# Can We Achieve Fairness Using Semi-Supervised Learning?

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# **ABSTRACT**

Ethical bias in machine learning models has become a matter of concern in the software engineering community. Most of the prior software engineering works concentrated on finding ethical bias in models rather than fixing it. After finding bias, the next step is mitigation. Prior researchers mainly tried to use supervised approaches to achieve fairness. However, in the real world, getting data with trustworthy ground truth is challenging and also ground truth can contain human bias.

Semi-supervised learning is a machine learning technique where, incrementally, labelled data is used to generate pseudo-labels for the rest of data (and then all that data is used for model training). In this work, we apply four popular semi-supervised techniques as pseudo-labelers to create fair classification models. Our framework, Fair-SSL, takes a very small amount (10%) of labeled data as input and generates pseudo-labels for the unlabeled data. We then synthetically generate new data points to balance the training data based on class and protected attribute as proposed by Chakraborty et al. in FSE 2021. Finally, classification model is trained on the balanced pseudo-labeled data and validated on test data.

After experimenting on ten datasets and three learners, we find that Fair-SSL achieves similar performance as three state-of-theart bias mitigation algorithms. That said, the clear advantage of Fair-SSL is that it requires only 10% of the labeled training data.

To the best of our knowledge, this is the first SE work where semi-supervised techniques are used to fight against ethical bias in SE ML models. To facilitate open science and replication, all our source code and datasets are publicly available at https://github.com/joymallyac/FairSSL.

# **KEYWORDS**

Machine Learning with and for SE, Ethics in Software Engineering

# 1 INTRODUCTION

Machine learning software has become ubiquitous in our society. Software is making autonomous decisions in criminal sentencing [74], loan approvals [5], patient diagnosis [19], hiring candidates [22], and whatnot. It is the duty of software researchers and engineers to produce high-quality software that always makes fair decisions. However, in recent times, there are numerous examples where machine learning software is found to have biased behavior based on some protected attributes like sex, race, age, marital status, etc. Google translate, the most popular translation engine in the

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world, shows gender bias. "She is an engineer, He is a nurse" is translated into Turkish and then again into English becomes "He is an engineer, She is a nurse" [41]. YouTube makes more mistakes when it automatically generates closed captions for videos with female than male voices [73]. Amazon's automated recruiting tool was found to be biased against women [14]. A widely used face recognition software was found to be biased against dark-skinned women [20]. Angel et al. commented that software showing bias is considered as poor quality software and should not be used in real life applications [33]. It is time for software engineering researchers to dive into the field of software fairness and try to build fairer software to prevent discriminative behaviors.

A machine learning software can acquire bias in various ways [39]. Prior studies [49, 58] mentioned that most of the time bias comes from the training data. If training data contains improper labels, that bias gets induced into model while training. In an ACM SIG-SOFT Distinguished award winning paper, Chakraborty et al. [43] found out that bias comes from improper data labels and imbalanced data distribution. They said if the training data contains more examples of a certain group getting privileged (males being hired for a job) and another group getting betrayed (females getting more rejections); the machine learning model acquires that bias while training and in the future makes unfair predictions. Their algorithm, Fair-SMOTE, improved both the fairness and performance of the model and broke the premise of Berk et al. [35] who claimed "It is impossible to achieve fairness and high performance simultaneously (except in trivial cases)".

We consider Fair-SMOTE [43] as our baseline method. It is a supervised approach and uses 100% training data labels. But gathering good quality labeled data is very challenging. Human labeling is an extremely costly process [27, 29, 75, 78] and there is a high possibility of human bias getting injected into the training data [57, 83]. That said, blindly trusting ground truth labels may induce bias in the machine learning model. Hence, it is timely to ask:

Can we reduce the labelling effort associated with building fair models?

In this work, we try to answer that question by using semi-supervised learning [96] that works with a small amount of labeled data and a large amount of unlabeled data. We build a framework called **Fair-Semi-Supervised-Learning (Fair-SSL)** that uses four state-of-the-art semi-supervised techniques - self-training, label propagation, label spreading, & co-training. Fair-SSL is a pseudo-labeling framework. It learns from the combination of labeled & unlabeled

data and then pseudo-labels the unlabeled data. Results show that Fair-SSL performs as good as three other state-of-the-art fairness algorithms [42–44]. That means even if available ground truth is corrupted or a very few labeled data points are available initially, fairness could still be achievable. Overall, this paper makes the following contributions:

- This is the first SE work using semi-supervised learning to generate fair classification models.
- Fair-SSL works with a very small amount of labeled training data (10%). Thus, we can avoid the costly process of data labeling. Hence, it is cost effective.
- We have shown a technique based on "situation testing" [4] to create fairly labeled data without using any human intervention.
- We have given a comparative analysis of four popular semisupervised algorithms in the context of software fairness.
- Our results show that semi-supervised algorithms can be used to generate fairer and better performing models.

#### 2 BACKGROUND

#### 2.1 Software Fairness

Big software industries have started putting more and more importance on ethical issues of ML software. IBM has created a software toolkit called AI Fairness 360 [13] which is considered to be an extensible open-source library for software fairness. Facebook developed a tool called Fairness Flow [16] to determine model fairness. Similarly, Microsoft has created Fairlearn [26]. Besides, they have a dedicated research group called FATE [18] where researchers particularly focus on fairness and ethics in AI.

In the academic domain, the ML community has started working in the area of fairness since last decade. ACM has created a separate conference series for fairness, accountability, and transparency called ACM FAccT [23]. The software community, in spite of having a delayed start, is taking initiatives to fight against this critical social bane. ICSE 2018 hosted Fairware, an international workshop on software fairness [17]. ASE 2019 organized another workshop called EXPLAIN to concentrate on ethical issues of AI software [21]. The IEEE [69], the European Union [15] recently published the ethical principles of AI. It is stated there that an intelligent system or machine learning software must be fair when it is used in real-life applications. Thus, testing software for bias and mitigating bias have now become an unavoidable step in software life cycle.

# 2.2 Fairness Testing & Supervised Bias Mitigation Algorithms

Research in machine learning fairness can be broadly classified into two segments - fairness testing (finding bias) and bias mitigation. Galhotra et al. proposed THEMIS [33], a causality based testing tool using the random test input generation technique to evaluate model fairness. The main idea of THEMIS is to perturb features of an instance to generate discriminatory samples. It is not very efficient in general since it relies on random sampling without any guidance on the generation. Udeshi et al. proposed AEQUITAS [80] which is a better version of THEMIS, and focused on better sample generation. Instead of random sample generation, AEQUITAS used

semi-directed and fully-directed instance generation. Later, Agarwal et al. proposed a new testing method for black-box models [31]. Their method is called Symbolic Generation (SG) which comprises symbolic execution and local model explanation techniques to generate individual discriminatory instances. In ICSE 2020, Zhang et al. presented how adversarial sampling can be used as a white-box testing tool to test fairness of DNN models [92].

In case of bias mitigation, there are three different kinds of algorithms - pre-processing, in-processing, and post-processing. In case of pre-processing, training data is pre-processed or massaged to remove bias. Some popular works are Fair-SMOTE [43], Reweighing [59], and Optimized pre-processing [42]. The in-processing algorithms divide the dataset into three parts - train, validation, and test set. After ML model is trained on training data, model is optimized on the validation set. Finally, tuned model is used for prediction on test set. Some popular works are Prejudice Remover Regularizer [61], and Adversarial debiasing [89]. In case of post-processing algorithms, the class labels are changed to reduce discrimination after classification. Most popular works are Reject option classification [60], and Equality of Opportunity [55].

Some prior works combine more than one of the above mentioned techniques such as Fairway [44] is a combination of preprocessing and in-processing. We have chosen three prior works to compare with Fair-SSL. Our first two selections, Fairway [44] and Fair-SMOTE [43], are from the SE community and the third one, Optimized pre-processing [42], is a highly cited work from the ML community. But all these works are supervised algorithms that require a large amount of labeled training data.

# 2.3 Semi-supervised Learning

Supervised machine learning models, specially the deep learning models, require a huge amount of labeled data for training. Gathering good quality labeled training data is the most expensive part of ML pipeline [27, 29]. The majority of the time, data comes in the form of partly labeled and mostly unlabeled. While human beings can be used for data labeling, gathering human labelers with the appropriate domain knowledge is challenging and expensive [27, 29]. Even then, the possibility of human bias getting injected into data is quite high [57, 83].

Semi-supervised learning (SSL) can address all these issues. SSL requires a small amount of labeled data to begin with [96], then using an incremental approach, unlabeled data is pseudo-labeled, and the combined data is used for model training. SSL has been used in various domains of software engineering such as defect prediction [78, 94], finding relevant papers [87], test case prioritization [86], static warning analysis [75], software vulnerability prediction [88] and many more.

To the best of our knowledge, this paper is the first to try SSL in the context of fairness. Outside of SE, we found only one study by Zhang et al. [93] studying SSL and fairness. They used self-training (a type of SSL) with ensemble models to generate fair results. They made one assumption that the initial labeled data is fair and also used ensemble models which are very slow to train. Our work differs to theirs, as follows: (a) we did not assume the initial data as fair; (b) we used the concept of *situation testing* [4] to select fairly labeled data from the available data; (c) whereas they used

Dataset	#Rows	#Cols	Protecte	ed Attribute	Class Label		
			Privileged	Unprivileged	Favorable	Unfavorable	
Adult Census Income [1]	48.842	14	Sex-Male	Sex-Female	High Income	Low Income	
Addit Celisus Income [1]	40,042	14	Race-White	Race-Non-white	Trigii income	Low micome	
Compas [8]	7,214	28	Sex-Male	Sex-Female	Did not reoffend	Reoffended	
Compas [8]	7,214	28	Race-Caucasian	Race-Not Caucasian	Did not reoliend	Reollellueu	
German Credit [2]	1,000	20	Sex-Male	Sex-Female	Good Credit	Bad Credit	
Default Credit [10]	30,000	23	Sex-Male	Sex-Female	Default Payment-Yes	Default Payment-No	
Heart Health [3]	297	14	Age-Young	Age-Old	Not Disease	Disease	
Bank Marketing [11]	45,211	16	Age-Old	Age-Young	Term Deposit - Yes	Term Deposit - No	
Home Credit [12]	3,075,11	240	Sex-Male	Sex-Female	Approved	Rejected	
Student Performance [6]	1,044	33	Sex-Male	Sex-Female	Good Grade	Bad Grade	
MEPS15 [7]	35,428	1,831	Race-White	Race-Non-white	Good Utilization	Bad Utilization	
MEPS 16 [9]	34,656	1,941	Race-White	Race-Non-white	Good Utilization	Bad Utilization	

Table 1: Details of the datasets used in this research.

Table 2: Definition of the performance and fairness metrics used in this study.

Performance Metric Ideal Value		Fairness Metric				
Recall = TP/P = TP/(TP+FN)	1	Average Odds Difference (AOD): Average of difference in False Positive Rates(FPR) and True Positive Rates(TPR) for unprivileged and privileged groups [34]. TPR = TP/(TP + FN), FPR = FP/(FP + TN), $AOD = [(FPR_U - FPR_P) + (TPR_U - TPR_P)] * 0.5$	0			
False alarm = $FP/N = FP/(FP+TN)$	0	<b>Equal Opportunity Difference (EOD)</b> : Difference of True Positive Rates(TPR) for unprivileged and privileged groups [34]. $EOD = TPR_U - TPR_P$	0			
Accuracy = $\frac{(TP+TN)}{(TP+FP+TN+FN)}$	1	<b>Statistical Parity Difference (SPD)</b> : Difference between probability of unprivileged group (protected attribute PA = 0) gets favorable prediction ( $\hat{Y} = 1$ ) & probability of privileged group (protected attribute PA = 1) gets favorable prediction ( $\hat{Y} = 1$ ) [40]. $SPD = P[\hat{Y} = 1 PA = 0] - P[\hat{Y} = 1 PA = 1]$	0			
Precision = TP/(TP+FP)	1	<b>Disparate Impact (DI)</b> : Similar to SPD but instead of the difference of probabilities, the ratio is measured [52]. $DI = P[\hat{Y} = 1 PA = 0]/P[\hat{Y} = 1 PA = 1]$	1			
$F1 Score = \frac{2 * (Precision * Recall)}{(Precision + Recall)}$	1					

only self-training, we used three other semi-supervised methods along with self-training. (d) we evaluated our results based on nine metrics, ten datasets, and three different learners whereas they used only two metrics, three datasets and two learners.

# 2.4 Fairness Terminology & Metrics

Before going into too much detail, at first, we need to define some fairness related terms. Table 1 contains ten datasets used in this study. Most of the prior works [42, 45, 46, 53, 60, 89] used one or two datasets whereas we used ten of them. All these datasets are binary classification datasets i.e. class labels have two values. A class label is called a *favorable label* if it gives an advantage to the receiver such as receiving a loan, being hired for a job. A *protected attribute* is an attribute that divides the whole population into two groups (privileged & unprivileged) that have differences in terms of receiving benefits. For example, there are two protected attributes in the *Adult Census Income* dataset. Based on "sex", "male" is privileged and "female" is unprivileged. Based on "race", "white" is privileged and "non-white" is unprivileged. In the context of classification, the goal of fairness is *giving similar treatment to privileged and unprivileged groups*.

Table 2 contains the definitions of the five performance metrics and four fairness metrics used in this study. All these metrics can

be calculated from the confusion matrix. We chose these metrics because they were widely used in the literature [37, 43–46, 55]. For recall, precision, accuracy, & F1 *larger values* are *better*; For false alarm, AOD, EOD, & SPD *smaller values* are *better*. DI is a ratio and there is no bias when the value of DI is 1. For readability, while showing results we compute abs(1 - DI) so that all four fairness metrics are lower the better (0 means no bias).

#### 3 METHODOLOGY

Fair-SSL contains three major steps:

- (1) Select a small amount of labeled data (10%) in a way that initial labeling does not contain bias (see §3.1).
- Pseudo-label the unlabeled data using semi-supervised approaches (see §3.2).
- (3) Balance the combined training data (labeled + pseudo labeled) based on protected attribute and class label (see §3.3).

Finally, we train ML models on the generated balanced data and test on the test data. For all the datasets, we divide them into 80% training and 20% testing. We keep test data completely separate and use them only for final score reporting.

# 3.1 Prepare the Fairly Labeled data

Our first task is preparing the initial fairly labeled set. All the datasets in Table 1 are already labeled. But are those labels fair? Can we just randomly pick one portion of that data as fairly labeled? How much labeled data is required to start with? We are going to find all the answers soon.

Prior studies [43, 50, 58, 71] have experimented with the datasets of Table 1 and found out that these datasets contain unfair labels. That means there are examples of biased ground truth based on protected attributes. Chakraborty et al. [43] used the same datasets and found out that more or less 10% data labels contain unfair decisions. That means if we randomly pick up some portion of the data, we may end up selecting some improperly labeled rows and training ML models on that corrupted data will introduce bias. Thus, at an early stage, we decided to discard the available ground truth (or labels) and use human evaluation to re-label the data.

In literature, there are mainly two approaches for executing the labelling process. The first one is *manual labeling/crowdsourcing*. The second one is *semi-supervised pseudo-labeling* that starts with a small amount of labeled data and using that, pseudo-labels the remaining data. In this work, we tried both of them and got success with the latter one.

3.1.1 *Crowdsourcing:* We decided to use crowdsourced workers via Amazon Mechanical Turk [24] to label these datasets. We applied best practices in crowdsourcing as described by Chen et al. [48] and gave the workers more than the USA minimum wage [70]. Instead of depending on a single opinion, for every data point, we considered using majority voting from five workers. That means if a data point is labeled positive by three workers and negative by two other workers, we mark it as positive. We used 200 Mechanical Turk workers and then took a break to evaluate their labeling. Unfortunately, we found out the labels given by crowdsourced workers are extremely noisy. One point to mention here is that we used "Gold" standard tasks [32, 68] in our study to make sure the workers pay full attention while labeling. We selected only those responses where workers gave correct answers for gold questions. We understood lack of attention is not the reason for noise, the reason is lack of domain expertise. The datasets we use in the fairness domain are not very easy to be labeled by common people. Most of them [1, 10, 11] are financial datasets; Compas [8] is a criminal sentencing dataset; Heart health [3] is a medical dataset. Thus special expertise is needed to label these kinds of data. It was out of our scope to find that kind of experienced people. Also, this manual labeling is a super expensive process. We not only had to bear the charges from Amazon but also the university was taking a 50% overhead tax on grants for using crowdworkers. Another reason for caution is even if we could hire people having the domain expertise to label these kinds of datasets, there would still be a chance of human bias getting injected into the ground truth [57, 83]. Thus we decided to stop using human intervention and started to find an alternative cheap way of labeling.

3.1.2 **Situation Testing**: Chakraborty et al. reported that in these datasets, around 10% of the labels are unfair labels [43]. Thus we could select only fairly labeled rows from the available data and

treat the rest as unlabeled data. By that way, our initial set will not contain unfair labels. To achieve that, we used the concept of *situation testing* [91]. It is a research technique used in the legal field [4] where decision makers' candid responses to applicant's personal characteristics are captured and analyzed.

In every dataset, a protected attribute divides the population into two groups - privileged and unprivileged. For example, in case of the "Adult" dataset, based on protected attribute "sex", privileged group is "male" and unprivileged group is "female". At first, we divide the data based on the protected attribute. Then, we train two different logistic regression models (any other simple statistical model can be used) on those two subgroups (for example - "male" and "female"). Then for all the training data points, we check the predictions of these two models. For a particular data point, if the predictions of two models match with the ground truth label, we keep the data point with the same label as it was fairly labeled. If

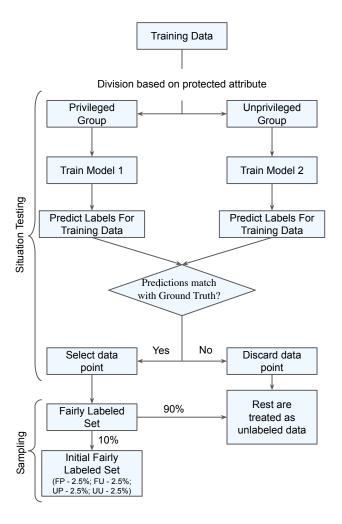


Figure 1: Algorithm (inspired from situation testing [4]) for selecting/sampling fairly labeled data points from the available data.

the model predictions contradict with each other or the ground truth, we discard the label and treat the data point as unlabeled.

After this situation testing phase, we get fairly labeled data points. We call this set the *fairly labeled set*. But we do not use this whole set for training. We take a small portion (10%) of this set to start. This selection is not a random selection. The normal trend of semisupervised learning is keeping the initial labeled data balanced based on class so that the semi-supervised model gets an opportunity to learn features from all the classes equally [56, 63, 72, 94]. In fairness, data balancing helps more if instead of just class, protected attributes are also balanced [43, 49, 84]. We apply the same balancing strategy while making the initial fairly labeled set. We select data points in a way that the *initial fairly labeled set* has equal proportion of "favorable-privileged (FP)" (for "Adult" dataset - "high income" & "male"), "favorable-unprivileged (FU)" ("high income" & "female"), "unfavorable-privileged (UP)" ("low income" & "male" ), & "unfavorable-unprivileged (UU)" ("low income" & "female") samples. Figure 1 shows the block diagram of the combined process of situation testing and sampling that generates perfectly balanced initial fairly labeled set.

To summarize, at first, we do *situation testing* to create the *fairly labeled set*. Then we create an *initial fairly labeled set* by choosing samples from the *fairly labeled set* in a way that based on target class and protected attribute combination, we have an equal proportion of examples. In §4, we will show how the performance of the model changes based on the size of the *initial fairly labeled set*.

# 3.2 Pseudo Labeling the Unlabeled data

We have the *initial fairly labeled set* from the previous step. We remove the labels of the rest of the training data and treat it as unlabeled data. In this step, we pseudo-label the unlabeled data using four different semi-supervised techniques [96]. This is called pseudo labeling because the generated labels are predicted labels, not actual labels. These four approaches differ in internal logic. But to make the study comprehensible, we followed a single pattern while applying these techniques. Algorithm 1 shows our approach. We start with labeled dataset  $D_l$  (initial fairly labeled set), and unlabeled dataset  $D_u$ . Our goal is to get a new training dataset (pseudo-labels added). To do that, we select a baseline model (based on the technique). The baseline model is trained on the initial fairly labeled set. Then baseline model predicts labels of the unlabeled data. We consider prediction of only those data points as valid where the confidence of the predictor is very high. There are two kinds of selection criterion used - (a) select k\_best data points based on prediction probability, or (b) select data points where prediction probability is above a certain threshold. Based on scikit-learn semi-supervised article [25], the ideal probability threshold is 0.7. We have used the same value. The data points being predicted with more than 70% confidence along with their predicted labels are added to the training data. This process is repeated until max iteration is reached. Now we will describe four semi-supervised approaches in detail.

3.2.1 **Self Training:** The self-training approach is based on Yarowsky et al.'s algorithm [85]. The advantage of using self-training is that any supervised classifier with good calibration can be used as the baseline model. We have used logistic regression because it returns well calibrated predictions by default as it directly optimizes *log* 

*loss.* Prior works [28, 30] found out logistic regression is a much better choice than random forest, naive bayes or svm as baseline model.

At first, a supervised classifier (here logistic regression) is trained on the *initial fairly labeled set* and then incrementally unlabeled data points are predicted. At each iteration, the data points having prediction probability more than "probability\_threshold" (0.7) are selected and added to the training set with the predicted labels. This process continues until max\_iteration is reached. Finally, as a result, we get a new training dataset which contains *initial fairly labeled set* and pseudo-labeled data points (by self-training).

3.2.2 **Label Propagation**: Label propagation is a semi-supervised graph inference algorithm. The core algorithm was developed by Zhu et al [97]. It is a type of "community detection algorithm". The algorithm starts with building a graph from the available labeled and unlabeled data. Each data point is a node in the graph and edges are the similarity weights. The graph is represented in the form of a matrix. The algorithm has four main steps [82, 97].

- A unique label is assigned to each node in the network. At time t = 0, for a node x, let its label is  $C_x(0) = x$
- The value of t is incremented. t += 1
- For each node x in the network, the most frequently occurring label among all the nodes with which x is connected is found out. Ties are broken using uniform logic.

$$C_x(t) = f(C_{x1}(t-1), C_{x2}(t-2), ...., C_{xk}(t-k))$$

 Convergence condition is checked. If not met, we go to step 2, else stop.

It uses a 'kernel' function to project data into alternate dimensional spaces. We tried with 'rbf' and 'knn' kernels and found better performance with 'rbf'. The 'knn' kernel is memory-friendly because it creates a sparse matrix. As most of the elements in the sparse matrix are zero, all the matrix operations become faster. On the other hand, 'rbf' kernel generates a fully connected graph which is represented by a dense matrix. Thus, matrix operations become time consuming. So, 'rbf' kernel performs better but slower than 'knn' kernel. While reporting results, we reported 'rbf' kernel results for label propagation.

**Algorithm 1:** Pseudo-labeling Algorithm. We used probability\_threshold = 0.7 and max\_iteration = 100 in our implementation.

Input: Labeled dataset  $D_l$ , unlabeled dataset  $D_u$ , max\_iteration, probability\_threshold

Output: New training dataset (pseudolabels added)

- 1 Select a baseline model
- <sup>2</sup> Train baseline model on  $D_1$
- $_3$  Predict on  $D_u$
- Select data points based on the selection criterion (probability\_threshold)
- 5 Add selected data points with predicted class to the  $D_1$
- 6 Re-train baseline model on  $D_1$
- 7 Repeat steps 3-6 until max\_iteration is reached

3.2.3 Label Spreading: Label spreading is also a graph inference algorithm but has some differences from label propagation. The algorithm was invented by Zhou et al. [95]. Label propagation uses the raw similarity matrix constructed from the data with no modifications. It believes that the original labels are perfect. On the contrary, label spreading does not blindly believe the original labels and make modifications to the ground truth. The method of changing the ground truth labels is called "clamping". Label propagation is a "hard clamping" approach because it does not change the original ground labels. In contrast, label spreading is a "soft clamping" approach and more robust to noise. The label spreading algorithm iterates on a modified version of the original graph and normalizes the edge weights by computing the normalized graph Laplacian matrix. Here also we tried with two different kernels ('rbf', 'knn') and got better results with 'rbf' kernel.

3.2.4 **Co-Training**: Co-training is a very popular semi-supervised approach developed by Blum et al. [38]. Here the feature set is divided into two mutually exclusive sets. Then two separate classifiers are trained on those two different feature sets (using the labeled data). Then both classifiers predict on the unlabeled data. For example, we take two classifiers clf1 and clf2. The data points confidently predicted by clf1 are used for clf2 training and data points confidently predicted by clf2 are used for clf1 training. If clf1 and clf2 both are confident for a data point, that is added to the training-set with the predicted label. Co-training has had great success in the text mining [66, 81] and the image domain [36, 67]. The success of co-training depends on a very specific assumption. The assumption is "Original feature set can be divided into two mutually exclusive subsets which are conditionally independent given the class." Here we are using tabular (row-column) data and sub-diving features according to that assumption is not always possible. Thus, instead of using an off-the-shelf co-training approach, we developed a similar but slightly different majority voting technique. Our proposed majority voting algorithm is as follows:

- Build separate models from each attribute of *initial fairly* labeled set.
- Use each model to predict labels for the unlabeled data.
- For every data point, check predictions for all the models. Get the majority voting.
- Add the data point to the training set with the majority label.
- Incrementally repeat for all the unlabeled data points.

Here also, we use logistic regression model (one model per feature) for good calibration. The number of features in our datasets is not very high, thus this majority voting technique is feasible. In cases where the number of features is very high, instead of creating a new model for each feature, some kind of grouping of features (maybe choosing only important features based on information gain and then creating two or more subgroups with top K features) can be used. We keep this for our future work.

#### 3.3 Synthetic Oversampling & Balancing

Our training data is now labeled. We can go for model training. But some prior works [43, 49] claimed that training data needs to be balanced in order to achieve fair prediction. Here data balancing means the number of examples based on protected attribute and class should be almost equal. We can undersample majority

**Algorithm 2:** Oversampling pseudocode inspired from [43]

```
Input: Dataset, Protected Attribute(p_attrs), Class Label(cl)
   Output: Balanced Dataset
  Def Fair-SMOTE(Dataset, p_attrs, cl):
        count_groups = get_count(Dataset, p_attrs, cl)
        max size = max(count groups)
        cr, f = 0.8, 0.8 (user can pick any value in [0,1])
              for attr in p attrs do
                   sub_data = Dataset(cl=c & p_attrs=attr)
                   sub_group_size = count_groups[c][attr]
                   to_generate = max_size - sub_group_size
                   knn = NearestNeighbors(sub_data)
10
11
                   \textbf{for} \ \textit{iin range}(to\_generate) \ \textbf{do}
                        parent = Dataset[rand_sample_id]
12
                        ngbr = knn.kneighbors(parent, 2)
                        c1, c2 = Dataset[ngbr[0]], Dataset[ngbr[1]]
14
                        new_candidate = []
15
                        for col in parent.columns do
16
                              if cr > random(0,1) then
17
                               \label{eq:new_val} \begin{tabular}{ll} & new\_val = p[col] + f^*(c1[col]-c2[col]) \end{tabular}
18
19
                                   new_val = p[col]
20
                             new_candidate.add(new_val)
                   Dataset.add(new candidate)
22
        return Dataset
23
```

examples to obtain that data balance. But Yan et al. [84] said increasing the amount of training data instead of decreasing is likely to produce better trade-off between performance and fairness. Thus we decided to use synthetic generation of minority examples to balance the training data.

Traditional class balancing techniques such as SMOTE [47] only balances the class by oversampling the minority class. But, we want to balance based on two conditions - target class and protected attribute. For that, we use the Fair-SMOTE algorithm by Chakraborty et al. [43]. At first, we divide the training data into four groups (Favorable & Privileged, Favorable & Unprivileged, Unfavorable & Privileged, Unfavorable & Unprivileged). Initially, these subgroups are of unequal sizes. Then we find out the group with maximum size. Our target is to create new data points of other groups to make them equal to the group with the maximum size. Algorithm 2 shows the pseudocode of oversampling inspired from Fair-SMOTE [43]. Fair-SMOTE synthetically generates new data points of minority groups. It starts with randomly selecting a data point (parent point p) from a minority sub-group. Then using K-nearest neighbor, two data points (c1, c2) are selected which are closest to p. Next, according to the algorithm described, a new data point is generated. There are two hyperparameters ("mutation amount" (f) and "crossover frequency" (cr)) that control the extrapolation. In our experiment, we used a grid search approach to find out the best values of cr & f. After synthetic oversampling, the training data becomes balanced based on target class and protected attribute i.e. above mentioned four groups become of equal sizes.

We have now described all the major components of Fair-SSL that generates pseudo-labeled, and balanced training data from a very small set of labeled examples. Figure 2 shows Fair-SSL framework.

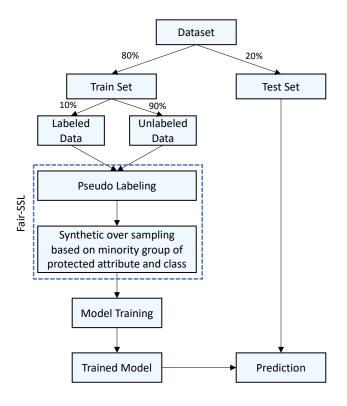


Figure 2: Framework of Fair-SSL

# 3.4 Experimental Setup

We conducted our experiments on ten datasets described on Table 1. We split the datasets using 5 fold cross-validation (train - 80%, test - 20%) and repeat 10 times with random seeds and finally report the median for every experiment. Standard data pre-processing techniques are used such as (a) ignoring rows with missing or corrupted values (b) continuous columns are converted to categorical (e.g., age<25: young, age>=25: old) (c) non-numerical features are converted to numerical (e.g., male: 1, female: 0) (d) finally, all the numerical feature values are normalized (converted between 0 to 1 using scikit-learn MinMaxScaler). Source code is written in Python and scikit-learn semi-supervised library 1 has been used. All experiments were conducted on a Windows laptop (x64) with a 2.7 GHz 8-Core Intel i7 CPU and 12GB of main memory. We run all the experiments for three different learners - a) logistic regression b) random forest & c) support vector machine (svm). We used scikit-learn version of these models along with off-the-shelf hyperparameters. Most of the prior works [37, 42-44, 46, 61] in fairness domain chose simple models like us instead of deep learning models. The main reason behind that is the fairness datasets are comparatively less complicated as they are small in size with respect to number of rows and columns. In future, we will use DL models if larger fairness datasets are available.

#### 3.5 Statistical Tests

We compare Fair-SSL with three state-of-the-art prior fairness algorithms - Optimized Pre-processing [42], Fairway [44], and Fair-SMOTE [43]. We use Scott-Knott statistical test [54, 65] for this comparison. Scott-Knott test recursively bi-clusters a sorted set of numbers. The result of the Scott-Knott test is ranks assigned to each result set; higher the rank, better the result. If two clusters are statistically indistinguishable, Scott-Knott reports them both as belonging to the same "rank". Note that we have nine metrics in total. We want to maximize recall, precision, accuracy & F1; and minimize false alarm, AOD, EOD, SPD & DI.

#### 4 RESULTS

Our results are structured around four research questions. For all the results, we repeat our experiments ten times with data shuffling and report the median. For answering RQ3 (Table 5), we vary the size of *initial fairly labeled set*. For all other cases (Table 3, 4, & Figure 3), size of *initial fairly labeled set* is 10% of the training data.

#### **RQ1.** Can Fair-SSL reduce bias?

The premise of this paper is finding out whether semi-supervised techniques can be helpful to achieve fairness or not. RQ1 directly asks that question. Table 3 answers the question. It contains the results for six datasets. "Default" rows signify when a logistic regression model is trained on the available labeled training data with no modification. We see for every dataset, the values of AOD, EOD, SPD, and DI are very high indicating bias in prediction. For every dataset, the last four rows show the results of Fair-SSL with four different algorithms used as pseudo-labeler inside. That means, 10% labeled training data is used and rest of the training data has been pseudo-labeled. After that combined training data is oversampled to be balanced based on protected attribute and class. Finally, the generated data has been used for model training. We see all four versions of Fair-SSL significantly reduce the values of four bias metrics (AOD, EOD, SPD, and DI) for all the datasets (for more results please visit this<sup>2</sup>). That means Fair-SSL can successfully reduce bias. In Table 3, first five columns are showing the performance metrics. We see in some of the cases, recall and F1 are better than "Default". But there are some damage in case of false alarm, and accuracy. Prior fairness works [42, 44, 59, 60, 89] also damaged performance of the model while achieving fairness. This is called the "fairnessperformance" trade-off in the literature. The answer for RQ1 is "Yes, Fair-SSL can significantly reduce bias. It improves recall and F1 and sometimes damages false alarm, and accuracy."

**RQ2.** How well does Fair-SSL perform compared to the state of the art bias mitigation algorithms?

Fair-SSL improves fairness of the prediction with a minor damage in performance. Here we are comparing Fair-SSL with three other state-of-the-art bias mitigation algorithms - Optimized Preprocessing [42], Fairway [44] and Fair-SMOTE [44]. If we look at

 $<sup>^{1}</sup> https://scikit-learn.org/stable/modules/semi\_supervised.html$ 

 $<sup>^2</sup> https://github.com/senthusiast/Fair-SSL/blob/main/results/Results.md \\$ 

Table 3, the last four columns are bias scores where Fair-SSL is performing as good as the others. In case of performance metrics (first five columns), we see it is losing sometimes but not by much. To get a clear picture, we take a look at Table 4. Here we show the summarized results for all ten datasets (Adult and Compas have two protected attributes each, i.e. 10 + 2 = 12 cases) and three learners (logistic regression, random forest, and svm). We have implemented four different versions of Fair-SSL (ST, LP, LS, CT). For comparison purpose, for every dataset, we have created a validation set (20%) from the train set. On the validation set, we tried all four versions of Fair-SSL and chose the best one to run on the test set. Thus, Table 4 contains comparison of the best version of Fair-SSL (best is selected based on validation results) with three other state-of-the-art bias mitigation algorithms. We see in bias scores, Fair-SSL is as good as other three. In 'recall' and 'F1 score', it performs better than Optimized Pre-processing and Fairway. One important point to mention here is that other three algorithms take advantage of full training data where Fair-SSL takes only 10% of labeled training data. The answer for RO2 is "Fair-SSL is as good as others in reducing bias, sometimes better in "recall" and "F1" than Optimized Pre-processing and Fairway."

# RQ3. How much labeled data is required to begin with?

Semi-supervised algorithms work with a small amount of labeled data and a large amount of unlabeled data. However, it is crucial to know how much labeled data is needed to start. Table 5 shows results for three datasets where size of the initial fairly labeled set has been varied from 1% to 20%. Here also we used the best version of Fair-SSL based on validation set results. We see the trend of increasing accuracy, F1 and decreasing AOD, EOD with increasing size of initial fairly labeled set. Even when using 5% labeled training data, we see Fair-SSL can significantly reduce bias. However, for accuracy and F1, Fair-SSL with 10% labeled training data performs much better than 5% version and very similar to 20% version. This gives a strong indication of semi-supervised learning being successful to achieve fairness. Hence, to answer RQ3, we say that "Fair-SSL can significantly reduce bias even when a very small amount of labeled data points are available. Performance of Fair-SSL gets better with increasing size of initial labeled training set."

**RQ4.** Which semi-supervised approach is the best to reduce bias?

The results so far can be summarized as follows: semi-supervised algorithms can be useful to augment bias mitigation process. That raises our next research question: which one of our four different semi-supervised techniques performs the best in this context?

Table 3 shows all four versions of Fair-SSL are reducing the bias scores. In case of performance metrics (the first five columns), all four of them are doing just the same (with minor differences). That means there is no way to choose one best method among the four methods. This reminds us of the popular "No free lunch

theorem" for machine learning [51]. We can certainly say semisupervised pseudo-labeling improves fairness but which one is the best depends on the specific dataset. Thus it is wise to try all of them and find out the best one in case of real life applications.

When we are comparing the performance of the semi-supervised techniques, the execution time comparison also makes sense (as higher execution time means higher cost). Figure 3 shows the execution time (log scale) of four approaches for Adult and Compas dataset. We used 5-fold cross validation and 10 repeats i.e. every bar in the figure shows execution time for 5\*10 = 50 runs. For both datasets, label propagation is the slowest and self-training is the fastest method. We used logistic regression as self-training baseline model. Choosing a different model may change the scenario. Nevertheless, it would seem that label propagation and label spreading can be slow where self-training can be very fast if a simple statistical model is chosen.

Hence, our answer for RQ4 is "Semi-supervised techniques help but there is no winner based on performance. We should try all the approaches for a particular dataset to find out the best one. However, based on execution time, self-training with simple statistical model works the fastest."

# 5 DISCUSSION: WHY FAIR-SSL?

Here we discuss what makes Fair-SSL unique and more useful than prior works in the fairness domain.

- Inexpensive Real world data comes as a mixture of labeled and unlabeled form. Available data labels can be of poor quality. Hiring Crowdsource workers for human labeling is not always an affordable solution. Tu et al. estimated that labeling GitHub issues as buggy/non-buggy for 500 projects would require \$320K [79]. That said it is worth exploring alternative inexpensive ways of data labeling. Fair-SSL pseudo-labeler serves that purpose. It takes a very small amount of labeled data and then pseudo-labels the unlabeled data. We believe this will definitely help the domains where finding good quality labeled data is really challenging and expensive.
- Performance Fair-SSL performs similar to the state-of-theart supervised bias mitigation algorithms. Our results based on 10 datasets and three learners show that Fair-SSL can significantly reduce bias, improves recall & F1 score and sometimes damages accuracy, false alarm. To the best of our knowledge, all the prior supervised bias mitigation algorithms (except Fair-SMOTE [43]) damage performance of the model while making it fair [37, 62, 64, 74]. Fair-SSL uses similar data balancing strategy as Fair-SMOTE and that is why achieves similar results of higher recall & F1 but uses only 10% labeled data. However, the damage of accuracy, false alarm, and precision will remain a concern for future research. Since fairness always comes with a cost of affecting performance, it is the responsibility of the stakeholders to prioritize their objectives.
- Model-agnostic Fair-SSL is a data pre-processor. That means after pseudo-labeling the data, any supervised model can be used for final prediction. Thus Fair-SSL is model agnostic.
- Incremental Update In software industries, a common trend is incrementally updating the model or retraining the model with newer data. Most of the time this new data is unlabeled. Fair-SSL pseudo-labeler instead of supervised algorithms can

Table 3: Results for RQ1, RQ2, and RQ4. In this table "Default" means off-the-shelf logistic regression; Optimized Preprocessing [42], Fairway [44], Fair-SMOTE [43] are bias mitigation algorithms that use 100% training data labels. Fair-SSL uses 10% training data labels. Fair-SSL-ST is using self-training; Fair-SSL-LP is using label-propagation; Fair-SSL-LS is using label-spreading; Fair-SSL-CT is using co-training. Cells show medians for 10 runs. Here, the darkest cells show top rank (note: for the metrics with '+' more is better and for the metrics with '-' less is better). The lighter and lightest cells show rank two and rank three respectively; the white cells show the worst rank. Rankings were calculated via Scott-Knott test (§3.5).

Adult Census Income	Dataset	Protected	Algorithms	Recall	False alarm	Precision	Accuracy	F1 Score	AOD	EOD	SPD	DI
Adult Census Income		Attribute		(+)	(-)	(+)	(+)	(+)	(-)	(-)	(-)	(-)
Part												
Adult Census Income   Sex   Fair-SMOTE   0.71   0.25   0.51   0.73   0.62   0.01   0.02   0.03   0.08												
Rincome	4.1.11.0										ł.	
Fair-SSI-LE		Sex									l l	
Fair-SSI-LTS   0.72   0.31   0.42   0.71   0.55   0.03   0.04   0.06   0.08	Income											
Fair-SSI-CT   0.76   0.35   0.44   0.68   0.57   0.06   0.04   0.03   0.08												
Adult Census   Race												
Adult Census Income   Pace   Fairway   Adult Census												
Adult Census   Race   Fairway   0.36   0.04   0.70   0.73   0.24   0.60   0.05   0.06   0.05   0.16												
Adult Census   Income   Race     Fair-SMCTE   0.7   0.22   0.51   0.74   0.66   0.05   0.08   0.09   0.18   0.05   0.18   0.74   0.66   0.05   0.08   0.09   0.18   0.1												
Pair-SSL-ST   0.7	Adult Census											
Pair-SSI-LP   0.72   0.31   0.49   0.72   0.59   0.02   0.00		Race										
Fair-SSL-IS			Fair-SSL-LP		0.31		0.72	0.59	0.02	0.03	0.02	0.16
Compas				0.7		0.51	0.71	0.58	0.02	0.02	0.05	0.19
Compas   Pair   Salitation   Pair   Pair   Salitation   Pair   Pair   Salitation   Pair   Pair   Salitation   Pair   P			Fair-SSL-CT	0.72	0.31	0.48	0.71	0.58	0.03	0.05	0.05	0.21
Compase         Fairway Early Sex (Fair-SMCTE)         0.62 (0.22) (0.57) (0.58) (0.55) (0.55) (0.65) (0.02) (0.07) (0.08) (0.09) (0.12) (0.12) (0.65) (0.05) (0.05) (0.08) (0.09) (0.12			Default	0.67	0.38	0.66	0.64	0.61	0.09	0.19	0.18	0.28
Compase         Sex Fair-SSL-ST         0.62 Pair-SSL-ST         0.32 0.21         0.36 0.05         0.55 0.58         0.02 0.09         0.09 0.09         0.12 0.09         0.12 0.09         0.12 0.09         0.12 0.09         0.12 0.09         0.12 0.09         0.19 0.09         0.10 0.09         0.09 0.09         0.19 0.09         0.09 0.09			OP	0.71	0.36	0.64	0.62	0.60	0.04	0.03	0.05	0.08
Pair-SSL-ST   0.42			Fairway	0.56	0.22	0.57	0.58	0.58	0.03	0.03	0.06	0.08
Fair-SSL-SI   0.42   0.21   0.65   0.58   0.54   0.02   0.06   0.09   0.19   0.12   0.21     Fair-SSL-IS   0.52   0.34   0.62   0.64   0.65   0.05   0.05   0.09   0.19   0.19     Fair-SSL-IS   0.52   0.33   0.61   0.62   0.62   0.62   0.03   0.03   0.05   0.07     Fair-SSL-IS   0.59   0.39   0.65   0.64   0.68   0.05   0.11   0.12   0.21     OP   0.68   0.39   0.65   0.64   0.68   0.05   0.11   0.12   0.21     OP   0.68   0.39   0.65   0.64   0.68   0.05   0.11   0.12   0.21     Fair-SSL-IS   0.52   0.30   0.56   0.55   0.66   0.01   0.05   0.06   0.12     Fair-SSL-IS   0.51   0.23   0.67   0.59   0.58   0.03   0.09   0.12   0.11     Fair-SSL-IS   0.51   0.23   0.67   0.59   0.58   0.03   0.09   0.12   0.11     Fair-SSL-IS   0.51   0.23   0.67   0.59   0.66   0.62   0.61   0.03   0.07   0.08   0.14     Fair-SSL-IS   0.51   0.23   0.67   0.59   0.66   0.62   0.61   0.03   0.07   0.08   0.14     Fair-SSL-IS   0.51   0.23   0.67   0.66   0.62   0.61   0.03   0.07   0.08   0.14     Fair-SSL-IS   0.58   0.35   0.64   0.63   0.63   0.03   0.04   0.05   0.09     Fair-SSL-IS   0.58   0.35   0.64   0.63   0.63   0.03   0.04   0.05   0.06   0.12     Fair-SSL-IS   0.51   0.27   0.66   0.62   0.61   0.03   0.07   0.06   0.12     Fair-SSL-IS   0.51   0.27   0.73   0.71   0.04   0.05   0.06   0.12     Fair-SSL-IS   0.51   0.52   0.70   0.73   0.71   0.04   0.05   0.06   0.12     Fair-SSL-IS   0.51   0.52   0.66   0.66   0.66   0.06   0.02   0.05   0.06   0.12     Fair-SSL-IS   0.51   0.52   0.26   0.75   0.54   0.56   0.66   0.06   0.02   0.05   0.06   0.12     Fair-SSL-IS   0.42   0.77   0.75   0.54   0.56   0.66   0.06   0.03   0.07   0.12     Fair-SSL-IS   0.48   0.12   0.53   0.54   0.56   0.66   0.06   0.03   0.07   0.12     Fair-SSL-IS   0.48   0.12   0.53   0.54   0.56   0.66   0.06   0.03   0.05   0.05     Fair-SSL-IS   0.59   0.35   0.36   0.35   0.67   0.44   0.05   0.05   0.05     Fair-SSL-IS   0.59   0.36   0.36   0.37   0.07   0.14   0.05   0.05   0.05     Fair-SSL-IS   0.59   0.36   0.36   0.37   0.07   0.11	Compas	Sev	Fair-SMOTE	0.62	0.32	0.56	0.55	0.65	0.02	0.05	0.08	0.09
Fair-SSL-IS   0.52   0.33   0.61   0.62   0.62   0.03   0.03   0.05   0.09     Fair-SSL-CT   0.49   0.28   0.62   0.61   0.57   0.03   0.02   0.05   0.09     Fair-SSL-CT   0.49   0.28   0.62   0.61   0.57   0.03   0.02   0.05   0.09     Fair-SSL-DT   0.69   0.39   0.65   0.64   0.68   0.05   0.11   0.12   0.21     Fair-SSL-DT   0.62   0.30   0.56   0.55   0.66   0.02   0.04   0.03   0.11     Fair-SSL-ST   0.49   0.24   0.66   0.60   0.57   0.04   0.05   0.06   0.11     Fair-SSL-IS   0.49   0.24   0.66   0.60   0.57   0.04   0.07   0.08   0.12     Fair-SSL-IS   0.51   0.27   0.66   0.62   0.61   0.03   0.07   0.08   0.12     Fair-SSL-IS   0.51   0.27   0.66   0.62   0.61   0.03   0.07   0.08   0.14     Fair-SSL-IS   0.58   0.35   0.64   0.63   0.63   0.03   0.07   0.08   0.14     Fair-SSL-IS   0.59   0.75   0.73   0.71   0.73   0.71   0.04   0.05   0.05     Fair-SSL-IS   0.79   0.75   0.73   0.71   0.73   0.71   0.04   0.05   0.05     Fair-SSL-IS   0.62   0.36   0.71   0.64   0.71   0.05   0.05   0.05   0.05     Fair-SSL-IS   0.61   0.32   0.72   0.61   0.69   0.02   0.05   0.05   0.13     Fair-SSL-IS   0.57   0.74   0.75   0.54   0.56   0.06   0.02   0.03   0.08   0.03     Fair-SSL-IS   0.59   0.75   0.70   0.78   0.34   0.05   0.06   0.03   0.09   0.02     Fair-SSL-IS   0.58   0.26   0.39   0.68   0.44   0.05   0.08   0.05   0.05     Fair-SSL-IS   0.59   0.36   0.34   0.64   0.42   0.05   0.04   0.05   0.05     Fair-SSL-IS   0.59   0.36   0.34   0.64   0.42   0.05   0.04   0.05   0.05     Fair-SSL-IS   0.59   0.36   0.34   0.64   0.64   0.04   0.05   0.05   0.05     Fair-SSL-IS   0.59   0.35   0.36   0.65   0.66   0.44   0.05   0.03   0.09     Fair-SSL-IS   0.59   0.35   0.36   0.65   0.66   0.44   0.05   0.03   0.05   0.03     Fair-SSL-IS   0.59   0.35   0.36   0.65   0.64   0.64   0.04   0.05   0.05     Fair-SSL-IS   0.66   0.37   0.66   0.66   0.64   0.64   0.04   0.05   0.05     Fair-SSL-IS   0.66   0.37   0.66   0.65   0.70   0.75   0.75   0.04   0.05   0.05     Fair-SSL-IS   0.66   0.37   0.66   0.65	Compas	JCA	Fair-SSL-ST	0.42	0.21	0.65	0.58	0.54	0.02	0.09	0.12	0.21
Fair-SSL-CT							0.54					
Pefault												
Compase   Race   Fairway   Cost   C												
Compas         Race         Fair-MOTE Fair-SMCTE Fair-SSL-ST Fair-SSL-ST Fair-SSL-ST Fair-SSL-ST Credit         0.52 Fair-SSL-ST Fair-SS												
Pair-SMOTE												
Fair-SSL-SSL-SSL-SSL-SSL-SSL-SSL-SSL-SSL-SS												
Fair-SSL-LP	Compas	Race										
Fair-SSL-LS   0.51   0.27   0.66   0.62   0.61   0.03   0.07   0.08   0.14	•										ł.	
Fair-SSL-CT   0.58   0.35   0.64   0.63   0.63   0.03   0.04   0.05   0.09												
German Credit         Sex         Default OP O.75 D.73 D.71 D.73 D.71 D.04 D.05 D.05 D.06 D.12 Pairway         O.75 D.073 D.71 D.073 D.71 D.04 D.05 D.05 D.06 D.12 D.07 D.07 D.07 D.07 D.07 D.07 D.07 D.07												
Cerman Credit   Sex   Fair-SMOTE   Credit   Fair-SSL-CT   Credit   Credit   Fair-SSL-CT   Credit												
German Credit         Sex         Fair-SMOTE 0.62 b.0.36 b.0.71 b.0.64 b.0.71 b.0.5 b												
German Credit         Sex         Fair-SMOTE Fair-SSL-ST 1 0.61 0.32 0.72 0.61 0.69 0.02 0.05 0.06 0.13											ł.	
Credit         Sex         Fair-SSL-ST         0.61         0.32         0.72         0.61         0.69         0.02         0.05         0.06         0.1           Fair-SSL-LS         0.42         0.17         0.56         0.66         0.06         0.02         0.03         0.08           Fair-SSL-LS         0.42         0.17         0.75         0.58         0.64         0.06         0.03         0.07         0.12           Pefault         0.25         0.07         0.70         0.78         0.34         0.05         0.08         0.06         0.35           OP         0.28         0.06         0.65         0.70         0.32         0.01         0.02         0.03         0.09           Fairway         0.21         0.04         0.67         0.67         0.33         0.01         0.04         0.03         0.04         0.05         0.03         0.02         0.03         0.05         0.03           Credit         Fair-SSL-LD         0.51         0.31         0.37         0.67         0.33         0.01         0.04         0.05         0.03           Credit         Fair-SSL-LP         0.51         0.31         0.37         0.67 <td< td=""><td>German</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></td<>	German											
Fair-SSL-LB		Sex										
Pair-SSL-CT   0.52   0.26   0.75   0.58   0.64   0.06   0.03   0.04   0.09					0.41			0.66	0.06	0.02	0.03	0.08
Default Credit   Sex     Default   O.25   O.07   O.70   O.78   O.34   O.05   O.08   O.06   O.35			Fair-SSL-LS	0.42	0.17	0.75	0.54	0.56	0.06	0.03	0.07	0.12
Default Credit   Sex   Fair-SMOTE   0.58   0.06   0.65   0.70   0.32   0.01   0.02   0.03   0.09			Fair-SSL-CT	0.52	0.26	0.75	0.58	0.64	0.06	0.03	0.04	0.09
Default Credit			Default	0.25	0.07	0.70	0.78	0.34	0.05	0.08	0.06	0.35
Default Credit			OP	0.28	0.06	0.65	0.70	0.32	0.01	0.02	0.03	0.09
Credit         Fair-SSL-ST Fair-SSL-LP         0.48 0.51         0.12 0.31         0.53 0.37         0.67 0.67         0.44 0.05         0.03 0.03         0.08 0.03         0.08 0.03           Bank Marketing         Age         Default Fair-SSL-LD 0P         0.72 0.72         0.21 0.20         0.74 0.75         0.75 0.75         0.04 0.04         0.03 0.03         0.05 0.08         0.08           Bank Marketing         Age         Default Fair-SMOTE Fair-SMOTE         0.76 0.16         0.72 0.72         0.71 0.73         0.71 0.73         0.71 0.71         0.71 0.04         0.03 0.03         0.05 0.02         0.04 0.03         0.05 0.02         0.04 0.03         0.05 0.02         0.04 0.03         0.05 0.02         0.04 0.03         0.05 0.02         0.04 0.05         0.02         0.04 0.03         0.05 0.02         0.04 0.05         0.02         0.04 0.05         0.02         0.04 0.05         0.05 0.05         0.06 0.05         0.06 0.05 0.03         0.07 0.07         0.04 0.05 0.05 0.03         0.05 0.05 0.03         0.07 0.01 0.05         0.02 0.03         0.07 0.05 0.05         0.01 0.05 0.05         0.04 0.04 0.04 0.04 0.05         0.05 0.05 0.05         0.01 0.05 0.05         0.04 0.04 0.04 0.05 0.05         0.05 0.05 0.05 0.05         0.06 0.05 0.05 0.05 0.05 0.05 0.05 0.05			Fairway	0.21	0.04	0.67	0.67	0.33	0.01	0.04	0.03	0.12
Credit         Fair-SSL-LP Fair-SSL-LD         0.48 0.51         0.12 0.31         0.53 0.37         0.67 0.64         0.44 0.05         0.03 0.03         0.08 0.08           Fair-SSL-LS         0.59 Fair-SSL-CT         0.59 0.36         0.34 0.36         0.64 0.64         0.42 0.05         0.04 0.03         0.03 0.09         0.08           Bank Marketing         Age         Default Fair-SMOTE Fair-SM-LD         0.72 0.72         0.74 0.73         0.77 0.73         0.71 0.73         0.71 0.71         0.04 0.03         0.05 0.02         0.04 0.05         0.02 0.04         0.05 0.06         0.06 0.06         0.06 0.07         0.77 0.77         0.08 0.02         0.24 0.03         0.01 0.02         0.04 0.05         0.02 0.04         0.03 0.05         0.00 0.05         0.00 0.06         0.04 0.06         0.05 0.06         0.77 0.72         0.74 0.71         0.04 0.04         0.05 0.05         0.06 0.05         0.06 0.06         0.06 0.05         0.06 0.06         0.04 0.04         0.03 0.07         0.07 0.09 0.07         0.11 0.03         0.02 0.04         0.03 0.07         0.11 0.03         0.02 0.09 0.07         0.12 0.09 0.07         0.12 0.09 0.01         0.02 0.09 0.07         0.01 0.02 0.09 0.01         0.02 0.09 0.01         0.02 0.09 0.01         0.02 0.09 0.01         0.02 0.09 0.01         0.02 0.09 0.01	Default	Sev		0.58	0.26	0.39	0.68	0.44	0.02	0.03	0.05	0.03
Fair-SSL-LS   0.59   0.36   0.34   0.64   0.42   0.05   0.04   0.03   0.09     Fair-SSL-CT   0.59   0.35   0.36   0.65   0.44   0.03   0.03   0.05   0.08	Credit	эех										
Bank Marketing         Age         Default Fair-SSL-CT Fair-SSL-LP Fair-SSL-LP Fair-SSL-ST O.69         0.35 0.35 0.36 0.65 0.64 0.77 0.77 0.08 0.02 0.24 0.31 0.76 0.77 0.77 0.08 0.22 0.24 0.31 0.77 0.77 0.77 0.08 0.22 0.24 0.31 0.77 0.77 0.77 0.77 0.08 0.22 0.24 0.31 0.77 0.77 0.77 0.77 0.77 0.77 0.77 0.7												
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Bank Marketing         Age         OP Fairway         0.72 0.20 0.74 0.73 0.71 0.71 0.71 0.04 0.05 0.02 0.04 0.05 0.06           Fairway         0.71 0.17 0.73 0.71 0.71 0.04 0.03 0.05 0.06           Fair-SMOTE 0.76 0.16 0.72 0.72 0.72 0.74 0.04 0.05 0.05 0.03 0.05 0.05 0.03 0.07 0.15 0.05 0.05 0.05 0.05 0.05 0.05 0.05												
Bank Marketing         Age         Fairway Fairway         0.71         0.17         0.73         0.71         0.71         0.04         0.03         0.05         0.06           Marketing         Fair-SMOTE         0.76         0.16         0.72         0.72         0.74         0.04         0.05         0.05         0.03           Fair-SSL-ST         0.66         0.37         0.6         0.64         0.64         0.04         0.08         0.05         0.11           Fair-SSL-LD         0.57         0.37         0.58         0.62         0.56         0.02         0.03         0.07         0.1           Fair-SSL-CT         0.69         0.18         0.74         0.72         0.71         0.05         0.09         0.01           Fair-SSL-CT         0.69         0.18         0.74         0.72         0.71         0.05         0.02         0.09         0.21           OP         0.79         0.06         0.85         0.88         0.83         0.06         0.05         0.06         0.12           OP         0.79         0.06         0.83         0.83         0.82         0.02         0.04         0.04         0.06           Fair-SM-CSL-ST												
Bank Marketing         Age         Fair-SMOTE         0.76         0.16         0.72         0.72         0.74         0.04         0.05         0.03         0.03           Fair-SSL-ST         0.66         0.37         0.6         0.64         0.64         0.04         0.08         0.05         0.11           Fair-SSL-LP         0.57         0.37         0.58         0.62         0.56         0.02         0.03         0.07         0.1           Fair-SSL-LS         0.62         0.35         0.62         0.64         0.62         0.07         0.09         0.07         0.12           Fair-SSL-CT         0.69         0.18         0.74         0.72         0.71         0.05         0.02         0.09         0.21           Default         0.81         0.06         0.85         0.88         0.83         0.06         0.05         0.06         0.12           OP         0.79         0.06         0.83         0.83         0.82         0.02         0.04         0.04         0.06           Fairway         0.76         0.05         0.81         0.84         0.84         0.84         0.84         0.84         0.84         0.04         0.04         <												
Marketing         Age         Fair-SSL-ST         0.66         0.37         0.6         0.64         0.64         0.04         0.08         0.05         0.11           Fair-SSL-LP         0.57         0.37         0.58         0.62         0.56         0.02         0.03         0.07         0.1           Fair-SSL-LD         0.62         0.35         0.62         0.64         0.62         0.07         0.09         0.07         0.12           Fair-SSL-CT         0.69         0.18         0.74         0.72         0.71         0.05         0.02         0.09         0.21           Default         0.81         0.06         0.85         0.88         0.83         0.06         0.05         0.06         0.1           Student         OP         0.79         0.06         0.83         0.83         0.82         0.02         0.04         0.04         0.06           Fairway         0.76         0.05         0.81         0.84         0.84         0.84         0.03         0.02         0.04         0.04         0.06           Fair-SMOTE         0.87         0.10         0.84         0.87         0.86         0.44         0.03         0.02	Bank											
Fair-SSL-LP   0.57   0.37   0.58   0.62   0.56   0.02   0.03   0.07   0.11		Age										
Fair-SSL-LS   0.62   0.35   0.62   0.64   0.62   0.07   0.09   0.07   0.12												
Fair-SSL-CT   0.69   0.18   0.74   0.72   0.71   0.05   0.02   0.09   0.21												
Default   O.81   O.06   O.85   O.88   O.83   O.06   O.05   O.06   O.12												
Student Performance         Sex         OP Fair-SSL-LP Fair-SSL-LP Fair-SSL-LS         0.05 0.84 0.14 0.87 0.80 0.83 0.83 0.83 0.83 0.02 0.04 0.04 0.04 0.08 0.07 0.21 0.09 0.84 0.87 0.86 0.04 0.04 0.08 0.08 0.09 0.09 0.09 0.09 0.09 0.09												
Student Performance         Sex         Fair-SMOTE Fair-SMOTE 1.87         0.05         0.81         0.84         0.84         0.03         0.02         0.04         0.07           Ferformance         Fair-SMOTE 5.87         0.80         0.10         0.84         0.87         0.86         0.04         0.04         0.04         0.08         0.08           Fair-SSL-ST 5.21         0.84         0.14         0.83         0.83         0.83         0.03         0.02         0.01         0.03           Fair-SSL-LP 5.21         0.84         0.14         0.79         0.84         0.82         0.03         0.02         0.05         0.05         0.05												
Student Performance         Sex         Fair-SMOTE Fair-SSL-ST 0.84 0.14 0.83 0.83 0.83 0.83 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.03 0.02 0.05 0.05 0.05 0.05 0.05 0.05 0.05	Student											
Performance         Fair-SSL-ST Fair-SSL-LP         0.84 0.14 0.83 0.83 0.83 0.83 0.83 0.83 0.00 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.01 0.03 0.02 0.03 0.02 0.03 0.02 0.05 0.05 0.05 0.05 0.05 0.05 0.05												
Fair-SSL-LP         0.83         0.19         0.82         0.82         0.83         0.04         0.03         0.07         0.21           Fair-SSL-LS         0.84         0.14         0.79         0.84         0.82         0.03         0.02         0.05         0.05		Sex										
Fair-SSL-LS 0.84 0.14 0.79 0.84 0.82 0.03 0.02 0.05 0.05												
Fair-SSL-CT 0.84 0.09 0.84 0.85 0.83 0.04 0.02 0.03 0.08									0.03		0.05	
			Fair-SSL-CT	0.84	0.09	0.84	0.85	0.83	0.04	0.02	0.03	0.08

Table 4: RQ2 results: Summarized information of comparing Fair-SSL with Optimized Pre-processing [42], Fairway [44], & Fair-SMOTE [43] based on results of 10 datasets and three learners (logistic regression, random forest, and svm). For every dataset, we have chosen the best performing method among the four methods in case of Fair-SSL. Number of wins, ties, and losses are calculated based on Scott-Knott ranks for each metric. Highlighted cells show Fair-SSL is performing similar/better than state-of-the-art bias mitigation algorithms.

		Recall	False alarm	Precision	Accuracy	F1 Score	AOD	EOD	SPD	DI	Total	
	Optimized Pre-processing vs Fair-SSL											
1	Win	8	2	4	3	10	2	2	1	2	34	
2	Tie	21	25	27	28	24	32	33	32	32	254	
3	Loss	7	9	5	5	2	2	1	3	2	36	
4	Win + Tie	29	27	31	31	34	34	35	33	34	288/324	
	Fairway vs Fair-SSL											
5	Win	10	2	5	5	19	2	3	3	4	53	
6	Tie	24	17	24	27	14	30	31	32	31	230	
7	Loss	2	17	7	4	3	4	2	1	1	41	
8	Win + Tie	34	19	29	33	33	32	34	35	35	283/324	
				Fair-Sl	MOTE vs Fai	ir-SSL						
9	Win	1	3	2	3	3	1	2	2	2	19	
10	Tie	28	30	30	28	29	34	33	32	31	275	
11	Loss	7	3	4	5	4	1	1	2	3	30	
12	Win + Tie	29	33	32	31	32	35	35	34	33	294/324	

Table 5: RQ3 results: The change of accuracy, F1, AOD and EOD for Fair-SSL with increasing size of labeled training data (learner is logistic regression). Dark = 1st Rank; Light = 2nd Rank; White = Last Rank

Dataset	Protected Attribute	Size of Labeled Set	Accuracy (+)	F1 Score (+)	AOD (-)	EOD (-)
		1%	0.61	0.44	0.04	0.06
Adult	Sex	5%	0.68	0.51	0.03	0.02
Addit		10%	0.71	0.54	0.03	0.03
		20%	0.71	0.58	0.02	0.02
	Sex	1%	0.47	0.44	0.07	0.12
Compac		5%	0.57	0.54	0.06	0.06
Compas		10%	0.58	0.61	0.03	0.07
		20%	0.61	0.64	0.01	0.05
		1%	0.67	0.65	0.18	0.12
Student	Sex	5%	0.78	0.75	0.05	0.07
		10%	0.83	0.82	0.02	0.02
		20%	0.85	0.83	0.02	0.01

be very handy in this situation as semi-supervised models are trained once but can be used for pseudo-labeling multiple times.

# **6 THREATS TO VALIDITY**

Sampling Bias - We have used ten well-known datasets and three classification models in our experiments. Most of the prior works [42, 46, 53, 60, 89] used one or two datasets where we used ten of them. In the future, we will explore more datasets and more learners. The conclusions may change a bit if other datasets and models are used. Evaluation Bias - We used the four most popular fairness metrics in this study. Prior works [44, 55, 61] only used two or three metrics although IBM AIF360 contains more than 50 metrics. In the future work, we will use more evaluation criteria.

**Conclusion Validity** - One assumption of evaluating our experiments is the test data is unbiased. Prior fairness studies also made similar assumption [37, 43, 46]. The only way to avoid this assumption will be use of domain experts that was beyond our scope. **Internal Validity** - We used four semi-supervised algorithms with

Internal Validity - We used four semi-supervised algorithms with mostly off-the-shelf parameters (except a few cases such as kernel function selection). However, hyperparameters play a crucial role in the performance of ML models. In the future, it makes sense to do hyperparameter optimization for performance improvement [76, 77]. Construct validity - Semi-supervised learning can be helpful when bias comes from improper data labels or sampling. But there could be some other reasons causing bias as well such as objective function bias, homogenization bias [50], feature correlation bias [90]. Semi-supervised techniques may not be very helpful there. External Validity - Our work is limited to binary classification and tabular data which are very common in AI software. However, all the methods used in this paper can easily be extended in case of multi-class classification, regression problems, and text mining. Our future work will be to experiment in other domains of SE and ML to see how semi-supervised methods fight against ethical bias.

# 7 CONCLUSION

Fairness in machine learning software has become a serious concern in the software engineering community. Prior works mainly used supervised approaches to achieve fairness in ML models. Supervised approaches require data with ground truth labels. However, labeled data is not always available in real-life and even if available, human bias may be present in the ground truth. Keeping that in concern, this paper shows how semi-supervised techniques can be used to achieve fairness by using only 10% labeled training data. We have implemented and compared four most popular semi-supervised techniques by doing experiments on ten real-world datasets and three learners. Our results show that Fair-SSL is as good as reducing

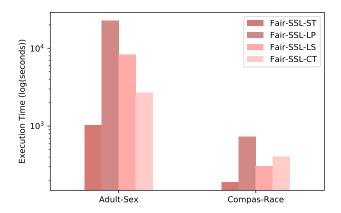


Figure 3: RQ4 results: Execution time comparison of the four semi-supervised methods for Adult (protected attribute - 'sex') and Compas (protected attribute - 'race') dataset.

bias (with minor damage in performance) as three state-of-the-art bias mitigation algorithms. We have made our source code and datasets publicly available for future researchers. We believe our work will educate the software engineering community about machine learning fairness and also encourage more and more software researchers to work in the software fairness domain.

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