# A Suite of Fairness Datasets for Tabular Classification

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Abstract There have been many papers with algorithms for improving fairness of machine-learning classifiers for tabular data. Unfortunately, most use only very few datasets for their experimental evaluation. We introduce a suite of functions for fetching 20 fairness datasets and providing associated fairness metadata. Hopefully, these will lead to more rigorous experimental evaluations in future fairness-aware machine learning research.

#### 1 Introduction

Many people share the goal of making artificial intelligence fairer to those affected by it. There is extensive debate about which fairness interventions are appropriate and effective to achieve this goal. This debate should be informed, at least in part, by rigorous experimental evaluation. Rigorous experiments can help stakeholders make more informed choices among existing fairness interventions, as well as help researchers invent better ones. Unfortunately, most papers about fairness interventions evaluate them on at most a handful of datasets. This is because historically, it was hard to find and fetch datasets relevant to fairness, as well as associate them with fairness metadata, such as favorable labels or protected attributes.

Table 1: Static information about the datasets. Column 'origin' specifies from where the data is downloaded. Columns '#rows' and '#cols' give the shape of X. Columns 'any cat.' and 'any mis.' indicate whether X has any categorical columns and any missing values, respectively. Column '#labels' shows the number of unique values in y and 'target name' shows the name of y. Columns 'favorable labels' and 'protected attributes' are part of the fairness metadata. \*For details see https://github.com/IBM/lale/blob/master/examples/demo\_fairness\_datasets.ipynb.

name	origin	#rows	#cols	any	any	#la-	target	favorable	protected attributes	
				cat.	mis.	bels	name	labels	(first)	(second)
ricci	OpenML	118	5	yes	no	2	promotion	Promotion	race	
tae	OpenML	151	5	no	no	3	class_attribute	3	whether*	
heart_disease	OpenML	303	13	no	no	2	target	1	age	
student_math	OpenML	395	32	yes	no	2	g3_ge_10	1	sex	age
student_por	OpenML	649	32	yes	no	2	g3_ge_10	1	sex	age
creditg	OpenML	1,000	20	yes	no	2	class	good	personal*	age
titanic	OpenML	1,309	13	yes	yes	2	survived	1	sex	
us_crime	OpenML	1,994	102	yes	no	2	crimegt70pct	0	blackgt6pct	
compas_violent	ProPublica	4,020	51	yes	yes	2	two_year_recid	0	sex	race
nlsy	OpenML	4,908	15	yes	no	2	income96gt17	1	age	gender
compas	ProPublica	6,172	51	yes	yes	2	two_year_recid	0	sex	race
speeddating	OpenML	8,378	122	yes	yes	2	match	1	samerace	importa*
nursery	OpenML	12,960	8	yes	no	5	class	spec_prior	parents	
meps19	AHRQ	16,578	1,825	yes	no	2	UTILIZATION	1	RACE	
meps21	AHRQ	17,052	1,936	yes	no	2	UTILIZATION	1	RACE	
meps20	AHRQ	18,849	1,825	yes	no	2	UTILIZATION	1	RACE	
law_school	OpenML	20,800	11	yes	no	2	ugpagt3	TRUE	race1	
default_credit	OpenML	30,000	24	no	no	2	default.pay*	0	sex	
bank	OpenML	45,211	16	yes	no	2	class	1	age	
adult	OpenML	48,842	14	yes	yes	2	class	>50K	race	sex

```
1
    {
        "favorable_labels": ["good"],
2
        "protected_attributes": [
3
4
           {
               'feature": "personal_status",
5
              "reference_group": ["male div/sep", "male mar/wid", "male single"]
6
7
           },
8
           {
              "feature": "age"
9
              "reference_group": [[26, 1000]]
10
11
           }
12
       ]
13
    }
```

Figure 1: Example fairness metadata for the creditg dataset. The list "favorable\_labels" contains values of y that indicate a favorable outcome. The list "protected\_attributes" contains sub-objects indicating the name "feature" of the attribute of X, along with a list "reference\_group" specifying which values or ranges of that attribute indicate membership in the privileged group.

#### 1.1 Related Work

OpenML [8] provides thousands of datasets ready for machine learning experiments, but does not identify which of them are relevant to fairness and does not provide fairness metadata. AIF360 [2] provides functions for fetching 8 fairness datasets along with metadata, but requires using a special class or a multi-level pandas index. Quy et al. [7] describe 15 fairness datasets, but do not provide code for fetching them, do not provide machine-readable metadata for them, and some of their datasets are difficult to obtain. We applaud OpenML, AIF360, and Quy et al. for getting most of the way towards a suite of fairness datasets and build upon their work to take the last missing step.

#### 1.2 Contribution

This paper describes a suite of 20 Python functions to fetch 20 datasets along with fairness metadata (see Table 1). It focuses on tabular data with classification targets, which is the most wellstudied setting. (Other settings also have merit but are beyond the scope of this paper.) To make these functions easy to use, they simply return data in pandas format [6] along with fairness metadata in JSON format.

# 2 Functions for Fetching Datasets

Our suite of dataset fetching functions grew over time in an effort to gather fairness datasets that are available for easy download with reasonable terms and usage restrictions. Most of them are used in the literature, and where possible, the fairness metadata returned by our functions emulates prior work. Each of the 20 functions does three things: first download the data, second minimally process the data, and third provide fairness metadata to go along with the data.

**Download the data**. Our library distributes only functions for fetching data, but the data itself is not part of the library. When you consume the data, it is your responsibility to honor its licenses and terms of use. As shown in Table 1, 15 of the datasets are from OpenML [8], which uses a CC-BY license as explained here: https://www.openml.org/terms. Our functions download these 15 OpenML datasets. On the other hand, for the remaining 5 datasets from AHRQ and ProPublica, our functions do not download the data, but instead print instructions for downloading them manually. Once downloaded, our functions return them from local disk. The data use information for the MEPS datasets from AHRQ is at https://meps.ahrq.gov/data\_stats/data\_use.jsp, and the ProPublica data is at https://github.com/propublica/compas-analysis. Our functions are themselves part of the open-source Lale library [1], distributed under an Apache license.



Figure 2: Example pipeline for the speeddating dataset. (The preprocessing shown here is not part of the fetching function, but instead, is done on its result.) Referring to Table 1, since 'any cat.' is true, there are separate sub-pipelines with Lale Project operators for categorical and numerical columns. Since 'any mis.' is true, the sklearn SimpleImputer operators fill in missing values. And since '#cols' is greater than 32, an sklearn SelectKBest operator reduces it to 32.

Minimally process the data. Our functions perform only limited preprocessing, because preprocessing impacts fairness and can be difficult to invert. That said, some preprocessing already happened at source before downloading, beyond our control. Where the prediction target is not yet categorical, our functions discretize it. Where necessary, our functions drop the feature column from which the discretized target was derived. There are some other cases where our functions drop additional feature columns because they are not useful. Finally, some feature columns lack a meaningful name and our functions rename them, e.g. from "v1" to "age". See the code for details.

**Provide fairness metadata**. Each of the functions returns a JSON object with fairness metadata. Figure 1 shows an example. The fairness metadata comprises a list of favorable labels (i.e., favorable values in y) and a list of protected attributes (i.e., column names in X). For each protected attribute, it gives a list of either ranges or values that indicate membership in the privileged group. In practice, features and labels relevant to fairness considerations are subject to interpretation and should be determined through careful consultation with stakeholders. Hence, we opted for a simple format that is easy to change.

How to use the functions. First install the Lale library [1] by doing pip install lale. Then you can call the functions as illustrated by the following two lines of Python code for the creditg dataset:

- 1 import lale.lib.aif360
- 2 X, y, fairness\_info = lale.lib.aif360.fetch\_creditg\_df()

After this code, X and y contain the features and labels of the data, represented as a pandas dataframe and series [6], and fairness\_info contains the metadata, represented as a JSON object as illustrated in Figure 1. At this point, you can use your favorite library to split and preprocess the data, make predictions, evaluate metrics, and perhaps mitigate bias. A popular choice for many of these tasks would be the sklearn library [3]. While our dataset fetching functions are part of the Lale library [1], you do not need to use Lale to process their results. On the other hand, Lale contains additional code that uses the metadata, including bias mitigators and fairness metrics.

# 3 Characterization of the Datasets

We already saw some static information characterizing the datasets in Table 1. This section provides additional information based on dynamic experiments. Our experiments feed the result from the dataset fetching function into a pipeline of operators from Lale [1], sklearn [3], and XGBoost [4]. Exactly which operators are included in the pipeline depends on whether the dataset has categorical values and missing values and whether it has a large number of columns. Figure 2 shows an example pipeline for a dataset where all three of these are true; pipelines for other datasets are simpler. When you use the datasets, it is up to you what type of pipeline to use, which may or may not resemble our example.

Figure 3 shows the results. Subplot 'data\_ci' shows class imbalance; it is the ratio between the number of unfavorable and favorable outcomes, and higher values mean the data is more



Figure 3: Metrics characterizing the datasets. Subplot 'data\_ci' shows the class imbalance of the data based on binarizing y using the metadata. Subplot 'data\_di' shows the symmetric disparate impact of the data. Subplots 'xgb\_di', 'xgb\_eo', and 'xgb\_ba' show the symmetric disparate impact, equal opportunity difference, and balanced accuracy of predictions from XGBoost.

balanced. Subplot 'data\_di' shows the symmetric disparate impact [5]; it is the ratio of the favorable rates for the unprivileged and privileged groups. Higher disparate impact values mean the data is more fair, with values under 0.8 usually considered unfair [5]. The remaining three subplots show averages from 5-fold cross-validation experiments with a popular and well-performing classifier, XGBoost [4], with error bars showing standard deviations. Subplot 'xgb\_di' shows that while bias in the data does not always exactly equal bias in predictions of a classifier trained on the data, the trends are similar across the 20 datasets. Subplot 'xgb\_eo' shows equal opportunity difference, which is the difference of true positive rates between the unprivileged and privileged groups, with zero indicating perfect fairness. Subplot 'xgb\_ba' shows balanced accuracy, which is the average recall for the all classes, where higher values are better and the best value is 1. Despite using 5-fold cross-validation, the classifier overfit a couple of datasets with 100% balanced accuracy.

# 4 Conclusion

We hope our functions for fetching fairness datasets are useful and we welcome contributions to their open-source code. Ideally, future papers with experimental evaluations of fairness interventions will use at least 20, if not more, datasets.

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