ORIE 5355: People, Data, & Systems

Lecture 7: Recommendations – from predictions to decisions Part 2

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Course webpage: https://orie5355.github.io/Fall_2021/

Re-numbering lectures

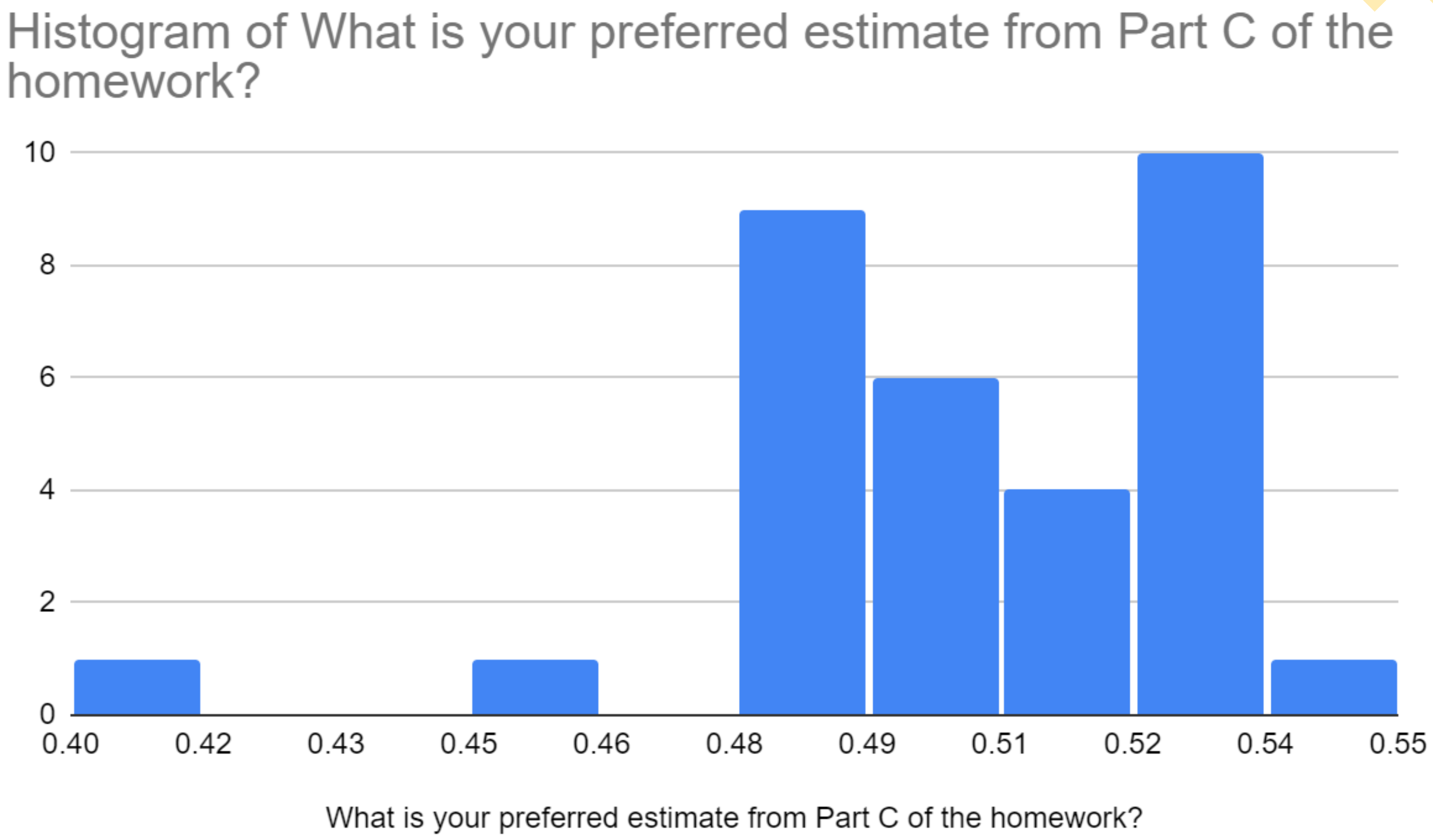
Announcements

- Guest lecture Neal Parikh on Monday 10/04
  - Regular class-time
  - **In person only**
- Additional office hours (me): Fridays before homeworks are due
  - Friday 10/1
  - 1:30 – 2:30 pm
  - Zoom only, available on canvas
- Homework 2 due *Tuesday* 10/5
- Quiz 2 next week as well

HW1 final estimates histogram

A lot of pollster discretion!

Even though we all had the same data, learned the same methods in class, and walked through the same analyses, a large range of estimates!



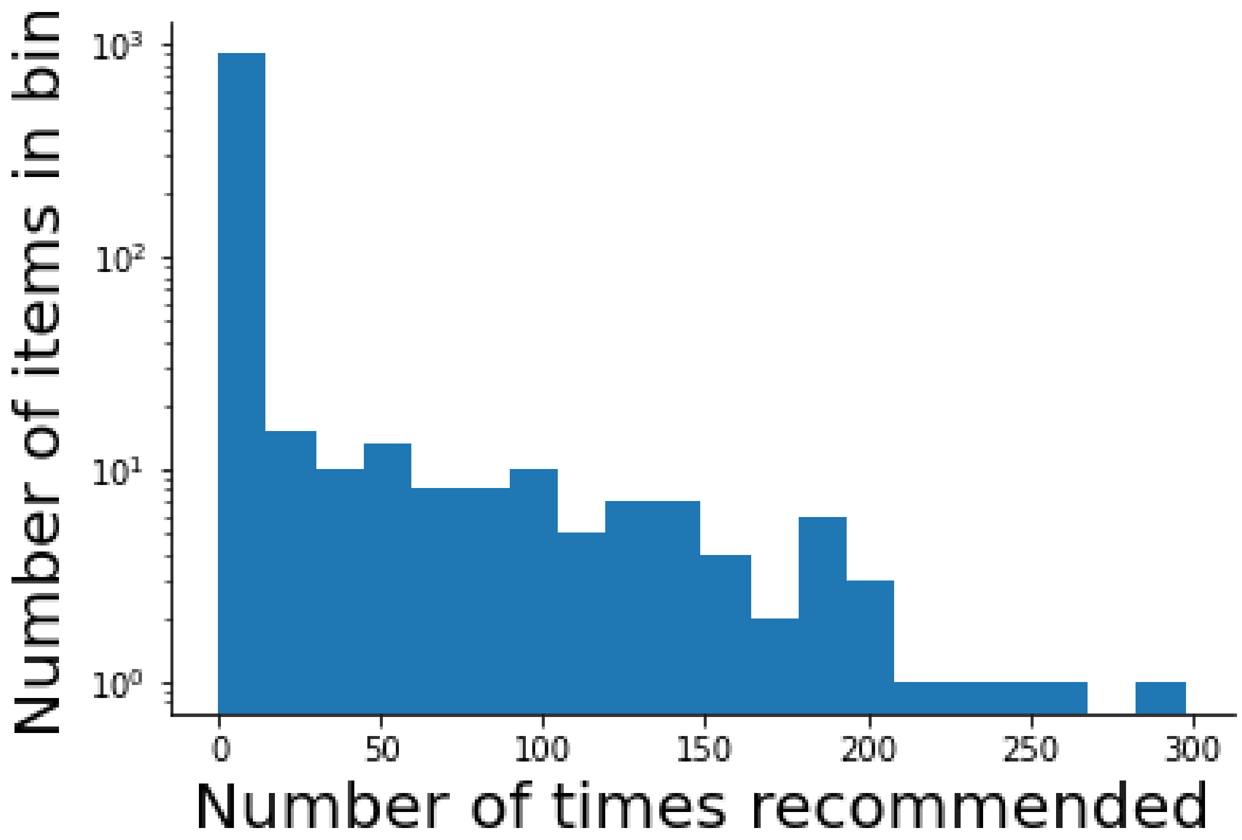
Dealing with capacity constraints

Overview

- What’s the challenge, exactly?
- Solving an “easier” problem: “maximum weight matching in a bipartite graph”
- Insights from the easier problem to real-life applications

An example

- In the homework, we ask you to first recommend using the “naïve” method of just recommending best prediction for each user
- You’ll observe a plot like the following



The challenge

- In many (non-online-media) settings, you are recommending “items” with capacity constraints:
  - You have a finite number of each item in your warehouse
  - An AirBnb can only be booked by one customer at a time
  - Workers can’t work for every client; a client can only hire 1 person
  - People on dating apps – can’t talk to everyone
- If you ignore these capacity constraints, then everyone may be recommended the same (limited) item

  Some people will be left out
- (How) should you factor in capacity in your recommendations?

The challenge, formally (simple version)

- You have N users and M items, but only 1 copy of each item
- You want to recommend 1 item $\mathrm{j(i)}$ to each user
- Each user i will consume the that you recommend them
- You want to maximize the sum of predicted ratings of consumed items

$$\sum_i \mathrm{r}_{ij(i)}$$

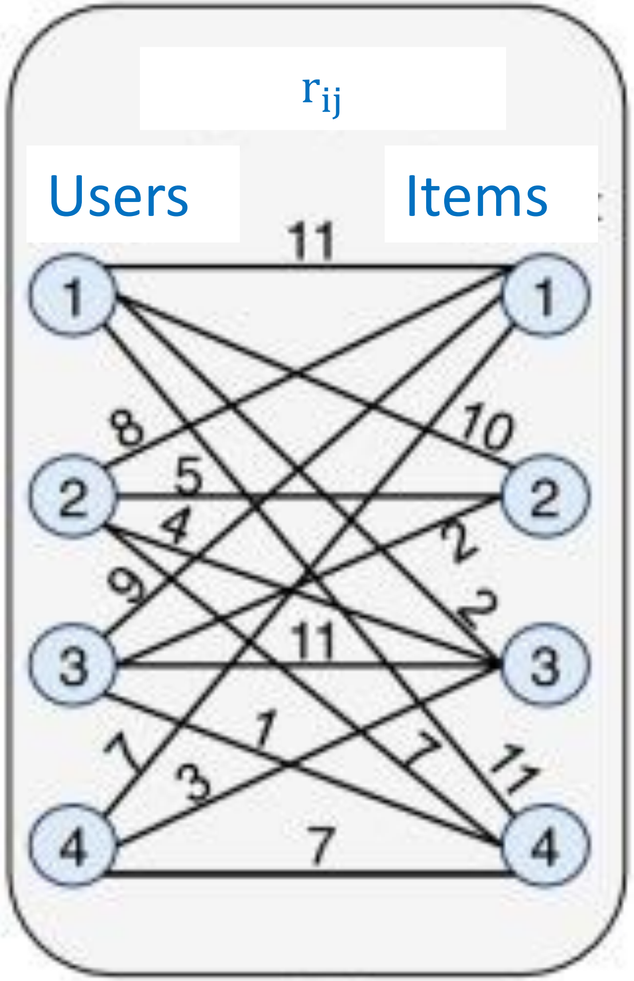
- However, each item can only be recommended once

$$j(i) \neq j(i') \text{ unless } i = i'$$

Solving the simple case

It turns out that this simple case is called “maximum weight matching”

Draw a graph with users on one side and items on the other



[OSA | Simulation and FPGA-Based Implementation of Iterative Parallel Schedulers for Optical Interconnection Networks (osapublishing.org)]

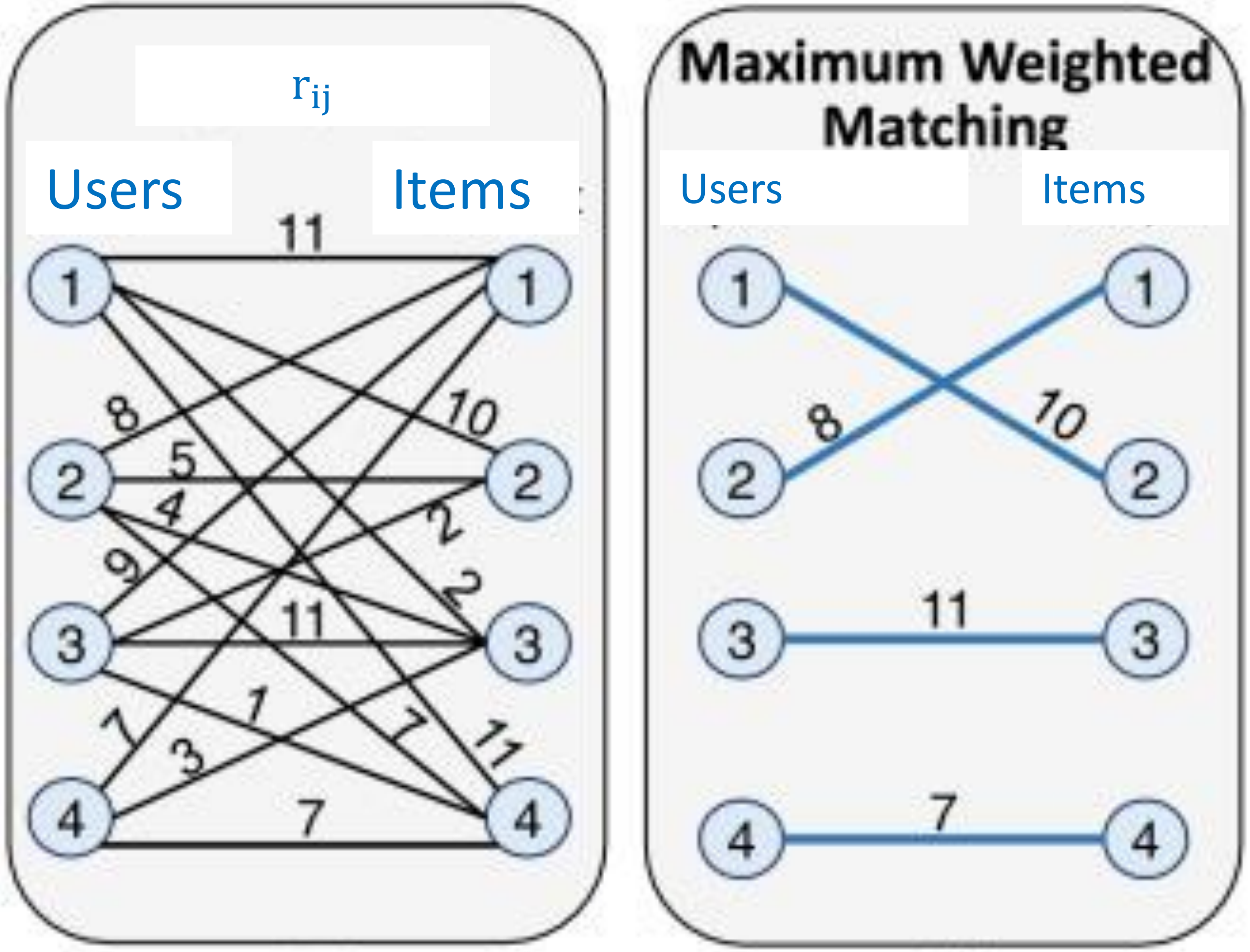
Solving the simple case

It turns out that this simple case is called "maximum weight matching"

Draw a graph with users on one side and items on the other

Find the "matching" that maximizes sum of edge weights

[scipy.optimize.linear_sum_assignment — SciPy v1.7.1 Manual]

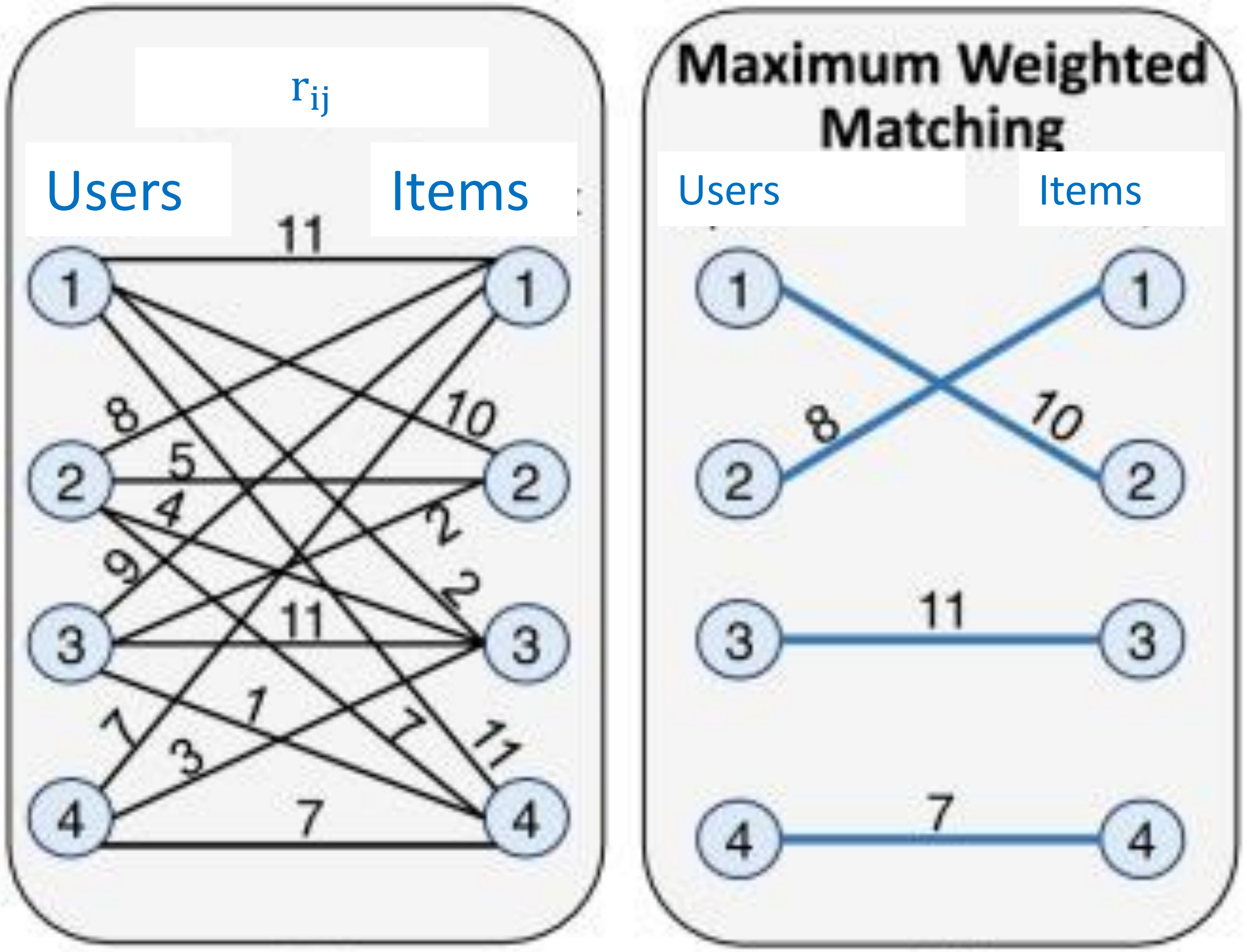


[OSA | Simulation and FPGA-Based Implementation of Iterative Parallel Schedulers for Optical Interconnection Networks (osapublishing.org)]

Insights from the simple case

In general, the actual solution might be combinatorial – a complex function of all the joint preferences

- Some *users* are not matched with their most preferred item!
- Some *items* are not matched with the user that likes it the most!
- If a user likes multiple items similarly, maybe they get their 2nd choice
- If only 1 user likes some item, make sure that item and user are matched



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Challenges in using max weight matchings

- Everyone doesn't show up at once

  New users come in tomorrow – have to leave items for them
- You can't "match" people, only recommend them items

  Someone may not consume the item!
- "Capacity" constraints are also soft
  - New items are shipped to warehouse all the time
  - Maybe you can spend more money to expedite shipment
- Computational constraints in rerunning large scale max weight matchings with every new user

What to do in practice

- Finding an “great” solution requires a lot of careful data science + modeling work
- Some reasonable heuristics:

  “Batching”: If you don’t have to give recommendations immediately, wait for some number of users to show up and solve max weight matching (for example, every hour)

  “Index” policies: For each user, create a “score” for each item and just choose recommend the item(s) with the highest score(s)

Index policies

- We want a score (index) between each item j and user i: $\mathrm{s_{ij}}$
- Then, for each item, pick the item with the max score: $\mathrm{argmax}_j\ \mathrm{s_{ij}}$
- We've already seen an example: if the only thing that matters is predicted rating, then $\mathrm{s_{ij}} = \mathrm{r_{ij}}$
- Why index policies?
  - They're efficient: for each user, only need to consider their scores
  - They can be *explained* to users
  - All information about other users is contained in how score is constructed

Constructing index policies

What matters in constructing an index policy?

- The higher the ratings by other users for an item, the smaller $\mathrm{s_{ij}}$ should be
- The less capacity C_j left for the item, the smaller $\mathrm{s_{ij}}$ should be

An *example* score function

$$\mathrm{s_{ij}} = \alpha_j \left[\frac{r_{ij}}{\overline{r_j}}\right] C_j^{\beta}$$

where α_j, β are some (learned) parameters over time

α_j: Item is "special" and should be over-recommended

β : Relative importance of capacity. ($\beta = 0$ means ignore capacity)

Many possible score functions! Should be application specific

Capacity constraints lessons

- If you just recommend each user their highest predicted scores, then you might not be *globally* efficient
- Even if you can’t implement it, taking intuition from the “optimal” solution is often valuable
- Index policies: even if “optimal” solution requires combinatorial constraints, “practical” solution can decompose the problem

Multi-sided preferences

Multi-sided preferences

- In many modern online markets, both sides have preferences
  - Freelancing markets (workers matched with clients), dating apps, volunteer platforms, etc
- A match only happens if *both* sides like each other
  - And have capacity…

The challenge, formally (simple version)

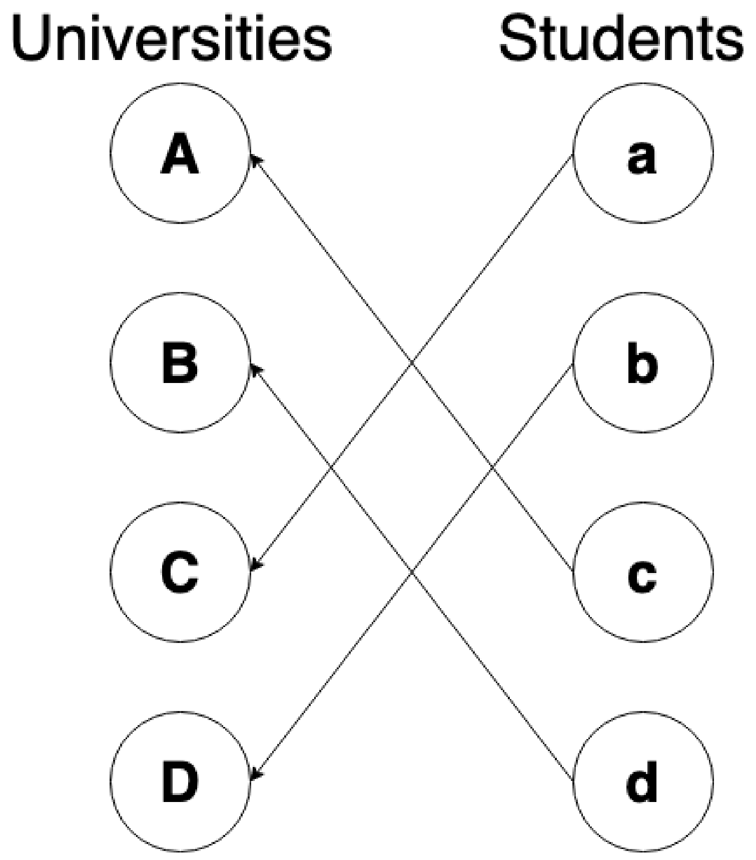
- You have N workers and N clients
  - Each worker can only work with 1 client; each client only hires 1 worker
- Each side has preferences (predicted ratings) over the other side
- You want to create “good” matches
  - Good for who? Workers? Clients? Some combination?
- Easier goal: create “stable” matches

“Stable matching” in 1 slide

- Stable matching:
  - Given rank order preferences from each person on each side
  - Match the sides such that matches are “stable”: No potential pair wants to abandon their current partners for each other.
- Efficient to find: “Gale-Shapley algorithm”
- Used to allocate:

  Medical students to residencies

  Students in NYC to high schools



Challenges in using stable matching

Same as from using maximum weight matchings

- Everyone doesn’t show up at once

  New users come in tomorrow – have to leave items for them
- You can’t “match” people, only recommend them items

  Someone may not consume the item!
- “Capacity” constraints are also soft
  - New items are shipped to warehouse all the time
  - Maybe you can spend more money to expedite shipment
- Computational constraints in rerunning large scale stable matchings with every new user

Just more complicated with both sides now having preferences

Intuition from stable matching to recommendations

What matters in constructing an index policy?

- The higher the ratings by other workers/clients, the smaller $\mathrm{s_{ij}}$ should be
- If either worker i or client j has been recommended to many other people in the past, the smaller $\mathrm{s_{ij}}$ should be
  - Equivalent of “capacity”
- Now, *both* i’s rating for j and j’s rating for i matter
- From stable matching: *both* i and j matter – one-sided high score can’t “make up” for the other side being a low score

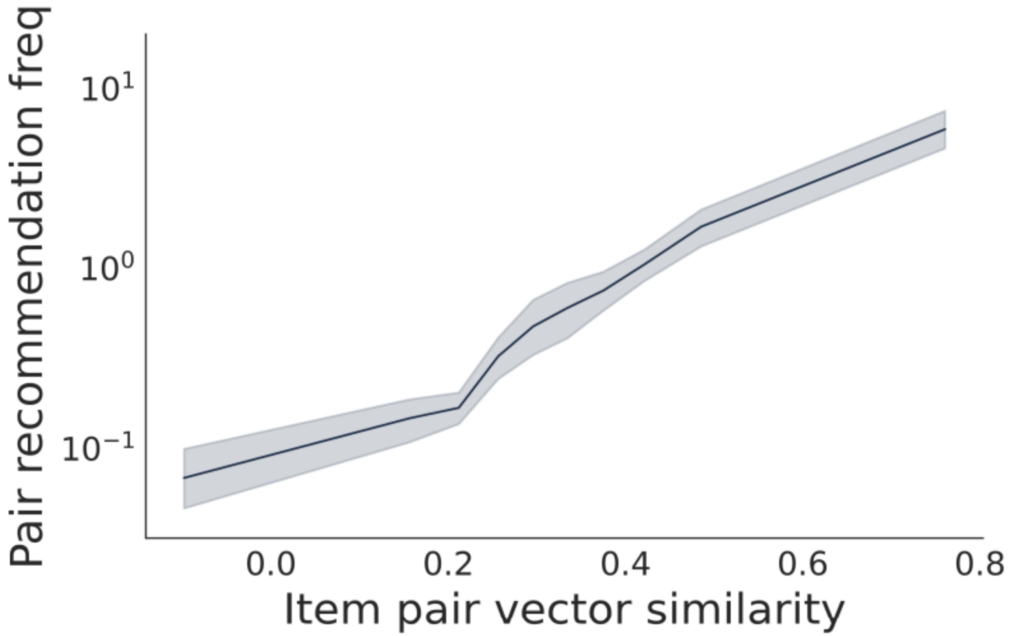
An *example* score function

$$\mathrm{s_{ij}} = \min\left(\frac{\alpha_j r_{ij} C_j^{\beta}}{\overline{r_j}}, \frac{\alpha_i r_{ji} C_i^{\beta}}{\overline{r_i}}\right)$$

Diversity in recommendations

Diversity of recommendations

- If you do the naïve method and recommend multiple items to each user, then you're not going to recommend a *diverse set* of items
- Why? If you have a single user vector $\mathrm{u_i}$, then if two items j and k both have large dot products $\mathrm{u_i} \cdot v_j$ and $\mathrm{u_i} \cdot v_k$, then they are likely to be similar, $v_j \approx v_k$

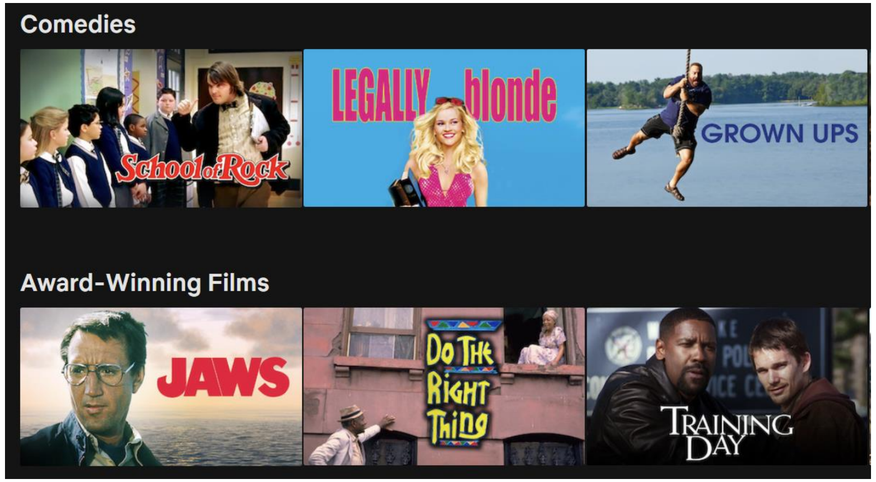


With the MovieLens dataset and recommending 2 items to each user. The more similar 2 items are, the more likely they are to be recommended together compared to their "marginal" distributions

Improving diversity of recommendations

Many possible approaches

- Create a “short list” of items based on just the prediction (“relevance”), and then select a diverse set from the short list
- Pre-select topics and then most relevant within each topic
- Start from most relevant item, filter other items that are too similar to items already recommended



Summary of recommendations

There are 3 steps to building a recommendation system:

- Choose the *data* that you will use
  - What does the data imply about people's opinions and future desires?
- Train a model to *predict* ratings between pairs of items and users
  - Different approaches (item- and user similarity, matrix factorization)
  - Can also combine approaches
- *Recommend* items based on predictions and other concerns
  - Capacity constraints, diversity, fairness considerations, long-term objectives

Questions?