**Supplementary material for:**

**An extensive investigation into inconsistent labels in multi-version-project defect data sets**

Shiran Liu1,2 Zhaoqiang Guo1,2 Yanhui Li1,2\* Chuanqi Wang1,2

Lin Chen1,2 Zhongbin Sun3,4 Yuming Zhou1,2\* Baowen Xu1,2

1State Key Laboratory for Novel Software Technology, Nanjing University

2Department of Computer Science and Technology, Nanjing University

3Mine Digitization Engineering Research Center of Ministry of Education, Xuzhou 221116, China

4School of Computer Science & Technology, China University of Mining and Technology

\*Corresponding author

# **Appendix A. The running time of our TSILI algorithm**

The method we adopted to generate the source code databases required by the TSILI algorithm is to download the codes corresponding to each version from the official website of each target project, and then use the Understand[[1]](#footnote-1) tool to parse the code to generate source code databases (.udb file). We write a Python[[2]](#footnote-2) script to implement the TSILI algorithm. In the second stage of TSILI, the source code of each module is parsed and filtered (b9 in Fig. 17) based on the Python API (application programming interface) provided by the Understand tool.

In order to observe the time required for the TSILI algorithm to detect inconsistent labels on projects of different orders of magnitude, we selected Log4j, Hive, and Eclipse projects from multi-version-project defect data sets Metrics-Repo-2010 [1], JIRA-RA-2019 [2], and ECLIPSE-2007 [3], respectively, and then ran TSILI and recorded the time spent. Table 1 lists the details of these three projects and the single thread running time of TSILI. The 2nd column lists the versions included in each project. The 3rd column lists the order of magnitude of the project size, where *n*, *totalIns*, and *sumSLOC* represent the number of versions, the total number of instances of all versions, and the total number of code lines of all versions, respectively. The 4th column reports the running time of TSILI. These three projects (Log4j, Hive, and Eclipse) were selected because they represented orders of magnitude of the size of the projects in their respective data sets (the ECLIPSE-2007 data set only has the Eclipse project). In addition, the size of the total number of instances of these three projects varies in turn by one order of magnitude, which is conducive to observe the running time of TSILI under different orders of magnitude data sets.

Table 1 shows that the running time of TSILI is positively correlated with the size of the data set. For the project with hundreds of instances (i.e., Log4j project), the running time is at the second level. For the projects with ten thousands of instances (i.e., Eclipse project), the running time is at the hour level. Because TSILI is an offline algorithm, the hour-level (even minute-level or second-level) running time is acceptable in practice.

Table 1. Time consuming of the TSILI algorithm

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dataset | Project (versions) | n, totalIns, sumSLOC | Running Time | Experimental environment |
| Metrics-Repo-2010 | Log4j (1.0, 1.1, 1.2) | n=3, totalIns=411, sumSLOC=74857 | ≈ 25 seconds | Inter(R) Core(TM) i7-7700 CPU @ 3.6GHz and 16G RAM |
| JIRA-RA-2019 | Hive (0.9.0, 0.10.0, 0.12.0) | n=3, totalIns=5285, sumSLOC=974774 | ≈ 11 minutes |
| ECLIPSE-2007 | Eclipse (2.0, 2.1, 3.0) | n=3, totalIns=25203, sumSLOC=3089619 | ≈ 3 hours |

# **Appendix B. Software metrics** **used in the MA-SZZ-2020 and filtered IND-JLMIV+R-2020 data sets**

As mentioned in Section 6.2 of this paper, there are some versions in the IND-JLMIV+R-2020 data set [4] that are not suitable for model training or prediction. Therefore, before the experiments of RQ2 and RQ3, we filtered out the inappropriate versions and kept only 66 versions. Table 2 shows the version information of our filtered IND-JLMIV+R-2020 data set.

Table 2. The IND-JLMIV+R-2020 defect data sets used in our study

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Dataset | Project | Versions | #Instances (#IL-instances) | %Defective | #Metrics |
| Used in RQ1:  IND-JLMIV+R-2020  (semi-automatic SZZ-based) | 38 projects | 395 versions | 3~1708 (0~45) | 0~36% | 4198 (44) |
| Filtered for RQ2 and RQ3:  IND-JLMIV+R-2020  (semi-automatic SZZ-based) | Ant-ivy | 2.0.0, 2.1.0 | 352~257 (12~12) | 14~14% | 44 |
| Calcite | 1.0, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 1.10, 1.11, 1.12, | 1108~1415 (12~45) | 6~11% |
| Knox | 0.3.0, 0.4.0, 0.5.0, 0.6.0, 0.7.0, 0.8.0 | 388~594 (16~40) | 5~13% |
| Kylin | 1.0.0, 1.1.0, 2.0.0, 2.1.0, 2.2.0 | 504~1103 (11~18) | 3~6% |
| Mahout | 0.4, 0.5 | 763~777 (11~16) | 7~10% |
| Manifoldcf | 0.1, 0.2, 0.5, 0.6, 1.3, 1.4, 2.1, 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 2.8 | 430~1058 (10~16) | 1~10% |
| Nutch | 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 2.0, 2.1, 2.2 | 245~500 (10~15) | 3~13% |
| Systemml | 0.10, 0.11, 0.12, 0.13 | 884~1008 (10~17) | 8~9% |
| Tika | 0.8, 0.9, 0.10, 1.0, 1.2, 1.3, 1.4, 1.9 | 200~464 (10~16) | 6~20% |

Table 3 describes the size, complexity, coupling, and inheritance metrics in the MA-SZZ-2020 we collected and the filtered IND-JLMIV+R-2020 data set. In Table 3, column “Type” represents the type to which each metric belongs to, column “Name” gives the acronym of each metric, column “Deﬁnition” provides an informal description of the corresponding metric, and column “Tool for measuring metrics” gives the source of the tool that we measure metrics from. Note that inheritance metrics are indeed a form of coupling metrics. In practice, however, many researchers distinguish inheritance metrics from coupling metrics. Our study follows a metric classiﬁcation framework similar to that in Briand et al. [5].

Table 3. List of metrics in the MA-SZZ-2020 data set

|  |  |  |  |
| --- | --- | --- | --- |
| Type | Name | Deﬁnition | Tool for measuring metrics |
| Size Metrics | SLOC (loc in data set) | the non-commentary source lines of code in a class | We used the Perl script developed in previous studies [6, 7] to collect metrics based on the udb database, where the udb database is generated by the commercial software Understand. |
| NMIMP | the number of methods implemented in a class |
| NumPara | sum of the number of parameters of the methods implemented in a class |
| NM | the number of methods in a class, both inherited and non-inherited |
| NAIMP | the number of attributes in a class excluding inherited ones |
| NA | the number of attributes in a class including both inherited and non-inherited |
| Stms | the number of declaration and executable statements in the methods of a class |
| Nmpub | number of public methods implemented in a class |
| NMNpub | number of non-public methods implemented in a class |
| NIM | Number of Instance Methods |
| NCM | Number of Class Methods |
| NLM | Number of Local Methods |
| AvgSLOC | Average Source Lines of Code |
| Complexity Metrics | CDE | Class Definition Entropy |
| CIE | Class Implementation Entropy |
| WMC | Weighted Method Per Class |
| SDMC | Standard Deviation Method Complexity |
| AvgWMC | Average Weight Method Complexity |
| CCMax | Maximum cyclomatic complexity of a single method of a class |
| NTM | Number of Trivial Methods |
| Coupling Metrics | CBO | Coupling Between Object |
| DAC | Data Abstraction Coupling: Type is the number of attributes of other classes. |
| DACquote | Data Abstraction Coupling: Type is the number of other classes. |
| ICP | Information-flow-based Coupling |
| IHICP | Information-flow-based inheritance Coupling |
| NIHICP | Information-flow-based non-inheritance Coupling |
| Inheritance Metrics | NOC | Number Of Child Classes |
| NOP | Number Of Parent Classes |
| DIT | Depth of Inheritance Tree |
| AID | Average Inheritance Depth of a class |
| CLD | Class-to-Leaf Depth |
| NOD | Number Of Descendants |
| NOA | Number Of Ancestors |
| NMO | Number of Methods Overridden |
| NMI | Number of Methods Inherited |
| NMA | Number Of Methods Added |
| SIX | Specialization IndeX = NMO \* DIT / (NMO + NMA + NMI) |
| PII | Pure Inheritance Index. |
| SPA | static polymorphism in ancestors |
| SPD | static polymorphism in descendants |
| DPA | dynamic polymorphism in ancestors |
| DPD | dynamic polymorphism in descendants |
| SP | static polymorphism in inheritance relations |
| DP | dynamic polymorphism in inheritance relations |

# **Appendix C. Detailed data analysis method for RQ2 (influence analysis on prediction performance)**

**Prediction performance evaluation**. We evaluate the prediction performance of a defect prediction model under two scenarios: classification and ranking. For a given test data set, assume that: (1) *n*0 is the number of clean instances; (2) *n*1 is the number of defective instances; (3) *N* is the total number of instances; and (4) *q* is the actual defect percentage. Then, we have *N* = *n*0 + *n*1 and *q* = *n*1/*N*. For each instance in this test set, a defect prediction model can output a probability of being defective. In the classification scenario, a threshold (0.5 in default) is chosen to classify an instance as defective if the predicted probability is larger than the threshold and otherwise not defective. Consequently, there are four outcomes: *TP* (the set of modules correctly classified as defective), *TN* (the set of modules correctly classified as not defective), *FP* (the set of modules incorrectly classified as defective), and *FN* (the set of modules incorrectly classified as not defective). Clearly, *N* = |*TP*| + |*FP*| + |*TN*| + |*FN*|, and *q* = (|*TP*| + |*FP*|) / *N*. In our study, we use the following indicators to evaluate the classification performance of a RF model.

* Matthews Correlation Coefﬁcients (*MCC*) [8-10]. *MCC* measures a correlation coefﬁcients between actual and predicted outcomes using the following calculation: . An *MCC* value ranges from -1 to +1, where an *MCC* value of 1 indicates a perfect prediction, and -1 indicates total disagreement between the prediction.
* *F*1 [11]: the harmonic mean of precision (i.e. *p* = |*TP*| / (|*TP*|+|*FP*|)) and recall (i.e. *r* = |*TP*| / (|*TP*|+|*FN*|)), i.e. 2 × *p* × *r* / (*p* + *r*).
* *AUC* [12]: the area under ROC (Receiver Operating Characteristic) curve, which is defined on a 2-dimensional plot in which the *x*-axis is TPR (i.e. |*TP*|/(|*TP*|+|*FN*|)) and the *y*-axis is the FPR (i.e. |*FP*|/(|*TN*|+|*FP*|)).
* *ER* (Effort Reduction) [13]: the proportion of the reduced number of modules to be inspected (i.e., effort) compared with a random model that achieves the same recall. According to the prediction model, |*TP*|+|*FP*| modules will be inspected. According to a random model that achieves the same recall, |*TP*|/(|*TP*|+|*FN*|) × *N* modules will be inspected. Therefore, the reduced effort is:

* *RI* (Recall Increase) [13]: the proportion of the increased recall compared with a random model when inspecting the same number of instances (i.e., the same effort). According to a random model, inspecting |*TP*|+|*FP*| modules will lead to a recall of (|*TP*|+|*FP*|)*/N*. Therefore, the recall increase is:

Of the above five indicators, *MCC*, *F*1 and *AUC* are three popular classification performance indicators in the literature. However, they are non-effort-aware. In contrast, *ER* and *RI* are two effort-aware indicators. For each indicator, a larger value means a better performance.

In the ranking scenario, the instances in the test data set are ranked in descending order according to their predicted probability of being defective. In our study, we use the following indicators to evaluate the ranking performance of a RF model.

* *AP* (Average Precision): the average precision of defective instances. Let *p*(*k*) be the precision calculated by considering only the ranked instances from rank 1 through *k*. Assume that *rel*(*k*) indicates if the *k*th instance is defective (*rel*(*k*) = 1) or not (*rel*(*k*) = 0). Then, .
* *RR* (Reciprocal Rank): the reciprocal of the rank of the first real defective instance.
* *Popt* [14-16]: the area under the cost-effectiveness curve normalized to the optimal and worst models in an Alberg diagraph. In such a diagraph, the cumulative percentage of SLOC of the top modules selected from the instance ranking (the *x*-axis) is plotted against the cumulative percentage of defects found (the *y*-axis). Formally, for a model *m*, *Popt* can be deﬁned as:

Here, *Area*(*m*), *Area*(*optimal*) and *Area*(*worst*) represent the area under the curve corresponding to the prediction model, the optimal model, and the worst model, respectively. In the optimal model and the worst model, instances are, respectively, ranked in decreasing and ascending order according to their actual defect density.

* *ACC* [14]: the recall of defective instances when using 20% of the entire effort required to inspect all instances (i.e. 20% of the total SLOC) to inspect the top ranked instances.

Of the above four indicators, *AP*and *RR* are two non-effort-aware indicators, in which the order of defective instances in a ranking is considered. They are originally from the field information retrieval [17] but appropriate for evaluating the ranking performance of a defect prediction model. In particular, *RR* = 1 / (*IFA* + 1), where *IFA* is a recently proposed indicator [18] to characterize the number of Initial False Alarms encountered before the first defective instance is found in a rank. In contrast, *Popt* and *ACC* are two popular effort-aware indicators, in which the module size corresponding to an instance is used as the proxy of the effort to inspect the instance. For each indicator, a larger value means a better performance.

**Statistical performance comparison**. Let *perf*(*m*1) be the performance of model *m*1 and *perf*(*m*2) be the performance of model *m*2. In our context, the performance measure *perf* can be *MCC* or *ACC*. In particular, when investigating the influence of inconsistent labels in a training set, *m*1 is NC and *m*2 is CC; when investigating the influence of inconsistent labels in a test set, *m*1 is NN and *m*2 is NC. For a pair of training and test set, a nature idea is to use the absolute value of *diff* to evaluate the influence of inconsistent labels [19]:

As can be seen, a positive *diff* means that inconsistent labels lead to overestimation of the prediction model performance (optimistic estimation), while a negative *diff* means that inconsistent labels lead to underestimation of the prediction model performance (conservative estimation). No matter whether the *diff* is positive or negative, it is clear that the smaller the absolute value of *diff* is, the less the influence is. However, the above analysis only considers the absolute performance *perf*. In practice, for a given test set, it is easy to use a random model *random* to predict defect-proneness. The random model can be regarded as the description of the difficulty of the problem itself. For practitioners, the premise of using a model is that it should have a higher performance than *random*. In this sense, it is more important for practitioners to evaluate *perfGain*, the relative performance of a model with respect to *random* [20]. In our context, *perfGain*(*m*1) = *perf*(*m*1) − *perf*(*random*) and *perfGain*(*m*2) = *perf*(*m*2) − *perf*(*random*). Therefore, in this study, we also employ the absolute value of *pgr* (performance gain ratio) to evaluate the influence of inconsistent labels in *S* on prediction performance:

The advantage of using *pgr* (performance gain ratio) indicator [20] is that the influence of the difficulty of the problem itself is considered. By eliminating the impact of the difficulty of the problem itself, it will be more fair and meaningful to observe or compare the performance difference between the two models. Although the *pgr* indicator itself has not been widely used in the existing literatures, the indicator using similar ideas (subtracting the difficulty of the problem itself, i.e., subtracting the performance of the random model), such as CE indicator, has been widely adopted in the existing literatures [21, 22]. In summary, *diff*(NC, CC) and *pgr*(NC, CC) are used for investigating the influence of inconsistent labels in the training data, while *diff*(NN, NC) and *pgr*(NN, NC) are used for investigating the influence of inconsistent labels in the test data.

Assume that a test set consists of *N* instances, in which *n*1 are defective. For a random model *random*, an instance will have an equal probability (i.e. 0.5) to be predicted as clean or defective. Consequently, we can conclude that:

* TP = *N*/2 \* n1/*N* = *n*1/2
* FP = *N*/2 - *n*1/2 = (*N*-*n*1)/2
* TN = *N*/2 \* (1-n1/*N*) = (*N*-*n*1)/2
* FN = *N*/2 - (*N*-*n*1)/2 =  *n*1/2

Therefore, we calculate *MCC*, *F*1, *AUC*, *ER*, *RI*, *Popt*, *ACC*, *AP*, *RR*, as:

* *MCC* = 0
* *AUC(random) =* 0.5
* *ER(random) =* 0
* *RI(random) =* 0
* *Popt(random)=* 0.5
* *ACC(random)=* 0.2

**The reasoning process of *AP* formula**. We consider the calculation of *AP* as the sum of contribution of each position *i* (1≤ *i*≤ *N*) with defective modules. For each *i*, assuming that there are defective modules at the current position *i*, the remaining *n*1-1 defective modules need to be placed on both sides of position *i*, that is, one part of the defective modules should be placed on 1 to *i*-1, and the other part should be placed on *i*+1 to *N*. At this time, (1) the probability that there is a defective module at the current position *i* is ; (2) the probability that the defective module at the current position *i* is the *k*th defective module (i.e., *k*-1 (*k* ≤ *i*) defective modules are placed on 1 to *i*-1, and *n*1-*k* defective modules are placed on *i*+1 to *N*) is ; (3) the contribution value of position *i* with defective modules is *k*/*i*. Therefore, the total *AP* contribution value of upstream defective module on current position *i* is calculated as:

Further, we can derive the formula of AP as follows:

**The reasoning process of RR formula**. RR can be expressed as:

The first summation term indicates that if the first defective module appears in the first position, then the *RR* value is 1, and the probability of occurrence of this event is . Because the total possibility is (regarding the defective modules as repeated events), the possibility of the current situation is to select *n*1-1 positions from the subsequent *N*-1 positions to place the defective modules, that is, the total possibility is . By analogy, the first defective module can appear at most in the *N*-*n*1+1 position. After sorting out the above formulas, the results are as follows:

# **Appendix D. Supplementary results for RQ2 (influence on prediction performance)**

In Section 7.2 (RQ2), two model comparison schemes, “NC vs. CC” and “NN vs. NC”, are respectively used to investigate the influence of inconsistent labels on the prediction performance of a defect prediction model and the influence on the performance estimation of a defect prediction model. In this section, we report the results of more indicators including *MCC* and *ACC* for reference.

## *NC vs. CC*

Table 4~9, respectively, report the distributions of |*diff*| and |*pgr*| between the two model (NC and CC) with respect to nine performance evaluation indicators (i.e., *F*1, *AUC*, *ER*, *RI*, *MCC*, *AP*, *RR*, *Popt*, and *ACC*) for three classifiers (random forest (RF) [23], naive Bayes (NB) [24], and logistic regression (LR) [25]) respectively. In particular, the values in shown in the yellow background in the table indicate the maximum mean value of |*diff|* or |*pgr|* in six multi-version-project defect data sets. The values in shown in the green background in the table indicate the confidence interval of the corrected confidence level contains 0 (i.e. the difference between the indicators of the two models (NC and CC) is not significant).

As can be seen from tables 4~9, only for the *RR* indicator, when the classifier is Naive Bayes or Logistic Regression, neither |*diff*| nor |*pgr*| indicators are significantly different from zero (i.e., the confidence interval of the corrected confidence level contains 0) on the ECLIPSE-2007 data set. In other words, on the ECLIPSE-2007 data set, there is no significant difference in the *RR* indicator between model NC and model CC. This is understandable because there are three factors. First, *RR* is the reciprocal of the rank of the first real defective instance. The calculation of *RR* does not consider whether the prediction of the model for other instances is correct or not, nor whether the real defective instance with the same rank between the two models are the same instance, but only considers whether the highest rank of real defect instances is the same. Therefore, compared with other indicators, the *RR* indicator is more likely to be less influenced by inconsistent labels (noise). Second, the inconsistent label rate (noise rate) of the ECLIPSE-2007 data set is the smallest, so it is more difficult to influence the calculation of *RR*. Third, the number of data points on the ECLIPSE-2007 data set is the least (only 3). Once the difference of *RR* on two data points is 0, even if the difference of *RR* on the other data point is very large, the data points with difference of 0 will be more easily sampled when sampling is used to reflect the difference of population (1000 bootstrap sampling). This makes the difference of *RR* is not significant from the perspective of sampling group. The third point is particularly evident in Table 9.

Table 4. Random Forest: distribution of the prediction performance |*diff*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 3.87 | 0.71 | 0.99 | 2.82 | 4.85 | 3 | 908.33 | 2.14 | 2.83 |
| StdDev | 2.27 | 0.41 | 0.86 | 2.51 | 2.8 | 1.57 | 1465.08 | 0.95 | 2.73 |
| 95% CI  [LL, UL] | [1.52,5.37] | [0.28,0.99] | [0.36,1.53] | [0.99,4.39] | [2.3,7.85] | [1.25,4.02] | [50,1758.33] | [1.26,2.76] | [0,4.64] |
| Metrics-Repo-2010 | Mean | 7.36 | 6.29 | 31.36 | 37.42 | 37.12 | 9.67 | 33.09 | 10.14 | 25.95 |
| StdDev | 7.99 | 8.77 | 130.77 | 130.84 | 133.39 | 14.55 | 66.82 | 10.38 | 26.89 |
| 95% CI  [LL, UL] | [5.75,10.28] | [4.34,9.12] | [12.49,107.41] | [18.89,112.93] | [18.48,128.82] | [6.8,14.92] | [19.81,55.67] | [8.18,13.88] | [19.29,34.22] |
| JIRA-HA-2019 | Mean | 7.84 | 1.45 | 2.96 | 13.79 | 8.83 | 10.86 | 31.23 | 3.73 | 21.32 |
| StdDev | 8.93 | 1.42 | 3.16 | 13.68 | 10.81 | 11.99 | 73.15 | 3.33 | 38.75 |
| 95% CI  [LL, UL] | [5.2,11.19] | [1.1,2.02] | [2.15,4.22] | [10.32,18.95] | [6.08,12.6] | [7.93,15.75] | [15.61,66.44] | [2.9,4.93] | [14.17,41.23] |
| JIRA-RA-2019 | Mean | 7.21 | 1.28 | 3.45 | 12.8 | 8.43 | 9.21 | 62.25 | 3.11 | 9.26 |
| StdDev | 5.56 | 0.96 | 3.8 | 10.42 | 7.97 | 9.62 | 109.27 | 3.42 | 8.54 |
| 95% CI  [LL, UL] | [5.85,9.25] | [1.02,1.6] | [2.49,4.85] | [10.17,16.18] | [6.3,11.53] | [7.07,13.93] | [39.22,109.01] | [2.32,4.5] | [6.93,12.16] |
| MA-SZZ-2020 | Mean | 3.91 | 0.32 | 1.15 | 7.35 | 3.75 | 2.8 | 8.82 | 2 | 7.76 |
| StdDev | 6.08 | 0.41 | 1.21 | 10.38 | 4.97 | 4.54 | 41.54 | 2.67 | 10.75 |
| 95% CI  [LL, UL] | [3.21,4.89] | [0.27,0.37] | [1,1.34] | [6.14,8.94] | [3.16,4.62] | [2.24,3.57] | [5.04,18.79] | [1.67,2.42] | [6.49,9.64] |
| IND-JLMIV+R-2020 | Mean | 9.98 | 1.37 | 2.43 | 15.3 | 9.4 | 15.72 | 64.59 | 3.71 | 15.22 |
| StdDev | 11.03 | 1.8 | 3.39 | 17.51 | 10.59 | 21.61 | 188.8 | 3.77 | 19.7 |
| 95% CI  [LL, UL] | [8.85,11.39] | [1.18,1.58] | [2.1,2.93] | [13.69,17.85] | [8.39,10.84] | [13.66,19.08] | [48.98,98.39] | [3.32,4.15] | [13.34,17.99] |
| Range of mean | [minMean, maxMean] | [3.87,9.98] | [0.32,6.29] | [0.99,31.36] | [2.82,37.42] | [3.75,37.12] | [2.8,15.72] | [8.82,908.33] | [2,10.14] | [2.83,25.95] |

Table 5. Random Forest: Distribution of the absolute performance gain ratio |*pgr*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 10.21 | 2.06 | 0.99 | 2.82 | 4.85 | 5.05 | 204.72 | 13.86 | 5.83 |
| StdDev | 6.41 | 1.21 | 0.86 | 2.51 | 2.8 | 2.5 | 195.61 | 5.26 | 5.74 |
| 95% CI  [LL, UL] | [2.98,14.28] | [0.78,2.86] | [0.36,1.53] | [0.99,4.39] | [2.3,6.7] | [2.21,6.62] | [73.83,323.31] | [7.95,17.23] | [0,9.66] |
| Metrics-Repo-2010 | Mean | 79.21 | 20.13 | 31.36 | 37.42 | 37.12 | 22.33 | 130.72 | 121.31 | 129.11 |
| StdDev | 284 | 32.83 | 130.77 | 130.84 | 133.39 | 23.71 | 381.28 | 267.21 | 243.23 |
| 95% CI  [LL, UL] | [27.3,240.43] | [13.63,31.9] | [12.49,107.41] | [18.89,112.93] | [18.48,128.82] | [17.17,29.96] | [59.36,280.29] | [74.2,237.27] | [84.96,247.81] |
| JIRA-HA-2019 | Mean | 10.81 | 3.48 | 2.96 | 13.79 | 8.83 | 13.31 | 61.22 | 82.22 | 61.55 |
| StdDev | 12.29 | 3.48 | 3.16 | 13.68 | 10.81 | 13.84 | 192.58 | 241.57 | 117.97 |
| 95% CI  [LL, UL] | [7.44,15.93] | [2.61,4.96] | [2.15,4.23] | [10.37,18.96] | [6.08,12.6] | [9.77,18.77] | [24.94,176.65] | [30.27,211.09] | [36.14,122.53] |
| JIRA-RA-2019 | Mean | 11.2 | 3.16 | 3.45 | 12.8 | 8.43 | 11.97 | 159.11 | 28.72 | 63.66 |
| StdDev | 9.18 | 2.38 | 3.8 | 10.42 | 7.97 | 13.95 | 458.57 | 50.6 | 120.62 |
| 95% CI  [LL, UL] | [9.17,14.87] | [2.53,3.98] | [2.49,4.85] | [10.17,16.18] | [6.31,11.53] | [9.2,19.48] | [78.35,423.08] | [18.99,53.4] | [38.46,126.13] |
| MA-SZZ-2020 | Mean | 4.99 | 0.67 | 1.15 | 7.35 | 3.75 | 3.24 | 18.95 | 6.3 | 28 |
| StdDev | 7.26 | 0.91 | 1.21 | 10.38 | 4.97 | 4.86 | 85.06 | 11.48 | 92.52 |
| 95% CI  [LL, UL] | [4.16,6.15] | [0.56,0.81] | [1,1.34] | [6.13,8.94] | [3.16,4.62] | [2.63,4.06] | [10.73,38.64] | [4.98,8.34] | [19.18,51.1] |
| IND-JLMIV+R-2020 | Mean | 12.63 | 3.18 | 2.43 | 15.3 | 9.4 | 18.58 | 360.84 | 13.03 | 37.36 |
| StdDev | 14.94 | 4.58 | 3.39 | 17.51 | 10.59 | 28.68 | 2919.97 | 23.66 | 95.71 |
| 95% CI  [LL, UL] | [11.16,14.44] | [2.71,3.73] | [2.1,2.93] | [13.69,17.85] | [8.39,10.84] | [15.93,23.58] | [173.7,969.6] | [11.04,16.15] | [29.44,57.1] |
| Range of mean | [minMean, maxMean] | [4.99,79.21] | [2.06,20.13] | [0.99,31.36] | [2.82,37.42] | [3.75,37.12] | [3.24,22.33] | [18.95,360.84] | [6.3,121.31] | [5.83,129.11] |

Table 6. Naive Bayes: distribution of the prediction performance |*diff*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 4.57 | 0.75 | 3.28 | 8.03 | 6.24 | 2.78 | 22.22 | 0.74 | 0.92 |
| StdDev | 0.71 | 0.35 | 1.71 | 3.24 | 1.7 | 2.03 | 38.49 | 0.91 | 1.59 |
| 95% CI  [LL, UL] | [3.81,5.04] | [0.36,0.97] | [2.14,4.32] | [5.55,10.08] | [4.7,7.36] | [0.5,4.08] | [0,44.44] | [0.11,1.3] | [0,1.84] |
| Metrics-Repo-2010 | Mean | 7.73 | 4.96 | 22.25 | 28.41 | 23.03 | 9.47 | 21.02 | 15.78 | 39.32 |
| StdDev | 7.38 | 7.52 | 51.36 | 51.99 | 32.72 | 14.42 | 70.83 | 16.99 | 75.36 |
| 95% CI  [LL, UL] | [6.07,10.03] | [3.46,7.74] | [14.06,47.16] | [20.05,54] | [16.89,35.16] | [6.5,14.1] | [7.28,52.06] | [11.92,20.53] | [24.96,70.36] |
| JIRA-HA-2019 | Mean | 8.74 | 1.37 | 5.71 | 18.61 | 7.6 | 6.86 | 36.03 | 3.22 | 15.08 |
| StdDev | 9.86 | 1.49 | 7.85 | 22.29 | 7.93 | 6.14 | 56.52 | 3.33 | 14.3 |
| 95% CI  [LL, UL] | [6.02,12.64] | [1.01,2.03] | [3.77,9.66] | [13.33,27.33] | [5.7,10.4] | [5.3,9.54] | [21.79,55.38] | [2.38,4.64] | [11.61,21] |
| JIRA-RA-2019 | Mean | 6.82 | 0.94 | 3.74 | 13.18 | 6.46 | 5.7 | 32.79 | 3.27 | 9.6 |
| StdDev | 4.45 | 1.06 | 3.29 | 8.44 | 4.68 | 6.02 | 47.5 | 4.32 | 9.93 |
| 95% CI  [LL, UL] | [5.49,8.2] | [0.7,1.35] | [2.88,4.86] | [10.69,15.58] | [5.12,7.93] | [4.22,7.83] | [21.03,49.32] | [2.31,5.16] | [7.3,13.63] |
| MA-SZZ-2020 | Mean | 4.69 | 0.82 | 4.28 | 11.37 | 6.42 | 6.58 | 11.85 | 4.09 | 12.02 |
| StdDev | 4.33 | 0.75 | 4.76 | 12.23 | 5.63 | 10.09 | 35.63 | 4.05 | 11.28 |
| 95% CI  [LL, UL] | [4.14,5.33] | [0.72,0.94] | [3.73,5.12] | [9.89,13.35] | [5.66,7.27] | [5.55,8.32] | [7.8,17.98] | [3.59,4.67] | [10.48,13.55] |
| IND-JLMIV+R-2020 | Mean | 9.38 | 1.4 | 9.51 | 36.14 | 29.96 | 13.87 | 37.81 | 3.78 | 23.94 |
| StdDev | 22.39 | 2.55 | 84.69 | 372.78 | 360.61 | 30.25 | 81.34 | 3.71 | 49.28 |
| 95% CI  [LL, UL] | [7.8,14] | [1.21,1.87] | [4.4,33.81] | [13.79,165.61] | [8.63,114.51] | [11.64,20.51] | [29.45,49.75] | [3.4,4.29] | [19.47,30.9] |
| Range of mean | [minMean, maxMean] | [4.57,9.98] | [0.75,4.96] | [3.28,22.25] | [8.03,36.14] | [6.24,29.96] | [2.78,13.87] | [11.85,37.81] | [0.74,15.78] | [0.92,39.32] |

Table 7. Naive Bayes: Distribution of the absolute performance gain ratio |*pgr*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 9.98 | 2.24 | 3.28 | 8.03 | 6.24 | 4.49 | 30.08 | 2.31 | 1.43 |
| StdDev | 1.57 | 1.14 | 1.71 | 3.24 | 1.7 | 3.28 | 52.1 | 2.63 | 2.47 |
| 95% CI  [LL, UL] | [8.35,11.02] | [1.01,2.99] | [2.14,4.32] | [5.55,10.08] | [4.7,7.36] | [0.81,6.58] | [0,60.16] | [0.44,3.94] | [0,2.85] |
| Metrics-Repo-2010 | Mean | 38.06 | 16.99 | 22.25 | 28.41 | 23.03 | 21.78 | 55.64 | 91.89 | 109.21 |
| StdDev | 62.66 | 29.92 | 51.36 | 51.99 | 32.72 | 28.48 | 211.55 | 148.19 | 185.4 |
| 95% CI  [LL, UL] | [26.52,61.46] | [11.24,28.32] | [13.95,47.01] | [20.05,54] | [16.81,35.16] | [15.57,30.16] | [14.59,157.99] | [62.96,150.17] | [70.57,174.62] |
| JIRA-HA-2019 | Mean | 13.29 | 3.41 | 5.71 | 18.61 | 7.6 | 8.6 | 71.63 | 45.65 | 50.67 |
| StdDev | 14.95 | 3.71 | 7.85 | 22.29 | 7.93 | 7.45 | 169.55 | 83.51 | 65.92 |
| 95% CI  [LL, UL] | [9.25,19.29] | [2.5,5.01] | [3.77,9.66] | [13.32,27.33] | [5.7,10.4] | [6.63,11.5] | [38.55,173.48] | [28.08,87.51] | [34.9,77.03] |
| JIRA-RA-2019 | Mean | 10.1 | 2.31 | 3.74 | 13.18 | 6.46 | 7.09 | 72.13 | 28.29 | 40.38 |
| StdDev | 6.03 | 2.76 | 3.29 | 8.44 | 4.68 | 7.68 | 155.96 | 46.95 | 83.7 |
| 95% CI  [LL, UL] | [8.26,11.89] | [1.72,3.54] | [2.89,4.87] | [10.69,15.58] | [5.12,7.94] | [5.15,9.79] | [39.23,149.47] | [17.73,49.13] | [23.74,89.2] |
| MA-SZZ-2020 | Mean | 8.6 | 2.05 | 4.28 | 11.37 | 6.42 | 8.59 | 25.38 | 87.47 | 117.95 |
| StdDev | 8.21 | 1.98 | 4.76 | 12.23 | 5.63 | 12.74 | 121.27 | 433.31 | 292.93 |
| 95% CI  [LL, UL] | [7.61,9.91] | [1.8,2.36] | [3.73,5.11] | [9.89,13.35] | [5.66,7.27] | [7.32,11.03] | [14.45,54.4] | [46.37,177.67] | [81.63,170.59] |
| IND-JLMIV+R-2020 | Mean | 18.03 | 3.87 | 9.51 | 36.14 | 29.96 | 22.33 | 149.99 | 85.47 | 119.07 |
| StdDev | 95.07 | 11.07 | 84.69 | 372.78 | 360.61 | 120.46 | 899.06 | 787.54 | 244.26 |
| 95% CI  [LL, UL] | [11.98,39.84] | [3.14,6.23] | [4.4,33.81] | [13.79,165.61] | [8.63,114.51] | [14.69,51.5] | [84.81,329.27] | [36.05,267.78] | [96.2,153.36] |
| Range of mean | [minMean, maxMean] | [8.6,38.06] | [2.05,16.99] | [3.28,22.25] | [8.03,36.14] | [6.24,29.96] | [4.49,22.33] | [25.38,149.99] | [2.31,91.89] | [1.43,119.07] |

Table 8. Logistic Regression: distribution of the prediction performance |*diff*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 2.96 | 2.09 | 3.11 | 6.48 | 4.64 | 1.48 | 50 | 3.29 | 6.5 |
| StdDev | 3.35 | 1.54 | 4.66 | 9.37 | 5.93 | 1.9 | 50 | 4.29 | 4.61 |
| 95% CI  [LL, UL] | [0.08,5.14] | [0.43,3.11] | [0.36,5.82] | [0.9,17.31] | [0.2,11.37] | [0.37,3.67] | [0,83.33] | [0.35,5.91] | [3.53,9.27] |
| Metrics-Repo-2010 | Mean | 10.26 | 5.55 | 23.07 | 31.06 | 26.78 | 6.83 | 16.6 | 29.8 | 46.43 |
| StdDev | 10.12 | 7.11 | 33.12 | 43.24 | 34.8 | 8.7 | 31.07 | 70.46 | 128.79 |
| 95% CI  [LL, UL] | [8.02,13.41] | [4.09,7.79] | [16.27,35.52] | [22.99,48.7] | [19.92,39.01] | [5.02,9.91] | [9.49,25.34] | [17.83,66.67] | [25.33,104.18] |
| JIRA-HA-2019 | Mean | 8.53 | 2.13 | 11.37 | 22.66 | 13.71 | 12.02 | 44.44 | 4.47 | 23.61 |
| StdDev | 11.13 | 3.61 | 35.93 | 49.92 | 30.94 | 23.11 | 85.36 | 6.36 | 40.02 |
| 95% CI  [LL, UL] | [6.15,14.17] | [1.38,4] | [4.95,36] | [13.11,57.47] | [8.19,37.47] | [6.74,23.85] | [23.93,80.12] | [3.1,7.97] | [14.13,40.42] |
| JIRA-RA-2019 | Mean | 9.81 | 2.86 | 7.48 | 40.67 | 13.48 | 9.76 | 5.95 | 4.57 | 12.93 |
| StdDev | 27.96 | 5.46 | 23.59 | 190.07 | 40.82 | 10.6 | 19.76 | 6.33 | 19.98 |
| 95% CI  [LL, UL] | [5.03,27.02] | [1.81,5.73] | [3.46,21.58] | [10.56,186.93] | [6.58,38.17] | [7.03,13.79] | [1.19,13.1] | [3.13,6.96] | [8.75,21.58] |
| MA-SZZ-2020 | Mean | 5.04 | 1.23 | 3.35 | 9.07 | 7.22 | 6.38 | 20.89 | 5.57 | 33.04 |
| StdDev | 5.02 | 1.34 | 3.05 | 8.34 | 6.05 | 8.73 | 43.5 | 7.82 | 96.13 |
| 95% CI  [LL, UL] | [4.41,5.79] | [1.08,1.46] | [2.98,3.8] | [8.08,10.38] | [6.4,8.03] | [5.44,8.04] | [15.44,28.23] | [4.65,6.89] | [23.84,53.03] |
| IND-JLMIV+R-2020 | Mean | 10.34 | 1.78 | 4.39 | 14.42 | 11.78 | 15.22 | 56.75 | 6.31 | 31.48 |
| StdDev | 37.96 | 3.25 | 9.15 | 26.22 | 29.1 | 25.97 | 138.45 | 6.34 | 93.46 |
| 95% CI  [LL, UL] | [7.91,20.94] | [1.5,2.37] | [3.79,6.43] | [12.41,19.9] | [9.85,18.72] | [13.07,20.43] | [44.4,75.3] | [5.7,7.17] | [24.95,52.85] |
| Range of mean | [minMean, maxMean] | [2.96,10.34] | [1.23,5.55] | [3.11,23.07] | [6.48,40.67] | [4.64,26.78] | [1.48,15.22] | [5.95,56.75] | [3.29,29.8] | [6.5,46.43] |

Table 9. Logistic Regression: Distribution of the absolute performance gain ratio |*pgr*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 6.65 | 6.74 | 3.11 | 6.48 | 4.64 | 2.56 | 94.4 | 16.09 | 12.1 |
| StdDev | 7.19 | 5.07 | 4.66 | 9.37 | 5.93 | 3.33 | 106.19 | 20.49 | 12.23 |
| 95% CI  [LL, UL] | [0.19,11.38] | [1.3,10.08] | [0.36,5.82] | [0.9,11.95] | [0.2,8.36] | [0.63,4.49] | [0,164.2] | [1.73,39.55] | [4.69,26.21] |
| Metrics-Repo-2010 | Mean | 58.23 | 21.08 | 23.07 | 31.06 | 26.78 | 19.61 | 119.23 | 231.67 | 85.32 |
| StdDev | 103.31 | 30.56 | 33.12 | 43.24 | 34.8 | 26.06 | 357.16 | 1144.05 | 332.17 |
| 95% CI  [LL, UL] | [38.97,98.6] | [14.09,31.42] | [15.93,33.59] | [23.53,48.29] | [19.65,37.42] | [14.32,28.24] | [48.17,242.83] | [68.48,1007.07] | [36.58,255.87] |
| JIRA-HA-2019 | Mean | 20.59 | 10.88 | 11.37 | 22.66 | 13.71 | 25.34 | 78.65 | 117.3 | 75.93 |
| StdDev | 54.63 | 38.59 | 35.93 | 49.92 | 30.94 | 85.75 | 183.28 | 357.94 | 153.62 |
| 95% CI  [LL, UL] | [10.87,65.81] | [4.22,36.14] | [5.11,33.93] | [13.68,61.88] | [8.21,37.3] | [9.89,93.45] | [41.11,171.79] | [43,343.68] | [42.6,151.26] |
| JIRA-RA-2019 | Mean | 21.99 | 8.25 | 7.48 | 40.67 | 13.48 | 12.84 | 6.81 | 33.65 | 116.2 |
| StdDev | 84.14 | 18.19 | 23.59 | 190.07 | 40.82 | 15.31 | 22.66 | 50.12 | 252.75 |
| 95% CI  [LL, UL] | [8.33,85.77] | [4.34,16.95] | [3.58,22.7] | [10.74,158.92] | [6.57,37.79] | [8.97,18.37] | [2.62,17.96] | [21.93,51.87] | [56.81,227.89] |
| MA-SZZ-2020 | Mean | 8.94 | 3.25 | 3.35 | 9.07 | 7.22 | 9.16 | 89.12 | 78.04 | 162.87 |
| StdDev | 8 | 3.91 | 3.05 | 8.34 | 6.05 | 12.35 | 360.47 | 361.51 | 598.63 |
| 95% CI  [LL, UL] | [7.96,10.01] | [2.82,3.94] | [2.95,3.78] | [8.08,10.31] | [6.42,8.12] | [7.89,11.55] | [54.21,162.15] | [47.44,181.63] | [105.1,305.89] |
| IND-JLMIV+R-2020 | Mean | 13.43 | 6.86 | 4.39 | 14.42 | 11.78 | 24.95 | 1029.47 | 73.77 | 111.86 |
| StdDev | 22.62 | 35.75 | 9.15 | 26.22 | 29.1 | 88.79 | 15356.1 | 156.84 | 206.54 |
| 95% CI  [LL, UL] | [11.67,18.13] | [4.42,15.59] | [3.72,6.52] | [12.49,20.58] | [9.74,18.68] | [17.89,41.9] | [124.86,4621.18] | [59.66,97.87] | [92.83,142.22] |
| Range of mean | [minMean, maxMean] | [6.65,58.23] | [3.25,21.08] | [3.11,23.07] | [6.48,40.67] | [4.64,26.78] | [2.56,25.34] | [6.81,1029.47] | [16.09,231.67] | [12.1,162.87] |

## *NN vs. NC*

Tables 10~15, report the distributions of |*diff*| and |*pgr*| between the two model (NN and NC) with respect to nine performance evaluation indicators (i.e., *F*1, *AUC*, *ER*, *RI*, *MCC*, *AP*, *RR*, *Popt*, and *ACC*) for three classifiers (random forest (RF), naive Bayes (NB), and logistic regression (LR)) respectively.

From Tables 10~15, it is not difficult to find that the three observations to “NC vs. CC” (RQ2 in Section 7.2) are all applicable to “NN vs. NC”. The only difference is that for the *RR* indicator, “NN vs. NC” shows no significant difference on 3 or 4 data sets (count the cells shown in green background). However, “NC vs. CC” only shows no significant difference on the ECLIPSE-2007 data set (when the classifier is Naive Bayes or Logistic Regression). This shows that the *RR* indicator is more susceptible to inconsistent labels in test set than inconsistent labels in training set. The reason why the *RR* indicator between NN and NC models does not show significant differences on some data sets is the same as the three reasons analyzed in Appendix D.1.

(1) For “NC vs. CC”, inconsistent labels may lead to model performance improvement or degradation (compared with clean data). Only if inconsistent labels consistently benefit to improve model performance on all version pairs, inconsistent labels should not be removed or handled in practice. (2) For “NN vs. NC”, inconsistent labels will lead to overestimation or underestimation, and their existence will only lead to biased model evaluation. Combining (1) and (2), it is reasonable to remove the inconsistent labels, especially considering that inconsistent labels may mislead the interpretation of a defect prediction model.

Table 10. Random Forest: distribution of the prediction performance |*diff*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 2.63 | 2.37 | 2.51 | 6.79 | 4.67 | 1.47 | 0 | 4.36 | 5.38 |
| StdDev | 0.43 | 0.45 | 0.14 | 0.27 | 0.34 | 0.52 | 0 | 0.44 | 1.05 |
| 95% CI  [LL, UL] | [2.13,2.89] | [1.85,2.64] | [2.4,2.6] | [6.62,7.1] | [4.41,5.06] | [0.9,1.81] | [0,0] | [3.86,4.64] | [4.54,6.05] |
| Metrics-Repo-2010 | Mean | 15.41 | 10.22 | 47.76 | 55.53 | 36.33 | 12.36 | 10.03 | 13.63 | 16.59 |
| StdDev | 13.92 | 9.94 | 83.36 | 82.26 | 52.12 | 14.53 | 23.93 | 14.33 | 17.91 |
| 95% CI  [LL, UL] | [12.25,19.56] | [7.92,13.31] | [31.18,78.21] | [38.34,81.44] | [26.14,56.05] | [9.05,16.82] | [4.71,17.88] | [10.69,18.09] | [12.93,23.33] |
| JIRA-HA-2019 | Mean | 6.93 | 5.01 | 3.68 | 15.12 | 8.89 | 9.29 | 7.69 | 8.05 | 12.48 |
| StdDev | 7.73 | 4.19 | 3.5 | 13.32 | 7.58 | 9.52 | 48.04 | 7.11 | 11.58 |
| 95% CI  [LL, UL] | [5.14,10.1] | [3.75,6.48] | [2.83,5.08] | [11.43,19.92] | [6.8,11.73] | [6.82,12.72] | [0,23.08] | [6.22,10.63] | [9.45,16.71] |
| JIRA-RA-2019 | Mean | 6.03 | 4.18 | 4.32 | 16.06 | 9.92 | 8.67 | 0 | 7.56 | 14.25 |
| StdDev | 5.79 | 3.64 | 3.9 | 13.81 | 8.09 | 6.82 | 0 | 6.62 | 12.04 |
| 95% CI  [LL, UL] | [4.51,7.95] | [3.18,5.34] | [3.27,5.63] | [12.14,20.56] | [7.43,12.46] | [6.65,10.95] | [0,0] | [5.82,9.64] | [10.71,18.39] |
| MA-SZZ-2020 | Mean | 3.01 | 1.03 | 2.07 | 7.76 | 3.69 | 4.12 | 2.3 | 1.81 | 4.4 |
| StdDev | 4.19 | 1.46 | 2.31 | 7.91 | 4.95 | 7.83 | 12.04 | 2.39 | 6.23 |
| 95% CI  [LL, UL] | [2.47,3.78] | [0.83,1.27] | [1.71,2.41] | [6.57,9.02] | [2.98,4.61] | [3.17,5.61] | [0.63,4.59] | [1.44,2.16] | [3.45,5.36] |
| IND-JLMIV+R-2020 | Mean | 15.37 | 2.06 | 2.5 | 15.35 | 9.51 | 9.59 | 13.74 | 4.57 | 13.28 |
| StdDev | 20.35 | 2.75 | 1.84 | 8.16 | 9.82 | 12.89 | 61.46 | 4.44 | 9.75 |
| 95% CI  [LL, UL] | [13.26,17.92] | [1.77,2.41] | [2.3,2.73] | [14.53,16.35] | [8.49,10.8] | [8.25,11.35] | [8.57,23.76] | [4.13,5.14] | [12.25,14.56] |
| Range of mean | [minMean, maxMean] | [2.63,15.41] | [1.03,10.22] | [2.07,47.76] | [6.79,55.53] | [3.69,36.33] | [1.47,12.36] | [0,13.74] | [1.81,13.63] | [4.4,16.59] |

Table 11. Random Forest: Distribution of the absolute performance gain ratio |*pgr*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 13.4 | 6.89 | 2.51 | 6.79 | 4.67 | 5.88 | 6.33 | 26.44 | 10.74 |
| StdDev | 4.74 | 1.07 | 0.14 | 0.27 | 0.34 | 0.48 | 5.8 | 5.74 | 3.69 |
| 95% CI  [LL, UL] | [8.33,16.53] | [5.67,7.54] | [2.4,2.6] | [6.62,7.05] | [4.41,4.89] | [5.33,6.18] | [1.19,10.14] | [21.22,30.23] | [8.25,14.98] |
| Metrics-Repo-2010 | Mean | 86.92 | 37.73 | 47.76 | 55.53 | 36.33 | 48.36 | 56.3 | 172.19 | 87.67 |
| StdDev | 148.64 | 59.86 | 83.36 | 82.26 | 52.12 | 53.83 | 127.8 | 507.71 | 169.08 |
| 95% CI  [LL, UL] | [60.48,146.45] | [27.23,61.7] | [29.83,70.79] | [39.41,84.89] | [26.29,56.17] | [36.63,65.07] | [32.56,105.53] | [94.04,549.32] | [55.59,149.47] |
| JIRA-HA-2019 | Mean | 12.24 | 11.68 | 3.68 | 15.12 | 8.89 | 12.94 | 27.5 | 61.81 | 32.13 |
| StdDev | 10.44 | 9.35 | 3.5 | 13.32 | 7.58 | 11.71 | 107.7 | 90.6 | 38.39 |
| 95% CI  [LL, UL] | [9.26,15.73] | [9.11,14.99] | [2.82,4.99] | [11.71,20.29] | [6.91,11.59] | [9.89,17.57] | [3.56,91.83] | [40.08,97.1] | [23.86,49.66] |
| JIRA-RA-2019 | Mean | 12.73 | 9.87 | 4.32 | 16.06 | 9.92 | 13.73 | 5.59 | 126.65 | 69.15 |
| StdDev | 12.8 | 8.6 | 3.9 | 13.81 | 8.09 | 10.28 | 11.34 | 391.16 | 102.97 |
| 95% CI  [LL, UL] | [9.41,17.42] | [7.52,12.77] | [3.22,5.53] | [11.52,20.3] | [7.82,12.59] | [10.54,16.96] | [3.34,12.43] | [40.02,354.64] | [45.38,115.66] |
| MA-SZZ-2020 | Mean | 4.72 | 2.11 | 2.07 | 7.76 | 3.69 | 5.76 | 6.42 | 6.09 | 9.29 |
| StdDev | 5.88 | 2.96 | 2.31 | 7.91 | 4.95 | 9.63 | 22.53 | 10.12 | 14.98 |
| 95% CI  [LL, UL] | [3.92,5.75] | [1.71,2.71] | [1.74,2.46] | [6.5,8.98] | [2.97,4.6] | [4.54,7.61] | [3.72,10.91] | [4.74,7.89] | [7.37,12.22] |
| IND-JLMIV+R-2020 | Mean | 13.84 | 4.78 | 2.5 | 15.35 | 9.51 | 9.86 | 41.29 | 12.23 | 24.37 |
| StdDev | 19.04 | 7.29 | 1.84 | 8.16 | 9.82 | 13 | 249.74 | 12.52 | 41.25 |
| 95% CI  [LL, UL] | [11.97,16.38] | [4.06,5.75] | [2.31,2.73] | [14.47,16.34] | [8.35,10.71] | [8.59,11.63] | [23.04,95.84] | [11,13.77] | [21.05,31.96] |
| Range of mean | [minMean, maxMean] | [4.72,86.92] | [2.11,37.73] | [2.07,47.76] | [6.79,55.53] | [3.69,36.33] | [5.76,48.36] | [5.59,56.3] | [6.09,172.19] | [9.29,87.67] |

Table 12. Naive Bayes: distribution of the prediction performance |*diff*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 1.59 | 1.87 | 2.56 | 6.18 | 4.14 | 1.16 | 0 | 3.91 | 5 |
| StdDev | 0.73 | 0.52 | 0.42 | 0.3 | 0.3 | 0.48 | 0 | 0.51 | 0.5 |
| 95% CI  [LL, UL] | [0.76,2.03] | [1.27,2.18] | [2.19,2.83] | [5.88,6.38] | [3.84,4.34] | [0.63,1.47] | [0,0] | [3.34,4.24] | [4.48,5.33] |
| Metrics-Repo-2010 | Mean | 11.74 | 7.66 | 86.11 | 95.84 | 51.24 | 7.59 | 0 | 13.68 | 14.76 |
| StdDev | 12.25 | 7.29 | 334.27 | 336.93 | 151.68 | 10.51 | 0 | 16.78 | 14.34 |
| 95% CI  [LL, UL] | [9.11,15.52] | [6.12,9.97] | [38.92,302.82] | [45.28,279.52] | [28.52,148.39] | [5.52,11.57] | [0,0] | [10.1,18.79] | [11.79,19.34] |
| JIRA-HA-2019 | Mean | 4.74 | 5.16 | 4.82 | 16.49 | 10.1 | 9.46 | 0 | 8.78 | 16.25 |
| StdDev | 6.11 | 4.03 | 3.69 | 13.81 | 7.4 | 8.21 | 0 | 7.6 | 16.22 |
| 95% CI  [LL, UL] | [3.39,7.21] | [4.03,6.6] | [3.86,6.16] | [13.1,21] | [7.89,12.45] | [7.24,12.6] | [0,0] | [6.65,11.66] | [12.03,22.29] |
| JIRA-RA-2019 | Mean | 4.71 | 3.8 | 3.6 | 13.53 | 7.73 | 6.96 | 0.83 | 7.47 | 11.59 |
| StdDev | 5.98 | 3.39 | 3.36 | 13 | 7.66 | 5.94 | 5.27 | 6.62 | 10.72 |
| 95% CI  [LL, UL] | [3.12,7.13] | [2.86,4.96] | [2.74,4.71] | [9.91,18.11] | [5.63,10.48] | [5.32,9.14] | [0,2.5] | [5.62,9.89] | [8.66,15.14] |
| MA-SZZ-2020 | Mean | 2.47 | 1.32 | 2.63 | 5.54 | 4 | 2.9 | 1.78 | 2.56 | 4.29 |
| StdDev | 2.35 | 1.64 | 3.39 | 6.52 | 4.43 | 2.93 | 10.7 | 3.18 | 5.58 |
| 95% CI  [LL, UL] | [2.13,2.85] | [1.07,1.58] | [2.19,3.21] | [4.55,6.61] | [3.34,4.7] | [2.48,3.4] | [0.63,4.4] | [2.08,3.1] | [3.51,5.23] |
| IND-JLMIV+R-2020 | Mean | 24.76 | 2.31 | 4 | 11.12 | 13.1 | 13.33 | 8.29 | 6.31 | 16.49 |
| StdDev | 31.02 | 2.31 | 4.17 | 8.44 | 15.25 | 15.94 | 33.3 | 4.16 | 11.26 |
| 95% CI  [LL, UL] | [21.42,29.02] | [2.03,2.56] | [3.56,4.6] | [10.09,12.05] | [11.66,15.12] | [11.78,15.4] | [5,12.87] | [5.84,6.84] | [15.25,17.79] |
| Range of mean | [minMean, maxMean] | [1.59,24.76] | [1.32,7.66] | [2.56,86.11] | [5.54,95.84] | [4,51.24] | [1.16,13.33] | [0,8.29] | [2.56,13.68] | [4.29,16.49] |

Table 13. Naive Bayes: Distribution of the absolute performance gain ratio |*pgr*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 8.48 | 5.5 | 2.56 | 6.18 | 4.14 | 4.83 | 4.97 | 13.71 | 7 |
| StdDev | 1.25 | 1.18 | 0.42 | 0.3 | 0.3 | 0.4 | 6.26 | 3.91 | 1.23 |
| 95% CI  [LL, UL] | [7.1,9.29] | [4.14,6.18] | [2.19,2.83] | [5.88,6.38] | [3.84,4.34] | [4.39,5.1] | [1.36,8.59] | [9.27,16.16] | [6.05,8.38] |
| Metrics-Repo-2010 | Mean | 92.73 | 26.18 | 86.11 | 95.84 | 51.24 | 31.66 | 19.05 | 371.36 | 80.29 |
| StdDev | 194 | 29.01 | 334.27 | 336.93 | 151.68 | 33.66 | 25.74 | 2059.54 | 191.79 |
| 95% CI  [LL, UL] | [58.77,168.44] | [20.23,34.88] | [38.54,264.87] | [46.68,299.75] | [27.73,136.51] | [24.74,42.51] | [13.32,26.74] | [83.38,2049.23] | [47.23,165.24] |
| JIRA-HA-2019 | Mean | 11.65 | 12.44 | 4.82 | 16.49 | 10.1 | 14.33 | 3.41 | 84.42 | 52.87 |
| StdDev | 8.95 | 9.35 | 3.69 | 13.81 | 7.4 | 10.7 | 3.43 | 135.46 | 82.82 |
| 95% CI  [LL, UL] | [9.11,15] | [9.71,15.83] | [3.85,6.17] | [12.5,20.9] | [8.11,12.63] | [11.33,18.04] | [2.61,4.66] | [52.88,152.57] | [35.52,103.74] |
| JIRA-RA-2019 | Mean | 10.21 | 8.89 | 3.6 | 13.53 | 7.73 | 11.25 | 5.68 | 52.79 | 43.79 |
| StdDev | 12.25 | 7.88 | 3.36 | 13 | 7.66 | 9.04 | 11.12 | 75.04 | 87.53 |
| 95% CI  [LL, UL] | [6.89,14.29] | [6.58,11.4] | [2.7,4.74] | [9.69,17.66] | [5.62,10.53] | [8.46,14.14] | [3.47,11.94] | [35.36,89.01] | [28.06,100.88] |
| MA-SZZ-2020 | Mean | 5.53 | 3.28 | 2.63 | 5.54 | 4 | 5.26 | 7.27 | 230.44 | 33.33 |
| StdDev | 6.21 | 4.11 | 3.39 | 6.52 | 4.43 | 5.4 | 41.84 | 2652.38 | 113.55 |
| 95% CI  [LL, UL] | [4.67,6.66] | [2.7,3.93] | [2.16,3.24] | [4.68,6.62] | [3.37,4.75] | [4.43,6.1] | [3.34,23.7] | [17.61,1280.28] | [22.57,74.03] |
| IND-JLMIV+R-2020 | Mean | 20.65 | 6.29 | 4 | 11.12 | 13.1 | 14.9 | 20.56 | 54.11 | 67.78 |
| StdDev | 30.86 | 10.96 | 4.17 | 8.44 | 15.25 | 15.13 | 50.81 | 166.62 | 98.29 |
| 95% CI  [LL, UL] | [17.79,24.98] | [5.38,8.07] | [3.58,4.57] | [10.15,12.1] | [11.57,15.15] | [13.39,16.89] | [15.25,27.35] | [42.45,91.92] | [58.71,81.33] |
| Range of mean | [minMean, maxMean] | [5.53,92.73] | [3.28,26.18] | [2.56,86.11] | [5.54,95.84] | [4,51.24] | [4.83,31.66] | [3.41,20.56] | [13.71,371.36] | [7,80.29] |

Table 14. Logistic Regression: distribution of the prediction performance |*diff*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 1.28 | 1.41 | 2.23 | 5.14 | 2.98 | 0.46 | 0 | 2.78 | 4.86 |
| StdDev | 0.29 | 0.2 | 0.13 | 0.83 | 0.74 | 0.04 | 0 | 0.09 | 0.63 |
| 95% CI  [LL, UL] | [0.98,1.47] | [1.19,1.54] | [2.1,2.31] | [4.2,5.65] | [2.15,3.45] | [0.41,0.49] | [0,0] | [2.7,2.84] | [4.5,5.23] |
| Metrics-Repo-2010 | Mean | 11.08 | 6.64 | 109.88 | 119.58 | 59.04 | 7.71 | 12.87 | 13.27 | 14.04 |
| StdDev | 11.89 | 6.91 | 475.06 | 479.46 | 185.97 | 11.81 | 57.22 | 17.1 | 15.16 |
| 95% CI  [LL, UL] | [8.53,15.27] | [5.17,8.9] | [40.71,425.3] | [48.68,403.52] | [31.21,157.17] | [5.57,12.74] | [3.51,44.34] | [9.56,18.64] | [10.66,18.6] |
| JIRA-HA-2019 | Mean | 5.72 | 4.9 | 5.42 | 14.9 | 9.76 | 8.03 | 0 | 7.97 | 14.41 |
| StdDev | 8.98 | 4.16 | 4.13 | 12.5 | 6.41 | 7.32 | 0 | 7.34 | 13.74 |
| 95% CI  [LL, UL] | [3.76,10.25] | [3.78,6.39] | [4.43,6.92] | [11.64,19.36] | [7.89,12] | [6.17,10.74] | [0,0] | [6.01,10.62] | [10.73,19.13] |
| JIRA-RA-2019 | Mean | 5 | 4.44 | 4.26 | 13.12 | 7.48 | 6.91 | 0 | 7.1 | 13.19 |
| StdDev | 5.05 | 5.18 | 5.32 | 13.39 | 8.07 | 6.36 | 0 | 6.8 | 15.93 |
| 95% CI  [LL, UL] | [3.74,6.94] | [3.2,6.54] | [3.07,6.25] | [9.7,17.66] | [5.13,10.01] | [5.16,8.9] | [0,0] | [5.17,9.33] | [9.61,21.15] |
| MA-SZZ-2020 | Mean | 2.18 | 1.36 | 2.71 | 5.77 | 3.82 | 2.79 | 0.57 | 2.6 | 5.85 |
| StdDev | 2.17 | 1.5 | 3.18 | 6.12 | 4.16 | 2.58 | 3.87 | 3.05 | 6.85 |
| 95% CI  [LL, UL] | [1.86,2.56] | [1.14,1.63] | [2.29,3.3] | [4.85,6.84] | [3.23,4.54] | [2.41,3.27] | [0.16,1.5] | [2.21,3.11] | [4.86,6.96] |
| IND-JLMIV+R-2020 | Mean | 22.65 | 2.36 | 4.36 | 12.83 | 11.82 | 15.75 | 18.46 | 6.45 | 18.06 |
| StdDev | 31.47 | 2.27 | 3.61 | 8.59 | 14.78 | 22.44 | 73.49 | 4.26 | 15.36 |
| 95% CI  [LL, UL] | [19.49,26.85] | [2.1,2.61] | [3.95,4.78] | [11.9,13.87] | [10.34,13.84] | [13.41,18.67] | [11.77,28.04] | [6.01,6.95] | [16.5,20.11] |
| Range of mean | [minMean, maxMean] | [1.28,22.65] | [1.36,6.64] | [2.23,109.88] | [5.14,119.58] | [2.98,59.04] | [0.46,15.75] | [0,18.46] | [2.6,13.27] | [4.86,18.06] |

Table 15. Logistic Regression: Distribution of the absolute performance gain ratio |*pgr*| in CVDP

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | | Classification scenario | | | | | Ranking scenario | | | |
| *F*1 | *AUC* | *ER* | *RI* | *MCC* | *AP* | *RR* | *Popt* | *ACC* |
| ECLIPSE-2007 | Mean | 6.82 | 4.66 | 2.23 | 5.14 | 2.98 | 4.12 | 2.58 | 12.2 | 7.19 |
| StdDev | 3.12 | 0.38 | 0.13 | 0.83 | 0.74 | 0.18 | 2.26 | 3.08 | 1.28 |
| 95% CI  [LL, UL] | [3.34,8.83] | [4.23,4.9] | [2.1,2.31] | [4.2,5.65] | [2.15,3.45] | [3.92,4.23] | [1.19,3.91] | [8.7,13.75] | [6.41,7.95] |
| Metrics-Repo-2010 | Mean | 85.79 | 38.18 | 109.88 | 119.58 | 59.04 | 42.48 | 38.63 | 669.81 | 83.76 |
| StdDev | 184.85 | 108.65 | 475.06 | 479.46 | 185.97 | 79.56 | 84.88 | 3676.07 | 187 |
| 95% CI  [LL, UL] | [53.91,163.56] | [21.8,107.53] | [42.05,378.26] | [49.42,369.72] | [30.81,141.88] | [29.39,88.54] | [23.04,74.48] | [140.09,3049.32] | [43.88,146.68] |
| JIRA-HA-2019 | Mean | 11 | 12.33 | 5.42 | 14.9 | 9.76 | 13.18 | 4.27 | 56.61 | 89.5 |
| StdDev | 8.12 | 9.48 | 4.13 | 12.5 | 6.41 | 10.32 | 5.82 | 55.95 | 313.79 |
| 95% CI  [LL, UL] | [8.73,13.71] | [9.78,15.7] | [4.41,6.88] | [11.37,19.64] | [8.08,12.03] | [10.35,17.07] | [2.91,6.78] | [43.7,81.19] | [35.65,342.25] |
| JIRA-RA-2019 | Mean | 9.96 | 13.25 | 4.26 | 13.12 | 7.48 | 11.69 | 2.66 | 33.93 | 37.6 |
| StdDev | 10.89 | 26.58 | 5.32 | 13.39 | 8.07 | 10.2 | 3.02 | 35.11 | 46.2 |
| 95% CI  [LL, UL] | [7.04,13.76] | [8.06,29.44] | [3,6.43] | [9.31,17.78] | [5.2,10.2] | [8.7,15.1] | [1.86,3.76] | [25.56,47.18] | [27.12,58.07] |
| MA-SZZ-2020 | Mean | 5.37 | 3.51 | 2.71 | 5.77 | 3.82 | 5.2 | 3.05 | 41.06 | 24.34 |
| StdDev | 5.79 | 3.84 | 3.18 | 6.12 | 4.16 | 4.51 | 6.32 | 187.37 | 35.32 |
| 95% CI  [LL, UL] | [4.56,6.32] | [2.95,4.18] | [2.26,3.28] | [4.88,6.8] | [3.22,4.48] | [4.52,5.91] | [2.31,4.61] | [20.41,94.07] | [19.73,30.29] |
| IND-JLMIV+R-2020 | Mean | 18.89 | 6.76 | 4.36 | 12.83 | 11.82 | 16.7 | 94.15 | 99.71 | 103.08 |
| StdDev | 30.82 | 14.22 | 3.61 | 8.59 | 14.78 | 22.86 | 883.71 | 390.98 | 179.42 |
| 95% CI  [LL, UL] | [15.98,22.76] | [5.64,9.65] | [3.92,4.75] | [11.92,13.95] | [10.34,13.77] | [14.45,19.58] | [37.69,321.66] | [66.87,165.51] | [85.18,126.72] |
| Range of mean | [minMean, maxMean] | [5.37,85.79] | [3.51,38.18] | [2.23,109.88] | [5.14,119.58] | [2.98,59.04] | [4.12,42.48] | [2.58,94.15] | [12.2,669.81] | [7.19,103.08] |

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# **Appendix E. To what extent might previous studies be potentially influenced by inconsistent labels?**

In this section, we answer this question by investigating the number of previous studies that used them as the subject data sets to conduct their experiments.

In order to avoid ambiguity, we separate the two concepts of “number of citations” and “number of literatures that had experimented with the collected data sets”. The “number of citations” refers to the total number of citations by other literatures for the original papers that published the target multi-version-project defect data set. The “number of literatures that had experimented with the collected data sets” refers to the total number of other literatures, which not only cited the original papers of the target multi-version-project defect data set, but also used the target multi-version-project defect data set in their experiments. Generally, “number of citations” cannot be used as a proxy for the frequency of a data set usage, because other literatures may only introduce the methods or ideas of the cited paper. Therefore, we additionally count the “number of literatures that had experimented with the collected data sets” as a proxy for the frequency of a data set usage.

Table 9 in Section 8.4 summarizes the “number of citations” and “number of literatures that had experimented with the collected data sets” for the existing multi-version-project defect data sets investigated in our study. The 1st column lists five existing multi-version-project defect data sets investigated in our study. The 2nd column lists the original paper(s) publishing each multi-version-project defect data set. The 3rd column reports how many other literatures cite the original literature, i.e., “number of citations” (reported by Google scholar, March 26, 2021). The 4th column reports the total number of other literatures (written in English) that use the corresponding data sets to conduct their experiments, i.e., “number of literatures that had experimented with the collected data sets” (inspected by the first author and confirmed by the seventh author). The 5th column reports the list number range of “literatures that had experimented with the collected data sets”. Note that the Metrics-Repo-2010 data set was first published in [A2]. However, most literature cite [A3] and [A4] as its source. The reason was that [A3] was published in a well-known international conference on Predictive Models in Software Engineering (PROMISE), aiming to share publicly accessible data sets. In particular, Metrics-Repo-2010 was put on the corresponding promise repository website [A4]. Given this situation, we use them (i.e. [A2], [A3], and [A4]) as three sources to count the number of (different) citations. As can be seen, JIRA-RA-2019 (JIRA-HA-2019) and IND-JLMIV+R-2020 data sets were used by few studies (the “number of literatures that had experimented with the collected data sets” are 6 and 5 respectively), as they are two recently published multi-version-project defect data sets. However, ECLIPSE-2007 and Metrics-Repo-2010 data sets were widely used in previous studies (the “number of literatures that had experimented with the collected data sets” is 144 and 264 respectively). This indicates that inconsistent labels have a potentially wide influence on previous studies.

It is important to note that the influence of inconsistent labels on the existing literature may be overestimated, although the “number of literatures that had experimented with the collected data sets” is a more secure proxy for estimating the potential influence of inconsistent labels than the “number of citations”. This is because our study does not conduct replication experiments to investigate the specific influence of inconsistent labels on each of the existing literatures (it is a large amount of work that could not be done in our study alone). It is still an open problem to investigate the actual influence of each multi-version-project defect data set with inconsistent labels on the existing literatures, pending an in-depth or extensive empirical study in the future.

Table 9. Literatures potentially influenced by target multi-version-project defect data sets

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Defect data sets | Source | Number of citations | Number of literatures that had experimented with the collected data sets | List number range of literatures that had experimented with the collected data sets |
| ECLIPSE-2007 | [A1] | 817 | 144 | [1~144] |
| Metrics-Repo-2010 | [A2, A3, A4] | 453 | 264 | [145~408] |
| JIRA-HA-2019 / JIRA-RA-2019 | [A5] | 17 | 6 | [409~414] |
| IND-JLMIV+R-2020 | [A6] | 9 | 5 | [415~419] |

The literatures of five target multi-version-project defect data sets

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1. https://scitools.com [↑](#footnote-ref-1)
2. https://www.python.org [↑](#footnote-ref-2)