Evaluating Fairness of Ranking Algorithms

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MOTIVATION

- Investigating how hiring (and ranking algorithms in general) are biased and what are the effective ways to mitigate the bias.
- Experimenting the efficacy of removing gender, race, and class identifiers to generate fair ranking.

BACKGROUND

- Existing hiring algorithms that companies claim to be "unbiased" oftentimes only try to meet the Equal Employment Opportunity Commission (EEOC) basic requirements.
- Even when a hiring algorithm is "good enough" for EEOC standards, its interaction with humans such as hiring managers still encourages discriminatory actions.
- Two assessments of discrimination: [1]
  - *disparate treatment*
  - *disparate impact ("4/5" rule)*
- Two general categories of current approaches to mitigating bias in ranking algorithms:
  - *in-processing: data cleaning -> ranking (normally done WITHOUT machine learning)*
  - *post-processing: data cleaning -> ranking -> evaluating -> reranking (normally done WITH machine learning, and evaluating and reranking could happen multiple times)*

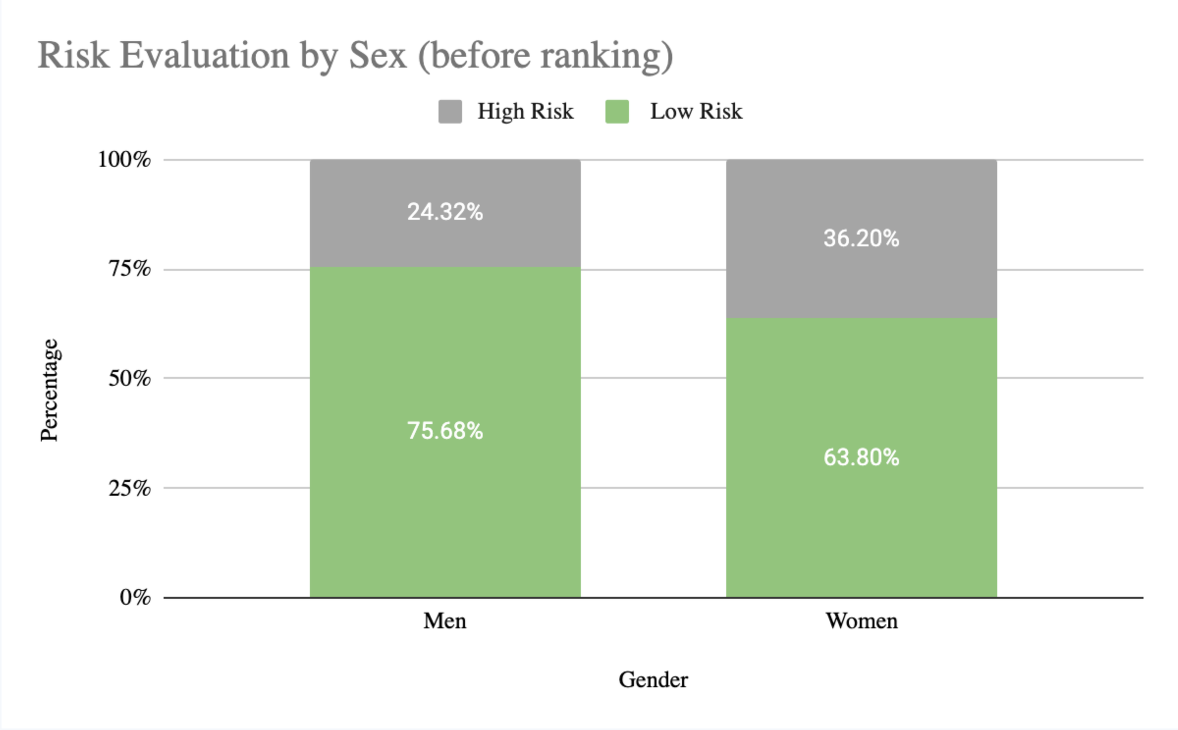
METHODOLOGY

- Understand, then Compare and Contrast various types of ranking algorithms.
- Experiment with a particular algorithm
  - *Themis-ml* [2]
  - *a fairness-aware *post-processing* machine learning algorithm*
- Four Training Models [2] (protected attribute = gender; training data = German Credit Score):
  1. ***Baseline (B):*** *classifier trained on all available input variables, including protected attributes.*
  2. ***Remove Protected Attribute (RPA):*** *classifier where input variables do not contain protected attributes.*
  3. ***Reject-Option Classification (ROC):*** *classifier using the reject-option classification method.*
  4. ***Additive Counterfactually Fair Model (ACF):*** *classifier using the additive counterfactually fair method.*

- Evaluate fairness by comparing the percentage of men and women classified as low-risk for a loan.
- Evaluate utility effectiveness by checking if the AUC value remains the same.

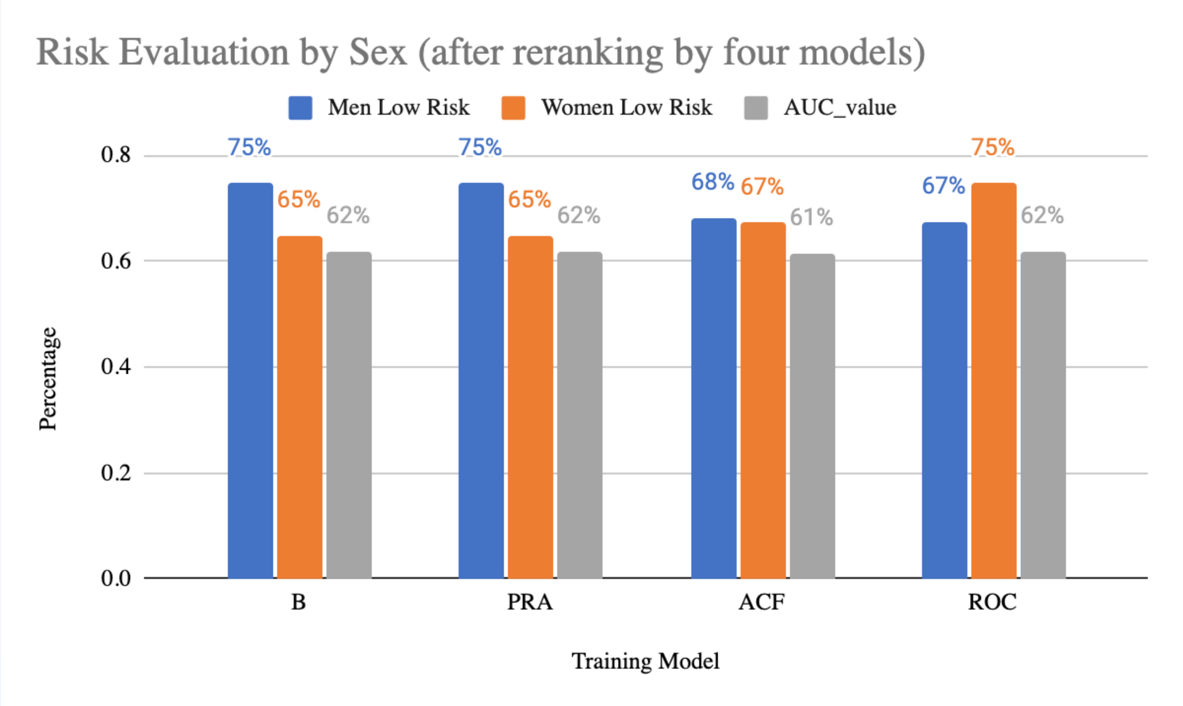
FINDINGS

- Raw Data



* Men (unprotected group) are 12% more likely to be labeled as low risk.

- Reranking Result



- For PRA and B, there is no noticeable change in distribution between the two gender groups.
- For ACF, the difference between the two gender groups is significantly decreased.
- For ROC, surprisingly, women are more likely to be labeled as low risk.
- All four training models maintain the utility AUC value.

CONCLUSION & EVALUATION

- Simply removing the identifiers related to certain attributes (e.g. gender, race, or class) can not improve the fairness of the ranking result.
- This is still a simple data set that produces binary classifications. We should deploy real-life evaluation on the algorithms to see if the algorithms can achieve better representation for the marginalized group.
- Future work should also focus on the social and systemic dimensions for ranking or hiring algorithms to be in place.

REFERENCE

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ACKONWLEDGEMENT

Thanks to Brown ExploreCSR program and my mentor Zainab Iftikhar for guiding this project.