



RUTGERS

# Recommender System: An Interdisciplinary Perspective

Technical, Ethical, Philosophical, Economic, and Legal Perspectives

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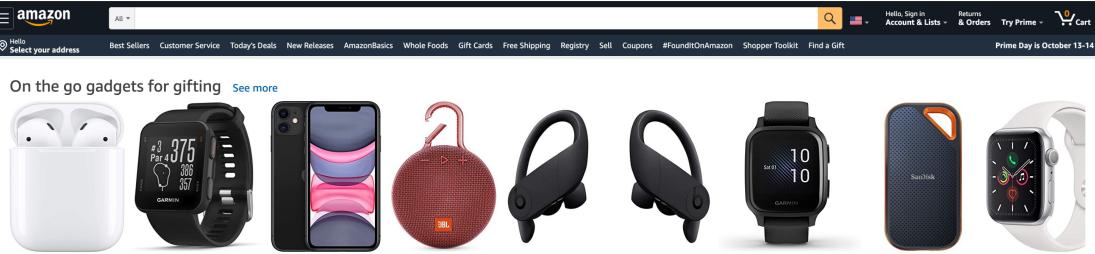
# Outline

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- Examples of Recommender Systems
- A Little Bit Models
- Ethics of Recommender Systems
  - Feedback Loop and Echo Chambers
  - Transparency
    - How to explain to users why certain things are recommended specifically for you
  - Bias and Fairness
    - Bias and Fairness on User-side (model bias)
    - Bias and Fairness on Provider-side (the Matthew Effect)
    - Advertising Fairness
  - Relationship between Transparency and Fairness
    - Legal Regulations on AI Ethics
- Open Discussions

# Recommender Systems are Ubiquitous

On the go gadgets for gifting [See more](#)



Trending deals [See all deals](#)

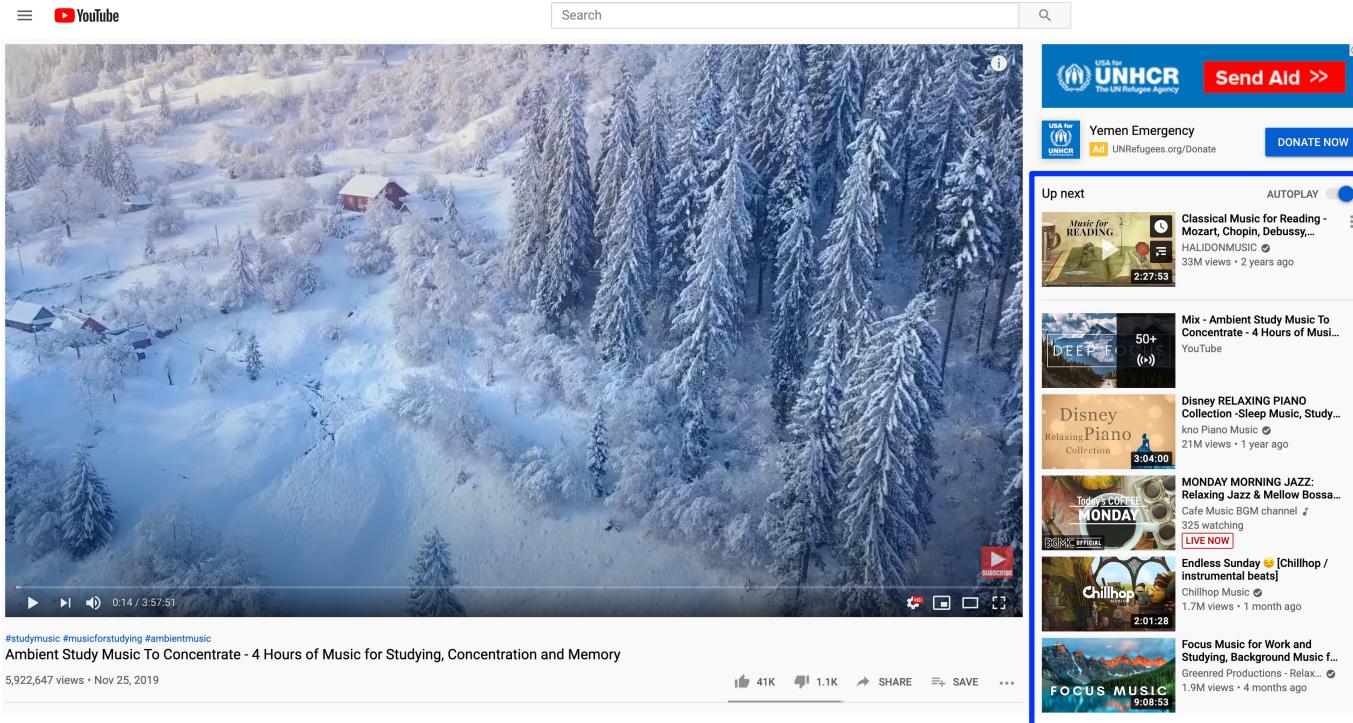
 \$19.99 - \$27.19 Scurtain Womens and Men Snow Boots Waterproof Ankle Anti-Skid Winter Fur Boo... Ends in 02:51:55	 \$28.17 - \$42.41 SONORO KATE Bed Sheet Set Super Soft Microfiber 1800 Thread Count Luxury Egy... Ends in 01:56:55	 \$16.50 \$22.99 Phone Holder Bed Gooseneck Mount - Lamicall Flexible Bed Gooseneck Mount - Lamicall Flexible Arm 360 Mount Clip Brack... Deal has ended	 \$14.44 - \$16.99 LET'S GO! Wireless Portable Handheld Bluetooth Karaoke Microphone - Best Gifts Deal has ended	 \$14.44 - \$16.99 U-Taste High Heat-Resistant Premium Silicone Spatula Set, BPA-Free One Piece Se... Ends in 03:51:55	 \$1 Bec Ends in 03:51:55
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Halloween costumes for all [Shop more costumes](#)



Product Recommendation  
(e.g., Amazon)

# Recommender Systems are Ubiquitous



The image shows a YouTube video player interface. The main video frame displays a scenic view of snow-covered pine trees and a small red cabin in a valley. The video has a duration of 3:57:51 and has been viewed 5,922,647 times since November 25, 2019. Below the video, the title reads "Ambient Study Music To Concentrate - 4 Hours of Music for Studying, Concentration and Memory". The YouTube interface includes a search bar at the top, a sidebar for UNHCR donations, and a "Up next" section highlighted with a blue border. This section lists several recommended videos: "Classical Music for Reading - Mozart, Chopin, Debussy..." by HALIDONMUSIC, "Mix - Ambient Study Music To Concentrate - 4 Hours of Music..." by YouTube, "Disney RELAXING PIANO Collection -Sleep Music, Study..." by km Piano Music, "MONDAY MORNING JAZZ: Relaxing Jazz & Mellow Bossa..." by Cafe Music BGM channel, "Endless Sunday 😊 [Chillhop / Instrumental beats]" by Chillhop Music, and "Focus Music for Work and Studying, Background Music f..." by Greenred Productions - Relax... Each video thumbnail includes its title, creator, view count, and upload date.

#studymusic #musicforstudying #ambientmusic

Ambient Study Music To Concentrate - 4 Hours of Music for Studying, Concentration and Memory

5,922,647 views · Nov 25, 2019

41K likes 1.1K dislikes SHARE SAVE

Up next

Classical Music for Reading - Mozart, Chopin, Debussy... HALIDONMUSIC 33M views · 2 years ago

Mix - Ambient Study Music To Concentrate - 4 Hours of Music... YouTube

Disney RELAXING PIANO Collection -Sleep Music, Study... km Piano Music 21M views · 1 year ago

MONDAY MORNING JAZZ: Relaxing Jazz & Mellow Bossa... Cafe Music BGM channel 325 watching

Endless Sunday 😊 [Chillhop / Instrumental beats] Chillhop Music 1.7M views · 1 month ago

Focus Music for Work and Studying, Background Music f... Greenred Productions - Relax... 1.9M views · 4 months ago

Video/Movie Recommendation  
(e.g., YouTube)

# Recommender Systems are Ubiquitous



[Home](#)

# Explore

Notifications

Messages

Bookmarks

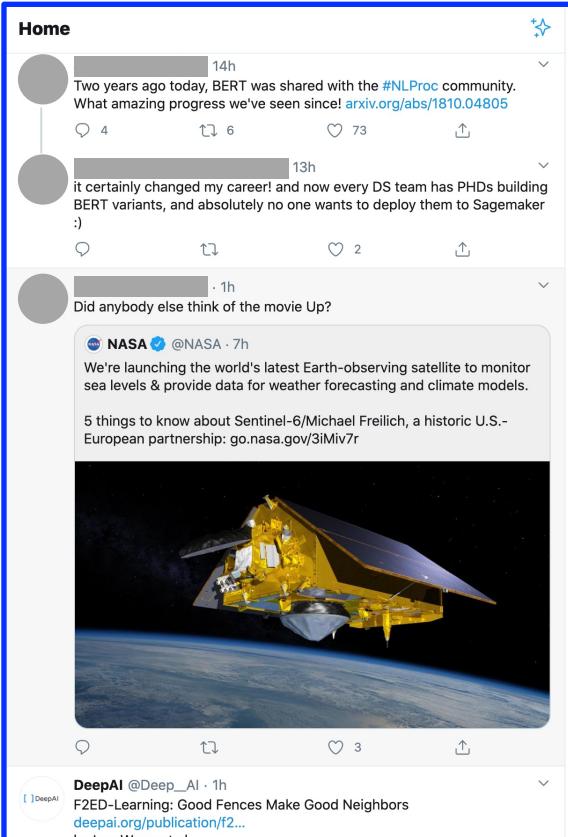
Lists

Profile

More

[Tweet](#)

News Feed Recommendation  
(e.g., Twitter)



The screenshot shows a Twitter home feed with three visible tweets:

- A tweet from BERT (@BERT) posted 14 hours ago: "Two years ago today, BERT was shared with the #NLProc community. What amazing progress we've seen since! arxiv.org/abs/1810.04805". It has 4 replies, 6 retweets, and 73 likes.
- A tweet from an anonymous user posted 13 hours ago: "it certainly changed my career! and now every DS team has PhDs building BERT variants, and absolutely no one wants to deploy them to Sagemaker :)" It has 1 reply, 2 retweets, and 2 likes.
- A tweet from NASA (@NASA) posted 1 hour ago: "Did anybody else think of the movie Up?". It includes a link to a NASA press release about launching the Sentinel-6 satellite. The tweet has 1 reply, 2 retweets, and 2 likes.

Topic Recommendation  
(e.g., Twitter)



The screenshot shows search results for the hashtag #JamieMovie. It includes a summary card for the film and a list of trending topics:

- Trending in United States: **Dwight** (59.8K Tweets)
- Sports - Trending: **Skip** (130K Tweets)
- Trending in United States: **JR Smith**

Below the trends, there's a card for the NBA Finals featuring JR Smith.

Friend Recommendation  
(e.g., Twitter)



The screenshot shows a list of recommended accounts to follow:

- uffizzi cloud** (@UffiziCloud) - Promoted
- Two other accounts represented by gray circles, each with a "Follow" button.

# Recommender Systems are Ubiquitous

**The New York Times**

PERSONAL TECH | Google Chromecast Review: A Streaming Device

More in Personal Technology



Arun Sankar/Agence France-Presse — Getty Images

Now You Can Use Instagram to Chat With Friends on Facebook Messenger

Sept. 30



via Ring

Amazon Unveils Drone That Films Inside Your Home. What Could Go Wrong?

Sept. 24

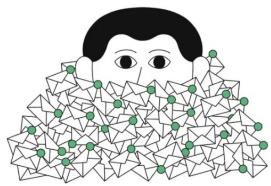


PAID POST: EMERGENT BIOSOLUTIONS

Requiem for a Vaccine

emergent biosolutions

News Recommendation  
(e.g., The New York Times)



Dominic Kesterton

How to Declutter Your Digital World

Sept. 15



Till Lauer

Who Gets Hurt When the World Stops Using Cash

Sept. 11



Continue Your Life's Education With Free Online Classes

Sept. 10

# Recommender Systems are Ubiquitous

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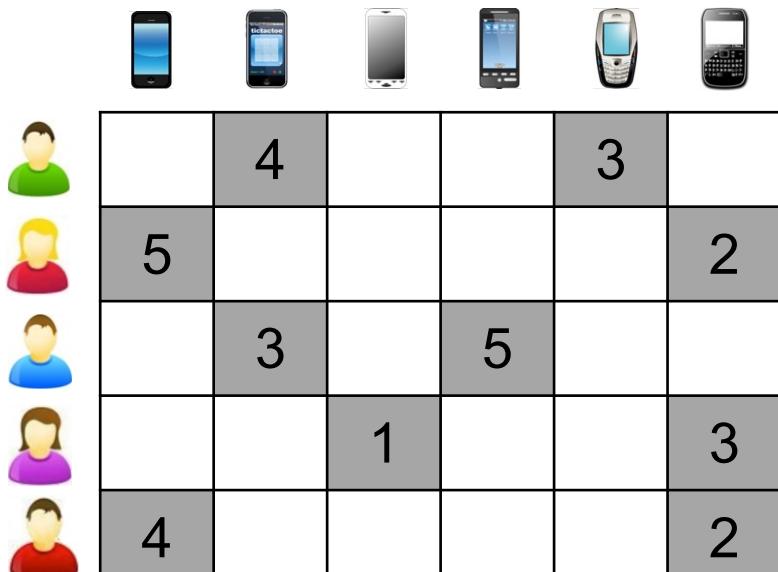
# Key of RS: Personalization

- The key feature of model recommender system is “Personalization”
  - Provide different and personalized items for different users



# (Just a little bit) Models

- Input



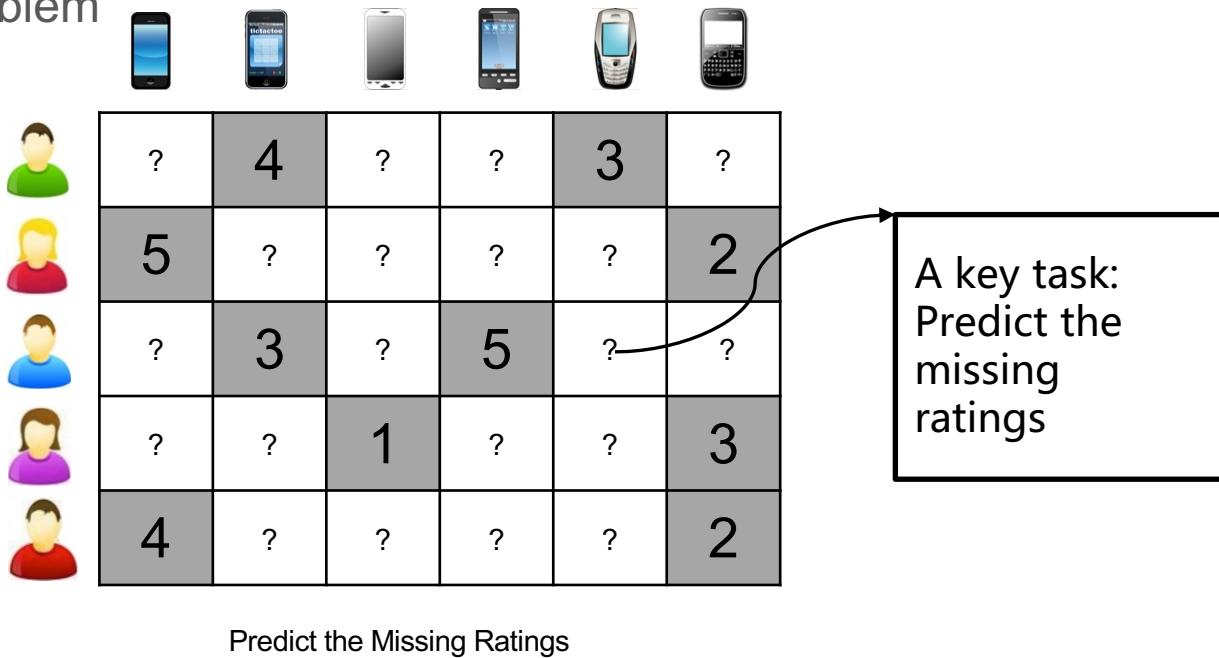
User-Item Rating Matrix



Example Rating on Amazon

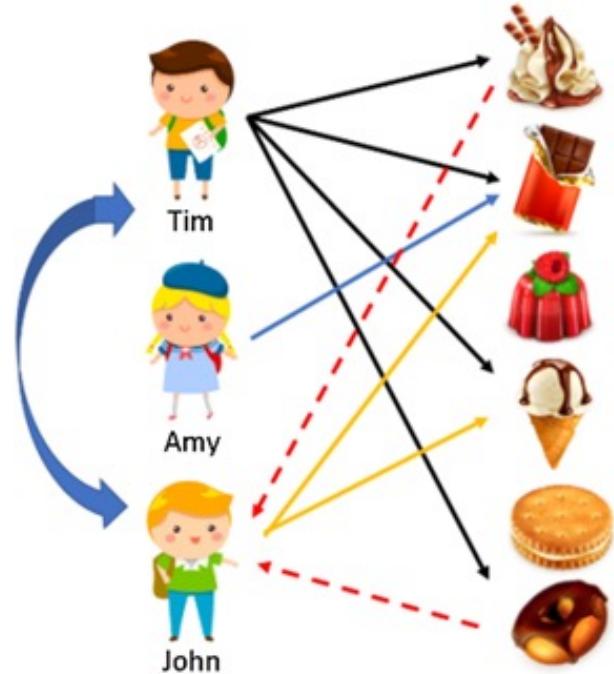
# (Just a little bit) Models

- The Key Problem



# User-based Collaborative Filtering

- Consider user  $x$
- Find set  $N$  of other users whose ratings are “**similar**” to  $x$ ’s ratings
  - $\text{sim}(x, y) = \cos(r_x, r_y) = \frac{r_x \cdot r_y}{\|r_x\| \cdot \|r_y\|}$
- Estimate  $x$ ’s ratings based on ratings of users in  $N$

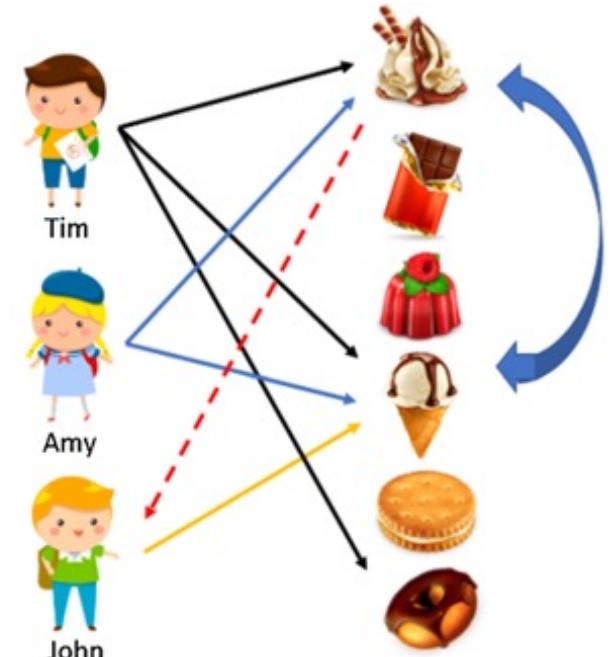


Key Idea: Recommend those items that other similar users liked

(a) User-based filtering

# Item-based Collaborative Filtering

- Consider user  $x$ , consider an item  $i$  the user liked
- Find set  $N$  of other items whose ratings are “**similar**” to  $i$ ’s ratings
  - $\text{sim}(i, j) = \cos(r_i, r_j) = \frac{r_i \cdot r_j}{\|r_i\| \cdot \|r_j\|}$
- Recommend these items



Key Idea: Recommend those items that are similar to what the user have already liked

**(b)** Item-based filtering

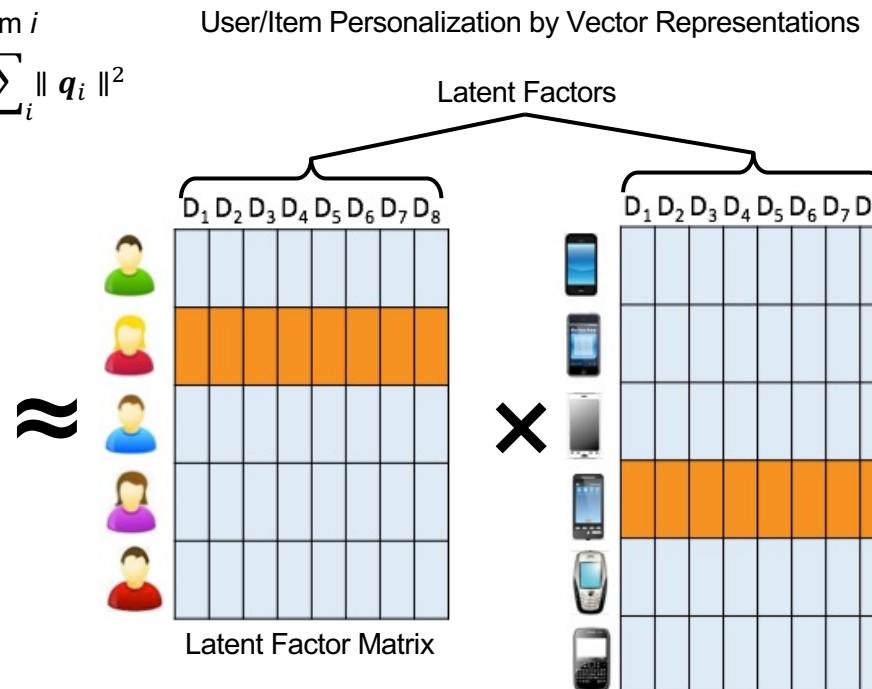
# A Machine Learning-based Model

- Latent Factor Models for Matrix Completion

$\hat{r}_{ui} = \mathbf{p}_u^T \mathbf{q}_i$     $\mathbf{p}_u$ : The “learned” feature vector for user  $u$   
 $\mathbf{q}_i$ : The “learned” feature vector for item  $i$

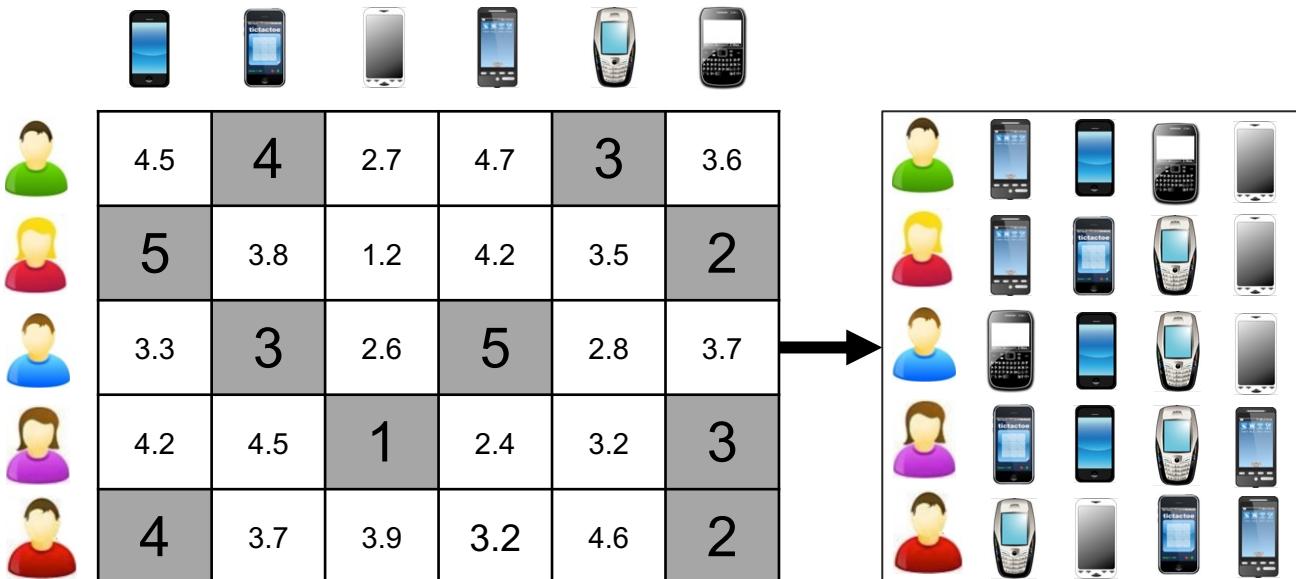
$$\min_{\mathbf{p}, \mathbf{q}} \sum_{(u,i) \in R} (r_{ui} - \mathbf{p}_u^T \mathbf{q}_i)^2 + \lambda_1 \sum_u \|\mathbf{p}_u\|^2 + \lambda_2 \sum_i \|\mathbf{q}_i\|^2$$

Goodness of fit      Regularization



# (Just a little bit) Models

- Providing Recommendations by Ranking





# Ethics of Recommender Systems

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- Feedback Loop and Echo Chambers
- Transparency
  - How to explain to users why certain things are recommended specifically for you
- Bias and Fairness
  - Bias and Fairness on User-side (model bias)
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# Ethics of Recommender Systems

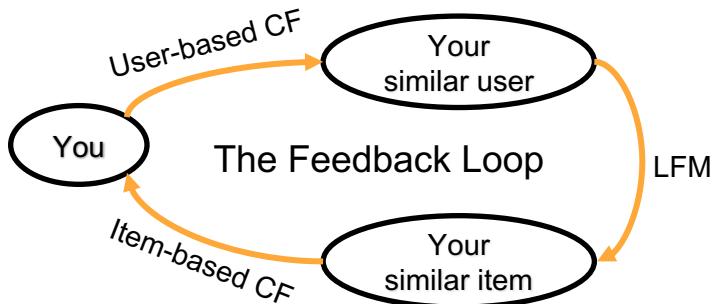
- Technology is neither good nor bad; nor is it neutral
  - It all depends on how we use it, and we should use technology in a responsible way
  - E.g., Atomic theory: nuclear power station and clean energy vs. nuclear bombs
- Recommender Systems
  - Helps users to find good items in a sea of items
  - May also bring counter-effects

**“Technology is  
neither good  
nor bad; nor is  
it neutral.”**

*– Melvin Kranzberg*

# Feedback Loops and Echo Chambers

- What is Echo Chamber  
An echo chamber is "an environment where a person only encounters information or opinions that reflect and reinforce their own."
- Why RS creates Echo Chambers



The more you like something, the more RS will recommend similar things, and thus you like them even more.



# Echo Chambers in E-commerce

- System always recommend similar products
- Even always recommend products that you already bought (e.g., phones)

## Products related to this item

Sponsored ⓘ



Net10 Samsung Galaxy  
A01 4G LTE Prepaid  
Smartphone - Black -  
16GB - Sim Card Includ...  
**\$58.05 ✓prime**



Total Wireless LG  
Journey 4G LTE Prepaid  
Smartphone (Locked) -  
Black - 16GB - Sim C...  
**\$39.99 ✓prime**



Simple Mobile Motorola  
Moto E6 4G LTE Prepaid  
Smartphone (Locked) -  
Black - 16GB - ...  
**\$39.88 ✓prime**



Tracfone Samsung  
Galaxy A01 4G LTE  
Prepaid Smartphone -  
Black - 16GB - Sim...  
**\$79.00 ✓prime**



Simple Mobile LG  
Journey 4G LTE Prepaid  
Smartphone (Locked) -  
Black - 16GB - Sim Ca...  
**\$29.99 ✓prime**



Tracfone LG Journey 4G  
LTE Prepaid Smartphone  
(Locked) - Black - 16GB -  
SIM Card In...  
**\$29.99 ✓prime**



Total Wireless LG Solo  
4G LTE Prepaid  
Smartphone (Locked) -  
Black - 16GB - Sim...  
**\$49.99 ✓prime**

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# Echo Chambers in Video/Movie/Book Recommendation

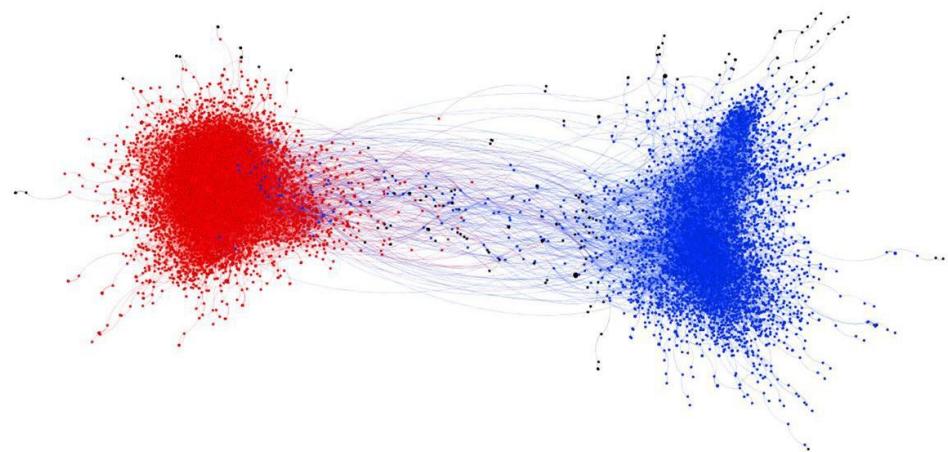
- Always recommend similar videos/movies/books
- Prevents you from exploring a much richer and diversified world
- Prevents you from thinking outside of the box



# Echo Chambers in Social Networks (e.g., Twitter)

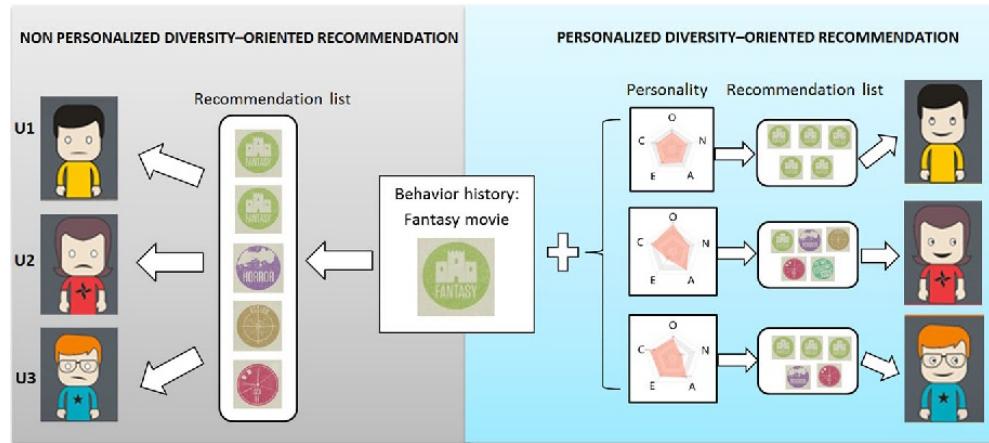
- The Social Echo Chamber

- Makes all your connections like-minded persons as you
- Makes all your news feed recommendation similar to what you have liked
- Makes it difficult to explore new ideas and opinions different from yours
- Makes everyone feel the whole world thinks the same way as you think
- May even reinforce someone's extremist ideas



# How to Avoid Echo Chambers

- An Active Research Area in RS, ML, AI
- The key is to take care of the diversity in recommendation
  - Provide similar item recommendations, and meanwhile some dis-similar recommendations
- A trade-off between utility and diversity
  - Best if the dis-similar recommendations are also what the user likes, e.g., personalized diversity



# Transparency of Recommendation

- Tell users why something is recommended: Explainable Recommendation
- Many machine learning models are black-boxes

$$\hat{r}_{ui} = \mathbf{p}_u^T \mathbf{q}_i \quad \mathbf{p}_u: \text{The "learned" feature vector for user } u \\ \mathbf{q}_i: \text{The "learned" feature vector for item } i$$

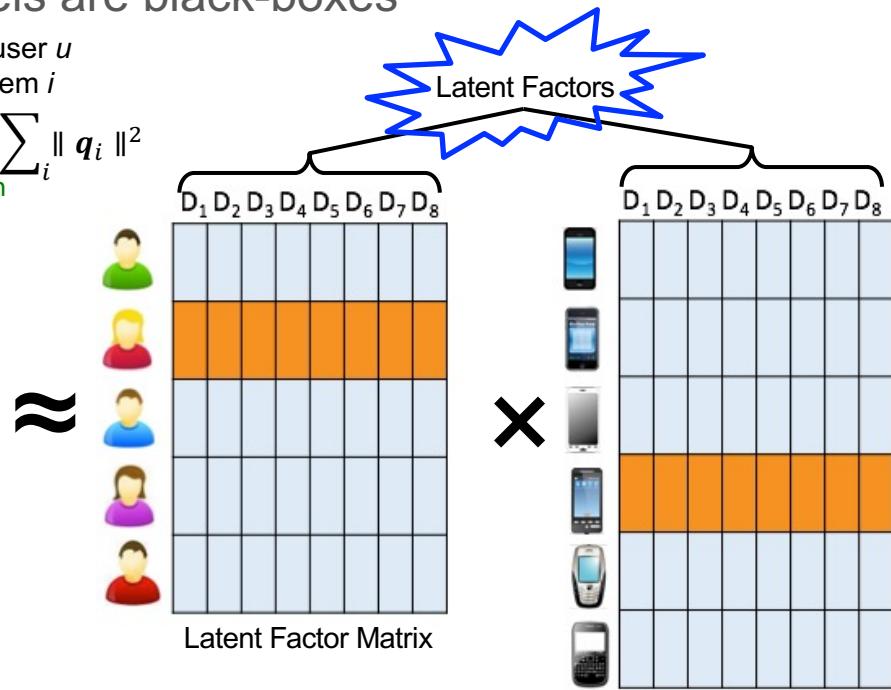
$$\min_{\mathbf{p}, \mathbf{q}} \sum_{(u,i) \in R} (r_{ui} - \mathbf{p}_u^T \mathbf{q}_i)^2 + \lambda_1 \sum_u \|\mathbf{p}_u\|^2 + \lambda_2 \sum_i \|\mathbf{q}_i\|^2$$

Goodness of fit      Regularization



		4			3	
5				2		
	3		5			
		1			3	
4			3		5	

Original Matrix



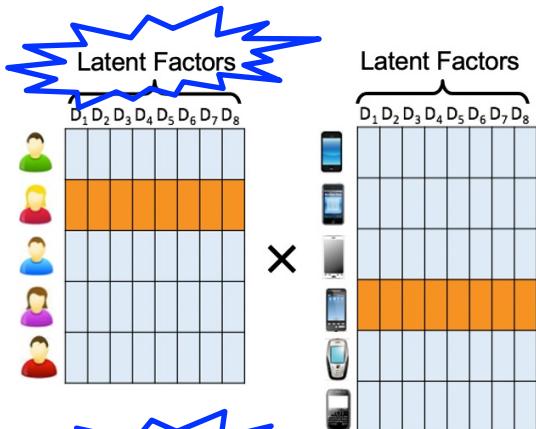
# Explainable Recommendation

- Letting the users know **why** is important
  - Help users to make the **right decisions**
  - Otherwise human might be “**controlled**” by algorithms
- Explainable Recommendation
  - More generally: Explainable AI (XAI)
  - An active Research area in AI
  - An example: Explicit Factor Model



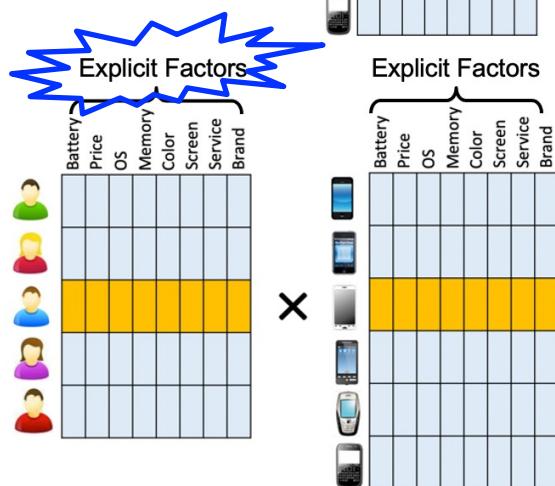
Latent Factor Model

≈



Explicit Factor Model

≈



# Bias and Fairness in Recommendation

- A broad problem, broadly classified into two problems
  - User-side fairness, Provider-side fairness
- Why? Usually RS works in two-sided markets/environments
  - RS is actually a resource allocation problem

The *Prosumer* Paradigm:  
*Consumers – items – Producers*

Buyers – Goods – Sellers

Freelancer – Jobs – Employers

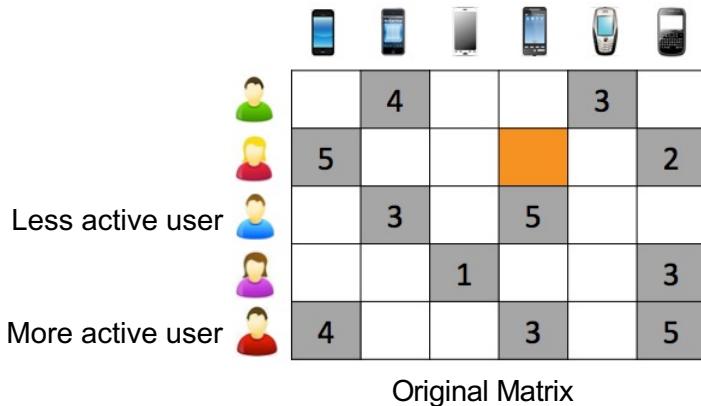
Borrowers – Money – Lenders

Passengers – Services – Drivers



# User-side Fairness in RS

- Where does unfairness come from?
  - Some users are **more active**
    - e.g., more time to explore items, more money to buy items
  - They contribute **more training data** to the ML model
  - The model behavior may be **dominated** by active users.
    - e.g., tend to recommend items that the active user likes to everyone



$$\hat{r}_{ui} = \mathbf{p}_u^T \mathbf{q}_i \quad \begin{aligned} \mathbf{p}_u &: \text{The "learned" feature vector for user } u \\ \mathbf{q}_i &: \text{The "learned" feature vector for item } i \end{aligned}$$

$$\min_{\mathbf{p}, \mathbf{q}} \sum_{(u,i) \in R} (r_{ui} - \mathbf{p}_u^T \mathbf{q}_i)^2 + \lambda_1 \sum_u \|\mathbf{p}_u\|^2 + \lambda_2 \sum_i \|\mathbf{q}_i\|^2$$

Goodness of fit      Regularization

# User-side Fairness in RS

Observation: Top 5% active users' data may dominate a ML algorithm

Dataset	CDs & Vinyl								Clothing							
	Overall		Inactive Users		Active Users		GRU		Overall		Inactive Users		Active Users		GRU	
Measures (%)	NDCG	F <sub>1</sub>	NDCG	F <sub>1</sub>	NDCG	F <sub>1</sub>	NDCG	F <sub>1</sub>	NDCG	F <sub>1</sub>	NDCG	F <sub>1</sub>	NDCG	F <sub>1</sub>	NDCG	F <sub>1</sub>
HeteroEmbed	6.992	3.576	6.526	3.373	15.843	7.429	9.317	4.056	3.221	1.404	3.121	1.348	5.130	2.461	2.009	1.113
Fair HeteroEmbed	8.094	4.019	7.674	3.820	16.074	7.801	8.400	3.981	3.494	1.536	3.484	1.482	3.691	2.556	0.207	1.074
PGPR	6.947	3.571	6.526	3.373	14.943	7.324	8.417	3.951	2.856	1.240	2.787	1.198	4.197	2.036	1.410	0.833
Fair PGPR	8.045	4.019	7.675	3.820	15.074	7.801	7.399	3.261	3.101	1.314	3.089	1.274	3.322	2.078	0.233	0.804
KGAT	5.411	3.357	5.038	3.162	12.498	7.046	7.460	3.884	3.021	1.305	2.931	1.254	4.741	2.259	1.810	1.005
Fair KGAT	5.640	3.492	5.295	3.318	12.366	6.791	7.081	3.473	3.206	1.393	3.119	1.347	4.843	2.262	1.724	0.915

$$\max_{Q_{ij}} \quad \mathcal{R} = \sum_{i=1}^m \mathcal{R}_{\text{rec}}(\mathbf{Q}_i)$$

$$\text{s.t.} \quad \sum_{j=1}^N Q_{ij} = K, \quad Q_{ij} \in \{0, 1\}$$

$$GRU(G_1, G_2, \mathbf{Q}) < \varepsilon_1$$

$$GREU(G_1, G_2, \mathbf{Q}) < \varepsilon_2$$

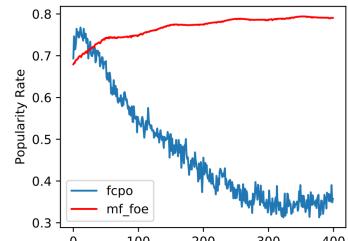
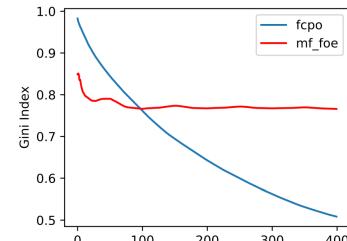
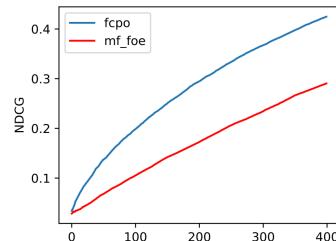
$$GRU(G_1, G_2, \mathbf{Q}) = \left| \frac{1}{|G_1|} \sum_{i \in G_1} \mathcal{F}(\mathbf{Q}_i) - \frac{1}{|G_2|} \sum_{i \in G_2} \mathcal{F}(\mathbf{Q}_i) \right|$$

$$GEDU(G_1, G_2, \mathbf{Q}) = \left| \frac{1}{|G_1|} \sum_{i \in G_1} f(\mathbf{Q}_i) - \frac{1}{|G_2|} \sum_{i \in G_2} f(\mathbf{Q}_i) \right|$$

# Item-side Fairness in RS

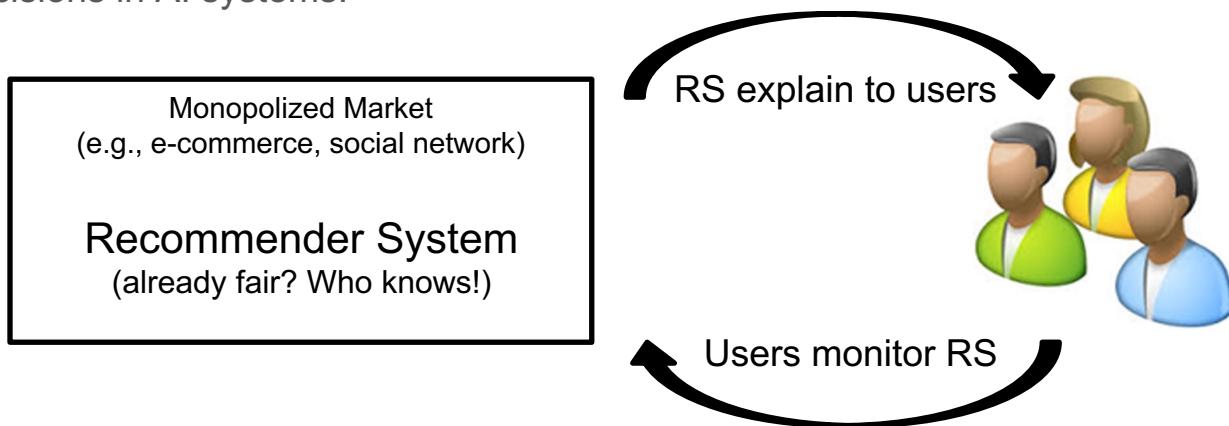
- Where does unfairness come from?
  - Some providers are big, some are small
    - Big retailers like Walmart vs Family-owned small-business retailers
  - Big providers have more budget for advertising and marketing
    - Thus their items get more exposure in E-commerce
  - The more exposure they get, the more users buy their items
  - RS thinks these items are more liked by users, and thus recommend these items even more
  - It becomes even more difficult for small-businesses to survive in the environment
  - **The Matthew Effect:** The rich get even richer and the poor get even poorer
  - This is unhealthy to the national economy!

$$Gini\ Index(\mathcal{G}) = \frac{1}{2|\mathcal{I}|^2\bar{g}} \sum_{i=1}^{|\mathcal{I}|} \sum_{j=1}^{|\mathcal{I}|} |g_i - g_j|$$



# Relationship between Transparency and Fairness

- Transparency and Fairness benefit each other: Explainable Fairness
- Legal Regulatory Approaches to AI Ethics
  - E.g., EU General Data Protection Regulation (GDPR), The California Privacy Act of 2018
  - Emphasize the trustworthiness, robustness, transparency, and fairness of algorithmic decisions in AI systems.



A healthy virtuous cycle between user and system, and thus a healthy online economy.



# Wrap up

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THANKS