Fair Active Learning

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Abstract

Machine learning (ML) is increasingly being used in high-stakes applications impacting society. Therefore, it is of critical importance that ML models do not propagate discrimination. Collecting accurate labeled data in societal applications is challenging and costly. Active learning is a promising approach to build an accurate classifier by interactively querying an oracle within a labeling budget. We design algorithms for fair active learning that carefully selects data points to be labeled so as to balance model accuracy and fairness. Specifically, we focus on demographic parity - a widely used measure of fairness. Extensive experiments over benchmark datasets demonstrate the effectiveness of our proposed approach.

1 Introduction

Data-driven decision making plays a significant role in modern societies. Data science and advanced computational methods provide an opportunity to make wise decisions and to make societies more just, prosperous, inclusive, and safe. However, this comes with a great deal of responsibilities as improper development of data science technologies can not only fail but make matters worse. Judges in US courts, for example, use criminal assessment algorithms that are based on the background information of individuals for setting bails or sentencing criminals. This is valuable as it can lead to safer societies, but if not properly developed, could result in deleterious consequences on people’s lives. For instance, the recidivism scores provided for the judges are highly criticized as being discriminatory, since it turns out they assign higher risks to African American individuals [1].

Machine learning (ML) is in the center of data-driven decision making as it provides insightful unseen information about phenomena based on available observations. Two major reasons of unfair outcome of ML models are Bias in training data and Proxy attributes. The former is related to the inherent bias (discrimination) in the historical data that reflects unfairness in society. For example, redlining is a systematic denial of services used in the past against specific racial communities, affecting historical data records [26]. Proxy attributes on the other hand, are often used due to the limited access to labeled data, especially in societal applications. For example, when actual future recidivism records of individuals are not available, one may resort to information such as “prior arrests” that are easy to collect and use it as a proxy for the true labels, albeit a discriminatory one.

Example 1. A company is interested in creating a model for predicting recidivism to help judges make wise decisions when setting bails; they want to find out how likely a person is to commit a crime in the future. Suppose the company has access to the background information of some criminal defendants. However, the collected data is not labeled. That is because there is no evidence
available at the time of the trial if an individual will commit a crime in the future or not. Considering
a time window, it is possible to label an individual in the dataset by checking the background of
the individual within the time window after being released. Nonetheless, this is not simple, may be
associated with a cost, and may require expert efforts for data integration and entity resolution.

Example 2. A loan consulting company is about to create models that will help financial agencies
identify “valuable customers” who will pay off their loans on time. The company has collected a
dataset of customers who have received a loan in the past few years. In addition to the demographic
information, the dataset includes information such as education and income level of individuals.
Unfortunately, at the time of approving loans, it is not known whether customers will pay their debt
on time, and hence, the data are not labeled. Nevertheless, the company has hired experts who, given
the information of an individual who has received a loan in the past, can verify their background and
assess if payments were made on time. Of course, considering the costs associated with a background
check, it is not viable to freely label all customers.

Both of the above examples use historical data for building their models that are biased. For instance,
the income in Example 2 is known to include gender bias [27]. Similarly, using prior count as a
proxy attribute in Example 1 is racially biased [11]. Also, in both examples the datasets are unlabeled.

A new paradigm of fairness in machine learning [7] has emerged to address the unfairness issues
of predictive outcomes. These work often assume the availability of (possibly biased) labeled data
in sufficient quantity. When this assumption is violated, their performance degrades. In a number
of practical societal applications such as Example 1, one operates in a constrained environment.
Obtaining accurate labeled data is expensive, and could only be obtained in a limited amount. A
simplistic approach would be to use a (problematic) proxy attribute as the true label and train the
model accordingly. However, this will result in an unfair model.

In this work, our goal is to develop efficient and effective algorithms for fair models in an environment
where the number of data that could be labeled is bounded. An obvious baseline is to randomly select
a subset of data (depending on the available budget), obtain the labeled data and use it for training.
However, a more sophisticated approach would be to use an adaptive sampling strategy. Active
learning [46] sequentially chooses the unlabeled instances where their labeling is the most beneficial
for the performance improvement of the ML model. By default, the adaptive sampling strategy in
active learning seeks to maximize the predictive accuracy of the model and hence could sustain or
intensify unfairness of the model. Despite its importance, to the best of our knowledge, none of the
existing work in active learning takes fairness into account. That is indeed our purpose in this paper.

We aim to develop an active learning algorithm that will yield fair results. Fairness has different
definitions and is measurable in various ways. Specifically, we consider a model fair if its outcome
does not depend on sensitive attributes such as race or gender. We adopt demographic parity (aka
statistical parity), one of the popular fairness measures [33, 15].

Summary of contributions. In this paper, we introduce fairness in active learning for constructing
fair models in the context of limited labeled data. We propose a fair active learning framework (FAL)
to balance model performance and fairness as defined by demographic parity. For the special case
of generalized linear models, we propose an efficient approach with the same asymptotic time complexity
as traditional active learning. We conduct comprehensive experiments on real datasets to show that
performing active learning while considering the fairness constraint can significantly improve the
fairness of a classifier without any major reduction in model accuracy.

2 Related work

Active Learning. Different active learning scenarios (Membership Query Synthesis, Stream-Based
Selective Sampling, pool-Based Active Learning) and sampling strategies (Uncertainty Sampling,
Query-By-Committee, Expected Model Change, Variance Reduction, etc.) have been proposed
and are surveyed in [46]. Uncertainty sampling is one of the most popular approaches for active
learning [54, 5, 50], which merely select data points based on the single objective function of
informativeness. There are several active learning approaches proposed to incorporate more than one
criteria for sampling, such as representativeness [54, 13, 24]. To the best of our knowledge, none of
the existing active learning works considers fairness of the predictive outcome.

2 In the rest of the paper we refer to true label as label.
Algorithmic Fairness in ML. Algorithmic fairness has been extensively studied in recent years. [6, 61, 43, 38] provide surveys on discrimination and fairness in algorithmic decision making and machine learning. Existing works have formulated fairness in classification as a constrained optimization [57, 58, 39, 12, 11, 21, 23]. A body of work focus on modifying the classifier, in-process, to build a fair classifiers [17, 19, 15, 31, 12]. Some others remove disparate impact through pre-processing the training data [36, 60, 28, 29, 16, 52, 49, 3, 44], while the last group post-process model outcomes to develop fairness [30, 21, 42, 22]. Our proposal is orthogonal to the fair ML literature. While our goal in this paper on selecting the samples to be labeled, fair ML algorithms aim to build fair models for a given set of labeled samples. As we shall show in § 6, the fair ML algorithms can be integrated with our proposal for building the model. Fairness has also been studied in special ML context such as reinforcement learning [25], adversarial networks [52, 53], and feature acquisition [41]. Fairness in data-driven decision making has also been studied in related topics, such as ranking [2, 20, 55, 59] and recommendation systems [10, 51, 56].

3 Background

In this section, we introduce the data model, the active learning framework with uncertainty sampling heuristic, and fairness model.

3.1 Learning Model

Given a classifier and a pool of unlabeled data \( U \), Active Learning (AL) identifies the data points to be labeled so that an accurate model could be learned as quickly as possible. \( U \) is assumed to be an independent and identically distributed (i.i.d) sample set collected from the underlying unknown distribution. For each data point \( P_i \in U \), we use the notation \( X^{(i)} \) for the \( d \)-dimensional vector of input features and \( X_j^{(i)} \) to refer to the \( j \)th feature, \( x_j \). Each data point is associated with a non-ordinal categorical sensitive attribute \( S \) such as gender and race. We use the notation \( S^{(i)} \) to refer to the sensitive attribute of \( P_i \). We also use \( y^{(i)} \) to refer to the label of a point \( P_i \) with \( K \) possible values of the label space \( Y = \{0, \cdots, K - 1\} \).

The goal is to learn a classifier function \( C : X \rightarrow Y \) that maps the feature space \( X \) to the labels \( Y \). Let \( \hat{y} = C(X) \) be the predicted label for \( X \). Pool-based active learning for classification [35], selects instances from the unlabeled dataset \( U \) to form a labeled set \( L \), sequentially for training. Active learning assumes the existence of an expert oracle that given a data point \( P \) provides its label. Labeling, however, is costly and usually there is a limited labeling budget \( B \). Using the sampling budget, one can randomly label \( B \) data points and utilize them to train a classifier. The challenge, however, is to wisely utilize the budget to build the most accurate model.

Different sampling strategies have been proposed in the context of active learning. Uncertainty sampling [35] is probably the most common strategy. It chooses the point \( P \in U \) that the current model is least certain about its label. The classifier \( C_t \) for iteration \( t \) chooses the data point that maximizes the Shannon entropy \( \mathcal{H} \) over the predicted label probabilities.

\[
X^* = \arg\max_{X \in U} \mathcal{H}(y|X, \mathcal{L})
\]  

Algorithm 1 presents the standard active learning algorithm, using Equation 1. Iteratively, the algorithm selects a point from \( U \) to be labeled next. It uses the classifier trained in the previous step to obtain probabilities of the labels. The algorithm obtains the label from the labeling oracle, and adds the point to the set of labeled dataset \( \mathcal{L} \), using it to train the classifier \( C_t \). This process continues until the labeling budget is exhausted.

3.2 (Un)Fairness Model

We develop our fairness model on the notion of model independence or demographic parity (DP) [7],[61],[40],[57], also referred by terms such as statistical parity [15],[48], and disparate impact [8],[16],[4]. We believe that machine learning practitioners are responsible to intervene in the modeling process
(in different learning stages) to mitigate model disparities. Given a classifier $C$ and a random point $(X, S)$ with a predicted label $\hat{y} = C(X)$, DP holds iff $\hat{y} \perp S$ [6,7]. For a binary classifier, let $\hat{y} = 1$ count as “acceptance” (such as receiving a loan). DP is the condition that requires the acceptance rate to be the same for all groups of $S$ i.e. female or male in this case. For a binary classifier and a binary sensitive attribute, the statistical independence of a sensitive attribute from the predicted label induces the following notions for DP:

1. $P(\hat{y} = 1 | S = 1) = P(\hat{y} = 1 | S = 0)$: The probability of acceptance is equal for members of different demographic groups. For instance, in Example 1 members of different race groups have an equal chance for being classified as low risk.

2. $P(S = 1 | \hat{y} = 1) = P(S = 1)$: If the population ratio of a particular group is $\rho$ (i.e. $P(S = 1)$), the ratio of this group in the accepted class is also $\rho$. For instance, in Example 2 let $\rho = \frac{\text{female ratio in the applicants' pool}}{\text{female ratio in the applicants' pool}}$. Under DP, female ratio in the set of admitted applications for a loan equals to $\rho$.

3. $I(\hat{y}; S) = 0$: Mutual information is the measure of mutual dependence between two variables. When $\hat{y}$ and $S$ are independent, their mutual information is zero. That is, the conditional entropy $H(S | \hat{y})$ is equal to $H(S)$.

4. $\text{cov}(\hat{y}, S) = 0$: When $\hat{y}$ and $S$ are independent, $\text{cov}(\hat{y}, S)$ is equal to zero.

A disparity (or unfairness) measure can be defined using any of the above notions. The absolute differences or the ratio of probabilities in bullets 1 or 2 provide four disparity measurement. In addition, mutual information and covariance (or correlation) provide two natural measures, since differences or the ratio of probabilities in bullets 1 or 2 provide four disparity measurement. In this paper, we do not limit ourselves to any of the unfairness measures (demographic disparity) and give the user the freedom to provide a customized measure. We use the notation $F(S, C)$ to refer to the (user-provided) measure of unfairness. We simplify the notation to $F(C)$ when $S$ is clear by context.

4 Fair Active Learning (FAL)

4.1 Objective Function for FAL

By carefully selecting samples to label, AL has the potential to mitigate algorithmic bias by incorporating the fairness measure into its sampling process. Still, not considering fairness while building models can result in model unfairness. As a naive resolution, one could decide to drop the sensitive attribute from the training data. This, however, is not sufficient since the bias in the features may cause model unfairness [9,26]. Hence, a smart sampling strategy is needed to mitigate the bias. On the other hand, blindly optimizing for fairness could result in an inaccurate model. For instance, in Example 1 consider a model that randomly classifies individuals as high-risk. This model indeed satisfies demographic parity since the probability of the outcome is (random and therefore) independent of $S$. However, such a model provides zero information about how risky an individual is.

Similar to AL, FAL is also an iterative process that selects a sample from the unlabeled pool $\mathcal{U}$ to be added to the labeled pool $\mathcal{L}$. However, FAL considers both fairness and misclassification error as the optimization objective for the sampling step. That is, to choose the next sample to be labeled, FAL selects the one that contributes the most to the reduction of the misclassification error as well as model unfairness. Specifically, for a sample point $(X^{(i)}, S^{(i)}) \in \mathcal{U}$, we consider the Shannon entropy measure $\mathcal{H}_{t-1}(y^{(i)})$ for misclassification error, while considering demographic disparity $F(C_{t}^{i})$ for unfairness — $C_{t}^{i}$ is the classifier trained on $\mathcal{L}$ at iteration $t$, after labeling the point $(X^{(i)}, S^{(i)})$ and $\mathcal{H}_{t-1}(y^{(i)})$ is the entropy of the $y^{(i)}$ based on the current model $C_{t-1}$. The formulation can be viewed as a multi-objective optimization for fairness and misclassification error. Another perspective is to view the fairness as a regularization term to the optimization. Equation 2 is consistent with both of these views and is therefore considered in our framework.

$$\underset{(X^{(i)}, S^{(i)}) \in \mathcal{U}}{\text{argmax}} \quad \alpha \mathcal{H}_{t-1}(y^{(i)}) + (1 - \alpha)(F(C_{t-1}) - F(C_{t}^{i}))$$

(2)

$(F(C_{t-1}) - F(C_{t}^{i}))$ is the unfairness reduction (fairness improvement) term and the coefficient $\alpha \in [0, 1]$ is the user-provided parameter that determines the trade-off between the model fairness and model performance. Values closer to 1 put greater emphasis on model performance, while smaller values of $\alpha$ put greater importance on fairness. As we elaborate in § 6, entropy and fairness values are standardized to the same scale before being combined in Equation 2.
4.2 Framework

As shown in Figure 1, the central component of FAL is the sample selection unit (SSU) that chooses an unlabeled point \((X^{(i)}, S^{(i)})\) from \(U\) and obtains the label from an oracle. The labeled point \((X^{(i)}, S^{(i)}, y^{(i)})\) is moved to \(L\), the set of labeled points. The set of labeled points are used to train \(C_t\), the classifier at iteration \(t\). In the next iteration, \(t+1\), SSU employs \(C_t\) and selects the next point to be labeled. This process continues until the budget for labeling is exhausted.

Equation 2 is the basis for balancing the trade-off between fairness and misclassification error for the next sample selection. A problem, however, is that at the time of evaluating the candidate points in \(U\), we still do not know their labels. However, to evaluate the impact of each point for fairness, we need to know what the model parameters will be after labeling and adding the point to \(L\). This requires knowing all labels beforehand which contradicts the fact that \(U\) is unlabeled.

To resolve this issue, using a decision theoretic approach [46], we consider the expected unfairness reduction: selecting the point that is expected to impart the largest reduction to the current model unfairness, after acquiring its label. Therefore, instead of \(F(C_t)\) in Equation 2, we plug in the expected fairness \(E[F_t]\). In this way, we are approximating the expected future fairness of a model using \(L \cup X, \forall X \in U\) over all possible labels under the current model. Consider a point \(P_i \in U\) and let \(C_{t,k}^{(i)}\) be the model after adding \(P_i\) to \(L\) if its true label is \(g^{(i)} = k\). Of course, SSU does not know the label in advance. Hence, it must instead calculate the unfairness as an expectation over the possible labels. Equation 3 denotes the expected (un)fairness computation used by SSU:

\[
E[F_t] = \sum_{k=0}^{K-1} F(C_{t,k}^{(i)}) \mathbb{P}(y = k | X^{(i)})
\]  

Algorithm 2 Fair Active Learning

```
1: for \(t = 1\) to \(B\) do
2: \(\max = 0\)
3: for \(i = 1\) to \(|U|\) do
4: \(H = -\sum_{k=0}^{K-1} \mathbb{P}(y = k | X) \log \mathbb{P}(y = k | X)\)
5: \(F = \text{ExpF}(X^{(i)}, S^{(i)}, L, C_{t-1})\)
6: \(\text{obj} = \alpha(i)H + (1 - \alpha(i))(F(C_{t-1}) - F)\)
7: if \(\text{obj} > \max\) then
8: \(\max = \text{obj}; \langle X^*, S^* \rangle = \langle X^{(i)}, S^{(i)} \rangle\)
9: end if
10: end for
11: \(y = \text{label} X^*\) using the labeling oracle
12: move \(\langle X^*, S^*, y \rangle\) to \(L\)
13: train the classifier \(C_t\) using \(L\)
14: end for
15: return \(C_t\)
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SSU uses the current model \(C_{t-1}\) for calculating \(\mathbb{P}(y = k | X^{(i)})\). Algorithm 2 shows the pseudo-code of FAL where Algorithm 4 is invoked for computing the expected unfairness.

Figure 1: FAL framework.

Figure 2: Evaluation of a point \((X^{(i)}, S^{(i)}) \in U\) for unfairness reduction.
4.3 Adaptive $\alpha$ parameter

The trade-off between the accuracy (entropy) and the fairness terms is controlled by a user-defined parameter $\alpha$ (in Equation 2). Selecting an appropriate $\alpha$ value might not be clear for the user. More importantly, FAL might find it challenging to use a fixed learning strategy based on $\alpha$ in different iterations.

In initial iterations, the model is not accurate because it was trained only on a few labeled instances, resulting in possibly inaccurate estimates of the label probabilities for a given unlabeled instance from $\mathcal{U}$. Computing the expected fairness values relies heavily on the probabilities of the label. The miscalculation of these probabilities leads to an inaccurate estimation of fairness; such erroneous values contribute to the selection of points that do not support (and may even deteriorate) the fairness of the model and may not be good for model accuracy. In the later iterations, the model may already be stable and accurate, and new labeled points may not significantly impact its accuracy. However, the model can provide better estimations of the label probabilities which results in more robust estimations of the expected fairness.

Instead of using a fixed $\alpha$ for all iterations, one can use a decay function that begins with a large value of $\alpha$, which improves the accuracy of the model. As the model becomes more stable, the value of $\alpha$ gets dropped, putting more weight on improving fairness. This concept is applied in different context, such as assigning learning rate [45], where a larger value is used initially that gradually decreases over time. Our approach is agnostic to the decay function used. In the experiments, we use a function that linearly interpolates between a given range (such as $[0.1, 0.9]$).

5 Efficient FAL by Covariance

Labeling is the major cost in active learning settings. In societal applications, the labeling cost often dominates the computation cost. Still, in this section we propose a computationally efficient alternative for FAL. The fair active learning algorithm proposed in § 4.2 requires to compute the expected fairness for every instance in the unlabeled pool $\mathcal{U}$ before deciding on the next sample point to label by building $K$ models, one for each possible label. Suppose the time to build a model is $T$; for the labeling budget $B$ and a constant value $K$, the algorithm requires the time complexity of $O(B \cdot T \cdot |\mathcal{U}|)$ to build the models.

For the special case of generalized linear models, we design an efficient algorithm that has the same asymptotic time complexity as traditional active learning. We achieve this by avoiding the retraining of models to calculate the expected fairness of unlabeled samples. Consider a generalized linear model in form of $\hat{y} = \theta^\top X$. Recall that under model independence (demographic parity) the covariance between the model and a sensitive attribute $S$ is zero. We make a key observation in Lemma 1 that shows this covariance, $\text{cov}(S, \hat{y})$, only depends on $\text{cov}(S, X)$ and $\theta$.

Lemma 1. For a generalized linear model in form of $\hat{y} = \theta^\top X$, $\text{cov}(S, \hat{y}) = \theta^\top \text{cov}(S, X)$.

According to Lemma 1, the covariance of the model with the sensitive attribute (that results in unfairness) depends only on the weight vector $\theta$ and the underlying covariance of features $X$ with $S$. To make the model fairer, we need to ensure that the model does not assign high weights to the problematic features (the features with high covariance with $S$). This observation allows us to indirectly optimize for fairness through covariance instead of computing expected fairness.

Consider a feature $x_i$ that is highly correlated with the sensitive attribute (i.e., $\text{cov}(x_i, S)$ is high) and also has a high weight $\theta_i$ in the current model. Our objective is to reduce the weight assigned to such features. The reason the model has assigned a large weight to $x_i$ is that $x_i$ is highly predictive of $y$ in $\mathcal{L}$. In other words, $x_i$ is a good signal for predicting $y$ according to $\mathcal{L}$. Therefore, in

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3The decision boundary of the classifier is viewed as a threshold value on $\hat{y}$ that separate different classes, using, for example, a sign function.

4The proof of Lemma 1 can be found in the Appendix.
order to reduce the weight $\theta_i$, we need to reduce $\text{cov}_L(x_i, y)$ in the labeled pool $L$ to make it less predictive of $y$ in $L$. Now, consider a point $P_j = \langle X^{(j)}, S^{(j)} \rangle \in \mathcal{U}$ and its value $X^{(j)}_i$ on feature $x_i$. Depending on $X^{(j)}_i$ and its label $y^{(j)}$ (after labeling), the point $P_j$ can impact $\text{cov}(x_i, y)$ in $L$. Of course we don’t know $y^{(j)}$; still, similar to §4, we can consider the probability distribution over $Y$ and calculate the expected improvement in covariance. Let $\text{cov}_i = \text{cov}_L(x_i, y)$ be the covariance of $x_i$ and $y$ in $L$ and $\text{cov}_{i,k} = \text{cov}_{L,\{X^{(j)}, S^{(j)}, y^{(j)}=k}\}}(x_i, y)$ the covariance of $x_i$ and $y$ after adding $(X^{(j)}, S^{(j)}, y^{(j)} = k)$ to $L$. The expected covariance improvement for $x_i$ after adding $P_j$ to $L$ is

$$E[\text{cov}_i^+ - \text{cov}_i^-] = \sum_{k=0}^{K-1} (|\text{cov}_i| - |\text{cov}_{i,k}|) \mathbb{P}(y = k | X^{(j)})$$

(4)

Following Lemma 1 the contribution of the covariance reduction for a feature $x_i$ to fairness is proportional to $\theta_i \text{cov}(x_i, S)$. Subsequently, it is important to reduce $\text{cov}_L(x_i, y)$ for the features that are highly correlated with the sensitive attribute and have a high weight $\theta_i$ in the model. Therefore, the (indirect) fairness improvement by covariance for a point $P_j \in \mathcal{U}$ can be computed as following:

$$E[FbC_j] = \sum_{i=1}^{d} \theta_i \text{cov}(S, x_i) E[\text{cov}_{i,j}^+]$$

(5)

Now, it is enough to replace the term for expected fairness improvement ($F(C_{t-1}) - F(C_t)$) in Equation 2 by $E[FbC_j]$. In the Appendix, considering the number of features $d$ as a constant, we show how, maintaining the aggregates from the previous steps, $E[FbC_j]$ can be computed in constant time. Therefore, the time complexity of the fair active learning framework (without considering the labeling cost) drops from $O(B \cdot T \cdot |\mathcal{U}|)$ to $O(B \cdot (|\mathcal{U}| + T))$, the same as traditional active learning.

6 Experiments

The experiments were performed on a Linux machine with a Core i9 CPU and 128GB memory. The algorithms were implemented using Python 3.7.

6.1 Datasets

COMPA$^3$ published by ProPublica $^1$, this dataset contains information of juvenile felonies such as marriage status, race, age, prior convictions, and the charge degree of the current arrest. We normalized data so that it has zero mean and unit variance. We consider race as sensitive attribute and filtered dataset to black and white defendants. The dataset contains 5,875 records, after filtering. Following the standard practice $^{[12, 33, 14, 18]}$, we use two-year violent recidivism record as the true label of recidivism: $y^{(j)} = 1$ if the recidivism is greater than zero and $y^{(j)} = 0$ otherwise. The dataset $^2$ contains 45,222 individuals income extracted from the 1994 census data with attributes such as age, occupation, education, race, sex, marital-status, native-country, hours-per-week etc. We use income (a binary attribute with values $\geq 50k$ and $\leq 50k$) as the true label. We consider sex as the sensitive attribute. We normalized data so that it has zero mean and unit variance.

6.2 Algorithms Evaluated

We evaluate the performance of the following approaches on the benchmark datasets in §6. We apply a regularized $l_2$ norm logistic regression with a regularization strength of one as the classifier in all of the cases. Algorithm 2 is our main proposal for fair active learning (FAL). We normalize the accuracy and fairness improvement values as $(v_{\text{min}})/(v_{\text{max}})$ before combining them in Equation 2. Besides, we evaluate the adaptive $\alpha$ parameter technique and the efficient FAL by covariance (FBC), proposed in §4 and §5 respectively. We consider the regular active learning based on Equation 1 (AL) and random labeling (RandL), where a random subset of $\mathcal{U}$ is selected for labeling, as baselines.

$^3$Our codes are publicly available: https://github.com/anahideh/FAL--Fair-Active-Learning

$^1$ProPublica, https://bit.ly/35pzGF

$^2$UCI repository, https://bit.ly/2GTwz9Z
As mentioned in §2, the focus of FAL is to create a labeled training dataset subject to a labeling budget from unlabeled pool. This is orthogonal to the body of work in fair ML that seek to build a fair classifier for a given labeled training dataset. Therefore, one can use FAL to form the training dataset and fit a fair ML model to the final set of labeled data point to achieve better level of fairness.

To support this statement, we compare the results of FAL using our default logistic regression versus FAL using a fair logistic regression (FAL-FairLR) at the very last iteration. We employed a fair logistic regression proposed in [57].

### 6.3 Performance Evaluation

We first evaluate the performance of FAL versus AL, and RandL using accuracy and fairness measures. We study the trade-off between the accuracy and fairness, by changing the coefficient $\alpha$ in Equation 2.

We perform the experiments using 10 random splits of the datasets into training $U$ (60% of the examples) and testing (40% of the examples). We consider the mean and variance over the 10 random splits. We specify the maximum labeling budget to 200 for COMPAS dataset and to 300 for Adult dataset, where the performance leveled off in our preliminary results. In each FAL and AL scenario, we start with six labeled points and sequentially select points to label, until the budget is exhausted. Mutual information is our default measure of demographic parity. We also use the Absolute Difference $|P(\hat{y}=1|S=0) - P(\hat{y}=1|S=1)|$ as another metric for measuring DP.

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8 We observed that using fair ML algorithms for building intermediate models during the FAL iterations is not effective and FAL with regular logistic regression (LR) outperformed fair LR. This is due to the fact that fair models trade-off accuracy for fairness that affects the ability of the model to accurately estimate the expected fairness of a data point.
Figures 3(a) and 3(b) provide the results of the evaluation of FAL for COMPAS dataset using $\{0.6, 0.8\}$ for $\alpha$. Figure 3(a) corresponds to the average (un)fairness on 10 random runs and Figure 3(b) shows the corresponding average accuracy score. In summary, the results of the experiment support the effectiveness of our proposal as FAL could significantly improve fairness by reducing the disparities while the model accuracy (fraction of correct predictions) does not significantly impact the overall accuracy of the model across different $\alpha$ values. Figure 3(c) presents a comprehensive comparison of FAL with user-defined $\alpha$ and adaptive alpha, versus AL and RandL on COMPAS dataset. The bars indicate the standard deviation on 10 random split of data. We observe that FAL with adaptive $\alpha$ dramatically mitigates the unfairness measure when compared to AL and RandL while sustaining a comparable accuracy. In particular, for COMPAS dataset using mutual information FAL with adaptive $\alpha$ outperforms FAL with user-defined $\alpha$ value from fairness perspective.

Figure 4 shows the results for adult dataset. Similar to previous experiments, FAL achieves lower unfairness compared to AL and RandL.

Figure 5 corresponds to the experimental setup where Absolute Difference is used for measuring fairness. The results indicate the effectiveness of FAL compared to AL and RandL. However, FAL with user-defined $\alpha$ slightly outperforms the adaptive idea from fairness perspective.

In our next experiment illustrated in Figure 6 we evaluate FAL-FairLR. We can observe that FAL achieved a good level of fairness by mitigating the bias while collecting the training data points, and applying fair LR on the labeled samples help to further improve fairness. However, the impact of fair LR is not pronounced. This is due the fact that the sample generated by FAL is already unbiased thereby achieving a fair classifier even when trained using a traditional classification algorithm.

Finally, in Figure 7 we evaluate the average performance of FBC, the efficient algorithm proposed in §5 and compare it against FAL. Figure 7(a) shows the computation time of each sampling iteration compared to the original FAL. Figures 7(b) and 7(c) show the average fairness and accuracy values. FBC is orders of magnitude faster than FAL as it avoids the need to compute expected fairness. On the other hand, since it indirectly optimizes for fairness, FAL outperforms it on fairness.

7 Conclusion

In this paper, we introduced a framework for fairness in active learning. This is especially relevant in a number of societal applications where obtaining labels is expensive. Our framework balances fairness and accuracy by selecting samples from the unlabeled pool that maximizes a linear combination of misclassification error reduction and improvement over expected fairness. We also proposed an efficient fair active learning algorithm with the same asymptotic time complexity as traditional active learning. We conducted extensive experiments to evaluate our proposal on real datasets using different measures of demographic parity. The results confirm that our proposed approach, compared with the standard active learning, produces a fair model while not significantly sacrificing the accuracy.
8 Broader Impact

The ML community has done an incredible amount of work in enabling fair classification. However, these works often assume the availability of sufficiently labeled data. In a number of societal applications such as recidivism, this assumption is incorrect. Obtaining true labels is expensive and time consuming. Hence, past work often relied on proxy attributes for labeling and used fair classification algorithms. Unfortunately, this approach does not fully solve the unfairness issue. Our work proposes an effective approach for this limited labeling scenario. Since active learning is widely used in this context, we are the first to propose fair active learning where the samples selected try to balance the trade-off between model accuracy and fairness. We hope that our proposed approach will have a positive impact by improving the model fairness in a number of real-world scenarios.

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APPENDIX

A Proof of Lemma 1

Lemma 1. For a generalized linear model in form of $\hat{y} = \theta^\top X$, $\text{cov}(S, \hat{y}) = \text{cov}(S, X)$.

Proof.

$$
\text{cov}(S, \hat{y}) = E[S \hat{y}] - E[S]E[\hat{y}]
$$

$$
E[S]E[\hat{y}] = \mu_S E\left[\sum \theta_i x_i\right] = \mu_S \sum \theta_i \mu_{x_i}
$$

$$
= \theta_1 \mu_S \mu_{x_1} + \theta_2 \mu_S \mu_{x_2} + \cdots + \theta_d \mu_S \mu_{x_d}
$$

$$
E[S \hat{y}] = E[S \sum \theta_i x_i] = E[\sum S \theta_i x_i]
$$

$$
= E[S \theta_1 x_1 + S \theta_2 x_2 + \cdots + S \theta_d x_d]
$$

$$
= E[S \theta_1 x_1] + E[S \theta_2 x_2] + \cdots + E[S \theta_d x_d]
$$

$$
= \theta_1 E[S x_1] + \cdots + \theta_d E[S x_d]
$$

$$
\Rightarrow \text{cov}(S, \hat{y}) = \theta_1 E[S x_1] + \cdots + \theta_d E[S x_d] - (\theta_1 \mu_S \mu_{x_1} + \cdots + \theta_d \mu_S \mu_{x_d})
$$

$$
= \theta_1 (E[S x_1] - \mu_S \mu_{x_1}) + \cdots + \theta_d (E[S x_d] - \mu_S \mu_{x_d})
$$

$$
= \sum_{i=1}^d \theta_i \text{cov}(S, x_i) = \theta^\top \text{cov}(S, X)
$$

\[\square\]

B Efficiently Computing Covariance of $X$ and $y$ in $\mathcal{L}$

In § we proposed the efficient FAL by covariance method that works based on Equation in the following we show the details of computing $E[FbC_j]$ for every point $P_j \in \mathcal{U}$ in constant time, maintaining the aggregates from the previous steps.

First, we note that $\text{cov}(x_i, S)$, the covariance of each feature $x_i$ with $S$, does not depend on $\mathcal{L}$ and can be computed in advance, using the unlabeled samples in $U$. It is computed once for every feature at the beginning of the process and the same numbers will be used in different iterations.

The values of $\text{cov}_i = \text{cov}_\mathcal{L}(x_i, y)$ and $\text{cov}_{j,i,k} = \text{cov}_{\mathcal{L} \cup \{X^{(i)}, S^{(i)}, y^{(i)=k}\}}(x_i, y)$ in Equation however, depend on the set of labeled data and should get recomputed at different iterations and for different points $P_j \in \mathcal{U}$. We maintain the following aggregates for efficiently computing these values:

$$
\mathcal{G}_y = \sum_{\forall (X^{(i)}, S^{(i)}, y^{(i)}) \in \mathcal{L}} y^{(i)}
$$

$$
\forall i \in [1, d] : \mathcal{G}_x[i] = \sum_{\forall (X^{(i)}, S^{(i)}, y^{(i)}) \in \mathcal{L}} X_i^{(i)}
$$

$$
\forall i \in [1, d] : \mathcal{G}_z[i] = \sum_{\forall (X^{(i)}, S^{(i)}, y^{(i)}) \in \mathcal{L}} X_i^{(i)} y^{(i)}
$$

Note that at every iteration each of the above aggregates can be updated in constant time by adding the corresponding value from the new point to it. Now, using these aggregates:

$$
\text{cov}_i = \text{cov}_\mathcal{L}(x_i, y) = \frac{\mathcal{G}_z[i]}{n} - \frac{\mathcal{G}_x[i]}{n} \times \frac{\mathcal{G}_y}{n}
$$
Similarly, for a point \( P_j = (X^{(j)}, S^{(j)}) \in U \) and a label \( y^{(j)} = k \):

\[
\text{cov}_{j,i,k} = \frac{G_x[i] + kX^{(j)}_i}{n + 1} - \frac{G_x[i] + X^{(j)}_i}{n + 1} \times \frac{G_y + k}{n + 1}
\]

C Additional Experimental Details

In the experiments, we do not recognize the sensitive attributes as model features, so as not to practice disparate treatment. We trained the logistic regression with liblinear optimizer and with maximum iteration of 100.

In the experiments, we use adaptive \( \alpha \) to control the accuracy and fairness trade-off instead of using a fixed \( \alpha \) value. As described in §4.3, in the experiments, we use a decay function that linearly interpolates between a given range. We chose \([1, 0]\) as the range of \( \alpha \). The \( \alpha \) value (weight on accuracy) continuously drops by 0.1 every \( \lceil B/11 \rceil \) iterations, so that it incorporates \( \alpha = [1, 0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1, 0] \) throughout a full FAL run.