ORIE 5355

Lecture 6: Intro to Recommendations Systems

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Announcements

- Quiz 1 released this week, due Sunday evening (via Canvas)
  - No late days applicable for quizzes
- HW 2 posted

Recommendation systems

Module overview

Part 1 (today) – Prediction

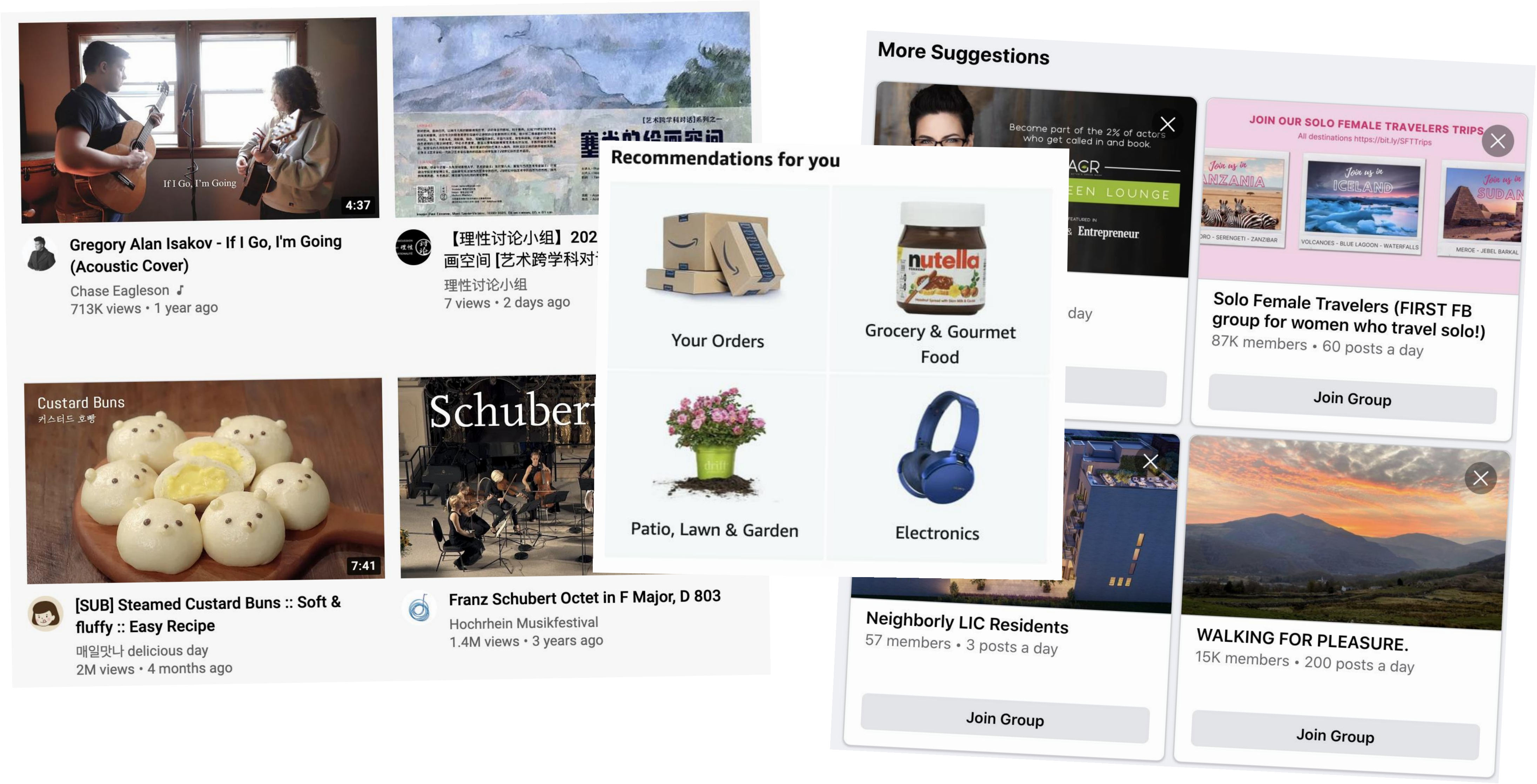
How much will a given user like an item?

- Problem formulation and some algorithms
- Data challenges

Part 2 (next time) – 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



Gregory Alan Isakov - If I Go, I'm Going (Acoustic Cover)
Chase Eagleson ♪
713K views • 1 year ago

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画空间 [艺术跨学科对
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매일맛나 delicious day
2M views • 4 months ago

Franz Schubert Octet in F Major, D 803
Hochrhein Musikfestival
1.4M views • 3 years ago

Recommendations for you

Your Orders

Grocery & Gourmet Food

Patio, Lawn & Garden

Electronics

More Suggestions

day

Solo Female Travelers (FIRST FB group for women who travel solo!)
87K members • 60 posts a day
Join Group

Neighborly LIC Residents
57 members • 3 posts a day
Join Group

WALKING FOR PLEASURE.
15K members • 200 posts a day
Join Group

If I Go, I'm Going
4:37
Custard Buns
커스터드 호빵
7:41
Schubert
Become part of the 2% of actors who get called in and book.
EN LOUNGE
Entrepreneur
JOIN OUR SOLO FEMALE TRAVELERS TRIPS
All destinations https://bit.ly/SFTTrips
Join us in ANZANIA
Join us in ICELAND
Join us in SUDAN
VOLCANOES - BLUE LAGOON - WATERFALLS
MEROE - JEBEL BARKAL

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

Slide credit: Amy Zhang, Cornell

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

J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

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

  (And more generally, many deep learning based approaches)

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

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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)

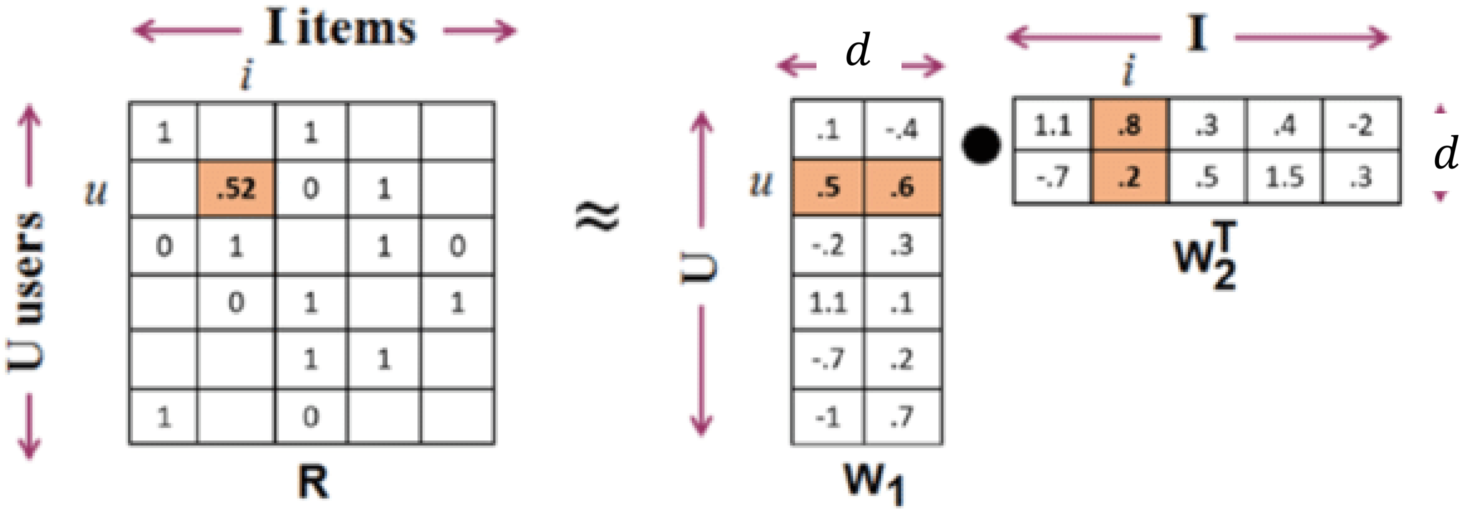
Matrix factorization – “Latent factor” models

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 $\mathrm{r_{ij}} = u_i \cdot v_j$



R

1		1		
	.52	0	1	
0	1		1	0
	0	1		1
		1	1	
1		0		

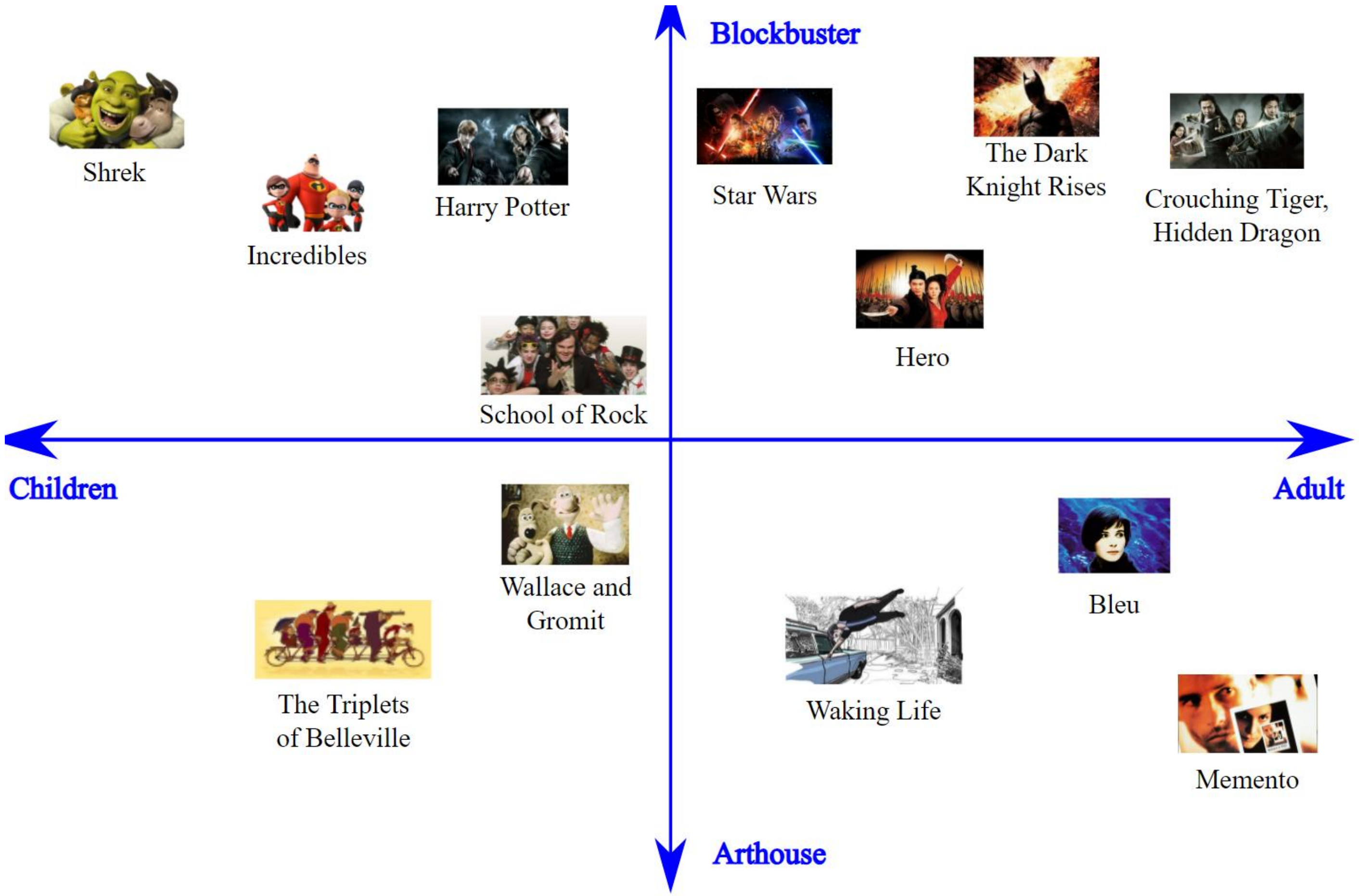
W_1

.1	-.4
.5	.6
-.2	.3
1.1	.1
-.7	.2
-1	.7

W_2^T

1.1	.8	.3	.4	-2
-.7	.2	.5	1.5	.3

Example vectors with d=2



[Embeddings | Machine Learning Crash Course | Google Developers](https://developers.google.com/machine-learning/crash-course/embeddings)

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

What to *do* with predictions? Naïve method

Train a single matrix factorization model using some data (what data?)

→I have predictions for each item and each user

For example, predict $\mathrm{r_{ij}} = u_i \cdot v_j$

For each user i, simply recommend the best item

$$\operatorname{argmax}_j u_i \cdot v_j$$

(Or K best items)

Issues with naïve method

- Capacities

  What if you only have 5 of item j, and everyone likes item j?

- Multi-sided preferences

  Recommendations in freelancing markets (workers matched with clients), dating apps, volunteer platforms, etc

- Challenges in recommending *sets* of items
  - *Diversity* of items recommended
  - Behavioral effects? Recommending one item makes another item more popular

Today: going from predictions → recommendations

Questions?