# Fairness Label for ML Pipeline

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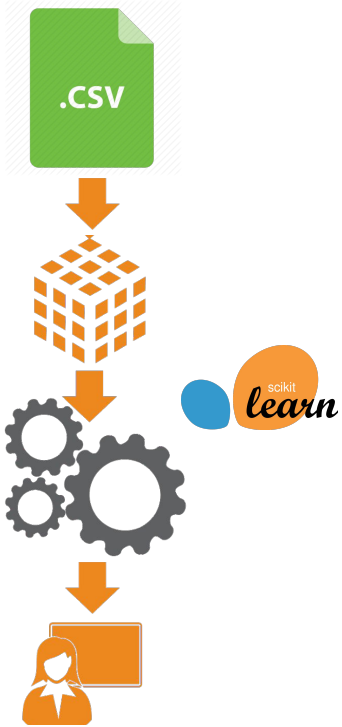
# Motivation

- No system-level support for **end-to-end responsible data analysis** for users' own dataset.
- No system-level support for evaluating the **fitness of fairness measures and interventions** for users' own dataset.
- No system-level support for evaluating **intersectional effects** caused by interaction among multiple sensitive attributes.



# Problem Statement - Goals

- Build a system to support standard operations in a ML pipeline
  - earlier life stages of data → ***scikit-learn preprocessing***
  - ML models → ***scikit-learn classification*** and ***model selection***
  - fairness interventions → ***AI Fairness 360***
- Design a component to track important fairness-related statistics → **Fairness Labels**
- Visualize high-dimensional fairness labels

# Approach - Fairness Labels

**Static label**: the distributions of ***target variable*** (+ or -) of all the sub-populations defined by a pair of sensitive attributes, like gender and race.

**Performance label**: the distributions of ***performance metric*** (*TPR*, *FPR*, *TNR*, *FNR*, *ACC*, ..., etc) of all the sub-populations defined by a pair of sensitive attributes.

**Adult Income: +: >50K, - : <=50K**

***race***

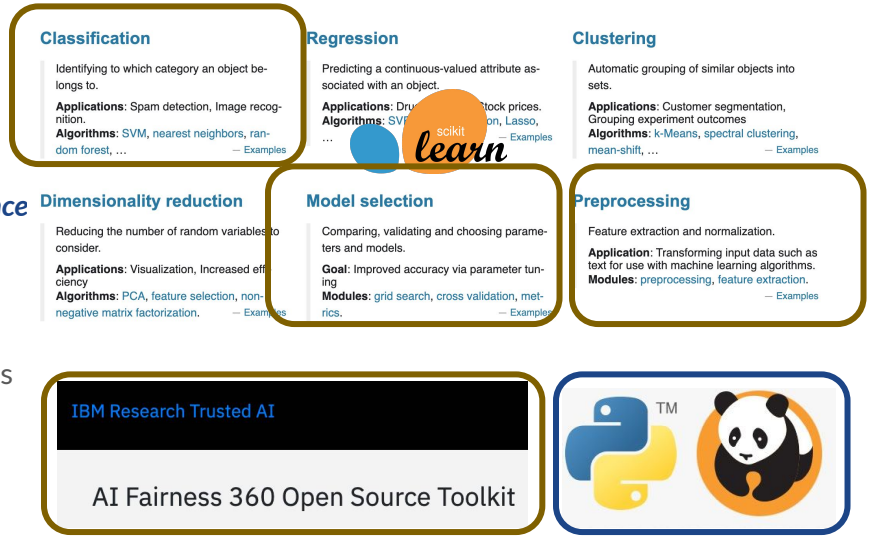
$$\{(white) : \{+ : 0.95, - : 0.88\},$$
$$(black) : \{+ : 0.05, - : 0.11\}\}$$

***race, gender***

$$\{(white, men) : \{+ : 0.86, - : 0.63\},$$
$$(white, women) : \{+ : 0.14, - : 0.37\},$$
$$(Black, men) : \{+ : 0.77, - : 0.46\},$$
$$(Black, women) : \{+ : 0.23, - : 0.54\}\}$$

# Implementation

- Pipeline
  - Integrated most of ***scikit-learn* preprocessing functionality**
  - Integrated fairness interventions in ***AI Fairness 360***
  - Developed components: ***Filter, Balance Sampler, Balance Splitter***
- Fairness labels
  - Extract static and performance label
  - Linear combination in the order of sensitive attributes
    - white, women, young, ...
- Visualization
  - Seaborn barplots
  - Tree-structure representation for high-dimensions *



# Experimental Setup

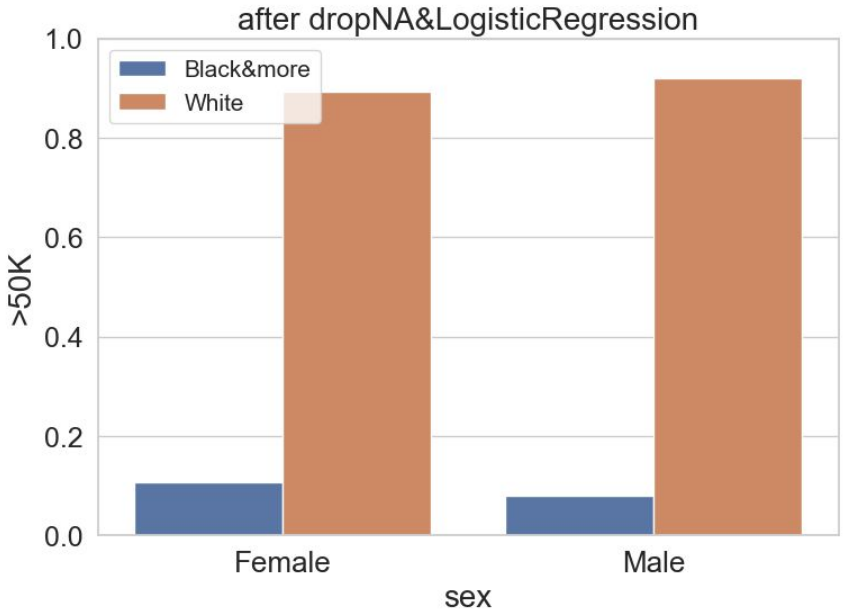
- **Robustness**
  - various input pipelines
  - new dataset
- **Intersectional effects**
  - use 2 sensitive attributes
  - evaluate existing fairness interventions
  - on benchmark datasets and new dataset

# Datasets

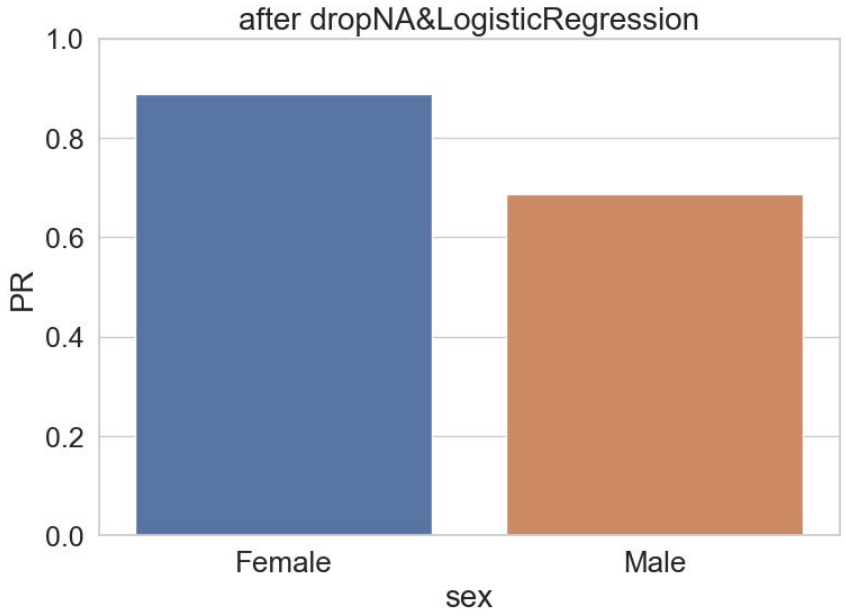
- Benchmark datasets:
  - **Adult Income**: **the fitness of fairness preprocessing interventions**
  - **German Credit**: **intersectional effects**
  - **COMPAS Score**: **intersectional effects**
- Explore new dataset:
  - **Law School Admissions**: **robustness**

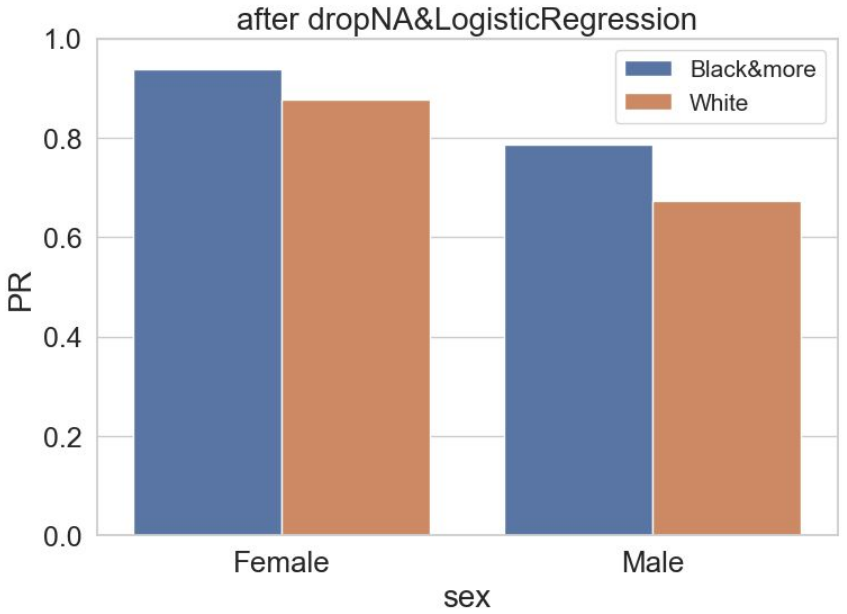
| dataset | size | target | 1st sensitive att | 2nd sensitive att | used in other papers |
|---|---|---|---|---|---|
| Adult Income | 32,561 | income per year | race | gender | Yes |
| German Credit | 1000 | credit worthiness | binned age | gender | Yes |
| COMPAS Score | 7,214 | whether recidivated | race | gender | Yes |
| Law School Admissions | 438,487 | application status | race | gender | No |

# Adult Income - static label - positive outcome

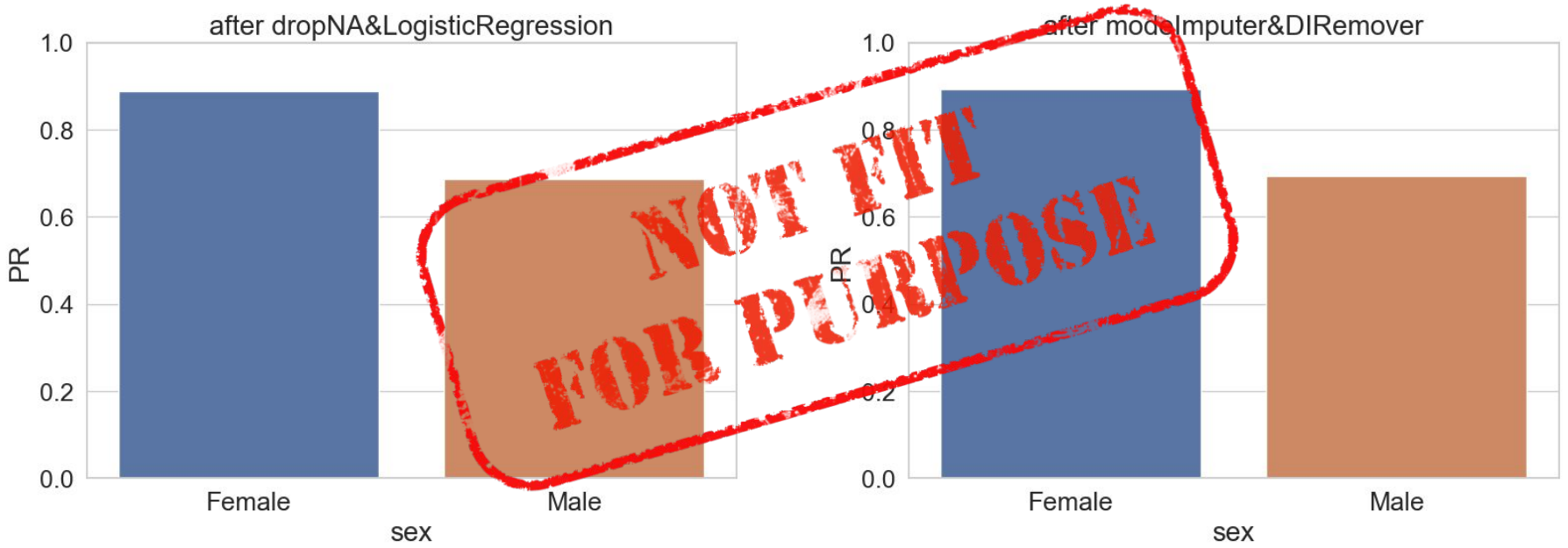



# Adult Income - performance label - selection rate



# Change of performance apply fair intervention



# Intersectional effects - selection rate


# Discussion

- ★ **Build a general system that supports responsibly ML pipeline**
  - *Integrate more modules
  - *Support flexible pipelines
- ★ **Track two types of fairness-related statistics through our system**
  - *High-dimensional fairness label
- ★ **Experiments on benchmark datasets and new dataset**
  - *Explore the unknown intersectional effects

# Thank you & QAs