**fairlib**: A Unified Framework for Assessing and Improving Classification Fairness

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**Abstract**

This paper presents **fairlib**, an open-source framework for assessing and improving classification fairness. It provides a systematic framework for quickly reproducing existing baseline models, developing new methods, evaluating models with different metrics, and visualizing their results. Its modularity and extensibility enable the framework to be used for diverse types of inputs, including natural language, images, and audio. In detail, we implement 14 debiasing methods, including pre-processing, at-training-time, and post-processing approaches. The built-in metrics cover the most commonly used fairness criterion and can be further generalized and customized for fairness evaluation.

**1 Introduction**

While neural methods have achieved great success for classification, it has been shown that naively-trained models often learn spurious correlations with protected attributes like user demographics or socio-economic factors, leading to allocation harms, stereotyping, and other representation harms to users (Badjatiya et al., 2019; Zhao et al., 2018; Li et al., 2018; Díaz et al., 2018; Wang et al., 2019).

Various bias evaluation metrics have been introduced in previous studies to gauge different biases. One common way of bias evaluation calculates the differences (“GAP”) between subgroup performances, such as equal opportunity and predictive equality, which evaluate the gap in the True Positive Rate (TPR) and True Negative Rate (TNR) respectively, across different protected attributes (De-Arteaga et al., 2019). The GAP metric is optimized such that a model treats all demographic groups equally, i.e., its performance is (near) identical across all subgroups. The computation details of GAP vary widely across previous work on debiasing, which impedes systematic analysis and comparison of proposed approaches.

In terms of bias mitigation, diverse debiasing methods have been proposed, including at-training-time (Li et al., 2018; Elazar and Goldberg, 2018; Shen et al., 2021), and pre- (Zhao et al., 2017; Wang et al., 2019) and post-processing approaches (Han et al., 2021a; Ravfogel et al., 2020). Although these methods have been proved effective for bias mitigation, it is challenging to reproduce results and compare methods because of inconsistencies in training strategy and model selection criterion which demonstrably affect the results.

We present **fairlib**, an open-source framework for bias detection and mitigation in classification tasks to address these issues. **fairlib** implements a number of common debiasing approaches in a unified framework that facilitates reproducible and consistent evaluation and provides interfaces for developing new debiasing methods. Moreover, a dataset interface supports adoption of both built-in and newly developed methods for new tasks and corpora. For better presentation, **fairlib** also provides well-documented utilities for creating \LaTeX tables as well as performance–fairness trade-off plots for model comparison under different conditions.

**fairlib** is implemented based on PyTorch and is easy to use: it can be run from the command line, or imported as a package into other projects. Model checkpoints and configuration files are saved to keep track of hyperparameters, which is essential for reproducibility. To demonstrate its utility, we use **fairlib** to reproduce a battery of debiasing results from the recent NLP literature, and show that improved and systematic hyperparameter tuning leads to demonstrable improvements over the originally reported results. **fairlib** is released under Apache License 2.0 at https://github.com/HanXudong/fairlib.
2 Fairness Criterion

fairlib includes a variety of evaluation metrics that have been proposed in previous work, as we outline in this section.

Group Fairness To evaluate whether or not a model’s predictions are fair towards the protected attributes, such as gender and age, a popular way is to measure performance gap (GAP) across instances within different protected groups. Barocas et al. (2019) present formal definitions of three types of group fairness criteria, which capture different levels of (conditional) independence between the protected attribute $g$, the target variable $y$, and the model prediction $\hat{y}$:

1. **independence** ($\hat{y} \perp g$), also known as Demographic Parity (Feldman et al., 2015), ensures that the positive rate of each protected group is the same;

2. **separation** ($\hat{y} \perp g \mid y$), also known as Equalized Odds (Hardt et al., 2016), acknowledges that in many scenarios $g$ is correlated with $y$; a relaxation of this is Equal Opportunity (Hardt et al., 2016);

3. **sufficiency** ($y \perp g \mid \hat{y}$) is satisfied if the predictions are calibrated for all groups, and is also known as Test Fairness (Chouldechova, 2017).

Per-group Fairness Instead of measuring performance gaps across groups, per-group fairness aims to measure each subgroup’s performance. Rawlsian Max-Min fairness, for example, corresponds to measuring the utility (i.e., the performance) of the group with the lowest utility (Rawls, 2001). Similarly, Max Violation (Yang et al., 2020) measures the maximum GAP across all protected groups.

3 Bias Mitigation

This section reviews the three primary types of debiasing methods, followed by a summary of bias mitigation methods implemented in fairlib.

Pre-processing adjusts the training dataset to be balanced across protected groups before training, such that the input feature space is expected to be uncorrelated with the protected attributes. A typical line of work adopts long-tail learning approaches for debiasing, such as resampling the training set such that the number of instances within each protected group is identical (Zhao et al., 2018; Wang et al., 2019; Han et al., 2021a).

At training time introduces constraints into the optimization process for model training. A popular method is adversarial training, which jointly trains: (i) a discriminator to recover protected attribute values; and (ii) the main model to correctly predict the target classes while at the same time preventing protected attributes from being correctly predicted (Wadsworth et al., 2018; Elazar and Goldberg, 2018; Li et al., 2018; Wang et al., 2019; Zhao and Gordon, 2019; Han et al., 2021c).

Post-processing aims to adjust a trained classifier according to protected attributes, such that the final predictions are fair to different protected groups. For example, Ravfogel et al. (2020) iteratively projects fixed text representations from a trained model to a null-space of protected attributes. Han et al. (2021a) adjust the predictions for each protected group by searching the best prior for each group-specific component.

Implemented Methods Table 1 lists 14 debiasing methods that are implemented in fairlib. It can be beneficial to employ different debiasing methods simultaneously (e.g., combine pre-processing and training-time methods (Wang et al., 2019; Han et al., 2021a)), which fairlib supports, and technically, every combination of these methods can be directly used without any further modifications.

4 Model Comparison

In contrast to single-objective evaluation, evaluation of fairness approaches generally reports both fairness and performance simultaneously. Typically, no single method achieves both the best performance and fairness, making the comparison between fairness methods difficult. In this section, we first introduce trade-off plots for model comparison and then discuss model selection criteria that can be used for reporting numerical results.

Performance–fairness Trade-off is a common way of comparing different debiasing methods without the requirement for model selection. Specifically, there is usually a trade-off hyperparameter for each debiasing method, which controls to what extent the final model will sacrifice performance for better fairness, such as the number of iterations for null-space projection in INLP, or
the strength of the additional contrastive losses in FAIRSCL. Figure 1 shows two trade-off plots over different values of the hyperparameter of FAIRSCL applied to two different datasets (see Sec 7.1 for details). In fairlib, setting the trade-off hyperparameter to 0 for a given method degrades to the STANDARD model, i.e., the naively trained model without explicit debiasing.

Typically, instead of looking at the performance–fairness with respect to different trade-off hyperparameter values, it is more meaningful to compute the maximum fairness that can be achieved by different models at a fixed performance level and vice versa. Figure 2a shows an example of comparing INLP with FAIRSCL over the BIOS dataset (De-Arteaga et al., 2019), where the results are obtained by varying the hyperparameters as illustrated in Figure 1b. One problem associated with such plots is that some models are strictly worse than others, i.e., achieve worse performance and fairness at the same time. Such models can be filtered by a simple model selection process and removed from the trade-off plots. Alternatively, the Pareto trade-off plot, as shown in Figure 2, can be used. It displays the set of Pareto optimal points, where no dimension can be improved without causing a degradation in the other.

**Model Selection** refers to the process of selecting a combination of hyperparameters that outperforms other combinations. In single-objective learning, model selection is based on a single metric, such as the minimum loss on the dev set. In debiasing, however, both performance and fairness need to be considered for model selection, and a common method is **Constrained Selection**, which selects the best results of one metric given a threshold of the other metric. This is illustrated in Figure 2b, where given a performance threshold (the red vertical line), the best fairness scores that FAIRSCL and INLP can achieve are around 0.89 and 0.95, respectively. Similarly, the best performance scores that can be obtained given a 0.96 fairness threshold are approximately 0.53 and 0.49 for FAIRSCL and INLP, respectively.

An alternative method for model selection using Pareto frontiers is the DTO metric (Han et al., 2021a), which measures the **Distance To the Optimal point** for candidate models and is widely used in multi-objective optimization (Salukvadze, 2021a). Specifically, DTO finds the candidate point that is closest (in terms of Euclidean distance) to the utopia point (Vincent and Grantham, 1981). As shown in Figure 2a, the candidate points are ordered pairs (Performance, Fairness), and the utopia point (optimum) represents the hypothetical system which achieves the highest-achievable performance and fairness for the dataset, shown as the green point on the top-right corner. Lower is better for this statistic, with a minimum of 0. Besides the ease of comparison between approaches, DTO has the additional advantage of being minimized by the Pareto optimal points, i.e., for non-frontier candidates, there must be at least one frontier that can achieve a smaller DTO.

5 **fairlib Design and Architecture**

In this section, we describe the four modules of fairlib, namely data, model, evaluation, and analy-
Figure 1: Tuning the same tradeoff hyperparameter of FAIRSCL over two datasets. Similar trade-offs can be obtained for other debiasing methods. All figures in this paper are generated using fairlib, including hyperparameter tuning and figure plotting. In this paper, we report the accuracy as the performance, and equal opportunity as the fairness criterion.

Figure 2: performance–fairness trade-offs of FAIRSCL (blue points) and INLP (orange crosses) over the BIOS dataset. The vertical and horizontal red dashed line in Figure 2b are examples of constrained model selection with respect to a performance threshold of 0.7 and fairness threshold of 0.96. Figure 2a also provides an example for DTO. The green dashed vertical and horizontal lines denote the best performance and fairness, respectively, and their intersection point is the Utopia point. The length of green dotted lines from A and B to the Utopia point are the DTO for candidate models A and B, respectively.

5.1 Data Module

The data module manages inputs, target labels, and protected attributes for model training and evaluation. To enable different pre-processing debiasing methods in supporting any types of inputs, the BaseDataset class is implemented for sampling and weight calculation based on the distribution of classes and protected attributes. Dataset classes inherit functionality from BaseDataset with an additional property for loading different types of inputs. Specifically, fairlib includes Dataset classes for vector, matrix, and sequential inputs, to support structural inputs, image inputs, and text inputs. Once inputs are loaded by Dataset, pre-processing debiasing methods are automatically applied.

Based on Dataset, the DataLoader class is responsible for building minibatches of samples. Overall, steps within this module can be described as: inputs → Dataset → DataLoader → models, and the data module is designed for efficient data handling and pre-processing.
### Table 2: Built-in fairness evaluation metrics in fairlib.

| Type         | Formulation                          |
|--------------|--------------------------------------|
| Independence | $\frac{TP + FP}{TP + FP + TN + FN}$ (Positive Rate) |
| Separation   | $\frac{TP}{TP + FN}$ (Recall or TPR)   |
|             | $\frac{FP}{FP + TN}$ (Fall-out or FPR) |
| Sufficiency  | $\frac{TP + TN}{TP + TN + FP + FN}$ (Precision) |
|             | $\frac{TN}{TP + TN}$ (NPV)            |

5.2 Model Module

This is the core module of fairlib, which implements the At-training-time and Post-processing debiasing methods described in Section 3 and Table 1. Specifically, the methods can be applied to instances of the BasicModel class. We provide two child classes of the BasicModels. First, for sequential input, we provide the implementation for BERT text classification, which combines the BERT encoder (Devlin et al., 2019) provided by transformers and our MLP classifier. Second, an MLP classifier child class of BasicModel is implemented for structural inputs, which can be fully integrated with HuggingFace’s transformers library.¹ fairlib supports combination of diverse bias mitigation methods with thousands of pre-trained models across classification tasks and data types, including text, image, and audio modalities.

5.3 Evaluation Module

This module implements the fairness metrics described in Section 2 and several performance measures. Performance measures are based on the classification evaluation metrics implemented in scikit-learn (Buitinck et al., 2013), including Accuracy, F-score, and ROC AUC. However, no established fairness evaluation suite exists. Noting that the calculation of existing fairness metrics are all based on confusion matrices, we implemented a Evaluator class which can calculate any confusion-matrix derived scores. Table 2 maps the statistical fairness criteria of Section 2 to confusion-matrix derived scores. The group fairness criteria (GAP) follow the difference of these scores across subgroups.

5.4 Analysis Module

This module provides utilities for model comparison as introduced in Section 4, and the two main functions are:

- model_selection_parallel conducts post-hoc early-stopping, which selects the best checkpoint of a model based on the desired criterion (DTO or constrained selection). Multi-processing is supported through the joblib library.² All results are stored for later analysis.³

- final_results_df performs model selection consistently for different methods with the same criterion and organizes the results as a Pandas DataFrame (pandas development team, 2020), which can be used to create plots and tables.

- interactive_plot takes the output DataFrame from final_results_df and creates interactive plots, covering different comparison settings such as Figures 2 and 3.

Figures 1 and 2 are examples of the types of visualization supported by this module. More examples are included in Sections 6 and 7.

6 Usage

In this section, we demonstrate how to use fairlib. Users can run existing models or add their own models, datasets, and metrics as needed.

6.1 Running Existing Models

The following command shows an example for training and evaluating a STANDARD model with fairlib:

```python
python fairlib --dataset Bios_gender --emb_size 768 --num_classes 28 --encoder_architecture BERT
```

where the task dataset, the number of distinct classes, the encoder architecture, and the dimension of embeddings extracted from the corresponding encoder need to be specified. The above case trains a BERT classifier over the Bios datasets, where there are 28 professions.

¹[https://github.com/huggingface/transformers](https://github.com/huggingface/transformers)

²[https://joblib.readthedocs.io/en/latest/](https://joblib.readthedocs.io/en/latest/)

³Experimental results are available at [https://github.com/HanXudong/Fair_NLP_Classification/tree/main/analysis/results](https://github.com/HanXudong/Fair_NLP_Classification/tree/main/analysis/results)
In order to apply built-in debiasing methods, additional options for each debiasing method can be added to the command-line simultaneously:

```
python fairlib --dataset Bios_gender
  --emb_size 768 --num_classes 28
  --encoder_architecture BERT --BT
  Resampling --BTObj EO
  --adv_debiasing --INLP
```

The above example employs BTEO (Pre-), ADV (At-), and INLP (Post-) at the same time for a BERT classifier debiasing over the Bios dataset.

`fairlib` also supports YAML configuration files with training options:

```
python fairlib --conf_file opt.yaml
```

which is useful for reproducing experimental results, as `fairlib` saves the YAML file for each run.

`fairlib` can also be used by being imported as a Python library, as follows:

```
from fairlib.base_options import options
from fairlib import networks

config_file = 'opt.yaml'
# Get options
state = options.get_state(conf_file=config_file)

# Init the model
model = networks.get_main_model(state)

# Training with debiasing
model.train_self()
```

Checkpoints, evaluation results, outputs, and the configuration file are saved to the default or a specified directory.

### 6.2 Performing Analysis

As introduced in Section 5.4, the first step to analyze a trained model is selecting the best epoch. Here we provide an example for retrieving experimental results for FAIRSCL, and selecting the best epoch checkpoint:

```
from fairlib.load_results import model_selection_parallel

FairSCL_df = model_selection_parallel(
  model_id= "FSCL",
  GAP_metric_name = "TPR_GAP",
  Performance_metric_name = "accuracy",
  selection_criterion = "DTO",
  n_jobs=20,
  index_column_names = ["fcl_lambda_y", "fcl_lambda_g"],
  save_path = "FairSCL_df.pkl",)
```

where the fairness metric is TPR GAP (corresponding to Equal Opportunity fairness); the performance is measured with Accuracy score; the best epoch is selected based on DTO; and the tuned trade-off hyperparameters are used as the index. `n_jobs` is an optional argument for multiprocessing, and the resulting DataFrame will be saved to the specified directory.

Assuming `Bios_gender_results` is a Python dictionary of retrieved experimental results from the first step, indexed by the corresponding method name, we provide the following function for model comparison:

```
from fairlib.tables_and_figures import final_results_df

Bios_results = {
  "INLP":INLP_df,
  "FairSCL":FairSCL_df,}

Bios_gender_main_results = final_results_df(
  results_dict = Bios_results,
  pareto = True,
  selection_criterion = "DTO",
  return_dev = True,
)
```

where model selection is performed based on DTO. Each method has one selected model in the resulting DataFrame, which can then be used to create tables.

If visualization is desired, users can disable the model selection by setting `selection_criterion = None`, in which case all Pareto frontiers will be included.

### 6.3 Customized Datasets

A custom dataset class must implement the `load_data` function. Take a look at this sample implementation; the split is stored in a directory `self.data_dir`. The `args.data_dir` is either loaded from the arguments `-data_dir` or from the default value. `split` has three possible string values, "train", "dev", "test", indicating the split that will be loaded.

Then the `load_data` function must assign the value of `self.X` as inputs, `self.y` as target labels, and `self.protected_label` as information for debiasing, such as gender, age, and race.

```
from fairlib.dataloaders.utils import BaseDataset

class SampleDataset(BaseDataset):
```

def load_data(self):
    # Load data from pickle file
    filename = self.split + "df.pkl"
    _Path = self.args.data_dir /
    # filename
    data = pd.read_pickle(_Path)

    # Save loaded data
    self.X = data["X"]
    self.y = data["y"]
    self.protected_label =
    # ["protected_label"]

As a child class of BaseDataset, Pre-processing related operations will be automatically applied to the SampleDataset.

6.4 Customized Models
Recall that our current MLP implementation (Section 5.2) can be used as a classification head for different backbone models, and the new model will support all built-in debiasing methods.

Take a look at the following example: we use BERT as the feature extractor, and then use the extracted features as the input to the MLP classifier to make predictions.

We only need to define three functions: (1) __init__, which is used to initialize the model with pretrained BERT parameters, MLP classifier, and optimizer; (2) forward, which is the same as before, where we extract sentence representations then use the MLP to make predictions; and (3) hidden, which is used to get hidden representations for adversarial training.

```python
from transformers import BertModel
from fairlib.networks.utils import BaseModel

class BERTClassifier(BaseModel):
    model_name = 'bert-base-cased'

    def __init__(self, args):
        super(BERTClassifier, self).__init__()
        self.args = args

        # Load pretrained model parameters.
        self.bert =
        BertModel.from_pretrained(
            self.model_name)

        # Init the classification head
        self.classifier = MLP(self.args)

    # Init optimizer, criterion, etc.

    def init_for_training(self)

    def forward(self, input_data,
                group_label = None):
        # Extract representations
        bert_output =
        self.bert(input_data)[1]

        # Make predictions
        return self.classifier(bert_output,
                               group_label)

    def hidden(self, input_data,
               group_label = None):
        # Extract representations
        bert_output =
        self.bert(input_data)[1]

        return self.classifier.hidden(
            bert_output, group_label)
```

7 Benchmark Experiments
To evaluate fairlib, we conduct extensive experiments to compare models implemented in fairlib with their original reported results over two benchmark datasets.

7.1 Datasets
We conduct experiments over two NLP classification tasks — sentiment analysis and biography classification — using the same dataset splits as previous work (Elazar and Goldberg, 2018; Ravfogel et al., 2020; Han et al., 2021c; Shen et al., 2021; Han et al., 2021a).

**MOJI**: This sentiment analysis dataset was collected by Blodgett et al. (2016), and contains tweets that are either African American English (AAE)-like or Standard American English (SAE)-like. Each tweet is annotated with a binary ‘race’ label (based on language use: either AAE or SAE), and a binary sentiment score determined by (redacted) emoji contained in it.

**BIOS**: The second task is biography classification (De-Arteaga et al., 2019), where biographies were scraped from the web, and annotated for binary gender and 28 classes of profession.

7.2 Evaluation Metrics
Following Han et al. (2021a), we report the overall Accuracy as the performance, and the Equal Opportunity as the fairness criterion, calculated based on the Recall gap across all protected groups.
Table 3: Evaluation results ± standard deviation (%) on the test set of sentiment analysis (MOJI) and biography classification (BIOS) tasks, averaged over 5 runs with different random seeds. DTO is measured by the normalized Euclidean distance between each model and the ideal model, and lower is better. Due to the fact that INLP is a post-processing approach and its results with respect a given number of iterations are highly affected by the random seed, we only report results for 1 run. One way of getting statistics of INLP is selecting the trade-off hyperparameter of INLP for each random seed, however, this may not be a fair comparison with other methods as fixed hyperparameters have been used.

| Method  | MOJI   | BIOS    |
|---------|--------|---------|
|         | Performance↑ | Fairness↑ | DTO ↓ | Performance↑ | Fairness↑ | DTO ↓ |
| STANDARD | 72.30 ± 0.46 | 61.19 ± 0.44 | 47.68 | 82.25 ± 0.24 | 85.11 ± 0.81 | 23.17 |
| BTEO    | 75.39 ± 0.14 | 87.75 ± 0.38 | 27.49 | 83.83 ± 0.25 | 90.54 ± 0.91 | 18.73 |
| Adv     | 75.64 ± 0.73 | 89.33 ± 0.56 | 26.59 | 81.66 ± 0.22 | 90.74 ± 0.77 | 20.54 |
| DAdv    | 75.55 ± 0.41 | 90.40 ± 0.12 | 26.27 | 81.85 ± 0.19 | 90.64 ± 0.48 | 20.42 |
| ADAAdv  | 75.02 ± 0.69 | 90.87 ± 0.17 | 26.60 | 81.91 ± 0.34 | 88.96 ± 0.59 | 21.19 |
| FairBatch | 75.06 ± 0.60 | 90.55 ± 0.50 | 26.67 | 82.24 ± 0.13 | 89.50 ± 1.25 | 20.63 |
| FAIRSCL | 75.73 ± 0.34 | 87.82 ± 0.43 | 27.15 | 82.06 ± 0.16 | 84.27 ± 0.83 | 23.86 |
| EOCLA   | 75.28 ± 0.50 | 89.23 ± 0.79 | 26.97 | 81.78 ± 0.27 | 88.87 ± 0.94 | 21.35 |
| INLP    | 73.34 ± 0.00 | 85.60 ± 0.00 | 30.30 | 82.30 ± 0.00 | 88.62 ± 0.00 | 21.04 |

Table 3: Evaluation results ± standard deviation (%) on the test set of sentiment analysis (MOJI) and biography classification (BIOS) tasks, averaged over 5 runs with different random seeds. DTO is measured by the normalized Euclidean distance between each model and the ideal model, and lower is better. Due to the fact that INLP is a post-processing approach and its results with respect a given number of iterations are highly affected by the random seed, we only report results for 1 run. One way of getting statistics of INLP is selecting the trade-off hyperparameter of INLP for each random seed, however, this may not be a fair comparison with other methods as fixed hyperparameters have been used.

7.3 Models

For illustrative purposes, we report experiments over a subset of debiasing models in Table 1. Specifically, the selected models are: (1) BTEO (Han et al., 2021a), which has been shown to outperform other Pre-processing debiasing methods; (2) Adv (Li et al., 2018); (3) DADV (Han et al., 2021c), which is the current SOTA variant of Adv and outperforms EADV (Elazar and Goldberg, 2018); (4) ADAADV (Han et al., 2022), which is a augmented version of DADV that focuses on Equal Opportunity Fairness; (5) FAIRBATCH (Roh et al., 2021); (6) FAIRSCL (Shen et al., 2021); (7) EOCLA, which is also designed for EO fairness; and (8) INLP, which represents the Post-processing methods.

7.4 Experimental Results

Table 3 summarizes the results produced by Fairlib. Compared with previous work, STANDARD, BTEO, ADAADV, FAIRSCL and EOCLA achieve similar results to the original paper. In contrast, the re-implemented Adv, DADV, FAIRBATCH, and INLP outperform the results reported in their original paper due to the better-designed hyperparameter tuning and model selection.4

4We provide further details of hyperparameter tuning in https://github.com/HanXudong/fairlib/
Trade-off plots for the selected methods are shown in Figure 3. Over the MOJI dataset (Figure 3a), it can be seen that almost all methods lead to similar results, with a fairness score less than 0.9, except for INLP, which is substantially worse than the other methods. As increasing the values of each model’s trade-off hyperparameter (i.e., achieving better fairness at the cost of performance), ADAADV outperforms other methods.

The trade-off plot for BIOS is quite different to MOJI: (1) INLP becomes a reasonable choice; (2) FAIRSCL does not work well over this dataset, consistent with the original paper; (3) BTEO is the only method that achieves better performance than the STANDARD model while increasing fairness; (4) EO_CLA could be the best choice as it achieves much better fairness than others at a comparable performance level.

8 Related Work

Several toolkits have been developed for learning fair AI models (Bellamy et al., 2018; Saleiro et al., 2018; Bird et al., 2020). We discuss the two most closely-related frameworks.

The most related work to fairlib is AI Fairness 360 (AIF360), which is the first toolkit to bring together bias detection and mitigation (Bellamy et al., 2018). Like fairlib, AIF360 supports a variety of fairness criteria and debiasing methods, and is designed to be extensible. The biggest difference over fairlib is that AIF360 is closely integrated with scikit-learn, and as such does not support other ML frameworks such as PyTorch. This not only limits the applicability of AIF360 to a large portion of NLP and CV tasks where neural model architectures are now de rigueur, but also implies a lack of GPU support in AIF360, but also implies a lack of GPU support in AIF360. Moreover, AIF360 only provides fundamental analysis features, such as comparing debiasing with respect to a single evaluation metric, while the analysis module of fairlib has richer features for model comparison, for example, selecting Pareto-models and interactive visualization.

The second closely-related library is FairLearn (Bird et al., 2020), which is also targeted at assessing and improving fairness for both classification and regression tasks. However, similar to AIF360, FairLearn is mainly developed for scikit-learn, meaning complex CV and NLP tasks are un-supported. Additionally, FairLearn currently only supports four debiasing algorithms, as opposed to the 14 methods supported in fairlib, providing fuller coverage of different debiasing methods.

In sum, fairlib complements existing tools for bias detection and improvement by: (1) implementing a broad range of competitive debiasing approaches, with a specific focus on debiasing neural architectures which underlie many CV and NLP tasks; and (2) comprehensive tools for interactive model comparison to help users explore the effects of different debiasing approaches.

9 Conclusion and Future Work

In this paper, we present fairlib, a new open-source framework for bias detection and mitigation in classification models, which implements a wide range of fairness evaluation metrics and 14 different debiasing approaches. With better-designed hyperparameter tuning and model selection, the reproduced models in fairlib outperform the results reported in the original work. fairlib also has remarkable flexibility and extensibility, such that new models, debiasing methods, and datasets can be easily developed and evaluated.

For future work, we will keep fairlib up-to-date with the latest proposed debiasing approaches, and provide more model examples for other types of inputs, such as image and audio modalities. It is worth noting that a strong assumption that has been made in this paper is that protected attributes are accessible at the training time. In practice, protected labels are often unavailable or only available in limited numbers. Sourcing protected labels can also be difficult, for reasons ranging from privacy regulations or ethical concerns, to only a small subset of users explicitly publicly disclosing protected attributes. As such, another critical direction for future work is incorporating models that can debias with less protected labels in order to deal with real-world data, such as decoupled adversarial training (Han et al., 2021b) and adversarial instance reweighting (Lahoti et al., 2020).

Ethical Considerations

This work provides an unified framework for measuring and improving fairness. Although fairlib assumes access to training datasets with protected attributes, this is the same data assumption made

https://fairlearn.org/main/user_guide/mitigation.html
by all debiasing methods. To avoid harm and be trustworthy, we only use attributes that the user has self-identified for experiments or toy datasets. All data in this study is publicly available and used under strict ethical guidelines.

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