-1.4 dataset is present in four of the best training data sets which shows its usefulness. Investigating the properties of such data sets and their relationship with different test data sets could further guide the researcher toward detecting the best training datasets for each test set. Notice further that the test sets predicted are almost identical in all cases. We report only the best datasets for each learner. One however should note that there are lots of good datasets with similar performances to those listed in Table 11.

We will exploit this finding in our alternative proposed approach in the next sections. Especially, adjusting the acceptance criteria would probably lead to possibly better datasets in terms of average performance measures and number of predicted datasets.

5 Iterative Dataset Selection

While the proposed approach by He et al. provides some promising results, it does not seem to be the perfect option considering the following implications:
Fig. 4 Summary of the proposed search based training data selection process.
– It is computationally expensive: He et al. constructed a decision tree based on 160,586 predictions from DT learner by computing the distributional characteristics of both training and test datasets. This dataset hence, contains 160,586 instances, each having 640 features and a label (1 = success, 0 = failure). Building such datasets and training decision trees can be time consuming. Especially, He et al. limited the scope of their combinations to maximum three datasets and the number of utilized datasets to 34. Constructing such datasets for higher number of datasets and features is difficult or even impossible in some cases. The reason for such cases is the rapid growth of the number of possible combinations when larger combination sizes are considered.

– It enforces restrictions: The first restriction arises when the number of maximum elements in combinations are increased as pointed out earlier. Another limitation is related to the features. Performing feature selection becomes increasingly difficult for these datasets as the cost of training the datasets especially for wrapper approaches arises with the increase in the number of features. Some features may not be useful as they potentially may not provide useful information. If certain values, zero as an example exists in the measurements of a feature, the HMean column for example becomes meaningless. The probability of events like that occurring increases with the increase in the number of involved datasets in the combinations.

– It is difficult to modify: For each slight difference in the target performance criteria, a new dataset as well as new decision tree(s) should be created. The considered acceptance criteria by other researchers/practitioners leads to different set of rules for which a new decision tree is required.

– It is not efficient: The decision tree failed to detect suitable datasets for some of the datasets. This in turn has both its up and down sides. The performance on datasets like camel-1.0 and ant-1.5 are already poor and the tree in the original study does not report any datasets. However, the same tree fails to report any datasets for velocity projects and one lucene release for which very good performances are achieved by the trees in the replication study. While we argued about the design issue, this shows that the performance of the tree could be greatly impacted by including or excluding certain predictions during the training process dramatically, hence enforcing an extra supervised filtering step during the training process. The new trees however, find suitable datasets for the mentioned datasets as presented in the replication results which is not in agreement with the results of the original study.

– It is limited to binary defect prediction: Even though not explored in this study, using the current scheme is perhaps useful only for binary prediction and not suitable for regression studies. The regression studies however, are much more useful than binary prediction studies however, as the QA resources can be directed more efficiently toward modules with higher rate of bugs. The limited attention to regression studies in CPDP also, make the case of IDS more relevant and interesting. We have dedicated a subsection to the subject in the following.
One vs. Multiple objectives: Scen-D and exhaustive dataset selection approach, proposed in the original study, are limited to one objective due to the nature of the constructed decision tree(s). However, real world applications are usually involve multiple objectives, one of which could be cost as in cost-effectiveness objectives in defect prediction.

5.1 Proposed Approach

Alternative to the exhaustive data set selection approach proposed by He et al. [6], we propose an iterative dataset selection method (IDS) described in the following. The motivations for such an approach were described to some extent by explaining the weaknesses of the approach proposed by He et al. in the previous section. We will discuss the pros and cons of our proposed approach after explaining its details. The data selection was investigated by multiple earlier studies [22,11,6] at the levels of instances and datasets. Our proposed method tries to improve one of these approaches both computationally and performance wise.

Figure 4 depicts different steps of IDS. Using a search based approach, we combine multiple datasets into a single dataset to as potential final training dataset for each test set. The process starts by initializing a population containing a certain number of elements, a list of datasets each. These dataset are then evaluated and fitness values are assigned after which, they are combined and sorted based on their assigned fitness values. Half of the datasets with the highest fitness values are transferred to the next generation, until the stopping criteria are met. One can see that the slight difference in the proposed approach to genetic algorithm is the elimination of the mutation operation on the datasets as well as the absence of top parents’ transfer. The steps of this process are described in details in the following. We repeat these experiments multiple times to generate multiple training datasets for each test set.

Validation and Evaluation: each population member should be assigned a fitness as a measure to rank it in the population. From Scen-A of the replicated experiments, we observed that there exist datasets with high prediction powers, i.e. they predict many other datasets successfully. Inspired by the same idea, we try to find such datasets by evaluating population members on multiple small datasets generated randomly for validation purposes and assign a fitness values accordingly. We use the average F-measure of the predictions performed on multiple validation datasets as the fitness value for candidate training datasets. Therefore the dataset with the highest fitness value achieves the highest average F-measure value on validation datasets. These validation datasets are a collection of t datasets (t = 20 in the experiments) each containing c instances (c = 20 in this case) selected randomly from a large pool containing all the instances from all available training datasets. The number of items in each class (defective and non defective) are selected randomly to reflect the nature of the defect datasets.

Population members: The population contains p members (p = 60 in our experiments) each of which is a list of datasets like [DS1,DS2,DS3,...] where the
individual datasets belong to the other projects. The length of these lists, i.e. the number of datasets in the population members ranges from 1 to 10. Hence the training data could be the combination of at most 10 datasets from other projects. These datasets are not necessarily unique and multiple instances of the same dataset might be parts of the population member. This in turn is likely to affect the performance when the learner can handle weighting scheme by introducing multiple instances of an element. The ten datasets combinations considered for the members is difficult next to practically impossible for scenarios A and D. When evaluating the member, the instances from these datasets are combined into a candidate training dataset and are evaluated on the collection of validation datasets and a fitness value is assigned to it.

- Fitness: The average of the F-measure values from the predictions performed on the collection of validation datasets act as the fitness value of each population element.

- Selection and Combination: Similar to the cross over operation of the genetic algorithm, two members are selected randomly to generate two new members. The datasets in the two member are added to a list and are shuffled. Note that the list might contain repetition(s) of a dataset. We keep the repetitions and do not remove the duplicates as they potentially provide useful information as a simple weighting strategy for the instances that are repeated multiple times. We split the list in half to keep the number of datasets in a member less than the initial maximum number of dataset in one member, i.e. 10. Alternatives are to consider unique datasets and different cut points for spiting the list of datasets that are not considered in this study.

- Stopping Criteria: Generating new member continues until a max number of generations is reached (20 iterations in our experiments) or the average fitness of the last population and the current one is less than a certain $\epsilon$ which we set to 0.0001 in this case.

- Quality Control: The generated datasets have fitness values assigned to them by evaluating their predicting power on the validation datasets. The best dataset in the population, the one with the highest fitness value, is of our particular interest because it is one of the candidates to act as training data for the test dataset. We assess the usefulness of the best selected dataset of each population by comparing its fitness value to a threshold. We initially set the threshold value to 0.3. The average of the initial threshold and the fitness of the previous best datasets was used for accepting or rejecting a new candidate dataset.

Here is an example of how we check the quality of the generated datasets. We initially set the threshold to 0.3. If the best dataset generated from the first round has a fitness of 0.6 then it is accepted and the new threshold becomes $(0.3+0.6)/2 = 0.45$. We then generate a new set of datasets and check the fitness of its best dataset against the new threshold=0.45. For a fitness equal to 0.65 the dataset is accepted and the threshold is updated to $(0.3+0.6+0.65)/3=5.5$. If the best fitness is 0.4, we ignore the round and discard the generated datasets as we believe its
performance is probably low. We repeat these process until 30 datasets satisfying our threshold criterion are generated. As some of the datasets might converge slowly toward an acceptable threshold, we put another simple control measure to deal with the rejected datasets. For certain datasets with high rate of rejection, we disable rejection process if if ten consecutive generated datasets cause failed predictions. An alternative would be to accept the best dataset among the failed datasets (which is not considered in this study). These approaches provide the assurance of generating at least \( n \) datasets, for any arbitrary \( n \). Similar to Scen-D, another approach is to continue only for a fixed number of iterations and report the accepted datasets only, as training data for the test set. The former approaches, generate equal number of training sets for all test sets, while the later, provides only a limited (perhaps none) in a fixed number of items.

5.2 Results

The results of our experiments are presented in terms of the average ± standard deviation of precision, recall and F-measure values in Table 12. Due to the randomness involved in training and validation datasets generation steps as well as the quality control step mentioned earlier, the experiments are repeated 30 times revealing multiple training datasets for each test set. We decided to continue the experiments until a certain number of training datasets, equal for all test sets are selected. The last column of this table, labeled “\#Success” shows the number of successful predictions according to the defined criteria for success by He
Table 12 Average Recall, Precision and F-measure Values and Successful Predictions per Dataset for IDS

| Test Set   | Recall   | Precision | F        | #Success |
|------------|----------|-----------|----------|----------|
| ant-1.3    | 0.992±0.019 | 0.165±0.006 | 0.284±0.008 | 0        |
| ant-1.4    | 0.968±0.067 | 0.226±0.006 | 0.366±0.013 | 0        |
| ant-1.5    | 0.985±0.042 | 0.114±0.008 | 0.204±0.012 | 0        |
| ant-1.6    | 0.983±0.036 | 0.273±0.014 | 0.427±0.014 | 0        |
| ant-1.7    | 0.911±0.017 | 0.232±0.007 | 0.336±0.008 | 0        |
| camel-1.0  | 0.974±0.057 | 0.040±0.002 | 0.077±0.004 | 0        |
| camel-1.2  | 0.948±0.045 | 0.365±0.007 | 0.527±0.011 | 0        |
| camel-1.4  | 0.877±0.226 | 0.183±0.021 | 0.291±0.051 | 0        |
| camel-1.6  | 0.959±0.039 | 0.204±0.005 | 0.337±0.006 | 0        |
| ivy-1.1    | 0.946±0.062 | 0.579±0.022 | 0.717±0.013 | 0        |
| ivy-1.4    | 0.940±0.126 | 0.070±0.005 | 0.130±0.001 | 0        |
| ivy-2.0    | 0.939±0.116 | 0.121±0.019 | 0.212±0.015 | 0        |
| jedit-3.2  | 0.991±0.016 | 0.344±0.012 | 0.511±0.013 | 0        |
| jedit-4.0  | 0.992±0.012 | 0.254±0.010 | 0.404±0.012 | 0        |
| lucene-2.0 | 0.977±0.029 | 0.474±0.010 | 0.638±0.011 | 1        |
| lucene-2.2 | 0.956±0.082 | 0.391±0.012 | 0.729±0.025 | 28       |
| lucene-2.4 | 0.932±0.083 | 0.607±0.011 | 0.739±0.030 | 29       |
| poi-1.5    | 0.987±0.016 | 0.600±0.008 | 0.736±0.007 | 30       |
| poi-2.0    | 0.972±0.056 | 0.122±0.006 | 0.216±0.008 | 0        |
| poi-2.5    | 0.980±0.017 | 0.635±0.014 | 0.785±0.009 | 30       |
| poi-3.0    | 0.981±0.022 | 0.653±0.017 | 0.784±0.010 | 30       |
| synapse-1.0| 0.960±0.067 | 0.107±0.008 | 0.192±0.013 | 0        |
| synapse-1.1| 0.964±0.035 | 0.282±0.015 | 0.436±0.015 | 0        |
| synapse-1.2| 0.952±0.100 | 0.506±0.026 | 0.515±0.021 | 0        |
| velocity-1.4| 0.925±0.082 | 0.742±0.012 | 0.822±0.041 | 29       |
| velocity-1.5| 0.896±0.154 | 0.682±0.041 | 0.762±0.076 | 27       |
| velocity-1.6| 0.960±0.062 | 0.361±0.016 | 0.524±0.019 | 0        |
| xalan-2.4  | 0.936±0.116 | 0.163±0.016 | 0.276±0.014 | 0        |
| xalan-2.5  | 0.912±0.180 | 0.493±0.009 | 0.629±0.083 | 4        |
| xalan-2.6  | 0.938±0.050 | 0.472±0.019 | 0.632±0.024 | 1        |
| xerces-1.2 | 0.834±0.102 | 0.137±0.008 | 0.265±0.016 | 0        |
| xerces-1.3 | 0.942±0.079 | 0.171±0.028 | 0.291±0.032 | 0        |
| xerces-1.4 | 0.811±0.187 | 0.776±0.048 | 0.775±0.104 | 24       |
| xerces-init| 0.834±0.154 | 0.466±0.029 | 0.593±0.062 | 2        |

Median       0.984  0.327  0.446
Mean±Std     0.947±0.102  0.336±0.215  0.477±0.223  265/1,020

et al. among the 30 predictions for each dataset. Our approach finds acceptable predictions for 13 of the datasets, however, the number of successful predictions in four cases are low (lucene-2.0, xalan-2.5, xalan-2.6 and xerces-init with 1, 4, 1 and 2 datasets respectively). The average performances for 10 test sets satisfy the success criteria of recall ≥ 0.7 and precision ≥ 0.5.

Presented results reveal that IDS is recall based. The average recall performance for all test sets is 0.947 which is significantly higher than that from Scen-D. This in turn comes with a loss in precision. IDS has the lowest precision among the compared scenarios that use DT learner. IDS however, achieves comparable and better F-measure performances to those from scenarios A, B, C and D as illustrated in Figure 5. IDS achieves higher mean and median F-measure values in comparison with Scen-D.
Tables 13 summarizes the results of the statistical tests for comparison of IDS and Scen-D for F-measure, recall and precision performance measures. The first column of each entry in these tables is the $p$-value obtained from the test and the second column is the Cliff’s $d$ value associated with the performance difference of the two compared groups.

In terms of F-measure, IDS outperforms Scen-D in 15 cases while Scen-D achieves better performances in 13 cases ($\alpha = 0.05$). The performance difference between the two in terms of F-measure is insignificant for five datasets. Since the data is not available for ivy-2.0, no tests are performed for it and the respective row does not hold a value. The overall performances of these two scenarios are compared against each other through statistical tests and the effect sizes are also presented. IDS outperforms Scen-D significantly, but the effect size is tiny. We will argue later on, that this performance increase, despite being very small, is valuable considering the practical implications of using IDS over Scen-D.

In terms of recall, IDS is better in 32 cases significantly with medium and large effect sizes. The difference in one case (ivy-1.4) is insignificant. This good recall performance however come at the cost of losing precision. IDS underperforms Scen-D in 30 cases. The effect size for the increase in recall however is large (0.798) in favor of IDS while the effect size for precision is small to medium (0.245) for Scen-D.

5.3 Discussion

We observed the usefulness of search based approaches in practice by proposing an alternative dataset selection approach. The flexibility of IDS toward dataset selection, allows for more control over dataset acceptance and rejection. Specifically, the dataset selection approach in Scen-D can lead to test sets without any successful detected predictions (e.g. ivy-2.0) because (1) there decision tree will filter out all irrelevant datasets, and (2) practical limitations do not allow the method to consider arbitrary number of dataset combinations. IDS takes a different approach as described earlier which involves detecting “good” and “bad” performing datasets through a validation and fitness assignment approach based on multiple random datasets. This in turn allows IDS to (1) act similar to Scen-D, i.e. stop after constructing $t$ datasets (combinations), or (2) proceed long enough, to find datasets with acceptable performances (if any). More importantly, validation dataset selection is only based on the training data and the characteristics of the test dataset are not considered. Instead, we try to find those training datasets that show high performance on multiple datasets. Such datasets are likely to produce better results when they are used to predict one additional dataset, i.e. the test set. The considered training data selection based on evaluating on multiple validation datasets also helps to eliminate very poor performing datasets (small predicting power on multiple random datasets), i.e. a training dataset which achieves very low average performance on multiple validation datasets, is likely to perform equally bad on the test dataset as well, showing the usefulness of the included extra filtering step when accepting or rejecting certain datasets.

The limit of combinations of at most 10 datasets in this study is only for demonstration purposes and this limit can easily be modified without much extra
Table 13  Mann-Whitney U tests for comparison of IDS and Scen-D for Recall, Precision and F-measure. The positive $d$ values show a better performance toward IDS

| Test Set  | F  | Recall | Precision |
|-----------|----|--------|-----------|
|           | p-value | Cliff’s $d$ | p-value | Cliff’s $d$ | p-value | Cliff’s $d$ |
| ant-1.3   | ≪ 0.0001 | -0.850 | ≪ 0.0001 | 0.864 | ≪ 0.0001 | -0.949 |
| ant-1.4   | 0.494 | 0.082 | ≪ 0.0001 | 0.973 | ≪ 0.0001 | -0.757 |
| ant-1.5   | ≪ 0.0001 | -0.743 | ≪ 0.0001 | 0.913 | ≪ 0.0001 | -0.856 |
| ant-1.6   | ≪ 0.0001 | -0.819 | ≪ 0.0001 | 0.958 | ≪ 0.0001 | -0.957 |
| ant-1.7   | ≪ 0.0001 | -0.876 | ≪ 0.0001 | 0.992 | ≪ 0.0001 | -0.957 |
| camel-1.0 | 0.003 | -0.461 | ≪ 0.0001 | 0.891 | ≪ 0.0001 | -0.565 |
| camel-1.2 | ≪ 0.0001 | 0.838 | ≪ 0.0001 | 0.911 | ≪ 0.0001 | -0.629 |
| camel-1.4 | 0.030 | 0.900 | 0.037 | 0.900 | 0.022 | 1.000 |
| camel-1.6 | 0.039 | 0.900 | 0.020 | 1.000 | 1.000 | 0.000 |
| ivy-1.1   | 0.337 | 0.109 | ≪ 0.0001 | 0.444 | 0.001 | -0.596 |
| ivy-1.4   | 1.000 | 0.000 | 0.113 | 0.900 | 0.955 | -0.067 |
| ivy-2.0   | NA | NA | NA | NA | NA | NA |
| jedit-3.2 | 0.000 | -0.480 | ≪ 0.0001 | 0.971 | ≪ 0.0001 | -0.649 |
| jedit-4.0 | ≪ 0.0001 | -0.685 | ≪ 0.0001 | 0.999 | ≪ 0.0001 | -0.801 |
| lucene-2.0 | 0.213 | -0.145 | ≪ 0.0001 | 0.712 | ≪ 0.0001 | -0.740 |
| lucene-2.2 | ≪ 0.0001 | 0.553 | ≪ 0.0001 | 0.710 | ≪ 0.0001 | -0.463 |
| lucene-2.4 | ≪ 0.0001 | 0.622 | ≪ 0.0001 | 0.723 | 0.011 | -0.209 |
| poi-1.5   | ≪ 0.0001 | 0.721 | ≪ 0.0001 | 1.000 | ≪ 0.0001 | -0.758 |
| poi-2.0   | 0.004 | -0.408 | ≪ 0.0001 | 0.924 | ≪ 0.0001 | -0.630 |
| poi-2.5   | ≪ 0.0001 | 0.814 | ≪ 0.0001 | 0.994 | ≪ 0.0001 | -0.755 |
| poi-3.0   | ≪ 0.0001 | 0.874 | ≪ 0.0001 | 0.999 | ≪ 0.0001 | -0.884 |
| synapse-1.0 | 0.000 | -0.608 | ≪ 0.0001 | 0.924 | ≪ 0.0001 | -0.630 |
| synapse-1.1 | ≪ 0.0001 | -0.534 | ≪ 0.0001 | 0.905 | ≪ 0.0001 | -0.872 |
| synapse-1.2 | ≪ 0.0001 | -0.479 | ≪ 0.0001 | 0.935 | ≪ 0.0001 | -0.933 |
| velocity-1.4 | ≪ 0.0001 | 0.604 | ≪ 0.0001 | 0.758 | 0.000 | -0.139 |
| velocity-1.5 | ≪ 0.0001 | 0.530 | ≪ 0.0001 | 0.608 | 0.009 | -0.297 |
| velocity-1.6 | 0.008 | 0.215 | ≪ 0.0001 | 0.744 | 0.018 | -0.297 |
| xalan-2.4 | ≪ 0.0001 | -0.509 | ≪ 0.0001 | 0.879 | ≪ 0.0001 | -0.746 |
| xalan-2.5 | ≪ 0.0001 | 0.937 | ≪ 0.0001 | 0.946 | ≪ 0.0001 | -0.889 |
| xalan-2.6 | ≪ 0.0001 | 0.953 | ≪ 0.0001 | 0.999 | ≪ 0.0001 | -0.808 |
| xerces-1.2 | ≪ 0.0001 | 0.470 | ≪ 0.0001 | 0.934 | ≪ 0.0001 | -0.482 |
| xerces-1.3 | ≪ 0.0001 | -0.576 | ≪ 0.0001 | 0.947 | ≪ 0.0001 | -0.796 |
| xerces-1.4 | ≪ 0.0001 | 0.875 | ≪ 0.0001 | 0.882 | ≪ 0.0001 | -0.796 |
| xerces-init | ≪ 0.0001 | 0.730 | ≪ 0.0001 | 0.836 | 0.013 | -0.291 |
| Overall   | 0.001 | 0.679 | ≪ 0.0001 | 0.798 | ≪ 0.0001 | -0.245 |

This also opens up the possibility of utilizing much greater pools of datasets. Adding extra datasets to the included 34 datasets will make Scen-D approach very small, if not impractical due to adding large number of new combinations with the addition of extra datasets. Our proposed approach however is impacted small to none. The large collection of datasets from a study such as [25] is an example. The proposed approach can overcome another limitation which was described earlier, i.e. targeting multiple objectives. The fitness and evaluation steps could be easily modified to investigate, multiple (perhaps conflicting) goals.
Table 14 Accepted vs Rejected Datasets. Average F-measure Performances

| Test Set | Accepted Datasets | Rejected Datasets |
|----------|------------------|-------------------|
|          | VSet Fits | Testset Fits | VSet Fits | Test Fits | #Rejected |
| ant-1.3  | 0.71 ± 0.01 | 0.29 ± 0.01 | 0.17 ± 0.19 | 0.08 ± 0.12 | 9 |
| ant-1.4  | 0.74 ± 0.01 | 0.37 ± 0.01 | 0.43 ± 0.26 | 0.19 ± 0.17 | 10 |
| ant-1.5  | 0.71 ± 0.01 | 0.20 ± 0.01 | 0.30 ± 0.20 | 0.14 ± 0.11 | 9 |
| ant-1.6  | 0.67 ± 0.01 | 0.43 ± 0.01 | 0.27 ± 0.21 | 0.14 ± 0.18 | 11 |
| ant-1.7  | 0.66 ± 0.01 | 0.38 ± 0.01 | 0.24 ± 0.22 | 0.11 ± 0.15 | 14 |
| camel-1.0| 0.78 ± 0.01 | 0.08 ± 0.01 | 0.20 ± 0.05 | 0.04 ± 0.04 | 7 |
| camel-1.2 | 0.68 ± 0.01 | 0.51 ± 0.01 | 0.48 ± 0.22 | 0.23 ± 0.21 | 10 |
| camel-1.4| 0.55 ± 0.05 | 0.29 ± 0.06 | 0.18 ± 0.12 | 0.05 ± 0.05 | 17 |
| camel-1.6| 0.69 ± 0.01 | 0.34 ± 0.01 | 0.33 ± 0.24 | 0.16 ± 0.14 | 25 |
| ivy-1.1  | 0.67 ± 0.01 | 0.72 ± 0.01 | 0.34 ± 0.23 | 0.26 ± 0.29 | 14 |
| ivy-1.4  | 0.63 ± 0.05 | 0.13 ± 0.01 | 0.27 ± 0.18 | 0.12 ± 0.05 | 7 |
| ivy-2.0  | 0.55 ± 0.01 | 0.21 ± 0.02 | 0.31 ± 0.22 | 0.14 ± 0.13 | 17 |
| jedit-3.2| 0.73 ± 0.01 | 0.51 ± 0.01 | 0.20 ± 0.11 | 0.06 ± 0.10 | 8 |
| jedit-4.0| 0.79 ± 0.01 | 0.40 ± 0.01 | 0.45 ± 0.28 | 0.21 ± 0.19 | 12 |
| lucene-2.0| 0.66 ± 0.01 | 0.64 ± 0.01 | 0.25 ± 0.18 | 0.14 ± 0.21 | 8 |
| lucene-2.2| 0.79 ± 0.01 | 0.73 ± 0.02 | 0.24 ± 0.21 | 0.15 ± 0.21 | 19 |
| lucene-2.4| 0.76 ± 0.04 | 0.74 ± 0.04 | 0.29 ± 0.20 | 0.14 ± 0.23 | 12 |
| poi-1.5  | 0.79 ± 0.01 | 0.75 ± 0.01 | 0.36 ± 0.28 | 0.30 ± 0.33 | 15 |
| poi-2.0  | 0.66 ± 0.01 | 0.22 ± 0.01 | 0.23 ± 0.22 | 0.07 ± 0.08 | 18 |
| poi-2.5  | 0.79 ± 0.01 | 0.78 ± 0.01 | 0.31 ± 0.25 | 0.25 ± 0.32 | 25 |
| poi-3.0  | 0.61 ± 0.01 | 0.78 ± 0.01 | 0.24 ± 0.18 | 0.24 ± 0.25 | 13 |
| synapse-1.0| 0.57 ± 0.02 | 0.19 ± 0.01 | 0.29 ± 0.21 | 0.09 ± 0.10 | 24 |
| synapse-1.1| 0.72 ± 0.01 | 0.44 ± 0.01 | 0.36 ± 0.26 | 0.24 ± 0.19 | 12 |
| synapse-1.2| 0.62 ± 0.01 | 0.51 ± 0.02 | 0.31 ± 0.19 | 0.23 ± 0.22 | 11 |
| velocity-1.4| 0.66 ± 0.01 | 0.82 ± 0.04 | 0.29 ± 0.16 | 0.13 ± 0.11 | 10 |
| velocity-1.5| 0.69 ± 0.01 | 0.76 ± 0.08 | 0.28 ± 0.21 | 0.19 ± 0.24 | 17 |
| velocity-1.6| 0.64 ± 0.01 | 0.52 ± 0.02 | 0.21 ± 0.21 | 0.14 ± 0.17 | 18 |
| xalan-2.4 | 0.69 ± 0.01 | 0.28 ± 0.01 | 0.11 ± 0.09 | 0.09 ± 0.09 | 1 |
| xalan-2.5 | 0.69 ± 0.01 | 0.63 ± 0.04 | 0.24 ± 0.22 | 0.24 ± 0.24 | 9 |
| xalan-2.6 | 0.69 ± 0.01 | 0.64 ± 0.02 | 0.44 ± 0.26 | 0.34 ± 0.29 | 11 |
| xerces-1.2| 0.72 ± 0.01 | 0.27 ± 0.02 | 0.41 ± 0.23 | 0.12 ± 0.11 | 8 |
| xerces-1.3| 0.74 ± 0.01 | 0.29 ± 0.03 | 0.28 ± 0.22 | 0.14 ± 0.14 | 14 |
| xerces-1.4| 0.70 ± 0.03 | 0.77 ± 0.10 | 0.22 ± 0.16 | 0.11 ± 0.14 | 8 |
| xerces-init| 0.69 ± 0.01 | 0.39 ± 0.06 | 0.24 ± 0.11 | 0.09 ± 0.06 | 6 |

5.4 Validation, Training and Testing

We generated multiple small datasets from the pool of all training instances to act as validation datasets (average F-measure value as fitness in this study). The utilized control mechanism allowed removing/filtering potentially useless datasets based on a defined threshold. Table 14 summarizes the effect of the control step as well as the number of rejected datasets for each test set. The rejected datasets show the two types of behavior by IDS as opposed to the single approach of selecting eligible datasets in a limited number of combinations.

The table contains performance details for accepted datasets (left side) and rejected dataset (right side). For each group, two values are reported in the form of avg ± std. The average fitness of the best datasets (performances on validation datasets) are reported under “VSet Fits” column (validation datasets fitnesses) and the “Test Fits” column contains the average performance of the predictions.
performed on the test set using the detected datasets (30 best selected datasets, one per an accepted iteration).

We have allowed the IDS method to continue until a certain number of datasets are accepted. Therefore, all datasets, have a fixed number of predictions (30 in this study). As mentioned earlier long failure runs are controlled by accepting the best failed dataset, if the failures continue more than 10 consecutive times.

As for the performance report, consider ant-1.3 as an example. The number of rejected training datasets for ant-1.3 is equal to nine. This means that during the dataset generations, 30 out of 39 generated datasets (the top dataset in each iteration) were accepted and nine were rejected. The average performance of the 30 accepted datasets on the validation datasets is 0.71. These datasets have an actual performance (on the test set) equal to 0.28 for ant-1.3. The average fitness of the generated training datasets that were rejected (9 for ant-1.3) is 0.17 ±0.19 which is significantly lower than 0.71 for the accepted datasets. The final predictions of the test set using the failed datasets is also lower and is equal to 0.18, confirming the usefulness of the rejection method.

The effectiveness of the filtering/control step becomes more vivid when the majority of the datasets from the lucene, poi, synapse, velocity, xalan and xerces projects are considered even though the performance increase happens for every single dataset.

In practice, the generated datasets for predicting release $R_1$ of a project $P$ is suitable for predicting the other releases of $P$. One can see variations in the average fitness of the best datasets for different releases of a single project however. This variations are due to the randomness involved in generating training and validation datasets and dataset combinations which in turn cause generating different series of thresholds and discovering different (with possibly common) set of datasets.

6 Threats to Validity

It is important to be aware of the potential threats to the validity of the obtained results and derived conclusions [24] in an empirical study. The potential threats to the validity identified for this study are assessed in construct, conclusions and external validity categories.

6.1 Construct validity

The metrics used in this study are SCM, OO and LOC which are the only metrics present in the datasets. These metrics have been widely used in previous studies [5,4,19]. Even though these metrics can achieve good performances [19], the usefulness of this metrics has been also criticised [18,22,5]. The experimental datasets are collected by Jureczko et al. [13,14], who cautioned that there could be some mistakes in non defective labels as not all the defects had been found. This may be a potential threat for defect prediction models training and evaluation. Even though some studies try to address this issue, e.g. [11], our study and IDS do not consider the issue as the level of granularity is at dataset level which is different from individual instances. Another threat is the choice of the decision boundary.
In this study Recall greater than 70% and Precision greater than 50% are considered as the criteria of acceptance or rejection of a prediction. Other researchers might consider different criteria for acceptance and as a consequence, some of the observations and conclusions may change.

6.2 Conclusions validity

The experiments from our proposed approach are repeated 30 times to address the randomness and the results are compared using Mann-Whitney U tests. We performed pairwise tests to detect possible differences between IDS and Scen-D as well as the replicated comparisons from the original study. Moreover, to calculate the magnitude of the differences, Cliff’s $d$ was used as effect size. Another threat is the choice of the evaluation measure. Other researchers might consider different measures to evaluate the methods and as a consequence, some of the observations and conclusions may change. Even though our method works better for a large set portion of the datasets (compared with both WPDP and CPDP benchmarks), it is not necessarily better for all of them and further investigation is required.

6.3 External validity

It is difficult to draw general conclusions from empirical studies of software engineering and our results are limited to the analyzed data and context [1]. Even though many researchers have used subsets of our utilized datasets as the basis of their conclusions, there is no assurance about the generalization of conclusions drawn from these projects. Particularly the applicability of the conclusions for commercial, proprietary and closed source software might be different as there usually are more rigorous code quality standard associated with such projects. Further, all the projects contributing to our study are written in Java and including projects written in other languages surely would affect the generalizability of our findings. Moreover, we did not consider other sets of datasets as the replicated study depends on the used datasets. Instead, this study acts as a replication of the original study from the methodological and practical point of view. Having said that, we should note that the external validity threats are usually strong with defect prediction studies and neglecting such threats will bias the conclusions highly.

7 Conclusions

In this study, we investigated the usefulness of an iterative approach to data selection, i.e., IDS, in the context of cross project defect prediction. Through an iterative process, we aimed to converge to optimal training datasets by assessing the predicting power of the generated datasets according to our defined criteria. We used the lessons learned from replicating a previous study and generated collections of validation datasets to optimize the performance of our approach. We demonstrated the applicability of the approach, by pointing out its strengths in comparison with the previously proposed exhaustive data set selection approach.
in the literature. We not only addressed the limitations of the approach, but also presented possible corrections for the design and analysis of the approach in the first place. This in turn, acted as a replication of the original study which is the basis for IDS.

While presenting IDS, we pointed out its limitations as well. Fundamentally, since the data is selected in the level of datasets and not instances, useless or irrelevant items might find their way through the selection process as they are not filtered out in the instance level. This might contribute to the performance of the approaches as seen in the past studies. On the other hand this is a step toward optimizing the current approaches, overcome their limitations and making them useful for being considered in practice.

Despite addressing some of the issues, the proposed approach, itself opens up possibilities for future work. Specifically, the optimization in this study involved only the data. However, past studies have shown that there are other contributing factors to the performance, some of which already mentioned in this study. An interesting follow up study would investigate the effects of multiple sources of optimization (learner, instances, features) and maybe as important as the former aspects, the fitness function. The F-measure fitness function used in this study is used which makes our experiments comparable to those of the original study. However, targeting other measures, especially those which consider the effect of all components of confusion matrices, such as MCC, will perhaps reveal more information about the methods and might even more useful in practice.

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