About US

THAT RECOMMENDER SYSTEMS LAB

- Research Interests
  - Multistakeholder recommendation
  - Fairness-aware recommendation
  - Contexts:
    - Philanthropic – Kiva
    - Job Recommendation
    - Finance
- Our website:
  - http://www.that-recsys-lab.net/

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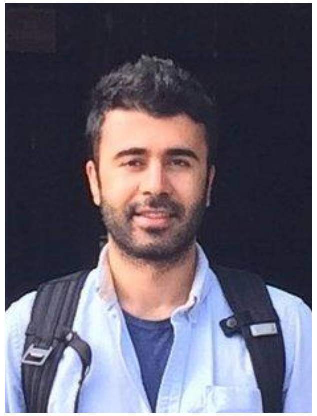

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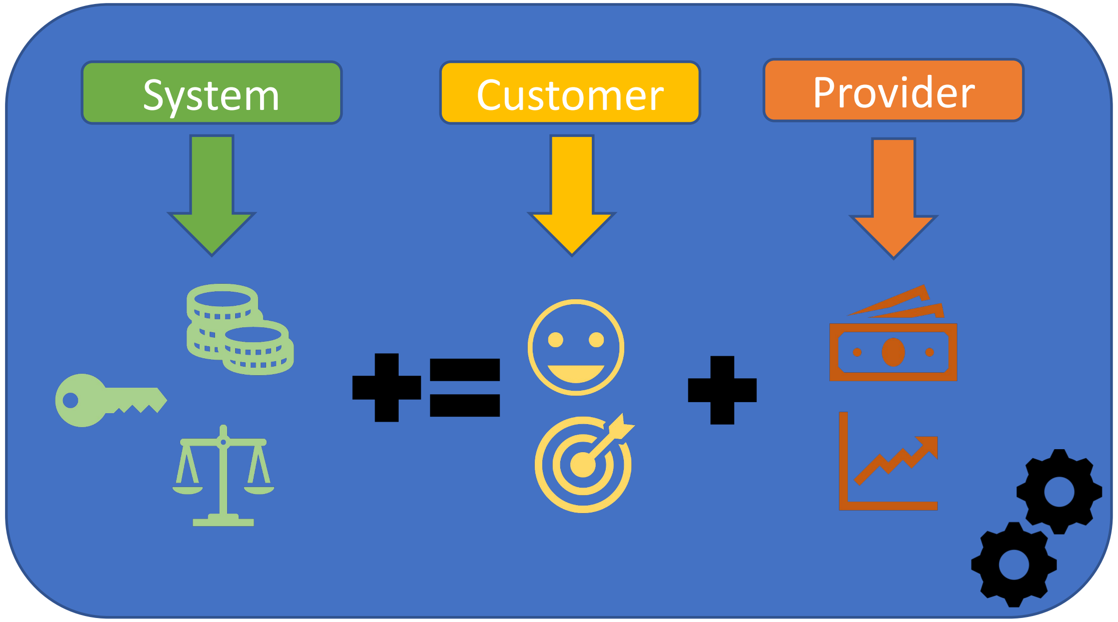
Recommender Systems

- Personalized access to information or items
- Typically involve the ranking of items by inferred preference
- A big part of online experience

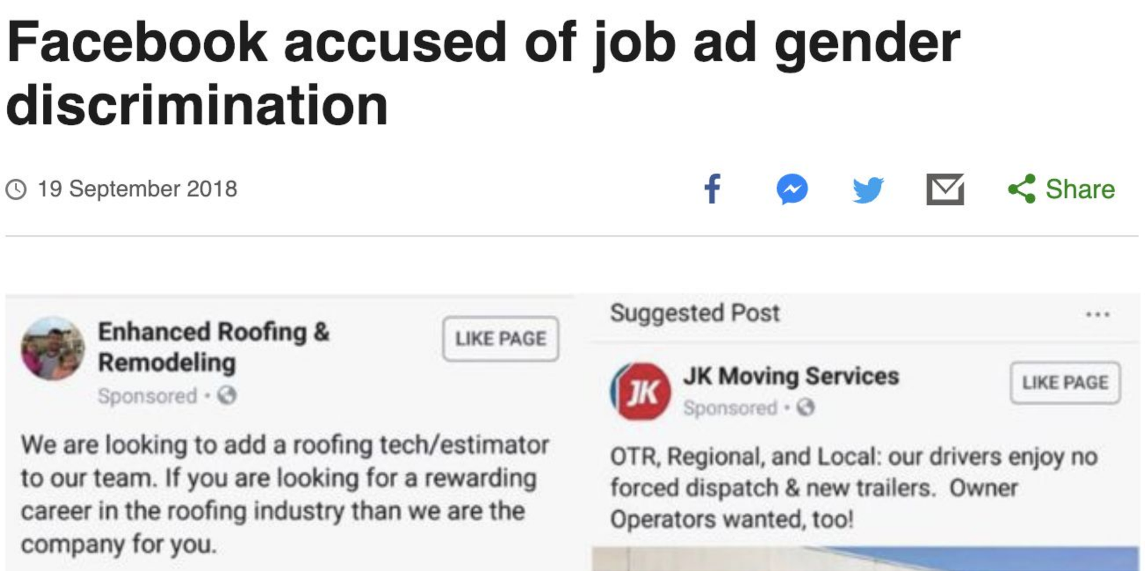
Multistakeholder Recommendation

- Recommendation in a multi-stakeholder environment
- Example:

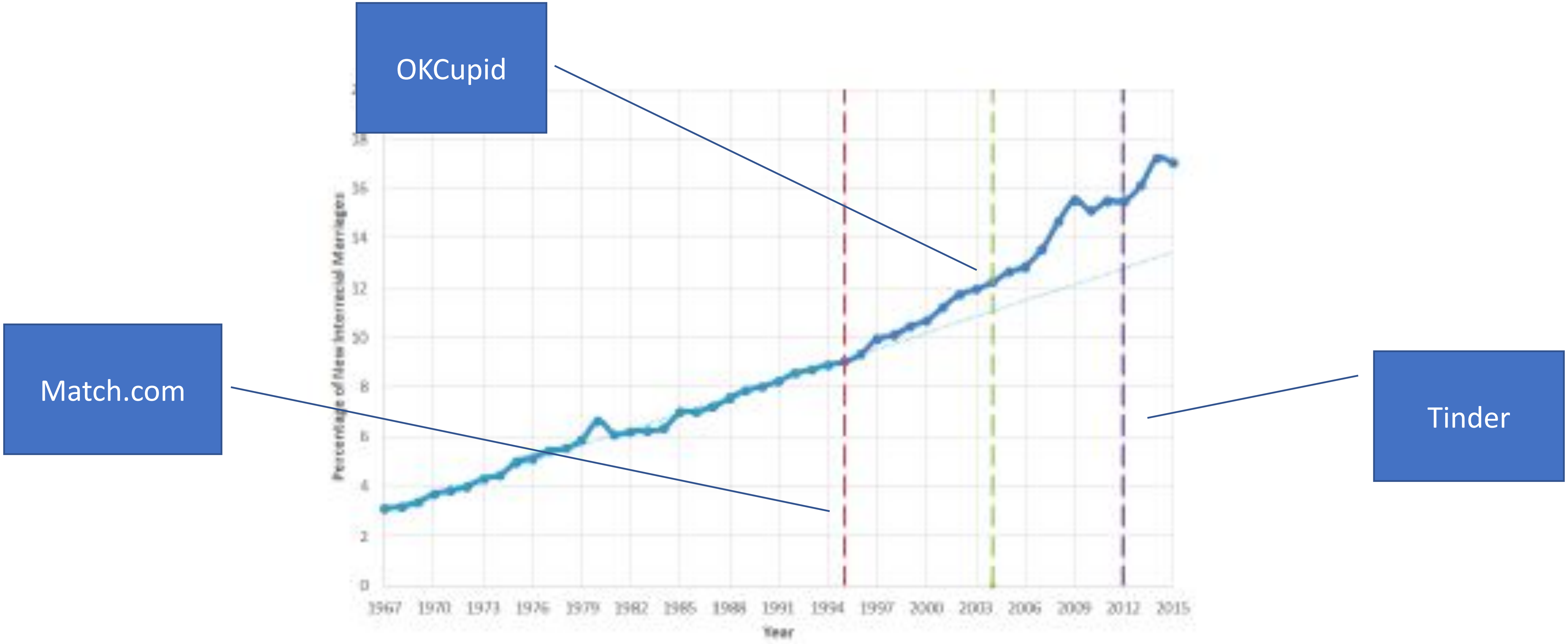


Fairness in recommendation

- What does it mean for recommendation to be fair?
  - ”Equals should be treated equally and unequals unequally.”
- Individuals have different preferences
  - should get different results
- But we have a sense that some kinds of recommendation outcomes can be unfair



Recommendation can enhance fairness!

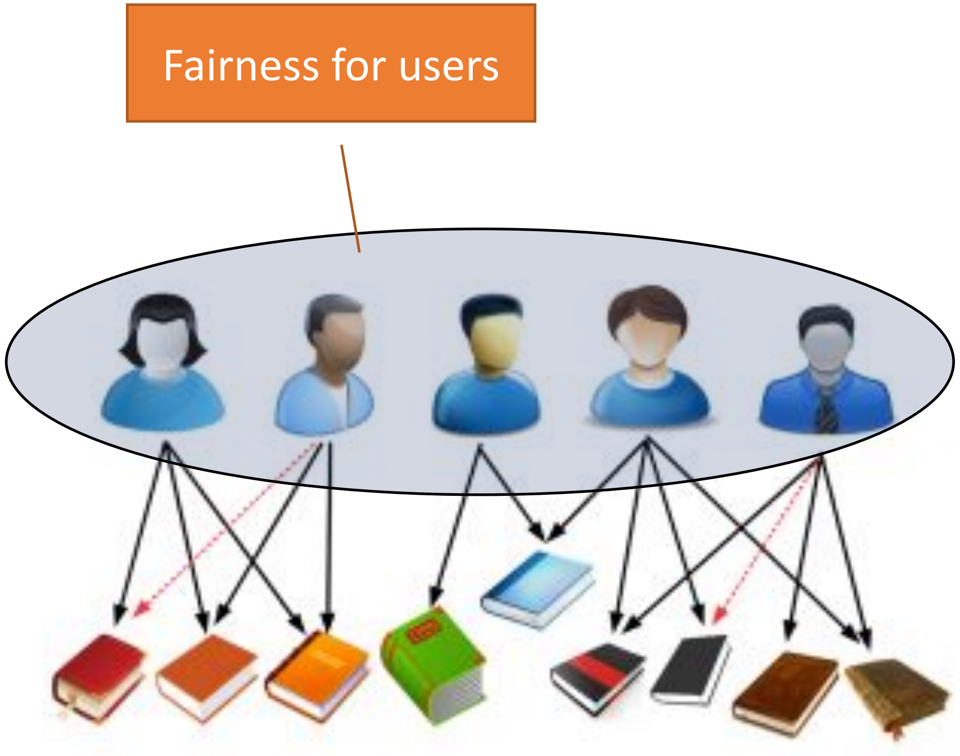


Ortega, Josué, and Philipp Hergovich. "The strength of absent ties: Social integration via online dating." *arXiv preprint arXiv:1709.10478* (2017).

Protected Class

- Protected attribute is Gender, religion, race, sexual orientation, etc.
- Goal:
  - Decisions should be independent of the protected attribute
  - Protected and unprotected cases treated the same if that’s the only difference

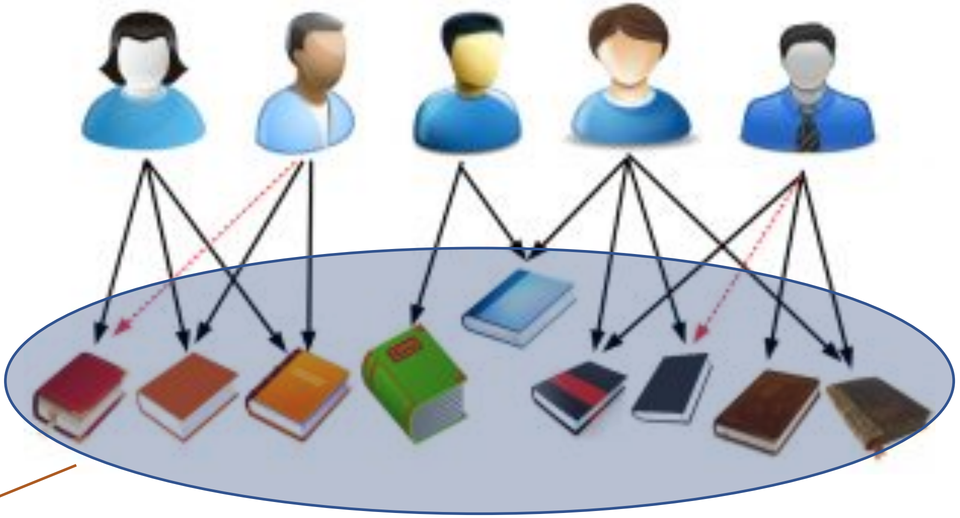
Consumer fairness case
C-fairness



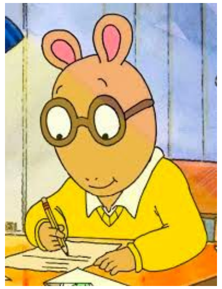
- Site may wish to be fair to the consumers of recommendations
  - Job seekers
- Example: male job seekers should not get better / different recommendations than female
  - Might be a legal requirement

Provider fairness case
P-fairness

- Fairness relative to items being recommended
- Kiva cares about being fair to borrowers
- Does each loan have a fair chance of being recommended?
- Items linked to people who may be in protected groups



Fairness across items



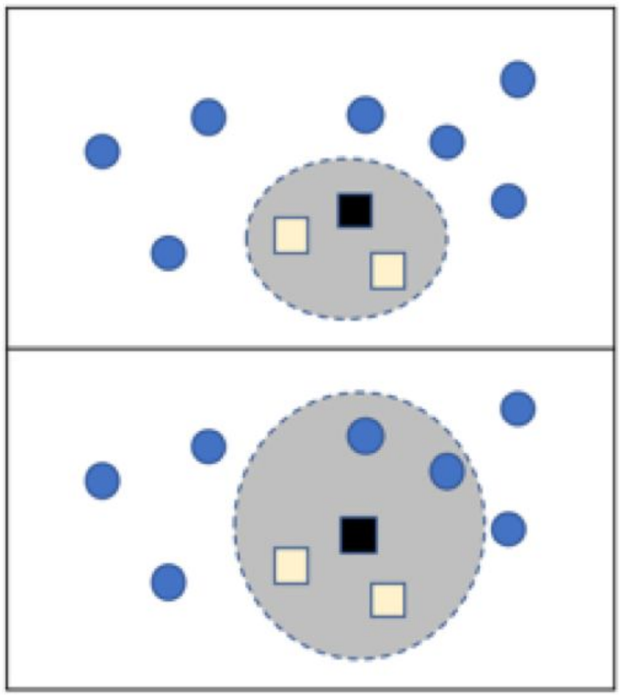
Because of creators / owners

CP-fairness (PC-fairness?)

- Might need to combine both concerns
- Fairness for consumers and providers at the same time
- Example
  - Job recommendation
  - Protected groups in the user community
    - Female job seekers
  - Protected groups among the providers
    - Minority-owned businesses

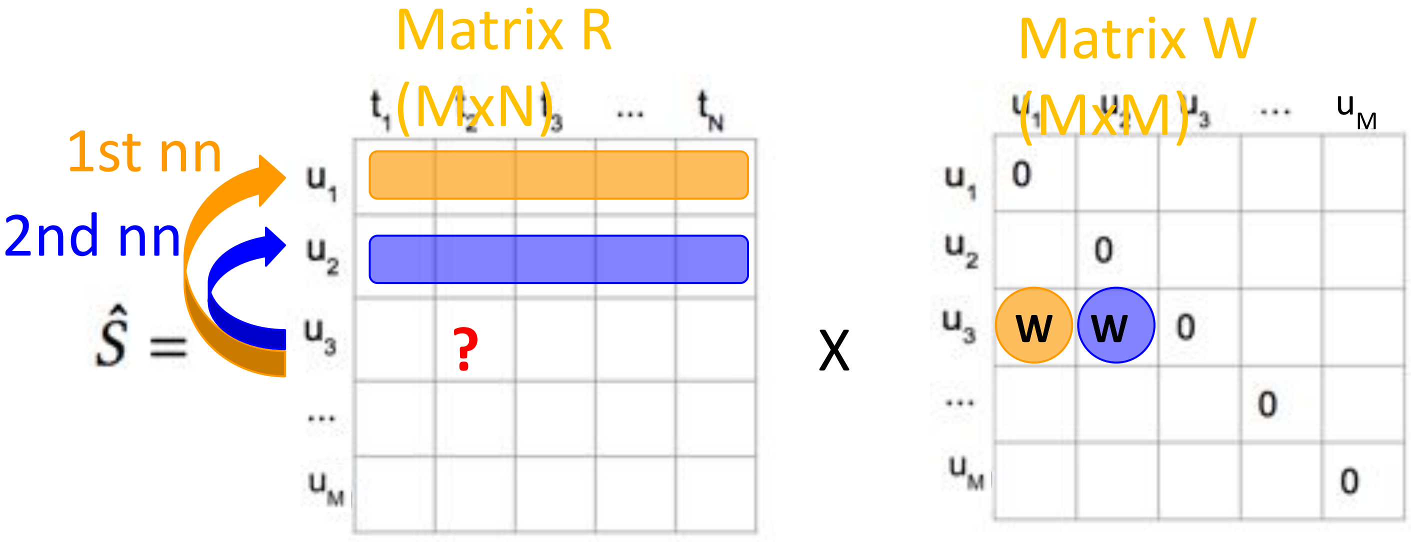
Balanced Neighborhood SLIM

- Old dataset
- User-based kNN
  - Recommendations generated by groups of similar users
- Result: Segregation
  - Protected group (square) is segregated
  - Recommendations come only from users in the same group
- Better: Balanced neighborhood
  - Generate recommendations from a group that has both protected and unprotected users



Unbalanced (top) and balanced (bottom) neighborhoods

User SLIM: Sparse Linear Methods



$$\hat{s}_{ij} = \sum_{k \in U} w_{ik} r_{kj} \qquad w_{ik} >= 0.$$

Minimization problem:

$$\min_W \frac{1}{2} \underbrace{\|R - WR\|^2}_{\text{Squared Error}} + \lambda_1 \underbrace{\|W\|^1}_{\substack{\text{L1 Norm} \\ \text{(Lasso Reg)}}} + \frac{\lambda_2}{2} \underbrace{\|W\|^2}_{\substack{\text{L2 Norm} \\ \text{(Ridge Reg)}}}$$

Neighborhood Balance

- neighborhood balance term for user i

$$b_i = (\sum_{w^+ in W_i^+} w^+ - \sum_{w^- in W_i^-} w^-)^2$$

- Another way to write

$$b_i = \left\| p^T w_i \right\|^2$$

- Where p is a vector of <+1, -1> representing protected and unprotected groups

U^+	Users in the protected class
U^-	Users in the non-protected class
W^+	The set of weights for U^+
W^-	The set of weights for U^-

BN-SLIM

- SLIM learning algorithm: coordinate descent
  - LibRec 2.0 implementation
- w_{ii}= 0, w_{ik} > 0, λ_3 = weight for the balance term, $S()_+$ is the soft threshold operator.

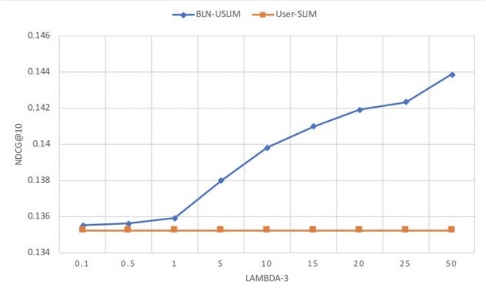
$$L = \frac{1}{2}\|R - WR\|^2 + \lambda_1 \|W\|^1 + \frac{\lambda_2}{2}\|W\|^2 + \frac{\lambda_3}{2}\sum_{i \in U}\left(\sum_{k \in U} p_i w_{ik}\right)^2,$$

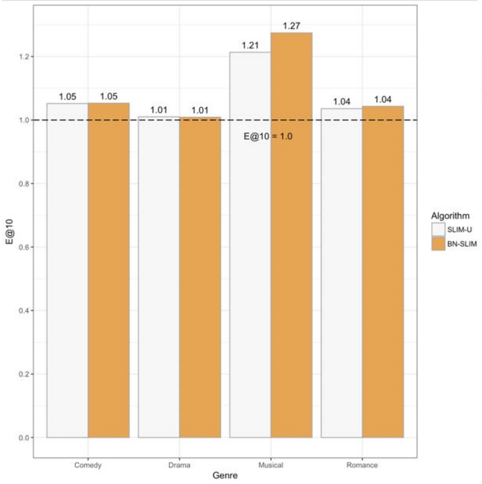
$$\frac{\partial L_i}{\partial w_{ik}} = \sum_{j \in I}(r_{ij} - \sum_{l \in U'} w_{il} r_{lj}) + w_{ik}\sum_{j \in I} r_{kj}^2 + \quad \lambda_1 + \lambda_2 w_{ik} + \lambda_3 p_k \sum_{l \in U'} p_l w_{il} \qquad U' = U - \{u_i, u_k\}$$

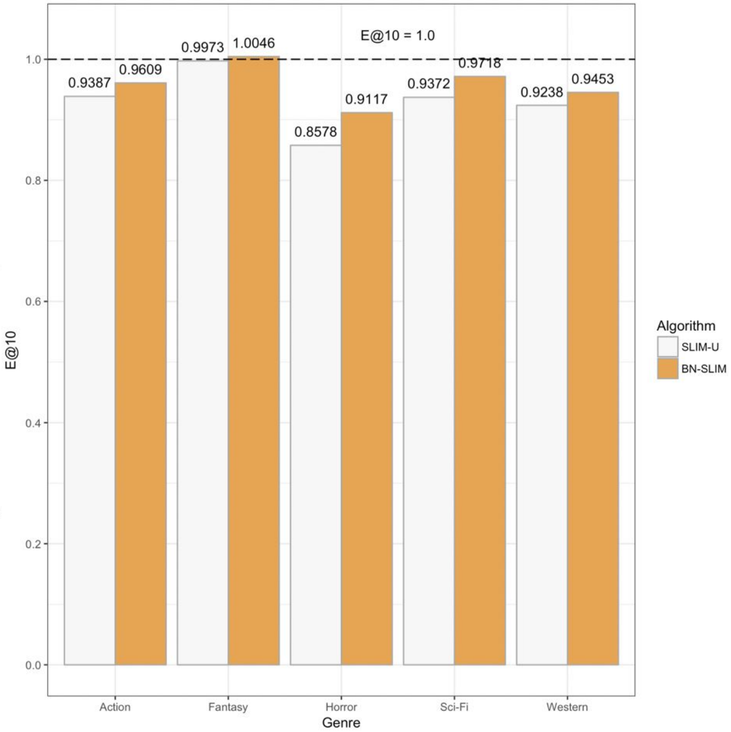
$$w_{ik} \leftarrow \frac{S\left(\sum_{j \in I}(r_{ij} - \sum_{l \in U'} w_{il} r_{lj}) + \lambda_3 p_k \sum_{l \in U'} p_l w_{il}, \lambda_1\right)_+}{\sum_{j \in I} r_{kj}^2 + \lambda_2 + \lambda_3}$$

Results

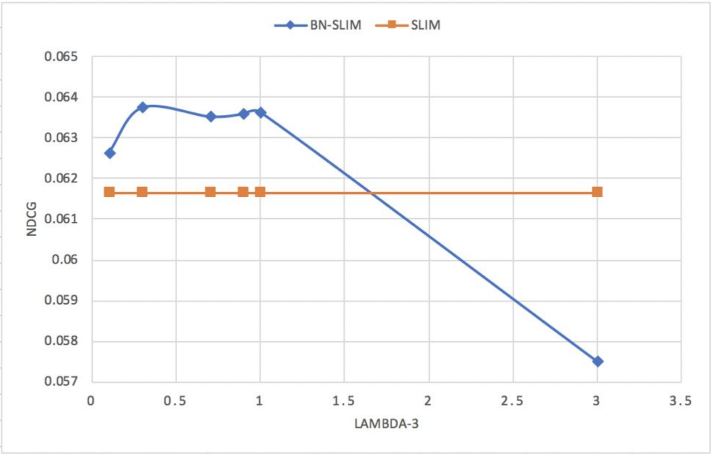
MovieLens 1M

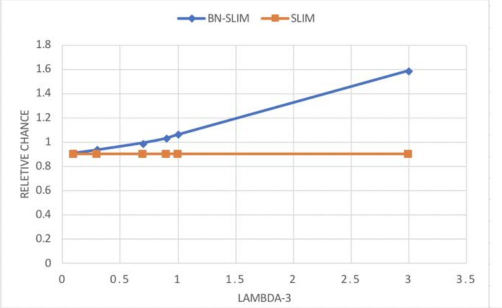


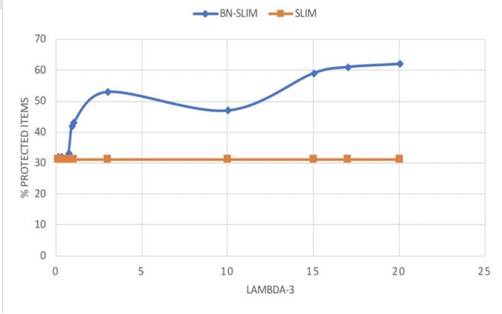




Kiva







Personalized Fairness

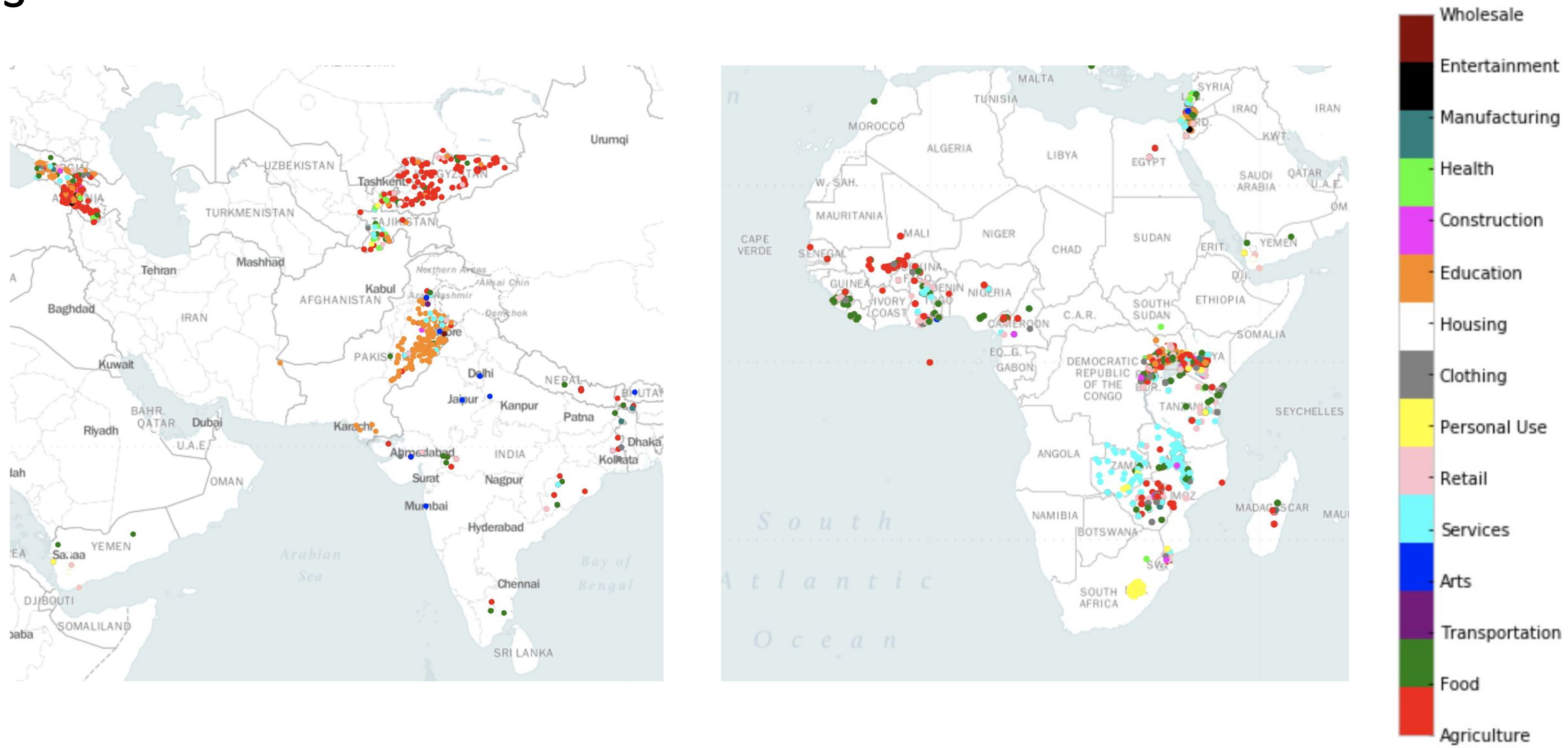
- FATREC 2019

Data Analysis

- Sparsity Issue
- Pseudo item creation

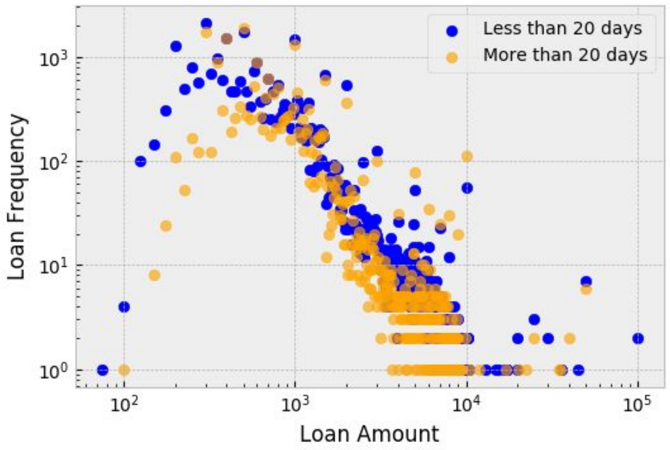
Localized Fairness

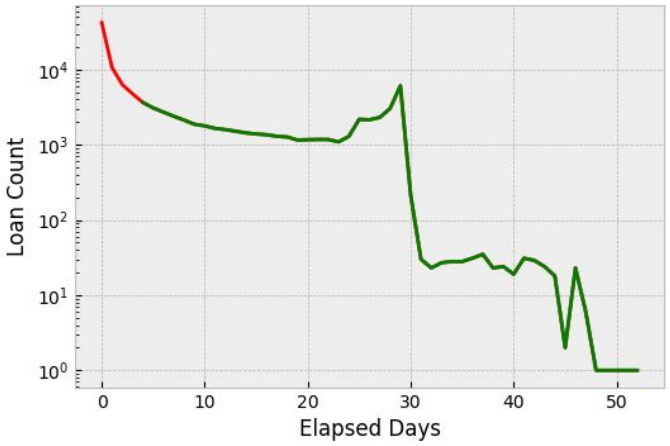
- A global measure of fairness might hide local conditions with different fairness issues



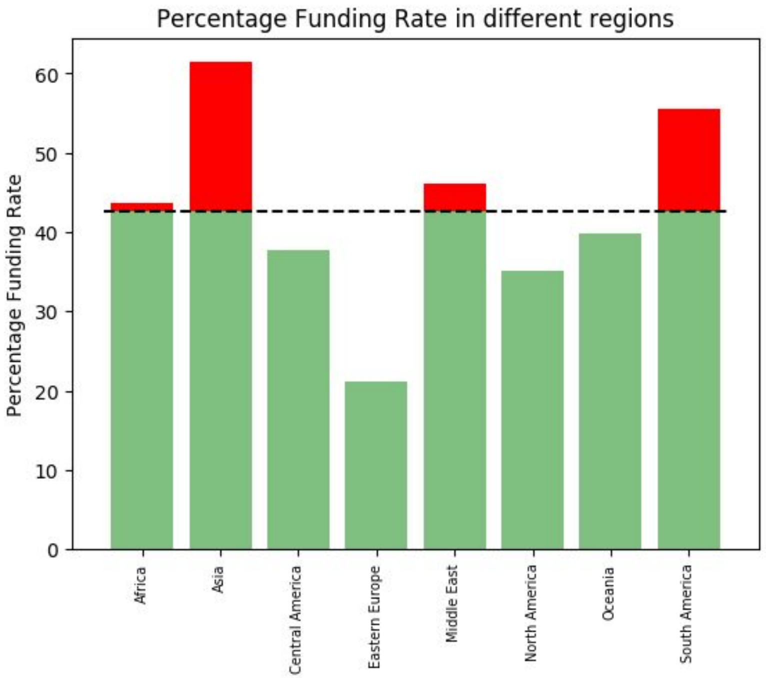
Defining the protected class in Kiva

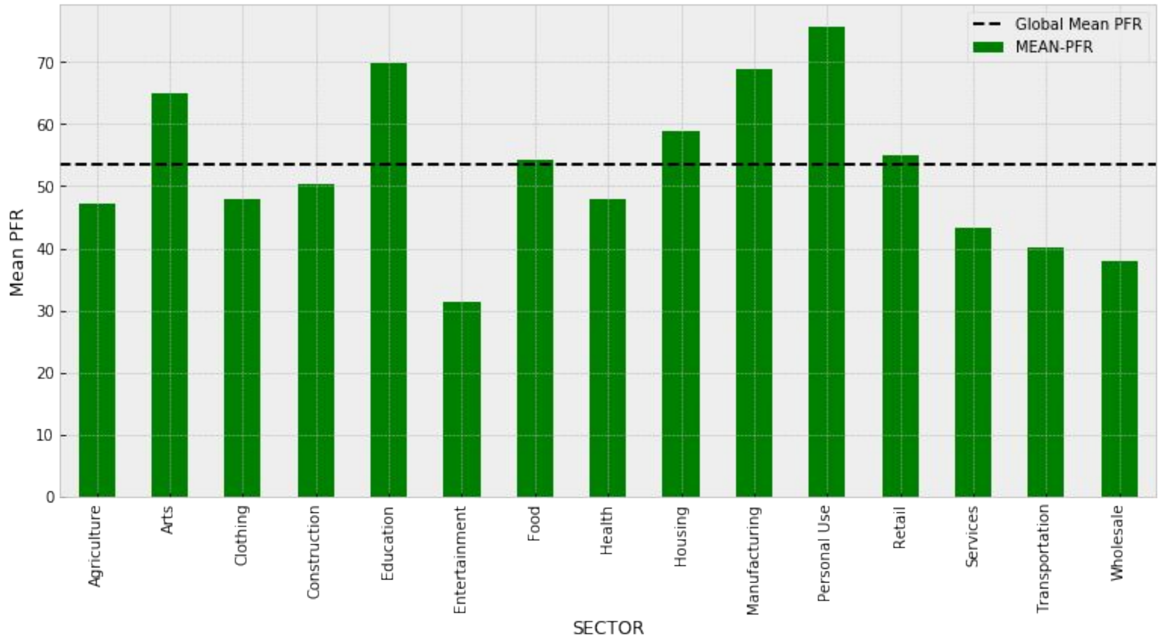
- Percentage Funding Rate
  - PFR = 1 / #days
- Kiva
  - Loans that are funded after 3 days need are the protected group.
  - They need promotion.

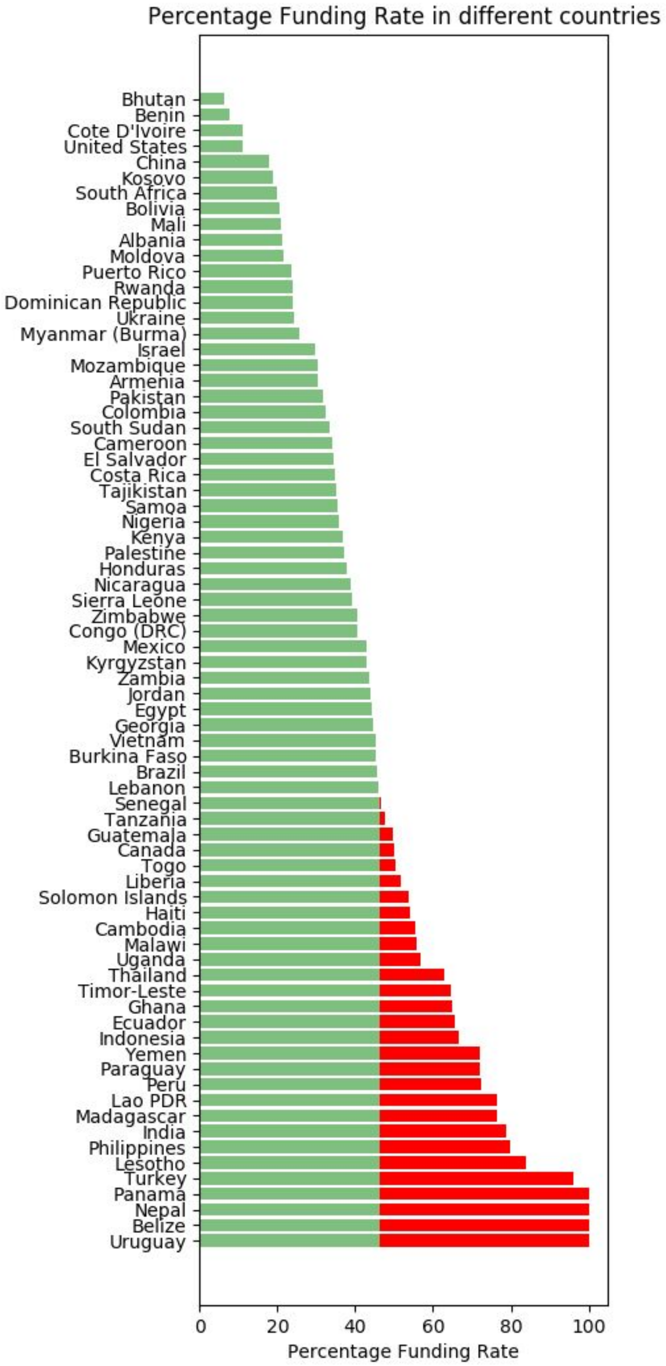




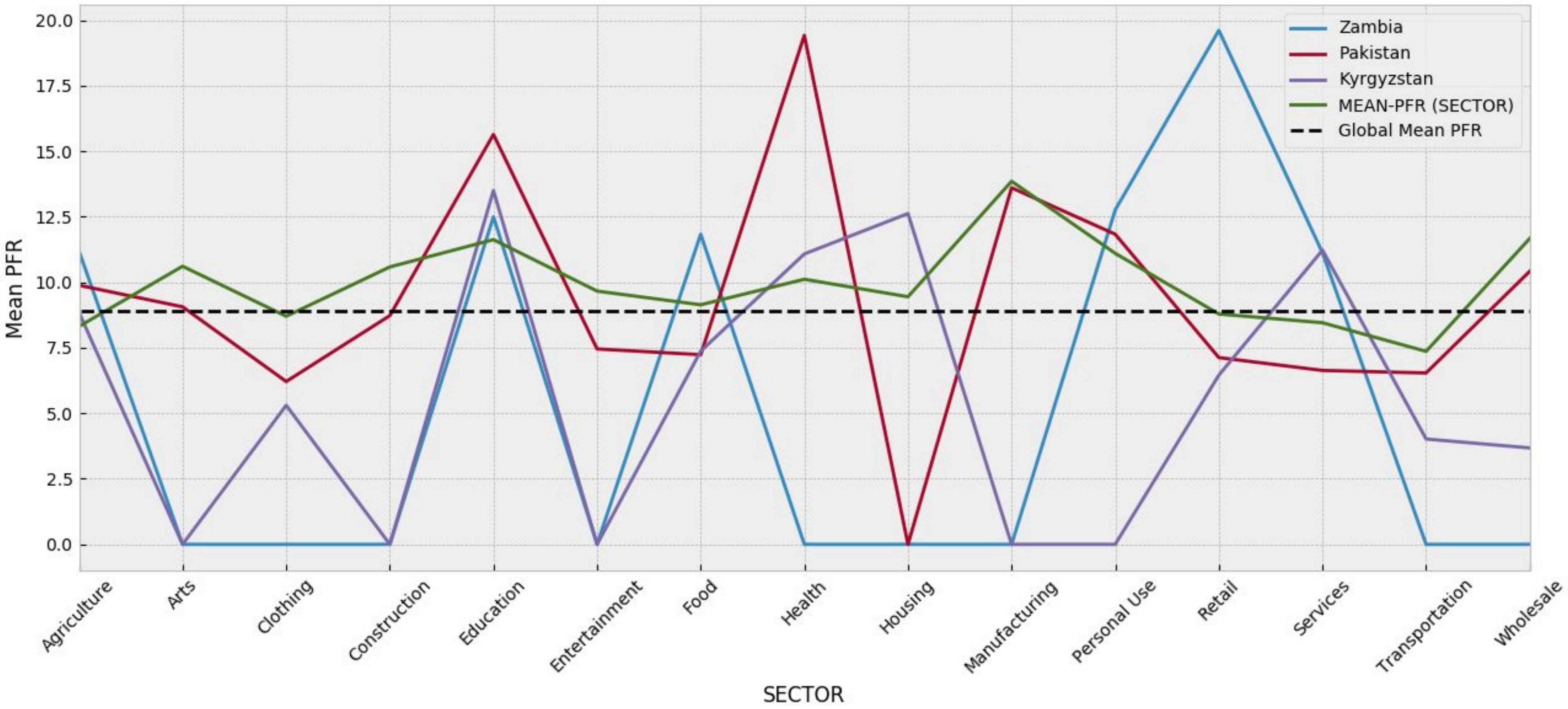
Localized Fairness



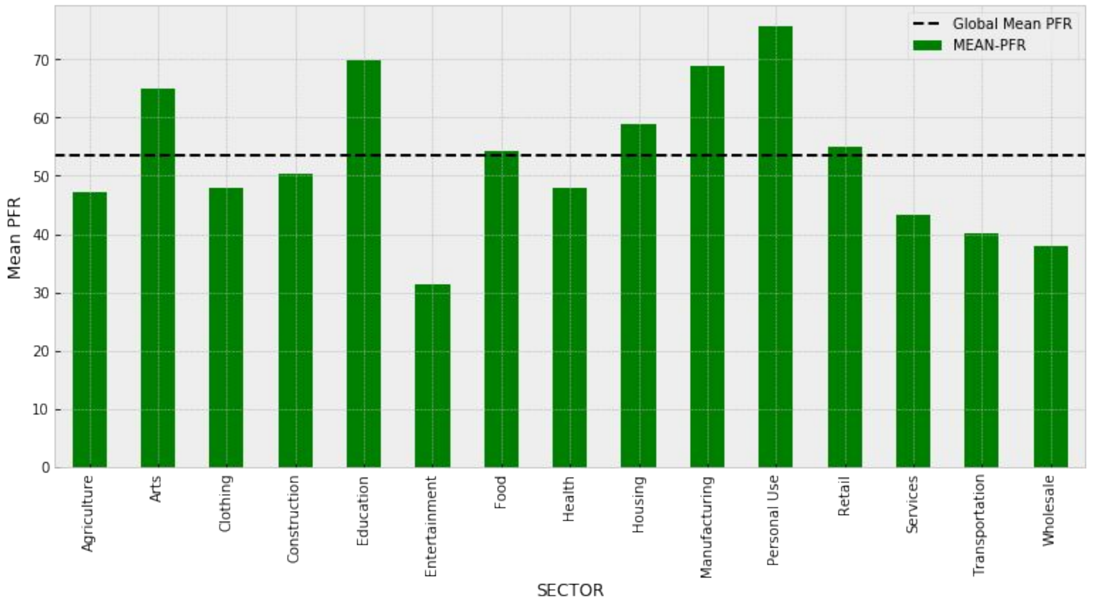




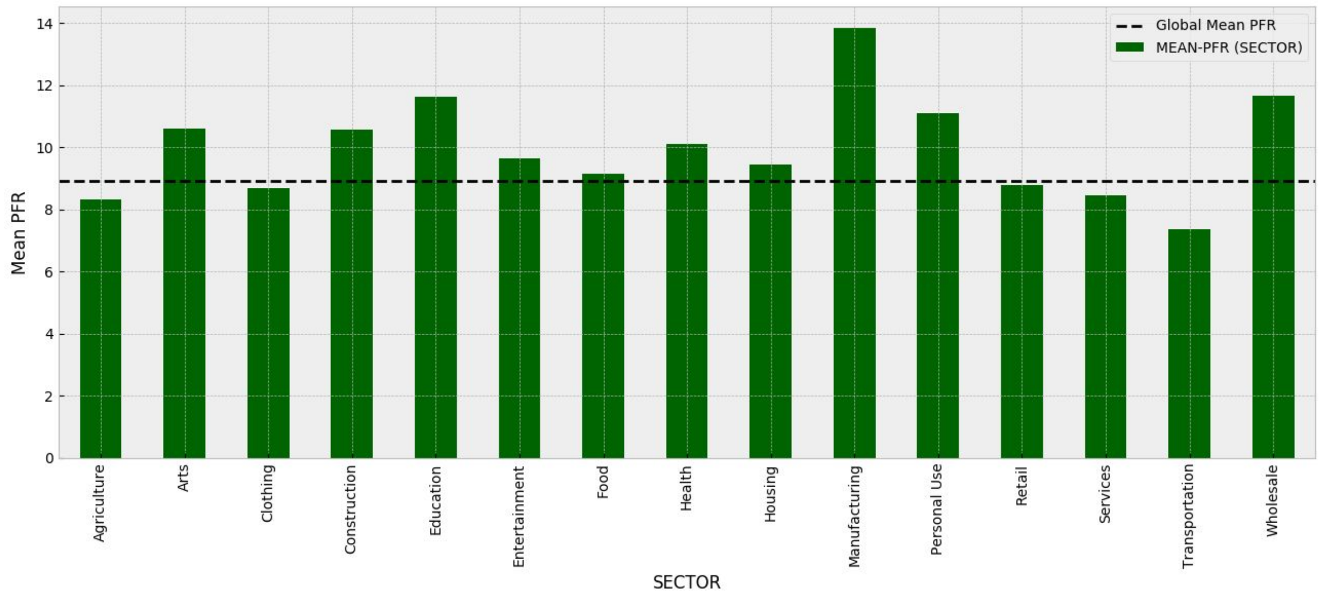
Locality of fairness – differences between countries



Influence of Philippines PFR - Popularity Bias



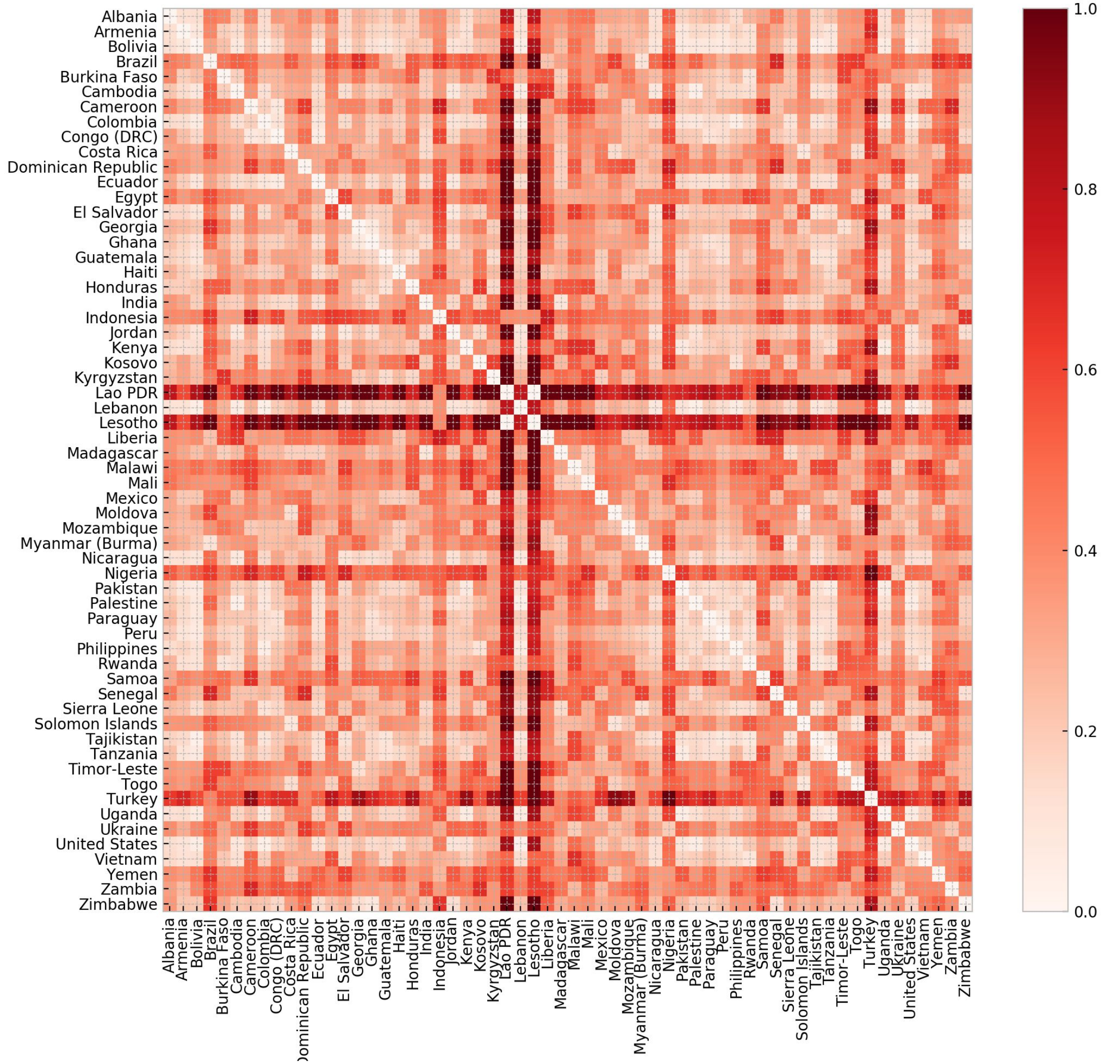
Sector Distribution in High demand dataset

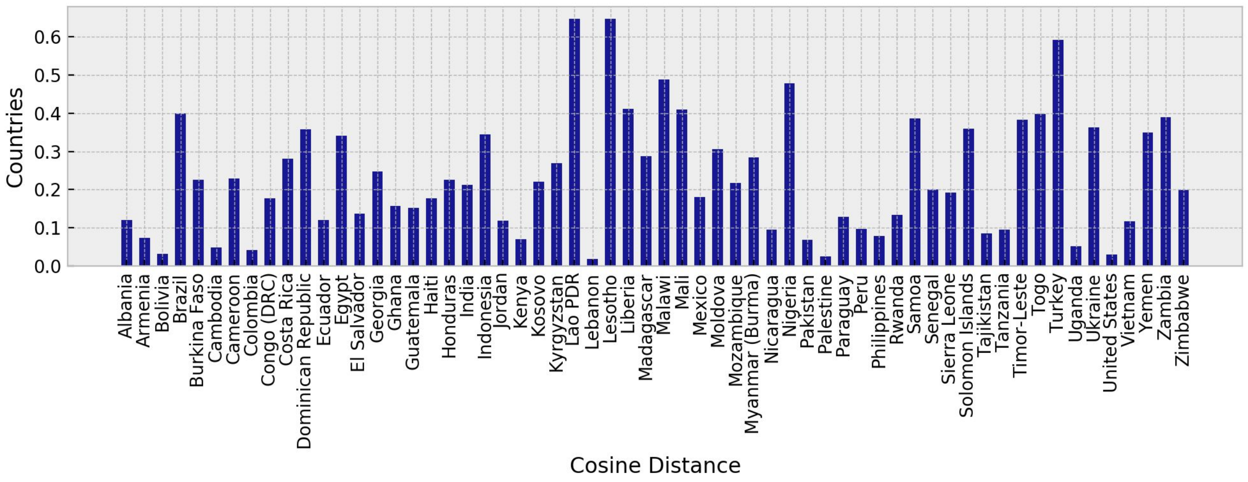


Sector Distribution Low-demand dataset

Pairwise cosine distance between countries

Each country is a PFR vector over sectors





Cosine distance between PFR of each country and mean FPR

Future Plans

- User Studies
- Applying localized fairness to recommendation algorithms
  - BN – Factorization
  - Factorization Machines
- Rich Subgroup Fairness

Questions

- What is
  - Kiva’s Current heuristics for organizing loans?
  - Some countries have a lot of loan requests and are funded faster such as Philippines. Why is that?
  - Kiva’s view of fairness?
  - Current state of the recommendation project?
  - Your opinion on our method of achieving fairness
    - Balanced neighborhoods
    - Promoting loans that have lower funding rates

Asks (Draft)

- Sparsity issue
  - A dataset containing clicks/views
- Closer relationship
    - Consulting on current rec. Algorithms
    - A/B testing
    - Access to user base for studies
    - Funding opportunities