# ORIE 5355: People, Data, & Systems

## Lecture 6: Intro to Recommendations Systems

Nikhil Garg

# Announcements

- Quiz 2 released yesterday, due Friday evening (via Canvas)
- HW 2 posted

# Recommendation systems

# Module overview

## Part 1 (today) – Prediction

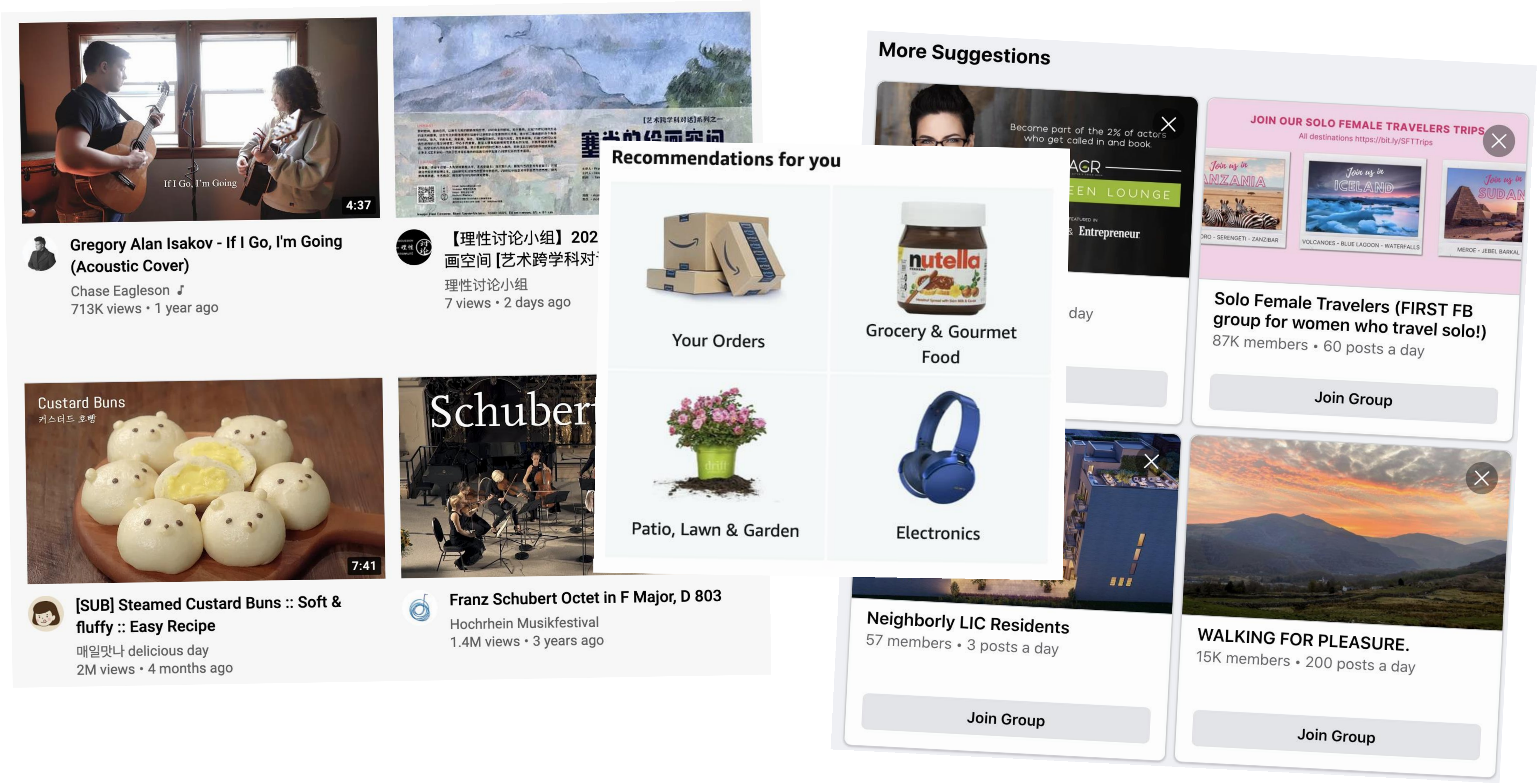
How much will a given user like an item?

- Problem formulation and some algorithms
- Data challenges

## Part 2 (next) – From predictions to decisions

How to use the predictions to recommend items in practice?

- Capacity constraints
- Recommendations in *2 sided* markets
- Feedback loops in recommendations




Slide credit: Amy Zhang, Cornell

# Types of Recommendations

**Editorial and hand curated**

- List of favorites
- Lists of “essential” items

**Simple aggregates**

Top 10, Most Popular, Recent Uploads

**Tailored to individual users (Personalized recommendations)**

Amazon, Netflix, …

# Personalized recommendations

- Motivation: filter the content to be more relevant for each individual
- Data Inferred from signals
    - Direct: ratings, feedbacks, etc
    - Indirect: purchase history, access patterns, etc
- Intermediate Goal: *predict* the relevance of each item for each user

# Formal Model

- $X$ = set of **Users**
- $S$ = set of **Items**

**Utility function** $u$: $X \times S \rightarrow R$

$R$ = Ratings that a user *would* give to an item if watched

$R$ is a totally ordered set

e.g., **0-5** stars, real number in **[0,1]**

# Ratings Matrix: suppose we have data $\hat{R}$

| | Avatar | LOTR | Matrix | Pirates |
|---|---|---|---|---|
| Alice | 1 | | 0.2 | |
| Bob | | 0.5 | | 0.3 |
| Carol | 0.2 | | 1 | |
| David | | | | 0.4 |

In reality, the vast majority of entries are missing

Goal: fill in the missing entries!

Metric: mean squared error

# Two Steps

Step 1: create a data matrix $\hat{R}$ from signals you have

Step 2:  fill in the missing entries using some prediction model

# Step 1: Using explicit data

Just ask people what they think

Challenges: all the opinion collection challenges already talked about!

- Answering rates
- Measurement error: does a scale reflect how much they like something?
- Are people consistent over time?

# Step 1: Implicit data

- You have many implicit signals about people’s opinions
  - Do they finish watching the show, or start watching the next episode?
  - Do they keep coming back and buying other things
  - Did they browse other items instead of putting something in their cart?
  - Do they re-hire the same freelancer/work with the same client again?
- These give *different* information than do explicit ratings
  - From a different population of users
  - Often more numerous, but harder to analyze
  - “revealed preference” – might be more predictive of future behavior
- Using such data
  - Train models to predict different future behavior, using various signals
  - Might take away “user agency” – what if they want to change their behavior?

# Step 2: Filling in the missing entries

| | Avatar | LOTR | Matrix | Pirates |
|---|---|---|---|---|
| **Alice** | 1 | | 0.2 | |
| **Bob** | | 0.5 | | 0.3 |
| **Carol** | 0.2 | | 1 | |
| **David** | | | | 0.4 |

# Possible strategies

- Content-based recommendations:
  Use existing data on items to group together similar items
- User-similarity-based recommendations
  Find similar users and use data from each other (e.g., demographics)
- Matrix factorization
  Automated way of finding the “dimensions” that matter

# Content-based Recommendations

- **Main idea:** Recommend items to customer ***x*** similar to previous items rated highly by ***x***

***Example:***

- **Movie recommendations**
  - Recommend movies with same actor(s), director, genre, …
- **Websites, blogs, news**
  - Recommend other sites with "similar" content

# Filling in entries with content-based

| | Avatar | LOTR | Matrix | Pirates |
|---|---|---|---|---|
| **Alice** | 1 | | 0.2 | |
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# Filling in entries with content-based

| | Avatar | LOTR | Matrix | Pirates |
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# Content-based Approach: Pros and Cons

**+: No need for data on other users**

No cold-start or sparsity problems for new items

**+: Able to provide explanations**

Can provide explanations of recommended items by listing content-features that caused an item to be recommended

**–: Finding the appropriate features is hard**

E.g., images, movies, music

**–: Recommendations for new users**

How to build a user profile?

**–: Overspecialization**

- Never recommends items outside user's content profile

# User-similarity based recommendations

| | Avatar | LOTR | Matrix | Pirates |
|---|---|---|---|---|
| Alice | 1 | .5 | 0.2 | .3 |
| Bob | 1 | 0.5 | .2 | 0.3 |
| Carol | 0.2 | | 1 | |
| David | | | | 0.4 |

Similar idea, now just clump together users

# User-similarity based pros and cons

**+ Works for any kind of item**

- No feature selection needed

**- Cold Start:**

- Need enough users in the system to find a match

**- First rater:**

- Cannot recommend an item that has not been previously rated
- New items, Esoteric items

**- Popularity bias:**

- Cannot recommend items to someone with unique taste
- Tends to recommend popular items

# Matrix factorization – “Latent factor” models

- In previous approaches, we assumed we knew how items are related to each other, and how users are related to each other
  - Items are represented by a “vector” of characteristics like genre
  - Users by a “vector” of demographics, location, etc
- In reality, tastes may be complicated and based on subtle preferences unrelated to these things
- Idea: why not *learn* the vectors for each user and item from the history?
  - Learn vector $u_i \in R^d$ for each user, $\mathrm{v_j} \in R^d$ for each item
  - Such that $u_i \cdot v_j \approx \widehat{r_{ij}}$ (the rating user gave to the item in the past)

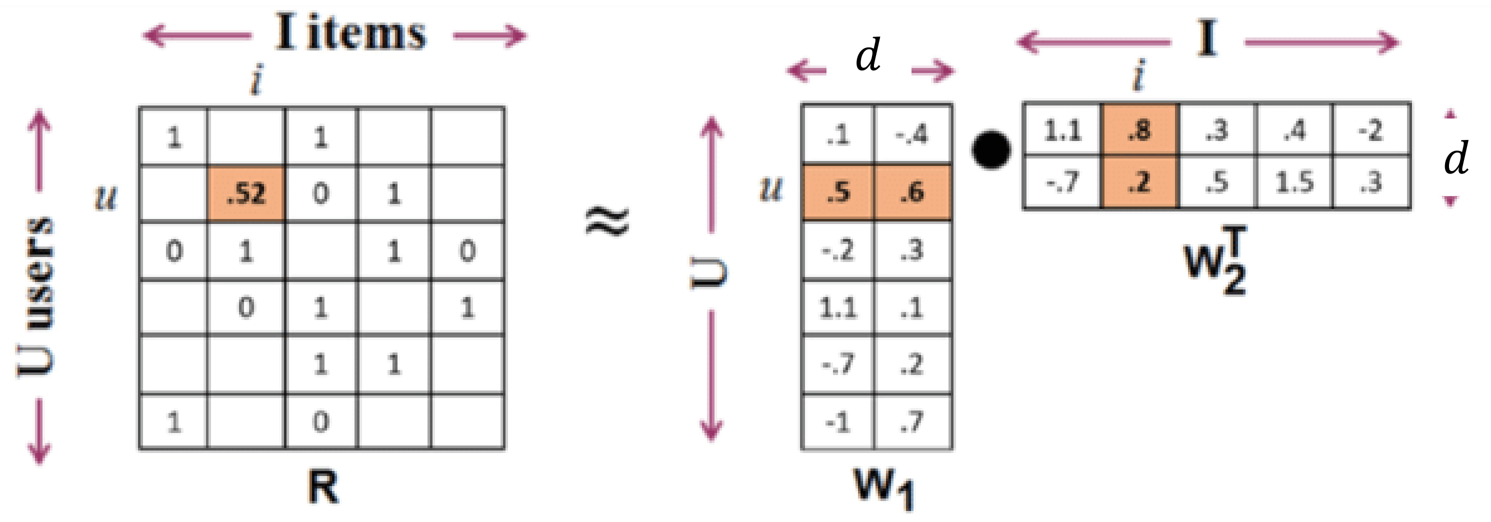
# Matrix factorization – “Latent factor” models

Once we have $u_i \in R^d$ for each user, $\mathrm{v_j} \in R^d$ for each item

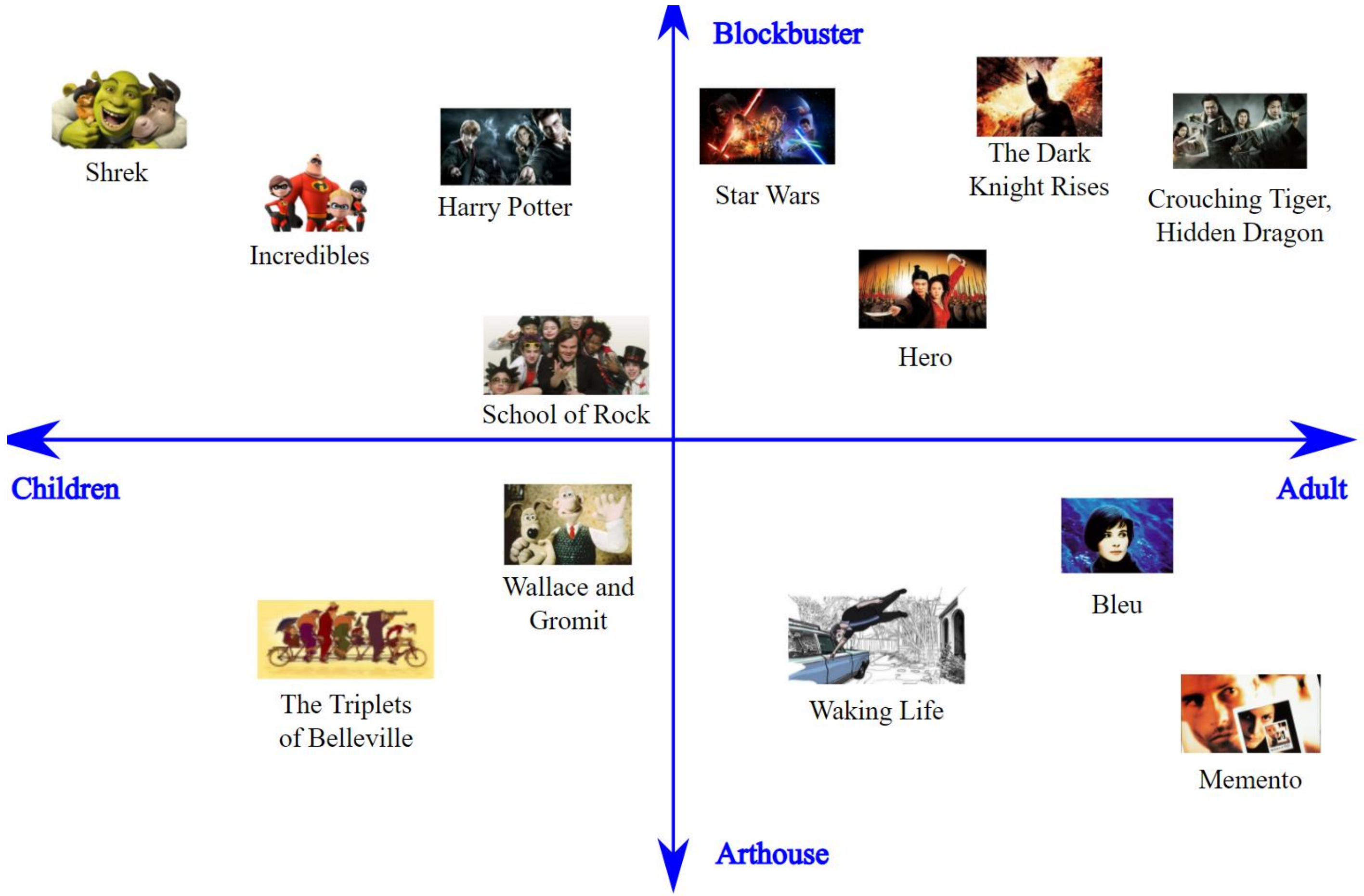
Such that $u_i \cdot v_j \approx \widehat{r_{ij}}$ (the rating user gave to the item in the past)

Then, for every pair of items and users that have not been rated:

Set predicted rating $\mathrm{r_{ij}} = u_i \cdot v_j$



# Example vectors with d=2




[Embeddings | Machine Learning Crash Course | Google Developers]

# Matrix factorization: Pros and Cons

**+: Don’t need to guess at what features matter**

**–: Need historical data about each item and user**

**–: Hard to provide explanations**

In practice, matrix-factorization-based methods (and modern deep learning successors) are used when you have enough data

# “Cold start” with matrix factorization

- Chief challenge in many settings: you don’t have (a lot of) historical data on some new users or new items
  - How do you make recommendations for new users or items?
- Idea: Combine matrix factorization with content- and user- similarity based approaches

  Step 1: Train matrix factorization model with dataset

  Step 2: For new users [items] find “nearby” users [items] to them and *initialize* their vector using the nearby users [items]

  Step 3: Over-time, *update* their vectors using their own history
- Determining “nearby” items: must use data like genre and demographics
- Key idea in many settings: At first without individual data, pretend someone is like the “average” user. Then with more data, start doing personalized things

# Step 2: Vectors from “nearby” users

Suppose we have a demographic vector for each new and old user:

[age, ethnicity, gender, income, …]

- Simple: K nearest neighbors
  - Define a distance function on the vector of demographics
  - For each new user, find the K closest old users and average their vectors
  - Challenge: defining the distance function!
- Also simple: train matrix factorization with known user vector
  - Instead of learning vector $u_i \in R^d$ for each user, $\mathrm{v_j} \in R^d$ for each item
  - Set $u_i$ to the demographic vector, and just learn $\mathrm{v_j} \in R^d$ for each item
- Many other approaches:

  Train a model using the demographics to predict $u_i^k$ , each dimension $k$ of $u_i$, using all the old users

# Questions?