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When Less is More: On the Value of “Co-training” for Semi-Supervised Software Defect Predictors

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Abstract Labeling a module defective or non-defective is an expensive task. Hence, there are often limits on how much-labeled data is available for training. Semi-supervised classifiers, use far fewer labels for training models but there are numerous semi-supervised methods including self-labeling, co-training, maximal-margin, graph based methods, to name a few. Only a handful of these methods has been tested in SE for (e.g.) predicting defects– and even that, those tests have been on just a handful of projects.

This paper takes a wide range of 55 semi-supervised learners and applies these to over 714 projects. We find that semi-supervised “co-training methods” work significantly better than other approaches. However, co-training need to be used with caution since the specific choice of co-training methods need to be carefully selected based on a user’s specific goals. Also, we warn that a commonly-used co-training method (“multi-view”— where different learners get different sets of columns) does not improve predictions (while adding too much to the run time costs 11 hours vs 1.8 hours).

Those cautions stated, we find using these “co-trainers”, we can label just 2.5% of data, then make predictions that are competitive to those using 100% of the data. It is an open question worthy of future work to test if these reductions can be seen in other areas of software analytics.

All the codes used and datasets analysed during the current study are available in the [GitHub repository link](https://GitHub.com/Suvodeep90/Semi_Supervised_Methods).
1 Introduction

In recent years, defect predictions have drawn considerable interest in software analytics [29, 35, 65–67, 79, 83, 88, 107, 126, 140, 141]. These metrics use process metrics (that describe how and who updates the code) or product metrics (such as the number of methods per class, and lines of codes, to name a few) to produce software quality prediction. A decade ago, a formal study in this field dealt with just 20 projects or fewer. Now we can access data on hundreds to thousands of projects. When the creation of such models is fully automated (using data mining), then this approach scales a large number of projects. Hence, data-driven decision-making is widely used in SE research and industrial [45,103,110].

One vital step in building these defect predictor models is finding the labels (or “ground truth”) for training data, as supervised learning requires all training data to be labeled. These supervised algorithms can perform poorly if they do not have adequate labeled training data. Generating these adequate labeled training data can be very expensive via human labor. For example, we have studied approximately 714 software projects, including 476K commit files. After an extensive analysis, Tu et al. [106] proposed a cost model for labeling that data. Assuming two people checking per commit, that data would need three years of effort to label the data.

Since labeling is so labor-intensive, often, a large amount of unlabeled data and a small amount of labeled data points are available. To make good use of these unlabeled data, researchers use many different processes to label them. Semi-supervised learning (SSL) [138,139] is a set of techniques that fall between unsupervised learning (that uses no labels [38,121,127,131]) Furthermore, supervised learning (that must label all training data [18,43,47,85,88]).

There are many ways to build a semi-supervised learner, such semi-supervised GMM [24,31] that builds a cluster with all the data on the independent attributes, then label one example per cluster, next, copy that label to all other items in that cluster. This paper explores 55 SSL methods, drawn across the hierarchy of Figure 1. The original motivation for this paper was that prior SE work on SSL used methods drawn from just a small section of that figure. For example, all the following methods come from the left-hand side of Figure 1. Li et al. [53] explored the coForest and AcoForest method, which is a co-training method that falls under wrapper-based methods. Li et al. [55] also studied a co-training-based method named Effort-Aware Tri-Training (EATT), which is an effort-aware semi-supervised method based on co-training. Fitting-the-confident-Fits (FTcF) is another semi-supervised algorithm used in defect prediction [58], which is a self-training-based method. ExtRF, as proposed by He et al. [34], is another example of a self-training-based semi-supervised method used for defect prediction. Zhang et al. [130] uses a label propagation algorithm, a graph-based semi-supervised algorithm, to find bugs in software systems. Hysom, as proposed by Abaei et al. [1] is a semi-supervised model based on a self-organizing map and artificial neural network, which falls under unsupervised preprocessing.
This paper explores 55 methods from the pink nodes. The other blue nodes are left for future work since these notes use methods that are either (a) very computational expensive or (b) have been developed for data types not relevant to our target (defect prediction).

To better understand the role of different SSL methods, this paper studies 55 semi-supervised models on a large dataset (of 714 projects) to answer the following research questions:

- **RQ1:** Are there SSL models which perform better or worse than others? We will find that co-training works best where multiple learners share their most confident answers.
- **RQ2:** How do SSL models perform with increased data size? We will find that only 2.5% of the data needs to be labeled.
- **RQ3:** Do all Semi-supervised learners perform the same? We will show that different learning goals (e.g., very low alarms) select for different learners.

More specifically, the semi-supervised literature often references a set of widely applied techniques (listed below in **bold face**). The following research questions assess the value of those specific techniques for software analytics and defect prediction:

- **RQ4:** Between single-view and Multi View models is one preferable than others? (Our answer will be that there is no performance difference and multi-view is much slower).
- **RQ5:** Should we prefer single vs multi classifier methods? (Our answer will be that multi is much better).
- **RQ6:** Should we prefer self or mutual-teaching? (Our answer will be that mutual-teaching is preferable.)
From these results, we summarize our contributions as follows:

- A experimental demonstration that certain SSL methods (single-view co-training) can decrease the labeling cost of defect prediction by a factor of $100/2.5=40$.
- A detailed empirical analysis and evaluation of semi-supervised algorithms and models to analyze the capabilities of these algorithms and to identify the best methods.
- One of the largest analysis of semi-supervised algorithms on 714 defect prediction projects to establish our claim.
- Analysis of model performance and labeled data availability by varying ratio of labeled data, and to identify relevant changes in performance.
- Implementation of all the semi-supervised algorithms used in this study in an open-source GitHub repository for future researchers[1].
- Detailed discussion about the performance of the models in different performance measures and how to select the best model for future research and comparison on semi-supervised algorithms in the defect prediction domain.

The rest of this paper is structured as follows. Some background and related work are discussed in section 2. Our experimental methods are described in section 3. Data collection in section 3.1 and learners used in this study are mentioned in section 3.2. Followed by the experimental framework in section 3.3. The evaluation criteria are in section 3.4. The results and answers to the research questions are presented in section 4. Next, the discussion about our result is in section 5. Threats to validity follow this in section 6. Finally, conclusion in section 7.

Before we start, we digress to make the following point. Since there are so many SSL methods, we had to limit the scope of this investigation for pragmatic reasons. Hence, here, we have not explored and used all of these semi-supervised methods as reported by Van et al. [108]. For example, we have excluded very computationally expensive methods (since that would complicate a large-scale analysis such as this one). In future work, it would be insightful to explore those excluded methods.

2 Background

This section comments on (a) standard defect prediction methods (that require labels on 100% of the training data) and (b) dozens of semi-supervised methods (that require much less than 100% of the labels).

2.1 Defect Prediction

Bugs are not evenly distributed across software [33, 49, 69, 80]. Hence it is impractical and inefficient to distribute equal effort to every component in a

[1] https://github.com/ai-se/Semi-Supervised
software system [16]. Algorithms that measure the criticality or bugginess of software using source code (product) or project history (process) are called defect prediction models. In a recent paper, Wan et al. [110], reported much industrial interest in these predictors since the alternative is much more time-consuming and expensive. Misirili et al. [69] and Kim et al. [46] report considerable cost savings when such predictors are used in guiding industrial quality assurance processes. Such defect predictors learned from static source code are remarkably effective compared to other methods. Rahman et al. [87] compared (a) static code analysis tools FindBugs, Jlint, and PMD with (b) defect predictors (which they called “statistical defect prediction”) built using logistic regression. No significant differences in cost-effectiveness were observed. This is significant since defect prediction can be quickly adapted to new languages (by building lightweight parsers). At the same time, other methods (e.g., static code analyzers) need extensive modification before they can be used in new languages.

Due to their ease of use, defect predictors are widely applied:

1. Application of defect predictors to locating security vulnerabilities [94].
2. Understanding what increases defects (e.g., ratio comment to code, cyclomatic complexity) [63,64] or process metrics (e.g. see Table 1).
3. Predicting where are the bugs, to allocate appropriate resources (e.g. [14])
4. Using predictors to proactively fix defects [77]
5. Release-level [21] change-level or just-in-time [88] prediction.
6. “Transfer learning” applies predictors built from one project to others [51,73].
7. Assessing different learning predictors [28]. This has led to the development of hyper-parameter optimization and better data harvesting tools [3,5].

Table 1: List of process metrics used in this study

| Metric       | Description                                           |
|--------------|-------------------------------------------------------|
| adev         | Active Dev Count                                      |
| age          | Interval between the last and the current change      |
| ddev         | Distinct Dev Count                                    |
| sctr         | Distribution of modified code across each file        |
| exp          | Experience of the committer                           |
| la           | Lines of code added                                   |
| ld           | Lines of code deleted                                 |
| lt           | Lines of code in a file before the change             |
| minor        | Minor Contributor Count                               |
| nadev        | Neighbor’s Active Dev Count                           |
| ncomm        | Neighbor’s Commit Count                               |
| nd           | Number of Directories                                 |
| nddev        | Neighbor’s Distinct Dev Count                         |
| ns           | Number of Subsystems                                  |
| nuc          | Number of unique changes to the modified files        |
| own          | Owner’s Contributed Lines                             |
| sexp         | Developer experience on a subsystem                   |
| rexp         | Recent developer experience                           |
As to what data to the collection, process metrics comment on “who” and “how” the code was written, while product metrics record “what” was written. Researchers and industry practitioners have tried many different ways to identify which features are important and why. Zimmermann et al. [112] recommended complexity-based product metrics, Zhou et al. [134] suggest size-based metrics. While Matsumoto et al. [62] and Nagappan et al. [72] recommend developer-related metric and change bursts metrics, respectively. Table 1 metrics for both theoretical and pragmatic reasons. Our metrics include the process metrics since prior studies have shown promising results and have been endorsed by Rahman et al. at ICSE’13 [86], Majumder et al. [60] and others.

After saying “what” data to collect, the next question is “how much” data to collect? In most of the above work, labels are needed for 100% of the data. However, in many situations, labels are missing or mistrusted, meaning we must collect some new labels before the work can proceed. The lesson of this paper will be that, with the semi-supervised learning methods described below, we only need labels on a small part of the data (specifically, just 2.5% ).

2.2 Semi-Supervised Learning

Semi-supervised learning avoids searching labeled data or manually annotating unlabeled data. Such methods combine supervised and unsupervised learning, which uses a small amount of labeled data and a large amount of unlabeled data.

According to Figure 1, SSL methods can be divided into inductive and transductive, where the former attempts to find a classification model. At the same time, the latter tries to obtain label predictions for the given unlabeled data points. After that, semi-supervised methods are divided based on how they utilize the unlabeled data points. This includes three categories, wrapper based, unsupervised preprocessing and intrinsically semi-supervised.

Inductive methods can further be divided into Wrapper-Based Methods, Unsupervised Pre-processing Methods, and Intrinsically semi-supervised methods. While transductive methods are graph-based methods.

2.2.1 Wrapper-Based Methods:

Wrapper methods loop over the data and, in every loop, apply training followed by pseudo-labeling phase. Starting with a very small of labels, the first training phase builds a model, which is then used to label the rest of the data. The labels that are “most confident” (defined below) are added to the pre-existing labeled data and these are used for training in the next loop. Our reading of the literature is that such wrappers are the most widely used algorithms in semi-supervised learning.

Wrapper-Based methods can differ according to how pseudo-labeling is performed:
Self-training methods use a supervised classifier that iterates and re-trains on its own most confident predictions.

In co-training, multiple supervised learners iterate and re-train on each other’s most confident predictions.

Boosting methods 

Further notes on these three methods are offered below.

**Self-training:** Self-training was first proposed by Yarowsky et al. for word sense disambiguation task. Dópido et al. used a self-training approach for hyperspectral image classification. The self-training process includes multiple design choices, including selecting pseudo-label data, re-using pseudo-labeled data, and stopping criteria. When selecting unlabeled data for pseudo-labeling, it is often based on prediction confidence from the last model. This directly influences the algorithm’s performance. If the base classifiers for the self-training have probabilistic predictions, then respective probabilities can be used directly. When the base classifiers do not natively support probabilistic predictions may require some adaptations for self-training. Decision trees and random forests are excellent examples of this; without any modifications, they show highly biased probability estimates. This is improved by either applying grafting or Laplace correction methods or by using the local distance-based measure to determine the confidence score between instances, as shown by Tanha et al. in their studies.

**Co-training:** Co-training is where two or more supervised classifiers are iteratively trained on the labeled data. At each iteration, models are trained on labeled data along with pseudo-labeled data, where pseudo-labeled data comes from the most confident predictions to the unlabeled data set of the other supervised classifiers. One basic assumption is that the base learners are not too strongly correlated in their predictions. That will hinder the ability to provide each other with useful information, usually referred to as the diversity criterion. In co-training, this diversity can be created in three different ways:

(a) Single-view co-training: This type of co-training is performed by promoting diversity in the learning algorithms themselves and not splitting the features. One way to achieve this is to use different hyper-parameters, another is to use different algorithms altogether. One prominent approach in single-view co-training is the tri-training method proposed by Zhou et al., where three classifiers are trained if two of the three classifiers agree, then the data point is passed to the other classifier along with the respective label. Tri-training does not rely on probabilistic predictions and thus can be used for a much broader range of learning algorithms. Zhou et al. proposed another method called co-forest. Here decision trees are independently trained on all labeled data. At each step, each classifier receives pseudo-labeled data using predictions from all other classifiers on the unlabeled data if it exceeds a certain threshold.
(b) **Multi-view co-training:** Here, two classifiers are trained on two distinct views-based subsets of data features. Like single-view co-training, after each iteration in the pseudo-labeling process, the most confident predictions for each model are added to the set of labeled data for the other model. This method was first proposed by Blum et al. [15]. Multi-view co-training adds a new assumption to the base assumption for co-training; first, each subset of features should be sufficient to obtain good predictions, and second, the subsets of features should be conditionally independent given the class label. Although many researchers have shown these assumptions are not strictly bound and can be relaxed as required [2, 10].

(c) **Co-regularization:** The goal of co-training is to minimize classifier disagreement along with the error rate of the ensemble. In co-regularization, both the disagreement between learners and the error rate of the ensemble are simultaneously optimized by generating one optimization function with two terms, one to penalize incorrect predictions, another to penalize different predictions [95].

**Boosting:** Basic ensemble models uses multiple base classifiers, and the prediction is independent and aggregates from all classifiers. In the case of boosting, each base learner depends on the previous base learners: it is provided with the entire data set, but weights are applied to the data points. The weights are generated based on performance from the previous learner. The final prediction is obtained as a linear combination of the predictions of the base classifiers. Boosting in a semi-supervised setting is achieved by introducing pseudo-labeled data after each learning step and using that pseudo-labeled data along with labeled data for the next training step. Bennett et al. [12] introduced ASSEMBLE (Adaptive Supervised Ensemble) algorithm, which is a boosting method to maximize the classification margin in function space. Another boosting algorithm is SemiBoost [2], which uses manifold assumptions from graph-based methods. Each unlabeled data point is assigned a pseudo-label, and the corresponding prediction confidence is calculated based on a predefined neighborhood graph encodes similarity between data points.

### 2.2.2 Semi-supervised preprocessing:

These methods use the data in two stages:

- **Stage1** uses hints from unlabeled data to extract or transform features or uses the features to form unsupervised clusters.
- **Stage2** uses the labeled data for training or labeling.

Based on the first stage of semi-supervised preprocessing, it can be further divided into two groups. (a) **Feature extraction based semi-supervised preprocessing:** As many feature extraction methods are unsupervised, they can be used to extract and transform the original data to a more linearly uncorrelated format. There are many such algorithms available i.e., principal component analysis (PCA) [114] and Multidimensional scaling (MDS) [23]. The extracted features and the labeled examples models are trained (similar to self-training). In their paper, Lu et al. [58] introduced one such method called FTcF.MDS.
where first MDS is used for transforming the features, and then FTcF, a self-training based on semi-supervised learning, is used for predictions. Recent semi-supervised feature extraction methods have also focused on finding latent representations of the input data using deep neural networks. However, we have not explored deep neural networks as part of this study as we know latent representations of defect prediction datasets are very simple (often dimensional reduced to one). (b) **Clustering based semi-supervised preprocessing**: Clustering is an unsupervised method and is widely used for creating disjoint sets of data only based on the features. When used in the context of semi-supervised preprocessing, the process is to apply a clustering algorithm to all available data (both labeled and unlabeled data) and use the resulting clusters to guide the classification process. One such method is where we cluster all the data (both labeled and unlabeled data) first, and then a self-training model trained independently for each cluster [31]. Another algorithm proposed by Demiriz et al. [24] clusters the data in a semi-supervised manner, where the clusters are formed in an unsupervised way. Then we label clusters based on the labeled data impurity and use that for prediction.

### 2.2.3 Intrinsically semi-supervised methods:

Suppose a learner that has learned a decision boundary from a few labels. Suppose further that that learner using some **objective function** to classify examples according to those labels. Intrinsic methods adapt the objective function to use information from the unlabeled examples found near the labeled examples. In this way, semi-supervised intrinsic learning can make do with a limited number of labels.

Several intrinsically semi-supervised methods are “maximum-margin” methods. Supervised maximum-margin methods maximize the distance between the given data points and the decision boundary. Maximum-margin methods are extended into semi-supervised settings by adding information from unlabeled data to the objective function, which decides the decision boundary. These methods are often applied within a support vector machine (SVM); e.g., using a low-density assumption to maximize the distance from the decision boundary to the closest points. Semi-supervised SVMs or S3VMs, as proposed by Vapnik et al. [109], utilize similar assumptions to maximize the margin and correctly classify the data. Here the objective function adds a new term that penalizes unlabeled data based on their distance to the closest margin boundary. Many such algorithms have been proposed, such as TSVM by Chapelle et al. [19], where they solve the optimization of the objective function using label assignments. Li et al. [56] introduced a new version called S4VM (safe S3VM), which consists of two stages:

- A diverse set of low-density decision boundaries is constructed.
- The decision boundary with maximal worst-case performance gain over the supervised decision boundary is chosen as the result of S4VM training.

There are other models as well, including perturbation-based or Generative model-based methods, which fall under intrinsically semi-supervised methods.
These methods mostly use computationally-expensive deep neural networks and are excluded from further study in this paper.

2.2.4 Graph-Based Methods:

The intuition with graph-based methods is that we do not need to label all data. Rather, given a few labels, the rest of the data can draw their labels from “nearby examples.” Graph-based methods differ on (a) how they find “nearby” examples then (b) how they move those labels to themselves.

For example, some graph-based methods create a graph that connects instances in the training dataset and propagates labels from labeled data to unlabeled data through the edges of the graph. The methods generally involve three separate steps: graph creation, graph weighting, and inference:

– First, data points are represented as a node in the graph that are connected based on some similarity measure. Consider the geometry of the dataset, which an empirical graph can represent \( g = (V, E) \), where nodes \( V = 1, ..., n \) denote the training data and edges \( E \) represent the similarities or affinity between adjacent nodes.
– Next, the resulting edges are weighted, yielding a weight matrix.
– Once the graph is constructed, it is used for predicting the unlabeled data points. While iterating to generate the graph, it uses an objective function with two terms, one which penalizes predicted labels that do not match the actual label (for labeled examples), and another penalizes differences in the label predictions for connected nodes (for both labeled and unlabeled examples).

Two representative graph-based algorithms are label propagation and label spreading, which we will introduce in details in Section 3.2. Compared with other semi-supervised learning algorithms, graph-based methods are fast and easy to use due to their linear time complexity and therefore explored in this study.

3 Experimental Methods

This section describes the methods used to evaluate 55 SSL drawn from the abovementioned methods.

3.1 Data Collection

The data used in this study come from different software development domains. The data is collected from GitHub open source repositories. GitHub stores millions of projects; many are trivially very small, not maintained, or are not about software development projects. To filter projects, we used the standard Github “sanity checks” recommended in the literature.
| Metric Name | Median | IQR   | Data Property | Median | IQR   |
|-------------|--------|-------|---------------|--------|-------|
| la          | 14     | 39.9  | Defect Ratio  | 37.6%  | 20.6% |
| ld          | 7.9    | 12.2  | Lines of Code | 82K    | 200K  |
| lt          | 92     | 121.8 | Number of Files | 171    | 358   |
| age         | 28.8   | 35.1  | Number of Developers | 31     | 34    |
| ddev        | 2.4    | 1.2   | Number of PRs. | 55     | 101   |
| nuv         | 5.8    | 2.7   | Number of Commits | 217    | 379   |
| own         | 0.9    | 0.1   | Duration      | 186(W) | 191(W) |
| minor       | 0.2    | 0.4   | Number of Releases | 20     | 32    |
| ndev        | 22.6   | 22.1  | Number of Defective Commits | 77     | 139   |
| ncomm       | 71.1   | 49.5  | Number of Issues | 46     | 67    |
| adev        | 6.1    | 2.9   | Number of unique PR submitter | 5      | 6     |
| nadev       | 71.1   | 49.5  |               |        |       |
| avg_nndev   | 2      | 1.8   |               |        |       |
| avg_nadev   | 7      | 5.2   |               |        |       |
| avg_ncomm   | 7      | 5.2   |               |        |       |
| ns          | 1      | 0     |               |        |       |
| exp         | 348.8  | 172.7 |               |        |       |
| sexp        | 145.7  | 70    |               |        |       |
| rexp        | 2.5    | 3.4   |               |        |       |
| nd          | 1      | 0     |               |        |       |
| sctr        | -0.2   | 0.1   |               |        |       |

Table 2: Statistical median and IQR values for the metrics used in this study (IQR denotes the (75-25)th percentile range). Table 1

- **Collaboration**: refers to the number of pull requests. This is indicative of how many other peripheral developers work on this project. We required all projects to have at least one pull request. This will prove the repository is a part of distributed development model where others have forked/created a branch on this repository to make independent changes and submitted those changes to the main repository to be merged with the main branch. We also validated and removed any project where the same developers submit all pull requests by checking the unique ids of the pull request submitter.

- **Commits**: The project must contain more than 20 commits as recommended in the literature. Commits in a GitHub repository represent the amount of activity in the project. More than 75% of the projects found on GitHub have less than 20; thus, 20 is a good number for this filtering criteria.

- **Duration**: The project must contain software development activity of at least 50 weeks. Kallianvakou et al. show in their paper that 75% of the projects are active for less than 14 weeks; thus, 50 weeks as a minimum duration for the filtering criteria is used as suggested by other researchers.

- **Issues**: The project must contain more than ten issues as recommended in the literature.

- **Releases**: The project must contain at least four releases. This is because the release-based validation strategy used in this study requires 3 test releases and at least one training release.
– **Personal Purpose**: The project must not be used and maintained by one person. The project must have at least eight contributors, as suggested by other researchers.

– **Software Development**: The project must only be a placeholder for software development source code.

– **Defective Commits**: The project must have at least ten defective commits with defects on Java files. This is because the SMOTE algorithm that we use to balance the datasets requires at least ten examples of the minority class.

– **Forked project**: The project must not be a forked project from the original repository. This is to remove any potential duplicity from the study that is not the project’s main branch. We used the GitHub API to check for the “Forked” flag, and we removed any project which is flagged as yes.

The initial project pull was approximately 714 projects. After applying the sanity checks mentioned above, we selected 714 projects. The Data Statistics section of Table 2 shows the median and IQR of each of the filtering criteria for the selected projects. We collected file-level process metrics for this research to answer our research questions.

This data was extracted once and stored as pickle files in the following three steps:

1. We collected 21 process metrics (following the definition either from commit.guru or from the definitions shared by Rahman et al.) for each file in each commit by extracting the commit history of the project, then analyzing each commit for our metrics. We used a modified version of Commit.Guru [89] code for this purpose, where instead of aggregating filespecific metric values for a commit, we store metric values for each file. We create objects for each new file we encounter and keep track of details (i.e., a developer who worked on the file, LOCs added, modified, deleted by each developer) that we need to calculate. We also keep track of files modified together to calculate co-commit-based metrics. After collecting the 21 metrics mentioned in Table 2 for each project, it is stored as a pickle file for prediction.

2. Secondly, we use Commit.Guru [89] code to identify buginducing and bugfixing commits. This process involves identifying bugfixing commits using a keyword-based search. Using these commits, the process uses the commit.guru’s SZZ algorithm [89, 113] to find commits that were responsible for introducing those changes and marking them as buginducing [3]. This process is performed on all commits throughout the project’s life cycle. Note here for a buginducing, each file labeled as a buggy file (buginducing) will have another instance of the same file, non-buggy (bugfixing). If a file has been fixed multiple times throughout the project history, it will have multiple instances in the dataset.

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2 The keywords used are - bug, fix, error, issue, crash, problem, fail, defect and patch. These keywords are taken used by Rosen et al. in their commit.guru [89] paper.

3 From this point onwards, we will denote the commit which has bugs in them as a “buginducing
3. Thirdly, we used GitHub tag API to collect the release information for each project. We use the release number, and release date information supplied from the API to group commits into releases and thus divide each project into multiple releases for each metric. Note here that we refer to a release number as the tags provided by the contributors of the repository, not by GitHub. Thus we apply regular expressions to match the release number to either “XXXX” or “XXX” format. Here for a tag to be considered as a release, it needs to be different in the section before the third dot.

Note that steps one and two require two days (on a single 16 cores machine). The data collected in this way are summarized in Table 2.

3.2 Learners

This section briefly explains the classification methods (both supervised and semi-supervised) we have used for this study. We selected the supervised methods following a prominent paper by Ghotra et al.’s [29]. Also, all these learners are widely used in the software engineering community. For all the supervised models, we use the implementation from Scikit-Learn. While for semi-supervised models, we have used the few available methods from Scikit-Learn, for the rest, we have either used the package created by the original authors of those methods or implemented the methods ourselves.

3.2.1 Supervised Learners:

This section describes the supervised learners used in this study, either for the supervised learner itself or for the base learner for wrapper-based methods. We have used the implementation and default parameters from Scikit-Learn.

**Support Vector Machine:** This is a discriminative classifier, which tries to create a hyper-plane between classes by projecting the data to a higher dimension using kernel tricks [17, 59, 90, 102]. The model learns the separating hyper-plane from the training data and classifies test data based on which side the example resides.

**Naive Bayes:** This is a probabilistic model, widely used in the software engineering community [68, 92, 93, 96, 111], that finds patterns in the training dataset and builds predictive models. This learner assumes that all the variables used for prediction are not correlated or identically distributed. This classifier uses Bayes rules to build classifier. When predicting test data, the model uses the distribution learned from training data to calculate the probability of the test example belonging to each class and report the class with maximum probability.

**Logistic Regression:** This is a statistical predictive analysis method similar to linear regression but uses a logistic function to make predictions. Given 2 classes $Y=(0 \text{ or } 1)$ and a metric vector $X = x_1, x_2, \ldots, x_n$, the learner first

* [https://scikit-learn.org/stable/index.html](https://scikit-learn.org/stable/index.html)
learns coefficients of each metrics vector to best match the training data. When predicting for test examples, it uses the metrics vectors of the test example and the coefficients learned from training data to make the prediction using a logistic function. Logistic regression is widely used in defect prediction [29, 30, 76, 81, 125].

**Random Forest:** This is a type of ensemble learning method which consists of multiple classification decision trees built on random metrics and bootstrapped samples selected from the training data. Test examples are classified by each decision tree in the Random Forest, and then the final classification decision is decided using a majority vote. Random forest is widely used in the software engineering domain [39, 40, 51, 99, 104, 105, 111, 123, 127, 128] and has proven to be effective in defect prediction.

**K Nearest Neighbor:** This is one of the simplest and most effective methods based on dissimilarities among a set of instances. It belongs to the lazy learning family of methods, which do not build a model during the learning process. With this method, confidence predictions can be approximated by the distance to the currently labeled set.

**Decision Tree:** This is a non-parametric learning method that uses different features of the dataset to divide the data into smaller groups, where each sub-group is less impure than the group itself. The goal is to divide the data into a tree-like structure by calculating the impurity of a node based on different criteria.

Another algorithm we take from standard software analytics is SMOTE (Synthetic Minority Oversampling Technique) [20]. SMOTE addresses data class imbalance issues. Imbalanced data is a problem since, if the target class is infrequent, it is hard for a learner to find the target. To mitigate class imbalance, SMOTE samples from the minority classes and choosing $k$ nearest neighbors for each chosen sample. A synthetic instance is created at a randomly selected point between each pair of chosen samples and its neighbor. The synthetic samples are added to the original dataset to balance the ratio between majority and minority classes. We use SMOTE here since it has found prior success on our kinds of data [1].

3.2.2 **Semi-supervised Learners:**

This section shows a detailed description of the semi-supervised methods used in this study. This includes a broader category of semi-supervised methods, which includes Wrapper-Based Methods, Semi-supervised preprocessing, Intrinsically semi-supervised methods, and Graph-Based Methods, as shown in figure [1]. All the following methods are available for download and execution from this paper’s reproduction package [https://github.com/ai-se/Semi-Supervised].

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5 When performing such re-balancing, it is a methodological error to re-balance both the training and test sets (since learned models should be tested on data with the naturally occurring class frequencies. We assert that we re-balance only the training data and not the test.
**Self-training:** It is a type of semi-supervised learning method which falls under wrapper-based methods [97,122]. This is a two-step process with multiple iterations. In the first step, the training phase, we train one of the supervised learners on the labeled data and possibly pseudo-labeled data from the last iteration. In the next phase, the pseudo-labeling phase, using the previous model, a portion of unlabeled data that the learners are most confident of their predictions are labeled for use in the next iteration. We have used all the supervised models described above as the base learner for self-training.

**Co-training:** This type of wrapper-based methods [2,10,32,133] also contains two steps. In the training phase, two or more learners are trained on the labeled data and possibly pseudo-labeled data instead of one learner. The pseudo-labeled is based on the most confident prediction of the other learners [26, 32]. If there are more than two learners, the pseudo-labeling can be achieved by majority voting, booting, or other strategies [2,136]. We have used all combinations of supervised learners mentioned above as base models in co-training methods, excluding the same learner combinations. In Co-training, we adapt both single-view and multi-view settings. In the case of single-view settings, all learners use the same set of features (all features), while for multi-view settings, all learners use a different set of features. In the case of multi-view co-training, the features are selected by dividing the features based on correlations.

**Effort Aware Tri-training (EATT):** EATT is a type of co-training method which uses three learners. Zhou et al. [136] originally proposed the tri-training method as a traditional semi-supervised method. Zhang et al. [129] included effort-aware criteria for the pseudo-labeling phase in the tri-training method and achieved better performance both in term of traditional metrics and effort-aware metrics.

**Co-forest:** It is an extension of the co-training algorithm, which incorporates Random Forest to tackle the problems of determining the most confident examples to label and produce the final hypothesis. Co-Forest first trains an ensemble of classifiers on the labeled data set, then during each iteration of Co-Forest, the training and pseudo labeling phase are performed [54,124]. In the case of the co-forest algorithm, during the pseudo labeling phase, when determining the most confidently labeled examples for one of the classifiers of the ensemble, all other classifiers in the ensemble are used except the current one. This new ensemble is called a *concomitant ensemble*. In that ensemble, the confidence for an unlabeled example can be estimated by the degree of agreement on the labeling across the concomitant ensemble. If the confidence of unlabeled examples exceeds a certain threshold, then it is added to the current classifier of the ensemble; this step is performed for each classifier in the ensemble. To remove any potential negative influence of using a large amount of pseudo-labeled data, each data point is weighted by the predictive confidence of a concomitant ensemble. Also, to remove any adverse effect of noisy examples, during the pseudo-labeling phase, error rates are calculated based on the confidence score, and examples are only selected if the combined er-
ror rate of the current classifier does not increase from the error rate of the previous iteration of the current classifier.

**FTcF MDS:** It is a self-training algorithm combined with a dimension reduction technique. It was proposed by Lu et al. \[58\] in their study as a combination of semi-supervised preprocessing along with self-training and is widely used \[39,118\]. Here Multidimensional Scaling (MDS) has been used as a semi-supervised preprocessing step. MDS calculates distances between each pair of points in the original high-dimensional space and then maps it to lower-dimensional space while preserving those distances between points as well as possible. In FTcF MDS, first, a tuning phase is performed using the labeled data to identify a number of dimensions for the reduced data set (ranging from 1 to \(d\), where \(d\) is the dimension of the original data set). The tuning criteria for \(d\) is the evaluation function of generalized cross-validation based on the error rate normalized using generalized degrees of freedom for the classifier. Here Random Forest has been used as a classifier. The final model is built using the reduced dimension, where the error is minimized.

**Semi-Boost:** It is semi-supervised boosting algorithm \[12,61\], which improves a base learner by:

- Iterative building of the base classifier with a small number of labeled data points;
- Moreover, all learned classification models at different iterations will be linearly combined at the end to form the final classification model.

Similar to other semi-supervised wrapper-based methods, first, a classifier is trained using the labeled data \[22,27\]. Next, multiple iterations are performed with training and pseudo-labeling phase. During this pseudo-labeling phase, labels are created following two main criteria: 1) The points with high similarity among unlabeled samples must share the same label, and 2) those unlabeled samples which are highly similar to a labeled sample must share its label. Semi-Boost thus relies on optimization of an objective function consisting of two parts, one measuring the inconsistency between labeled and unlabeled examples and the other measuring the inconsistency among the unlabeled examples. During each step, a new classifier is built, and a weight is assigned to the model using the labeled and pseudo-labeled data from previous steps. This model-building step also includes optimization for the weight calculation based on the objective function discussed above. The pseudo-labeling is performed using the weighted combined models till the last step.

**S3VM:** Semi-Supervised Support Vector Machines (S3VM) is an widely used \[52,57\] intrinsically semi-supervised method \[56,109\]. In the case of traditional SVM, a supervised classification technique, it tries to find an optimal classification hyper-plane that meets the requirements of the classification task. To achieve this hyper-plane is created surrounded by support vectors. The support vectors are denoted by two equation \(w \ast x = b + 1\) and \(w \ast x = b - 1\), and the SVM tries to maximize the separation between these two support vectors by minimizing the objective function \(||w||^2/2\), which is a regularization term. In the case of S3VM, another two terms are added with the objective function.
One is a penalty term for the slack variable, which is the acceptable deviation between the function margin and the corresponding data. This is denoted by $\|w\|_2^2 + C \sum_{i=1}^{l} \epsilon_i$, here $\|w\|_2^2$ is the regularization term, while $\epsilon_i$ is the loss function of labeled data. The other term is the loss function for unlabeled data. To calculate the loss on unlabeled data, we assume that the unlabeled data is labeled, and we add the term $\max(1 - |w^* x + b|, 0)$ to the objective function. The S3VM is built by minimizing the objective function discussed above, utilizing both labeled and unlabeled data simultaneously.

**Semi-Supervised Clustering:** This type of semi-supervised method falls under semi-supervised preprocessing, specifically clustering then labeled methods [9,24,31]. Here we use Gaussian Mixture Model(GMM), where model parameters are estimated using the Expectation Maximization(EM) algorithm. Here in the first step, we use the GMM model provided by Scikit-Learn to build an unsupervised cluster using both labeled and unlabeled data points. We use a tuning phase to identify the optimal number of components for the GMM model. The tuning is performed by minimizing an objective function containing two terms: BIC (Bayesian information criterion) and the error rate for the clusters. The BIC is calculated using the whole training data, while the error rate is calculated using the labeled training data. In the next step, based on the purity of the cluster, each cluster is labeled based on majority voting (i.e., if a cluster contains 90% class 1 example, it is labeled as class 1 or vice-versa). The final prediction for test data is performed using the cluster prediction followed by a label assigning phase based on a cluster to label assignment from the last step.

**Label Propagation:** This is a graph-based method that creates a graph that connects instances in the training dataset and propagates labels through all data points. It uses the network structure alone to guide its process and requires neither any parameters nor optimization of the objective function. It starts from a configuration where each node has a distinct label. At every step, one node (in the asynchronous version) or each node (in a synchronous version) makes its own decision to change its label to the one carried by the most significant number of its neighbors. By construction, as the algorithm converges, each node has more neighbors than any other community. To help the algorithm converge fast, a table is created to keep track of label changes; if a particular node’s (data point) all neighbors have the same label, then that node becomes a passive node, while the remaining ones are active nodes. During each iteration, only active nodes are selected and checked for a label change as it becomes a passive node. Thus during each iteration, the number of the active node that is checked for label propagation change keeps shrinking, and thus the model converges faster [117,137].

**Label Spreading:** Label spreading is also a graph-based algorithm proposed by Zhou et al. [132]. The algorithm works similarly to the Label propagation algorithm, where a graph is created using both labeled and unlabeled data points. Each node is a data point, and the edges between nodes are weighted. The weights from the similarity matrix are created using a Gaussian kernel. Unlike Label propagation, here, the similarity matrix is normalized before la-
bels are assigned to each node based on information from its neighbors. Here
neighbors are defined by all nodes which are one distance away. Now labels
are changed in iterations till the point the model converges by minimizing an
objective function with two terms, one is the information from its neighbors,
and the other is the initial information. The two terms are weighted by a
parameter $\alpha$, which specifies the relative amount of the information from its
neighbors and its initial label information. Finally, when all iterations end, the
label of each unlabeled point is set to be the class from which it has received
the most information during the iteration process.

**LSVM:** Laplacian Support Vector Machine (LSVM) is a semi-supervised
support vector machine that uses manifold regularization and falls under in-
trinsically semi-supervised methods. Regularization is necessary to produce
smooth decision functions and, thus, to avoid over-fitting the training data.

### 3.3 Experimental Framework

This section describes the experimental framework shown in Figure 2. The
framework consists of many sub-routines. The process starts with selecting
appropriate projects which meet the criteria by collecting meta-data about
each project (collected using the GitHub search API) and using the GitHub
filtering criteria mentioned in §3.1. Next, we use the filtered project list to
collect 21 process metrics using the commit guru. We also collect release infor-
mation using GitHub release API for each project using the process mentioned
in §3.1. We use the commit time for each file from the data collected using
commit guru and release time from the release information to mark each row
of the commit guru data with release numbers.

The evaluation of the models used in this study are based on two evaluation
strategy -

1. **release-based**
2. **cross-validation**

Both these strategies are defined below. We use both strategies for com-
pleteness, since both have been used widely in software analytics papers [11,
13,37,50,100,101,121] (though, as we should see, the two strategies offer very
similar results). We report on results from both strategies; it is more likely
that other researchers will be able to compare their results against ours in
future works.

In a **cross-validation study,** we select all the files collected using the process
described in Section 3.1. This includes the files labeled as buggy and non-buggy
(this can include multiple copies of the same file if it was committed multiple
times) throughout the project history. This data for each project is sorted
randomly $M$ times. Then, the data is divided into $N$ stratified bins each time.
Each bin, in turn, becomes the test set, and the remaining data is further
divided into training and validation sets. For this study, we used $M = N = 5$,
repeated five times.
An alternative to cross-validation is a release-based approach. Here, we sort the data chronologically in releases $R_1, R_2, \ldots$ etc. Then we trained on data from release 1 to $R-3$, then tested on release $R-2, R-1, \text{and } R$. This temporal approach has the advantage that future data never appears in the training data.

Note that for both cross-validation and release-based, after the labeled training data has been selected, we apply SMOTE algorithm to correct imbalances in the training data.

3.4 Evaluation Criteria

This section describes the widely used \cite{44,116,119,121} evaluation metrics used in this study. These evaluation criteria has been designed to effectively measure the performance of machine learning models (specifically classification models). All these metrics are based on true negative, false negative, false positive, and true positive (labeled TN, FN, FP, TP, respectively) reported from the machine learning models.

**Recall:** This is the proportion of inspected defective changes among all the actual defective changes, i.e., $\text{TP}/(\text{TP}+\text{FN})$. For recall, \textit{larger} is \textit{better}, as when a recall is maximal, we find all the target class items.

**Precision:** This is the proportion of inspected defective changes among all the inspected changes, i.e., $\text{TP}/(\text{TP}+\text{FP})$. \textit{Higher} precision is \textit{better} as precision reports all defect modules are defective.

**Pf:** This is the proportion of all suggested defective changes that are not actual defective changes divided by everything that is not defective, i.e., $\text{FP}/(\text{FP}+\text{TN})$. A high \textit{pf} suggests developers will inspect code that is not buggy. Hence we say that \textit{smaller} false alarms are \textit{better}.

**Popt20:** This is the proportion of changes inspected by reading 20\% of the code; it is computed as $m\%/M$. Where $M$ is the number of changes in the dataset with $N$ defects and $m$ changes and $n$ defects when inspected 100\% LOC\footnote{8}. To calculate Popt20, we first divide the test data into (a) those that

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig2.png}
\caption{Framework}
\end{figure}
are predicted to be defective and (b) those that are not. Second, we sorted the sets (a,b) on LOC. Third, we returned the test in the order sorted (a) followed by sorted (b). Within that sort, we then report the percent of actual bugs found by inspecting the first 20% of the code (measured in terms of LOC). We say that larger Popt20 values are better.

IFA: This is the number of initial false alarms encountered before we identify the first defective change. Parnin and Orso [82] warn that developers will ignore the suggestions of static code analysis tools if those tools offer too many false alarms before reporting something of interest. Other researchers echo that concern [48,82,115]. smaller IFA values are better for the model.

3.5 Statistical Tests

When comparing the results of different models in this study, we used a statistical significance test and an effect size test:

- The significance test helps detect if two populations differ merely by random noise.
- The effect sizes help check that two populations differ by more than just a trivial amount.

For the statistical test, we use the Scott-Knott test [29, 70]. This technique recursively bi-clusters a sorted set of numbers. If any two clusters are statistically indistinguishable, Scott-Knott assigns both the same “rank”. To generate these ranks, Scott-Knott first looks for a break in the sequence that maximizes the expected values in the difference in the means before and after the break. More specifically, it splits $l$ values into sub-lists $m$ and $n$ to maximize the expected value of differences in the observed performances before and after divisions. e.g., list $l,m$ and $n$ of size $ls,ms$ and, $ns$ where $l = m \cup n$, Scott-Knott divides the sequence at the break that maximizes:

$$E(\Delta) = \frac{ms}{ls} \times \text{abs}(m.\mu - l.\mu)^2 + \frac{ns}{ls} \times \text{abs}(n.\mu - l.\mu)^2$$ (1)

These ranks have different interpretations, depending on whether we seek to minimize or maximize those numbers. For our purposes:

- Rank 1 is worst for recall, precision, Popt20 since we want to maximize these numbers.
- Rank 1 is best for the false alarm, and IFA since we want to minimize those.
4 Results

This section describes our research questions and their findings in detail.

4.1 RQ1: Are there models which perform better or worse than others?

To answer this research question, we use Figure 3 to Figure 9. These results are somewhat extensive, so; first, we offer the following executive summary:

– Many of our performance measures give the same ranks across all treatments. However, a few most informative measures know how to distinguish different approaches.
– Across our two treatments (cross-based and released-based), there is much stability in our findings,
– Looking at the most informative findings and using the stable results between cross- and release-based treatments, we can see co-training models giving the best results (see Table 3).

Having offered that executive summary, we now turn to the details. About our tables: Each figure contains vertical box plots, where each box-plot represents the performance of an individual model:

– Box-plot graphically demonstrates data’s locality, spread, and skewness through their quartiles.
– Each box-plot is marked to separate the quartiles (25% divisions).
– The red line in the middle is the 50th quartiles (median).
– The two ends of the box are the 25th and 75th quartiles. Finally, the two ends of the line represent the 0th and 100th quartiles.

Each box-plot is generated using the respected performance evaluation criteria obtained using the five-fold five repeat cross-validation, which signifies that each box-plot is generated with 25 data points.

All the models are compared and ranked using statistical significance and effect size tests as mentioned in Section 3.5. Each rank is represented using a different color in the figures, with the lowest rank starting on the left side of the figures. As mentioned in Section 3.5:

– For precision, recall, f1-score, g-score and pci_20, higher ranked models are preferable;
– While for the false alarm and IFA, lower ranked models are preferable.

Results are primarily semi-supervised methods, but for comparison purposes, we include fully supervised methods (that use all the labels for building models). Those supervised methods are denoted as DT, RF, LR, KNN, and SVM.

Results show that:

– Many of our treatments tie, when measured in terms of precision, Popt_20, IFA, false alarm, F Score, and G-Score. These ties are intriguing since they
show that there may be little lost in moving from supervised learning (that uses all labels) to semi-supervised methods (that use only a tiny percentage of the labels).

Moving on to recall and false alarms, Figure 3 and Figure 5 show measured in terms of those performance scores, that a small group of treatments performs best. In these experiments, precision was not informative for selecting the “best” methods since most treatments were tied in terms of precision (see Figure 4). Also, not-so-informative (due to so many ties) were the F1 and G-Scores of Figure 6 and Figure 7.

Figure 3 shows the recall of all models used in this study. We can see from the figure that the model’s performance varies significantly. The statistical significance and effect size test generates five different ranks, each including a
subset of models (including both supervised and semi-supervised models). The green box-plot shows rank one, which includes self-training LR and CoForest, showing the lowest performance. While rank two contains 24 learners, 17 in rank three, six in rank four, and five in rank five with the highest recalls. Here in the case of recall, we can see a significant difference in performance between models in rank one (median near 0.38) and models in rank five (median near 0.86), indicating the choice of models can have an enormous impact on a model’s performance to select all the defects. When comparing semi-supervised models with supervised models, we see that none of the supervised models falls on the rank five or even rank four, showing recall supervised models perform similarly or better than supervised models.

Now, if we look at Figure 4, which shows precision reported by all models, we can see that although models’ performance varies, the differences are minor. Here we see, using the statistical tests, there are three different ranks. Rank one includes self-training LR showing the lowest precision, followed by three models in rank two and the remaining models in rank three. This indicates that for most models, the performance difference in the case of precision is negligible (as all except four models rank the same) with a median of 0.56, and the choice of models does not impact the models’ ability to select appropriate defective files.

Figure 5 shows the false alarm reported by the models. Applying the statistical tests on the false alarm, we see models are divided into five ranks based on their performance. Rank one here contains six models showing the lowest false alarm scores (best models based on false alarm criteria), followed by 26 models in rank two, 16 in rank three, five in rank four, and one in rank four, rank six. Here we see the performance difference between models in different ranks is significant, with rank one having a median false alarm of 0.26, while rank six models have a median false alarm of 0.68.
Figure 6 and Figure 7 show the performance of models on F1-score and g-score. F1-score is the harmonic mean between precision and recall, whereas the g-score is the geometric mean between recall and false alarm. In terms of recall, there are significant performance differences between different models, while Figure 4 shows that in the case of precision, the difference in performance is insignificant. Thus, when calculating the F1-score, the difference in performance between models (using a statistical test) is mostly insignificant. We see two ranks returned by the statistical test: rank one contains two models (with a median of 0.38), while rank two contains all other models (with a median of 0.58). Similarly, we see a significant difference in performance between models in different ranks in the case of false alarm. As g-score is the geometric mean of recall and false alarm, we can see from Figure 7 that there is a
significant difference in performance between models when applying statistical tests. Here rank one has a median g-score of 0.0, rank two shows a median g-score of 0.29, rank three shows a median g-score of 0.42, and finally, rank four has a g-score of 0.51. This indicates when selecting models for performance evaluation:

- If we only care about precision and recall together, then the choice of models does not make much difference;
- However, if we care about recall and false alarm, the choice of model matters and not all models perform similarly.

E.g., if we are building an automated skin cancer detection system, we want all actual cancer cases to be detected even if there are a lot of false positives,
in this scenario, we want a system that has a high recall. On the other hand, think of a system that detects the water level on a plant and sounds an alarm when the level is low; if there are too many false alarms it will needlessly waste time, and people might ignore the alarm.

Figure 8 and Figure 9 shows the performance of models based on Popt_20 and IFA, both of which are effort-aware performance measure. From Figure 8 using a statistical test on Popt_20, the models are ranked in three different ranks, rank one contains self_training_LR with a median score of 0.68, and rank two contains three models with a median score of 0.78. Finally, rank three contains all other models with a median score of 0.82. Figure 9 is not informative since all models are ranked the same. This indicates that for both effort-aware performance measures, the performance difference between different models is insignificant, and the choice of the model does not affect the performance significantly in most cases. The results shown in Figure 3-9 that except for recall, false alarm, and g-score, the remaining metrics are not informative as they show a statistically insignificant difference. Thus we have not shown precision, f1-score, Popt_20, and IFA for the remainder of this paper.

Summary of RQ1 Results: While evaluating the models, we used two evaluation strategies mentioned in Section 3.3. One is a release-based evaluation strategy, while the other is a cross-validation-based evaluation strategy. Both these strategies are widely used in software engineering literature to evaluate defect prediction models. As we have used both strategies in our evaluation on a large dataset, we check if there is a difference in performance in models (both supervised and semi-supervised) when the evaluation is performed using a release-based evaluation strategy vs. when the evaluation is performed using cross-validation based evaluation strategy. Table 3 shows the performance difference of all models when evaluation is performed on release-based evaluation strategy (denoted as R in the table) and cross-validation-based evaluation strategy (denoted as C in the table). Table 3 shows the performance of models in recall, false alarm and g-score evaluation criteria. The last line in the table shows the median performance of all models in both strategies.

From Table 3, we can see the median difference for recall between the two evaluation strategies is 0.03; for the false alarm, it is 0.05, and for the g-score, the difference is 0.05. This shows that both evaluation strategies evaluate models similarly, and the evaluation strategy does not significantly skew a model’s performance.

That being said, there are some models where the performance difference between the two evaluation strategies differs more than others. In both tables, the cells highlighted in red are the ones where the performance difference is more than 0.05. We can see in all performance measures that there are only a handful of models where the performance difference is more than 0.05, i.e., in the case of the f1-score, there are only seven models, in-case of the precision, there are ten models. Note that in most cases, where the difference is more than 0.05, the difference is very near to 0.05 except for all Boosting models. In case of Boosting models, the performance difference between the two evaluation
Table 3: Comparison between Cross val and Release based evaluation for recall, false alarm and g-Score. Here we only selected and showed models where for either release based or cross validation based strategy the recall is above 0.67 and false alarm is lower than 0.4. The cells highlighted in gray are methods beaten by at least one semi-supervised method. The cells highlighted in black are the models that show instability between cross validation (C) and release (R) based strategy.

In both our cross-validation and release-bases study, semi-supervised methods (that use only some of the data) can perform better than methods that use all the data.

4.2 RQ2: How does models perform with increased data size?

The previous research question concluded that we do not need labels on all examples. Given that result, the next question is “how much data can be ignored and still learn effective predictors?”

In this second research question, we try to analyze how the models perform with increasing data size. Here we vary the amount of labeled data by selecting 2.5%, 5%, 10%, and 20% (starting at 2.5% and doubling the data size after that) from the available training data. Here available training data is the training data used for training the supervised models. Table 4 shows performance of
ten selected models with increasing data size for all the performance measures mentioned in Section 3.4. Apart from the ten models shown in Table 4, the remaining models are also tested with increasing data availability. However, those values are placed in table format in the online GitHub repository due to page constraints. Looking at Table 4, we can see that the median precision of the models increases for precision with an increasing amount of labeled data. We see that at 2.5%, the median recall is 0.72; at 5%, it is 0.72; at 10% it is 0.77; at 20% it is 0.80. Similarly, for the false alarm, the values are 0.40 at 2.5% and 0.29 at 20%. We can see a trend that with an increasing amount of labeled data, the model’s performance improves. Between 2.5% and 5% labeled data, there is almost no performance difference for all measures, i.e., 0.0 for recall, 0.04 for the false alarm, and 0.05 for the g-score. Now between 2.5% and 20%, there are differences in performances, but in most cases, the difference is minimal (except for recall and g-score). That being said, the model’s performance at 2.5% is similar to or better than supervised models with only a fraction of the cost for the labeling effort.

In their study, Tu et al. [106] showed how expensive labeling efforts can be. Using the same assumptions as Tu et al., we calculated the time and money required if we use supervised learning vs. semi-supervised learning with labeled data required varying from 2.5% to 20%. Table 5 shows the number of files needed to be examined for labeling a file as defective vs. non-defective. The time and cost required for labeling effort are the same as what Tu et

| Model                  | recall   | pf       |
|------------------------|----------|----------|
|                        | 2.5%     | 5%       | 10%      | 20%      | 2.5%     | 5%       | 10%      | 20%      |
| co_training_sv_LR_RF   | 0.72     | 0.72     | 0.77     | 0.8      | 0.37     | 0.32     | 0.3       | 0.24     |
| co_training_sv_LR_KNN  | 0.76     | 0.77     | 0.77     | 0.8      | 0.35     | 0.38     | 0.37      | 0.32     |
| co_training_sv_RF_GNB  | 0.66     | 0.73     | 0.8      | 0.84     | 0.36     | 0.36     | 0.42      | 0.41     |
| co_training_sv_RF_KNN  | 0.74     | 0.76     | 0.76     | 0.8      | 0.4      | 0.35     | 0.32      | 0.26     |
| co_training_mv_LR_GNB  | 0.62     | 0.7      | 0.8      | 0.83     | 0.4      | 0.4      | 0.44      | 0.42     |
| co_training_mvc_LR_KNN | 0.74     | 0.74     | 0.75     | 0.8      | 0.46     | 0.4      | 0.38      | 0.32     |
| co_training_mvc_RF_GNB | 0.74     | 0.76     | 0.76     | 0.8      | 0.4      | 0.32     | 0.3       | 0.24     |
| co_training_mvc_RF_KNN | 0.74     | 0.73     | 0.73     | 0.78     | 0.4      | 0.36     | 0.33      | 0.26     |
| EATT                   | 0.72     | 0.7      | 0.8      | 0.82     | 0.36     | 0.29     | 0.32      | 0.27     |

Median recall: 0.72 0.72 0.77 0.8 0.36 0.29 0.32 0.27

| Model                  | g-score  |
|------------------------|----------|
|                        | 2.5%     | 5%       | 10%      | 20%      |
| co_training_sv_LR_RF   | 0.54     | 0.61     | 0.64     | 0.7      |
| co_training_sv_LR_KNN  | 0.5      | 0.56     | 0.6      | 0.64     |
| co_training_sv_RF_GNB  | 0.5      | 0.56     | 0.6      | 0.64     |
| co_training_sv_RF_KNN  | 0.52     | 0.57     | 0.6      | 0.66     |
| co_training_mvc_LR_GNB | 0.48     | 0.53     | 0.59     | 0.63     |
| co_training_mvc_LR_KNN | 0.5      | 0.54     | 0.58     | 0.6      |
| co_training_mvc_RF_GNB | 0.5      | 0.53     | 0.6      | 0.62     |
| co_training_mvc_RF_KNN | 0.49     | 0.52     | 0.62     | 0.66     |
| EATT                   | 0.52     | 0.55     | 0.6      | 0.64     |

Median g-score: 0.5 0.55 0.6 0.63

Table 4: Increased data size from 2.5% to 20% shown for first 10 models selected in Table 3 using the selection criteria mentioned. The cells highlighted in black are the models that have been ranked best according to the statistical tests.
Table 5: Time and Cost required for labeling effort

| percentage | # files | time(hours) | Cost($)  |
|------------|---------|-------------|----------|
| 2.5        | 119184  | 231         | 3811.5   |
| 5          | 238368  | 463         | 7639.5   |
| 10         | 476737  | 926         | 15279    |
| 20         | 953474  | 1853        | 30574.5  |
| 100        | 4767371 | 9269        | 152938.5 |

al. mentioned in their papers: seven seconds for each file, $8.25 per hour per person with two person required to validate each file. Here we can see that if we use supervised models, which require all data points to be labeled, it would require ≈ 9269 hours to label 4767371 files which would cost around $153K. While if we use semi-supervised learning with 20% data, it will take ≈ 1853 hours, and if we only require to label 2.5% of the data, the time required comes down to only 231 hours, costing $30k and $3.8K respectively. As we can see from Table 4 and Table 5 with a very small amount of data that need to be labeled, we can achieve comparable performance to supervised models.

Note, we also tried with only 1% data labeled, but the performances were sub-optimal, and thus we have not included them in the results.

To summarize, our results show that the semi-supervised models perform slightly better with increased data availability. However, with only 2.5% data being available, the semi-supervised models perform reasonably well with a significant reduction in potential labeling cost. Table 5 shows that if we want all data labeled, we would need approximately $150k for labeling all files while following the semi-supervised learning process with 2.5%, we would need significantly less effort to label, which would require only $3.8k.

4.3 RQ3: Do all Semi-supervised learners performs the same?

This research question analyzes if and how the model performances differ with increasing data capacity. Table 6 shows the number of ranks returned for each performance measure with an increasing amount of labeled data points. Here we analyzed with 1%, 2.5%, 5%, 10%, and 20% of the training data labeled, respectively. The ranks are generated using the statistical tests mentioned in Section 3.5. Looking at Table 6, we can see that at 1% of the data; all models fall in the same rank; this is because, as mentioned in RQ 4.2 all models perform significantly worse, and all of them perform similarly. Now, if we look at the number of ranks generated for each performance measure with 2.5%, 5%, 10% and 20% labeled data, we see that all performance measures between 2.5% and 5% have almost the same number of ranks generated using the statistical tests. Now with 10% labeled data number of ranks generated is slightly less (g-score and popt_20), and finally, for 20% labeled data, the number of ranks generated is even smaller. This shows that with increasing data size (at 10%
Table 6: Number of groups formed by all 55 models selected in this study based on their performance in each metrics.

| Metric  | 1% | 2.50% | 5% | 10% | 20% |
|---------|----|-------|----|-----|-----|
| Recall  | 1  | 5     | 5  | 5   | 4   |
| Precision | 1  | 3     | 3  | 3   | 3   |
| F1      | 1  | 5     | 6  | 6   | 4   |
| F1      | 1  | 2     | 2  | 2   | 1   |
| G-Score | 1  | 4     | 4  | 3   | 3   |
| Popt,20 | 1  | 3     | 3  | 2   | 2   |
| Ifa     | 1  | 1     | 1  | 1   | 1   |

and 20%), different semi-supervised models start to perform similarly. We see that when a minimal amount of labeled data is available, the model’s choice significantly impacts the model’s performance. Thus when selecting for semi-supervised learning, based on available labeled data, one should carefully select which model to use for research/industrial purposes.

In summary, based on statistical test all semi-supervised models can be grouped based on their performance. Our results show that, when available labeled data is scarce then certain models performs significantly better then others. And with more labeled data being available the gap in performance reduces. Thus when available labeled data is scarce then the choice of model is important.

4.4 RQ4: Between single-view and multi-view models is one preferable than others?

Section 3.2.2 mentioned that Co-training is a type of wrapper-based method, where two learners are trained on labeled and possibly pseudo-labeled data. The pseudo-labeled is based on the most confident prediction of the other learners. Here as a base learner, any learner can be used for prediction. In this study, we have used all combinations of supervised learners mentioned above as base models in co-training methods, excluding the same learner combinations. In Co-training, we adapt both single-view (same features between models) and multi-view (different features between models) settings. The key difference between the two models is that in the case of single-view models, both base learner sees the data with the same feature sets. During the pseudo labeling phase for both base learners, the prediction labels and confidence scores are based on the same features. While for multi-view co-training models, the two base learners are trained on different features with an assumption that the features are not correlated. Thus during the pseudo-labeling phase, when generating the prediction labels and confidence score, the models see completely different features (which should reduce over-fitting).
Table 7: Comparison for Multi View Models. Here the cells highlighted in pink denotes the models selected in Table 3.

| Rank | Model              | Median | Rank | Model              | Median |
|------|--------------------|--------|------|--------------------|--------|
| 1    | co_training_mv_DT_RF | 0.58   | 1    | co_training_mv_DT_KNN | 0.39   |
| 1    | co_training_mv_DT_SVM | 0.58   | 1    | co_training_mv_DT_GNB | 0.37   |
| 1    | co_training_mv_LR_DT | 0.6    | 1    | co_training_mv_LR_RF | 0.38   |
| 1    | co_training_mv_DT_KNN | 0.6   | 1    | co_training_mv_LR_DT | 0.38   |
| 1    | co_training_mv_DT_GNB | 0.62  | 1    | co_training_mv_RF_KNN | 0.39   |
| 1    | co_training_mv_DT_SVM | 0.62  | 1    | co_training_mv_RF_SVM | 0.4    |
| 1    | co_training_mv_RF_GNB | 0.66  | 1    | co_training_mv_RF_GNB | 0.4    |
| 1    | co_training_mv_GNB_KNN | 0.7   | 1    | co_training_mv_LR_GNB | 0.4    |
| 1    | co_training_mv_GNB_SVM | 0.7   | 1    | co_training_mv_LR_RF | 0.4    |
| 2    | co_training_mv_LR_RF | 0.72  | 2    | co_training_mv_DT_SVM | 0.4    |
| 2    | co_training_mv_LR_KNN | 0.73  | 2    | co_training_mv_GNB_SVM | 0.42   |
| 2    | co_training_mv_RF_KNN | 0.74  | 2    | co_training_mv_GNB_KNN | 0.42   |
| 2    | co_training_mv_RF_SVM | 0.74  | 2    | co_training_mv_SVM_KNN | 0.46   |
| 2    | co_training_mv_LR_KNN | 0.74  | 2    | co_training_mv_LR_KNN | 0.46   |
| 3    | co_training_mv_LR_SVM | 0.82  | 3    | co_training_mv_LR_SVM | 0.5    |
| Median | 0.67                 |        | Median | 0.4                 |        |

Now, if we look at Table 7 and Table 8 the median values are highlighted in pink in the last row for each of the performance measures. We can see that the median recall scores between single-view and multi-view co-training models are 0.66 and 0.67. The median false alarm is 0.38 and 0.4, 0.5 and 0.52 for g-score. This indicates that both single-view co-training and multi-view co-training models perform very similarly. Thus, in software engineering defect prediction datasets, the choice of different views does not affect the model performance much, and the extra time required to select the different features for the base learners is not justifiable.

Now we further analyze in the case of both model types if and how the choice of base learner affects models performance. Table 7 shows the performance of multi-view models and the performance measures (recall, false alarm, and g-score). In each performance measure, all models are ranked using statistical tests. In Table 8, we see that in the case of recall, the multi-view models are ranked into three ranks: the false alarm and g-score are ranked into two ranks. In a similar manner, Table 8 shows the performance of single-view models. Here also, we see a similar trend, where models are ranked three ranks for recall and two for false alarm and g-score.
Based on these results, we can say that the choice of base learners for the co-training model depends on the user’s goal. That is to say, if the goal is to select defective files regardless of the number of non-defective files predicted as defective, then co-training_mv_LR_SVM is the best choice of learner. At the same time, if you care about models where you want to minimize false alarm, the selected model should be co-training_mv_DT_RF, which has the lowest false alarm. Now, if the decision needs to be made using multiple goals, it can be achieved using the Zitler indicator dominance predictor [143]. So we can say that although the single-view and multi-view model both perform similarly and the choice of one is strictly based on resources, the choice of base classifier affects models significantly. It should be made based on the user’s goal in mind.

To summarize, both single-view and multi-view models perform very similarly; thus, choosing different views does not affect the model performance much. The extra time required to select the different features for the base learners is not justifiable.
4.5 RQ5: Between single vs. multi classifier which one performs better?

In the above, it was argued that co-trainers do better. Here, we “zoom in” (so to speak) to look at some details within co-trainers.

Figure 10 shows the difference in performance between a single classifier model and a multi-classifier model. A single classifier model is the one where the final prediction is made using only one classifier (the final classifier built using the semi-supervised algorithm), while in the multi-classifier model, the final prediction is performed using multiple classifiers. The examples of single classifier models are the self-training models like self-training LR, which, as mentioned in section 3.2 contains two phases one is pseudo labeling, and another is the training phase. Here one model is trained in each iteration, and the pseudo labeling for the next phase is based on the latest model only. Thus during the prediction, only one model is used. In the case of multi-classifier models like co-training, although the process of building the model is the same as self-training models and prediction is performed on the latest model, the prediction is based on two or more models. Another example of a multi-classifier model is semi-supervised boosting algorithms; here, the final prediction is based on combined prediction results from all models built throughout the algorithm’s training phase.

From Figure 10 we can see that performance of the single classifier model is shown in pink, while the performance of the multi-classifier model is shown in green. We can see from the box-plots of each performance measure that semi-supervised algorithms which use multi-classifier models show similar better performance when compared to single-classifier models. Also, if we take a look at the interquartile range (IQR) of each performance measure, we can see

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*IQR: the interquartile range is the difference between 75th and 25th quantile.*
that multi-classifier models show lower IQR when compared to single classifier models, i.e., for

Recall that the IQR for the single classifier model is 0.39 while for the multi-classifier model, it is 0.30; similarly, for pf, it is 0.35 and 0.25, respectively, and for g-score, it is 0.31 and 0.22. This indicates that multi-classifier models have more stability when compared to single-classifier models. Combined with higher median performance scores and lower IQRs, it is evident that the multi-classifier model shows superior performance compared to single-classifier models in the case of semi-supervised learning.

To conclude this research question, The result shows that between semi-supervised models which perform final prediction based on multiple parallel classifiers, the prediction performance based on the selected evaluation criteria is significantly better than models which perform the final prediction based on only one classifier.

4.6 RQ6: Between self-teaching and mutual-teaching is one preferable?

In this research question, we compare the performances of self-teaching and mutual-teaching models. A self-teaching model is where the most confident pseudo-labeled examples come from the same learner’s previous iteration during the pseudo-labeling phase. While in the case of mutual-teaching models, the most confident pseudo-labeled examples come from the other classifier. The difference between these two approaches is that in the case of mutual-teaching, each classifier in a model is initialized differently; the difference can be separate base algorithms, separate data views, or different examples of labeled data points. During each iteration for each learner, the amount of labeled data is increased by adding the most confident examples from the remaining classifiers; thus, under mutual-teaching, a learner never uses its prediction to increase the labeled examples doing the pseudo-labeling phase. In contrast, in the case of self-teaching, the learner always uses their own prediction to increase the amount of labeled examples.

Figure 11 shows the performance of the self-teaching and mutual-teaching models. Similar to Figure 10, the self-teaching models are represented by pink box-plots, while green box-plots denote mutual-teaching models. Looking at the box-plots of each performance measure, we can see that except for false alarm, models that use mutual-teaching perform similarly or better than models that use self-teaching. While similar to RQ 4.5, we can see that the IQRs for self-teaching are much higher than IQRs for models with mutual-teaching. In the case of mutual-teaching, the median false alarm is a little higher than its counterparts; we think as, during the pseudo-labeling phase, the most confident examples come from the remaining classifiers, and that can introduce more noise in the labeled data, as a confident example from one model might
not necessarily have the same confidence in the other model. That being said, the difference in performance in case of false alarm is minimal; thus, considering the performance from other evaluation criteria, we can say models which use mutual-teaching perform better than models which use self-teaching.

In summary, we see that when models use their own prediction during the pseudo-labeling phase, the effect of improvement is significantly reduced than when the pseudo-labels come from other supervised classifiers in each iteration.

5 Discussion

In this section, we discuss the finding and their implication for future research and verify what makes this research unique.

Researchers and industry practitioners create defect prediction models to identify defective modules. These defect predictors effectively save testing time, reduce the cost of software development, and create high-quality software. Most defect predictors are built with supervised classification algorithms; thus, they require a significant amount of labeled data points. Generating these adequate labeled training data can be costly via human labor. For example, we have studied approximately 714 software projects, including 476K commit files, which would have required over three years of effort. Since labeling is so labor-intensive, often a large amount of unlabeled data is available along with a small number of labeled data points; researchers have utilized semi-supervised learning to improve the performance of the classification algorithm by utilizing the additional information by inferring a mapping from the given unlabeled inputs.
When referring to Figure 3, Figure 4, Figure 5, Figure 6, Figure 7, Figure 8 and Figure 9, we see that in case of both our cross-validation and release-based study, semi-supervised methods (that use only some of the data) can perform better than supervised methods that use all the data. We can also see that not all semi-supervised methods perform similarly, specifically in case of recall and false alarm (please refer to Figure 5 and 7). Looking at Table 3, we see a set of methods that have been selected using model selection criteria. We see here that Co-training based methods perform consistently well, showing these models should perform significantly well across most defect prediction datasets. Our result also shows that the semi-supervised models perform slightly better with increased data availability. However, with only 2.5% data being available, the semi-supervised models perform reasonably well with a significant reduction in potential labeling cost. Table 4 shows that if we want all data labeled, we would need approximately $150k for labeling all files while following the semi-supervised learning process with 2.5%, we would need significantly less effort to label, which would require only $3.8k. Our result also shows that semi-supervised models can be grouped based on their performance, and when available labeled data is scarce, certain models perform significantly better than others. Moreover, with more labeled data being available, the performance gap reduces. Using these results, we can see that labeling costs can be reduced significantly without damaging model performance when using semi-supervised algorithms for defect prediction. Also, our finding on how different semi-supervised models perform under different amounts of data availability is significant as we know that in the defect prediction domain, most of the data is unlabeled. From our result, we saw that the choice of models is important when available data is less; thus, future researchers must be careful when selecting a semi-supervised model for the defect prediction domain, and select models appropriate based on available data.

Based on our result, in the defect prediction domain, Co-training based methods perform consistently and significantly well compared to other models. Figure 10 shows that between semi-supervised models which perform final prediction based on multiple parallel classifiers, the prediction performance based on the selected evaluation criteria is significantly better than models which perform the final prediction based on only one classifier. This also shows that Co-training based methods, which are based on multiple classifiers, perform better than methods that only use a single model. We also know that Co-training based models can be built using various strategies. Choosing between single-view and multi-view models, where different models see the same or different subsets of the features respectively, does not affect the model performance much. Selecting different features requires extra time, and spending the extra time to select the different features for the base learners is not justifiable. We also see that when models use their own prediction during the pseudo-labeling phase, the improvement effect is significantly reduced than when the pseudo-labels come from other supervised classifiers in each iteration. Combining these findings, we can say that when building defect prediction
models, researchers can use single-view Co-training models, which have been trained with a mutual-teaching strategy to achieve good performance.

This study is based on approximately 714 open-source software projects (one of the largest studies in semi-supervised defect prediction), comparing results from 55 semi-supervised models (one of the largest collections of semi-supervised models in a single study). As these results come from approximately 714 diverse open sources of GitHub projects, we believe this subset of projects is a good representative of the SE defect prediction domain and based on our findings; we summarize the results as follows - in the case of defect prediction, semi-supervised models can perform significantly well with only a fraction of data (approximately 2.5%). We also see that the choice of the semi-supervised method matters, specifically when the amount of available labeled data is scarce. Finally, we see that single-view Co-training models, which have been trained with a mutual-teaching strategy, perform significantly well. That being said, based on our findings, researchers can also select the best suitable methods based on their goal.

6 THREATS TO VALIDITY

As with any large-scale empirical study, biases can affect the final results. Therefore, any conclusions made from this work must be considered with the following issues in mind:

(a) Evaluation Bias: In all research questions in this study, we have shown the performance of 55 different models built with the process and metrics and compared them using statistical tests on their performance to conclude which is a better and more generalizable predictor for defects. While those results are accurate, that conclusion is scoped by the evaluation metrics we used to write this paper. It is possible that using other measurements, there may be a difference in these different kinds of projects. This is a matter that needs to be explored in future research.

(b) Construct Validity: At various places in this report, we made engineering decisions about (e.g.,) choice of machine learning models, selecting metric vectors for each project. While those decisions were made using advice from the literature, we acknowledge that other constructs might lead to different conclusions.

(c) External Validity: For this study, we have collected data from 714 GitHub Java projects. The process metrics were collected using our own code on top of the Commit_Guru repository. There is a possibility that the calculation of metrics or labeling of defective vs. non-defective using other tools or methods may result in different outcomes. That said, these tools have detailed documentation about the metrics calculations. We have shared our scripts and processes to convert the metrics to a usable format and have described the approach to label defects.

(d) Sampling Bias: Our conclusions are based on the 714 projects collected from GitHub. It is possible that different initial projects would have led to
different conclusions. That said, this sample is substantial, so we have some confidence that this sample represents an interesting range of projects.

7 Conclusion

Most techniques for finding defective modules using a defect prediction model are based on supervised classification algorithms, assuming sufficient labeled data is available for training the models. The drawback of supervised classification algorithms is the necessity of having a substantial number of software modules labeled as faulty or fault-free before the model can be created. Labeling is labor-intensive; an alternate approach is to use semi-supervised classification algorithms. However, the application of semi-supervised classification algorithms in defect prediction is far from adequate compared to the number of supervised classification algorithms. Literature review shows a plethora of semi-supervised classification algorithms available in the machine learning domain, and only a few of them have been studied in the defect prediction domain. Thus in this paper we -

- Compare 55 semi-supervised classification algorithms based on eight different groups of semi-supervised methods (techniques), one of the largest demonstrations of semi-supervised classification algorithms in the defect prediction domain.
- We compare the above-mentioned semi-supervised classification algorithms based on 714 open source GitHub projects, which is also one of the largest selection of projects to be used for demonstrating semi-supervised classification algorithms in the defect prediction domain.
- This paper compares these semi-supervised models. It shows that based on the researcher’s goal, the learner’s choice does matter, and it helps researchers and industry practitioners make an appropriate informed decision about the choice of models based on their application and goals.
- The study shows that by using semi-supervised models, we can reduce the effort required for labeling by many folds. We showed that even with as little as 2.5% of the labeled data, the models perform significantly well when compared to supervised models.
- This paper explains the main characteristics and advantages of each of the semi-supervised classification methods to make informed decisions based on the goal and the problem being solved by researchers.
- Semi-supervised classification algorithms are a growing but seldom explored field in the defect prediction domain. This paper explores many variants of semi-supervised algorithms, which have rarely been explored in this domain.
- This study highlights some aspects of semi-supervised learning and shows that how a semi-supervised co-training model is trained significantly impacts a model’s performance. Similarly, how the final classification is performed also shows a statistically significant impact on the model’s performance.
This study includes all methods studied as a package for future researchers in this field either to reproduce or use these models in their studies.

This study, we believe, is a significant empirical analysis of semi-supervised methods in defect prediction, exploring 55 semi-supervised models using approximately 714 open source software projects collected from GitHub. We hope this will help researchers select appropriate research methods with an informed decision using the results and findings shown here. Moreover, we say - in the case of defect prediction, semi-supervised models can perform significantly well with only a fraction of data, choice of semi-supervised classifier, the teaching of an individual base learner, and how the final prediction is performed do matter based on the goal of a researcher.

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9 COI

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