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Aequitas Flow: Streamlining Fair ML Experimentation

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Abstract

Aequitas Flow is an open-source framework and toolkit for end-to-end Fair Machine Learning (ML) experimentation, and benchmarking in Python. This package fills integration gaps that exist in other fair ML packages. In addition to the existing audit capabilities in Aequitas, the Aequitas Flow module provides a pipeline for fairness-aware model training, hyperparameter optimization, and evaluation, enabling easy-to-use and rapid experiments and analysis of results. Aimed at ML practitioners and researchers, the framework offers implementations of methods, datasets, metrics, and standard interfaces for these components to improve extensibility. By facilitating the development of fair ML practices, Aequitas Flow hopes to enhance the incorporation of fairness concepts in AI systems making AI systems more robust and fair.

Keywords: Fair machine learning, experimentation, ethical artificial intelligence, open-source framework, python

1 Introduction

Developing Machine Learning (ML) and Artificial Intelligence (AI) systems that result in fairness and equity is a critical topic, especially as such systems get used in high-stakes settings such as hiring (Dastin, 2018), healthcare (Igoe, 2021), criminal justice (Angwin et al., 2016; Chouldechova, 2017), and financial services (Zhang and Zhou, 2019; Bartlett et al., 2019; Jesus et al., 2022). While numerous studies define metrics and properties of algorithmic fairness (Chouldechova, 2017; Calders and Verwer, 2010; Dwork et al., 2012; Feldman et al., 2015; Hardt et al., 2016; Corbett-Davies et al., 2017) and propose methods for fairer models (Fish et al., 2016; Calmon et al., 2017; Zafar et al., 2017; Cotter et al., 2019), gaps in the implementation, user experience. and integration of existing tools hinder end-to-end experimentation (Lee and Singh, 2021) and benchmarking. This makes empirical studies and practical use challenging, scarce, and often limited in scope (Friedler et al., 2019; Lamba et al., 2021), ultimately affecting the adoption of fair ML methods in real-world high-stakes settings.

This paper introduces Aequitas Flow, an open-source framework for reproducible and extensible end-to-end fair ML experimentation that extends Aequitas, our original bias audit toolkit. The goal is to help 1)researchers compare and benchmark new methods they develop against existing methods in a systematic and reproducible manner and 2) practitioners easily evaluate existing bias mitigation methods and deploy ones that best match their goals.

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Table 1: Comparison of packages for training and evaluation of fair ML Methods.

	Packages			
Functionalities	AIF360	Fairlearn	Aequitas	Aequitas Flow
Group fairness metrics	◐	◐	●	●
Pre-processing methods	●	◐	-	●
In-processing methods	◐	●	-	●
Post-processing methods	●	●	-	●
Standardized interfaces for extensibility	◐	◐	-	●
Hyperparameter optimization pipeline	-	-	-	●
Binary classification	●	●	●	●
Regression	●	●	-	-
Model selection	-	-	◐	●
Methods comparison	-	-	-	●
Plotting methods	-	◐	●	●

● exists in package; ◐ partially exists in package; - does not exist in package.

Table 1 compares Aequitas Flow, the latest release of the Aequitas package [1] (Saleiro et al., 2018) to other fair ML packages to highlight some of the key gaps we aimed to fill with this paper.

Fairlearn (Weerts et al., 2023), and AIF360 (Bellamy et al., 2018) are popular fair ML packages to facilitate adoption by offering methods (Feldman et al., 2015; Hardt et al., 2016; Agarwal et al., 2018), fairness metrics (Hardt et al., 2016) and datasets available in the literature (Kohavi, 1996; Angwin et al., 2016; Dua and Graff, 2017; Ding et al., 2021). However, some issues hinder their usability as standard toolkits for fairness studies. First, both lack a defined experimentation pipeline, requiring users to opt for external packages for fundamental tasks, such as dataset splitting and hyperparameter optimization (Schelter et al., 2019). Second, inconsistency in class behavior and implementation force users to customize the code depending on the methods used. For instance, in AIF360's `DisparateImpactRemover` class, most of the parent class methods are not implemented. These issues create a high barrier for users to effectively use the packages. Our work tackles the lack of standardized tools for experimentation with fair ML, with an emphasis on the extensibility of methods, datasets, and metrics, the reproducibility of the experiments, as well as different levels of customization for different user needs.

2 Aequitas Flow

The Aequitas Flow package is a comprehensive framework that integrates the necessary elements for a complete fair ML experiment. These are methods, datasets, and optimization strategies. They can be accessed through a standardized pipeline defined by configuration files, Python dictionaries or instantiated independently. This provides a standardized platform for experimental fairness testing. Figure 1 represents the pipeline's structure, mapping the components and interactions and offering an overview of the fairness experimentation process.

Experiment: The `Experiment` is the main component that orchestrates the workflow within the package. It processes input configurations, which can be provided as either files[2] or Python dictionaries. These specify the methods, datasets, and optimization parameters. The Experiment component initializes and populates the necessary classes, ensuring they interact deterministically throughout the execution process. When an experiment is completed, the results can be analyzed directly within the class with the appropriate methods. A variant of this component allows for

1. `https://github.com/dssg/aequitas`
2. Examples provided in the repository.

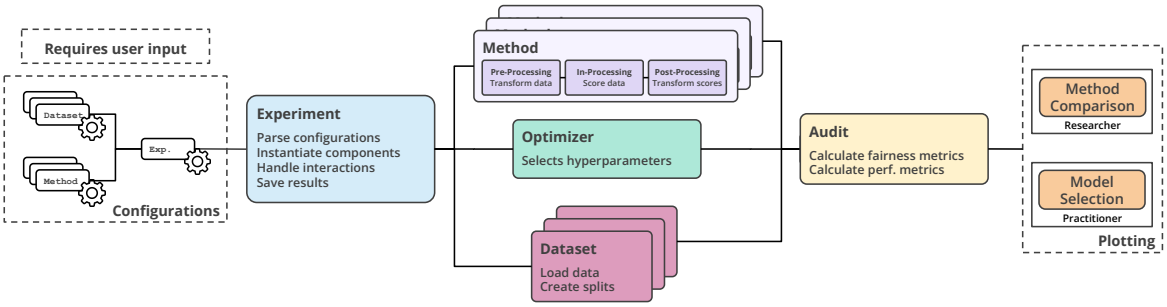


Figure 1: **Diagram of an Experiment in Aequitas Flow.** The user input is passed to the Experiment, which will instantiate the components (Methods, Datasets, and Optimizer) in the pipeline. For each target task (for a researcher or practitioner), different plotting methods can be used to analyze the experimental results.

simplified usage as it only requires the definition of a dataset. This feature is designed to streamline initial experiments and reduce configurations.

```
exp = Experiment(config_file="configs/experiment.yaml")
exp.run()
```

Optimizer: The `Optimizer` component manages hyperparameter selection and model evaluation. It receives the hyperparameter search space of the methods and a split dataset to conduct hyperparameter tuning. It evaluates the performance of models, and stores the resulting artifacts. The component uses Optuna (Akiba et al., 2019) for hyperparameter selection and the bias auditing functionality of Aequitas (Saleiro et al., 2018) for fairness and performance evaluation. This component should only be instantiated by an `Experiment`, to guarantee consistency in input arguments. Several attributes of the hyperparameter optimization can be determined by configurations, such as the number of trials and jobs, the selection algorithm (*e.g.*, random search, grid search), and the random seed.

Datasets: This component has two primary functions: loading the data and generating splits. It maintains information about the prediction target, typing, and sensitive features. The data is stored in a pandas dataframe format (pandas development team, 2020). The framework initially encompasses eleven tabular datasets, including those from the BankAccountFraud (Jesus et al., 2022) and Folktables (Ding et al., 2021). The component also permits user-supplied datasets in CSV or parquet formats with splits based on a column, or randomly.

```
dataset = datasets.FolkTables(variant='ACSIncome')
dataset.load_data()
dataset.create_splits()
dataset.train.X  # return the train feature matrix
```

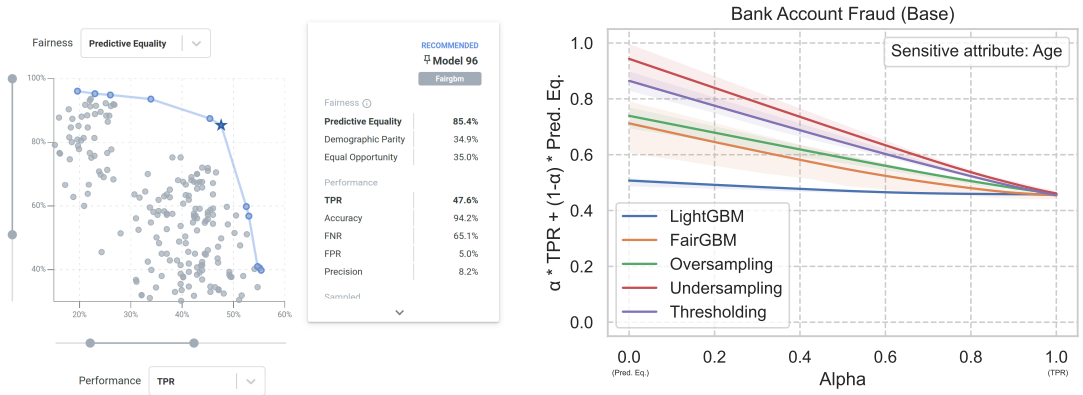
Methods: This group of components handles data processing and creates and adjusts predictions for validation and test sets. Aequitas Flow provides interfaces for the three recognized types of fair ML methods (Caton and Haas, 2023; Mehrabi et al., 2021; Pessach and Shmueli, 2022): pre-processing, in-processing, and post-processing. Pre-processing methods modify the input data, in-processing methods typically directly modify the objective function and generate prediction scores, and post-processing methods adjust these scores or rankings. Additionally, ML classification methods are included in the category of base estimators and function similarly to in-processing methods. The methods adhere to a standardized interface to facilitate calls within the experiment class. In the current version of Aequitas, 15 methods are supported.

```
model = methods.inprocessing.FairGBM()
model.fit(train.X, train.y, train.s)
preds = model.predict_proba(val.X, val.s)
```

Audit: The Aequitas toolkit offers a suite of metrics based on the confusion matrix for the protected groups in the dataset. Users may specify a group as a reference for comparison and select the appropriate fairness metric for their analysis. Experiments leverage the `Audit` class to calculate metrics and disparities when analyzing the produced prediction scores of a model.

```
audit_df = pd.DataFrame({"score": preds, "label": val.y, "group": val.s})
audit = Audit(audit_df)
audit.performance()  # Obtain performance metrics
audit.audit()  # Obtain fairness metrics
```

Plotting: Aequitas Flow provides two workflows based on the goal of the user. The first is around model selection (a), where users can plot the trained models with the desired metrics of fairness and performance in each axis. The Pareto frontier is displayed, with the model with the best fairness-performance trade-off highlighted. The second provides a comparison of methods (b). Confidence intervals for the combined performance and fairness are calculated for each tested method in the trade-offs of these metrics. Additional plotting methods are available for in-depth bias auditing. Figure 2 shows examples of both.



(a) (b)

Figure 2: Plots introduced in Aequitas Flow. Plot (a) is designed for model selection; Plot (b) compares the different tested methods.

3 Conclusion

Aequitas Flow is an open-source framework that makes end-to-end experimentation with fair ML easier through the use of customizable components, namely datasets, methods, metrics, and optimization algorithms. It enhances robustness and reproducibility by addressing the issues of ad-hoc and single-use setups in fair ML experimentation. This can lead to better benchmarking and adoption of fair ML techniques in real world settings. While initially focused on tabular datasets, the framework's flexible interfaces allow adaptation to other data formats, and ongoing updates will incorporate additional implementations, in a welcoming environment to community contributions. Recognizing the challenges associated with responsibly using this framework in real-world applications, we aim to support the widespread adoption of fair ML methodologies and increase their societal impact.

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