CSCE 670 - Information Storage and Retrieval

Lecture 20: Neural Collaborative Filtering and Sequential Recommendation

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Course Website: https://yuzhang-teaching.github.io/CSCE670-F25.html

Adapted from the slides by Prof. James Caverlee

Recap: Neural Collaborative Filtering

Generalized Matrix Factorization:

Input $\boldsymbol{x}_0 = [\boldsymbol{p}, \boldsymbol{q}]$

$$\text{score}_{\text{MF}}(u, i) = \text{Sigmoid}\big(\boldsymbol{w}(\boldsymbol{p} \odot \boldsymbol{q})\big) = \text{Sigmoid}(\boldsymbol{p}\ \text{diag}\{\boldsymbol{w}\}\ \boldsymbol{q}^T)$$

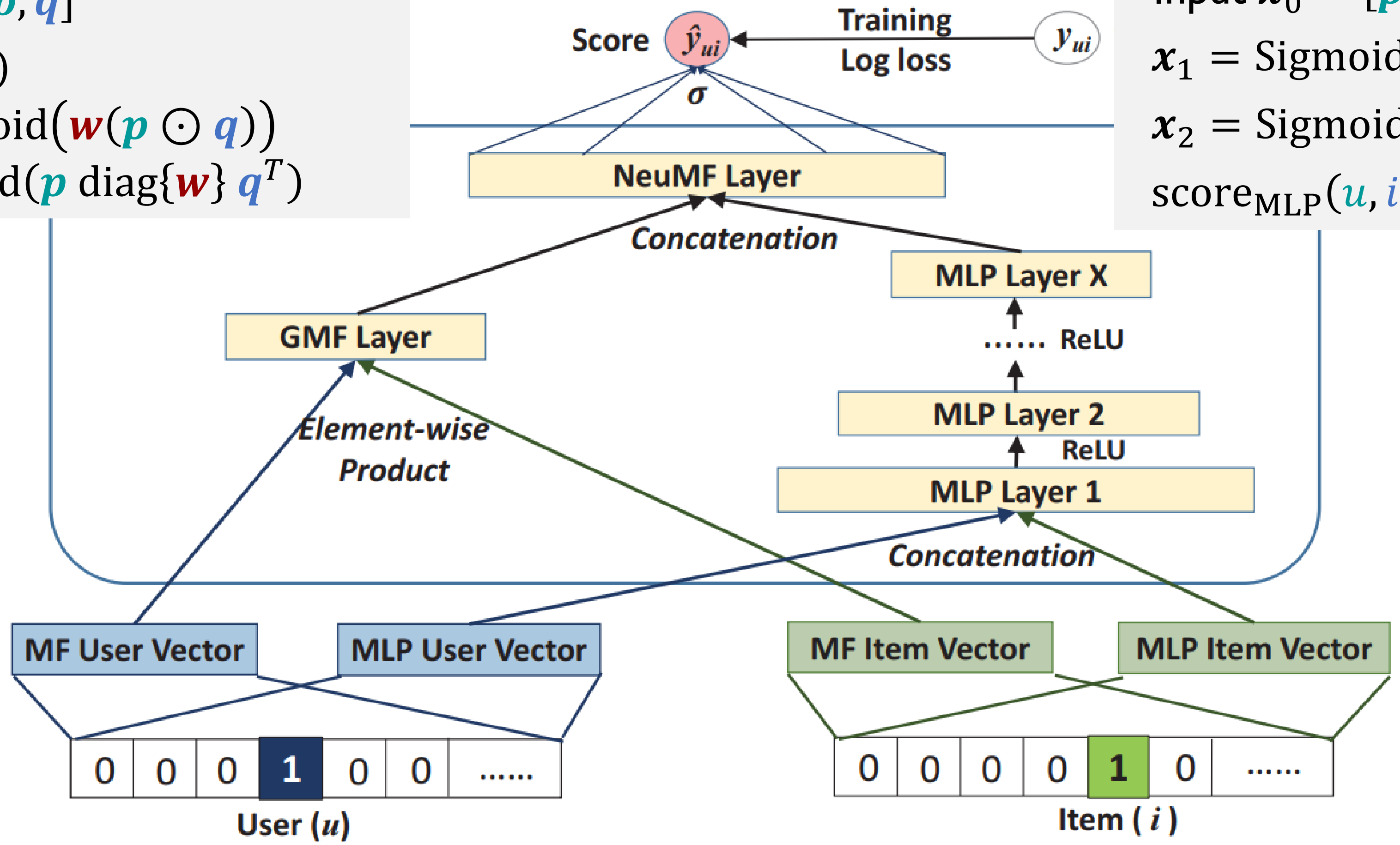
MLP (assuming 3 layers):

Input $\boldsymbol{x}_0 = [\boldsymbol{p}, \boldsymbol{q}]$

$$\boldsymbol{x}_1 = \text{Sigmoid}(\boldsymbol{W}_1 \boldsymbol{x}_0 + \boldsymbol{b}_1)$$

$$\boldsymbol{x}_2 = \text{Sigmoid}(\boldsymbol{W}_2 \boldsymbol{x}_1 + \boldsymbol{b}_2)$$

$$\text{score}_{\text{MLP}}(u, i) = \text{Sigmoid}(\boldsymbol{W}_3 \boldsymbol{x}_2)$$

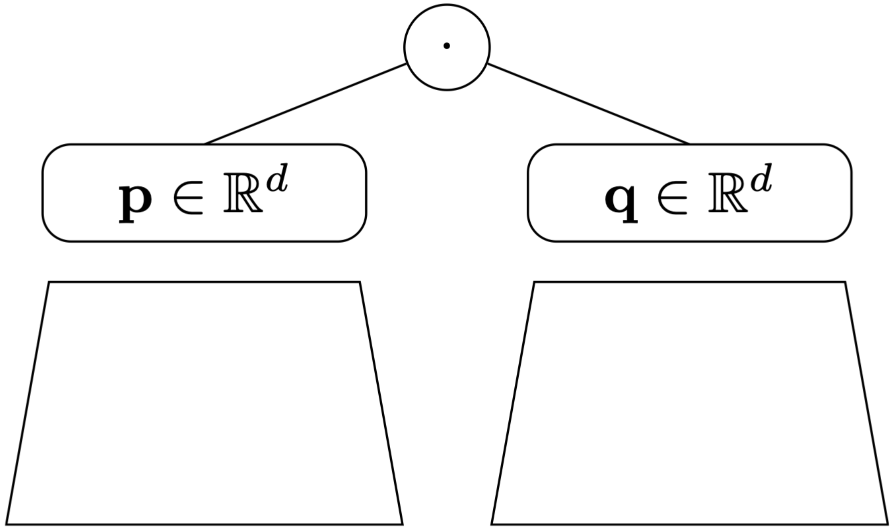


$$\text{score}(u, i) = \text{score}_{\text{MF}}(u, i) + \text{score}_{\text{MLP}}(u, i)$$

Matrix Factorization vs. Neural Collaborative Filtering

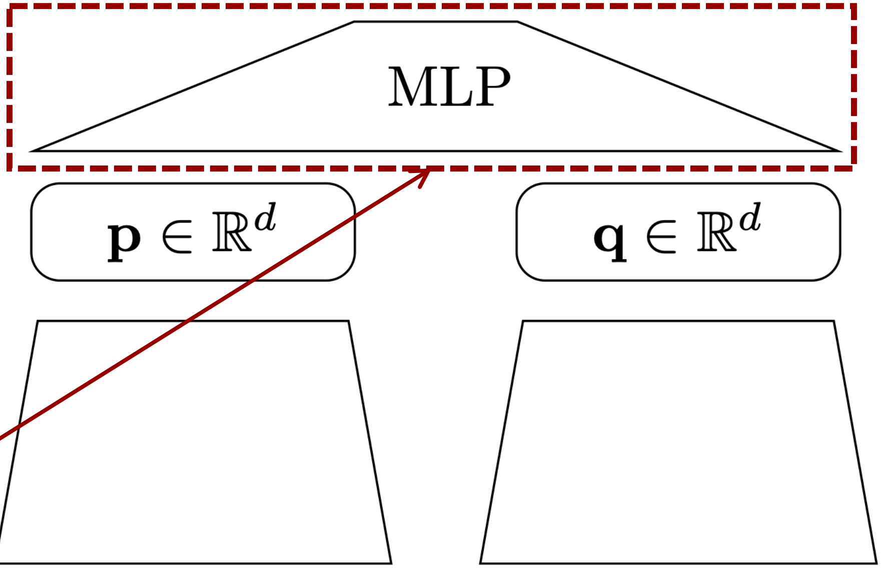
- Predefined similarity

$$\phi^{\mathrm{dot}}(\mathbf{p},\mathbf{q}) = \langle \mathbf{p},\mathbf{q} \rangle$$



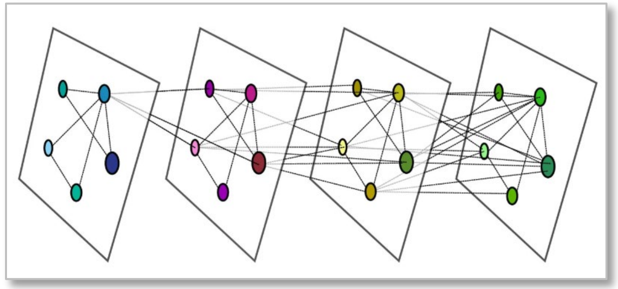
- Learned similarity

$$\phi^{\mathrm{MLP}}(\mathbf{p},\mathbf{q}) = \mathbf{f}_{W_l,\mathbf{b}_l}(\ldots \mathbf{f}_{W_1,\mathbf{b}_1}([\mathbf{p},\mathbf{q}])\ldots)$$

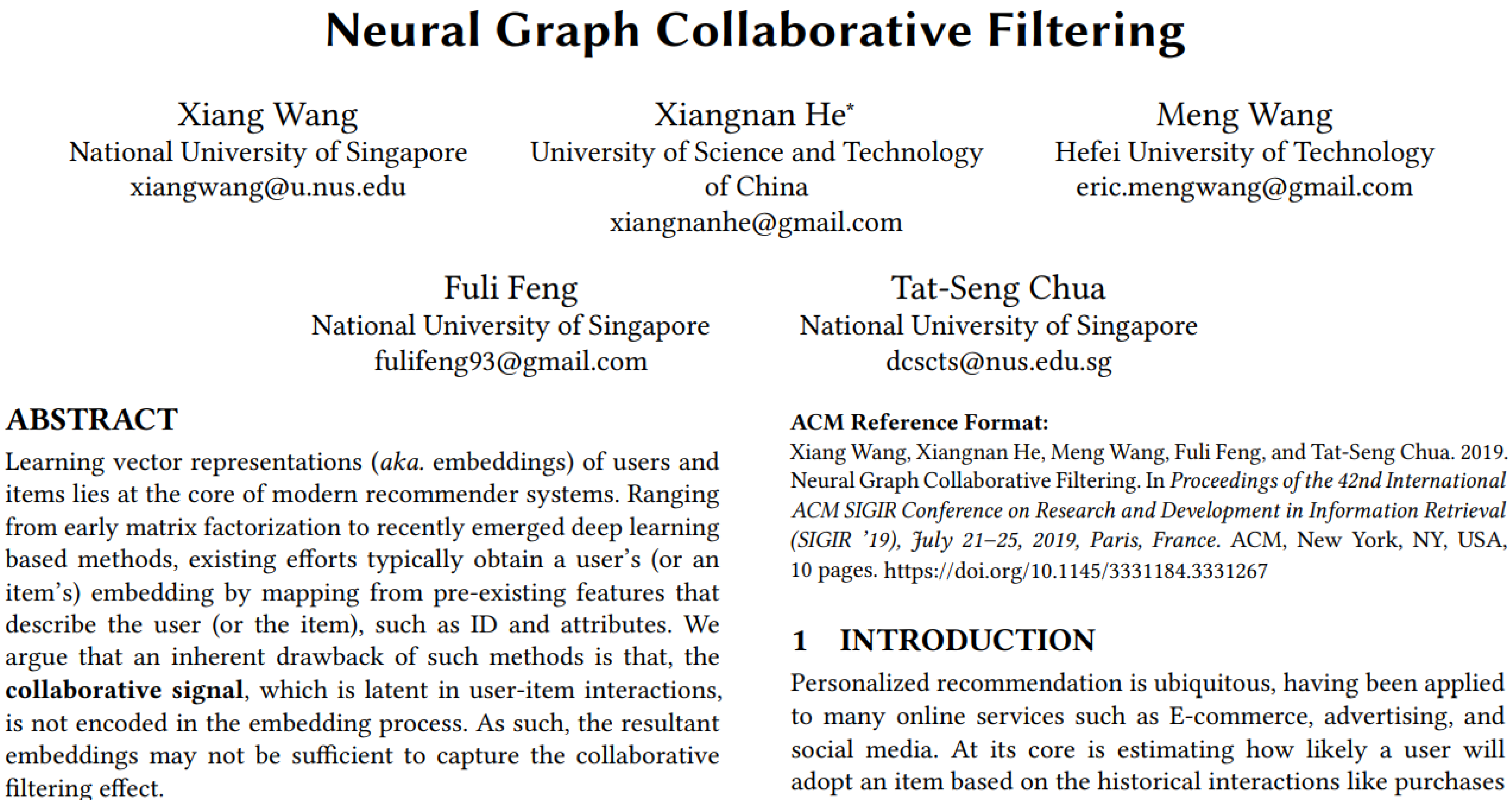


We can make this part even more complicated!

(E.g., graph neural networks)



Neural Graph Collaborative Filtering [Wang et al., SIGIR 2019]



Neural Graph Collaborative Filtering

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ABSTRACT

Learning vector representations (*aka.* embeddings) of users and items lies at the core of modern recommender systems. Ranging from early matrix factorization to recently emerged deep learning based methods, existing efforts typically obtain a user's (or an item's) embedding by mapping from pre-existing features that describe the user (or the item), such as ID and attributes. We argue that an inherent drawback of such methods is that, the **collaborative signal**, which is latent in user-item interactions, is not encoded in the embedding process. As such, the resultant embeddings may not be sufficient to capture the collaborative filtering effect.

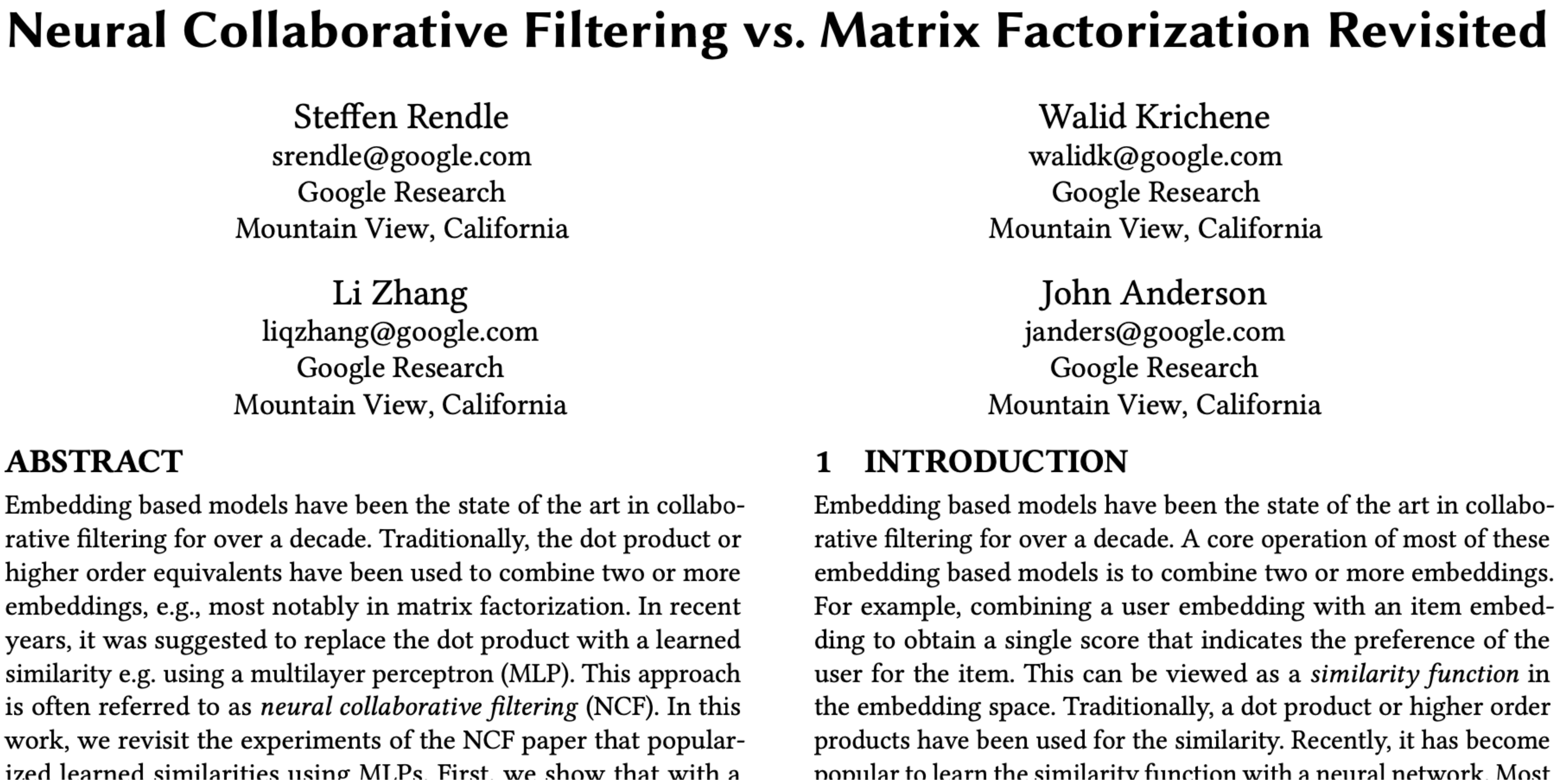
ACM Reference Format:
Xiang Wang, Xiangnan He, Meng Wang, Fuli Feng, and Tat-Seng Chua. 2019. Neural Graph Collaborative Filtering. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '19), July 21–25, 2019, Paris, France.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3331184.3331267

1 INTRODUCTION

Personalized recommendation is ubiquitous, having been applied to many online services such as E-commerce, advertising, and social media. At its core is estimating how likely a user will adopt an item based on the historical interactions like purchases

But is inner product really that bad?

Performance Revisited [Rendle et al., RecSys 2020]



Neural Collaborative Filtering vs. Matrix Factorization Revisited

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ABSTRACT

Embedding based models have been the state of the art in collaborative filtering for over a decade. Traditionally, the dot product or higher order equivalents have been used to combine two or more embeddings, e.g., most notably in matrix factorization. In recent years, it was suggested to replace the dot product with a learned similarity e.g. using a multilayer perceptron (MLP). This approach is often referred to as *neural collaborative filtering* (NCF). In this work, we revisit the experiments of the NCF paper that popularized learned similarities using MLPs. First, we show that with a

1 INTRODUCTION

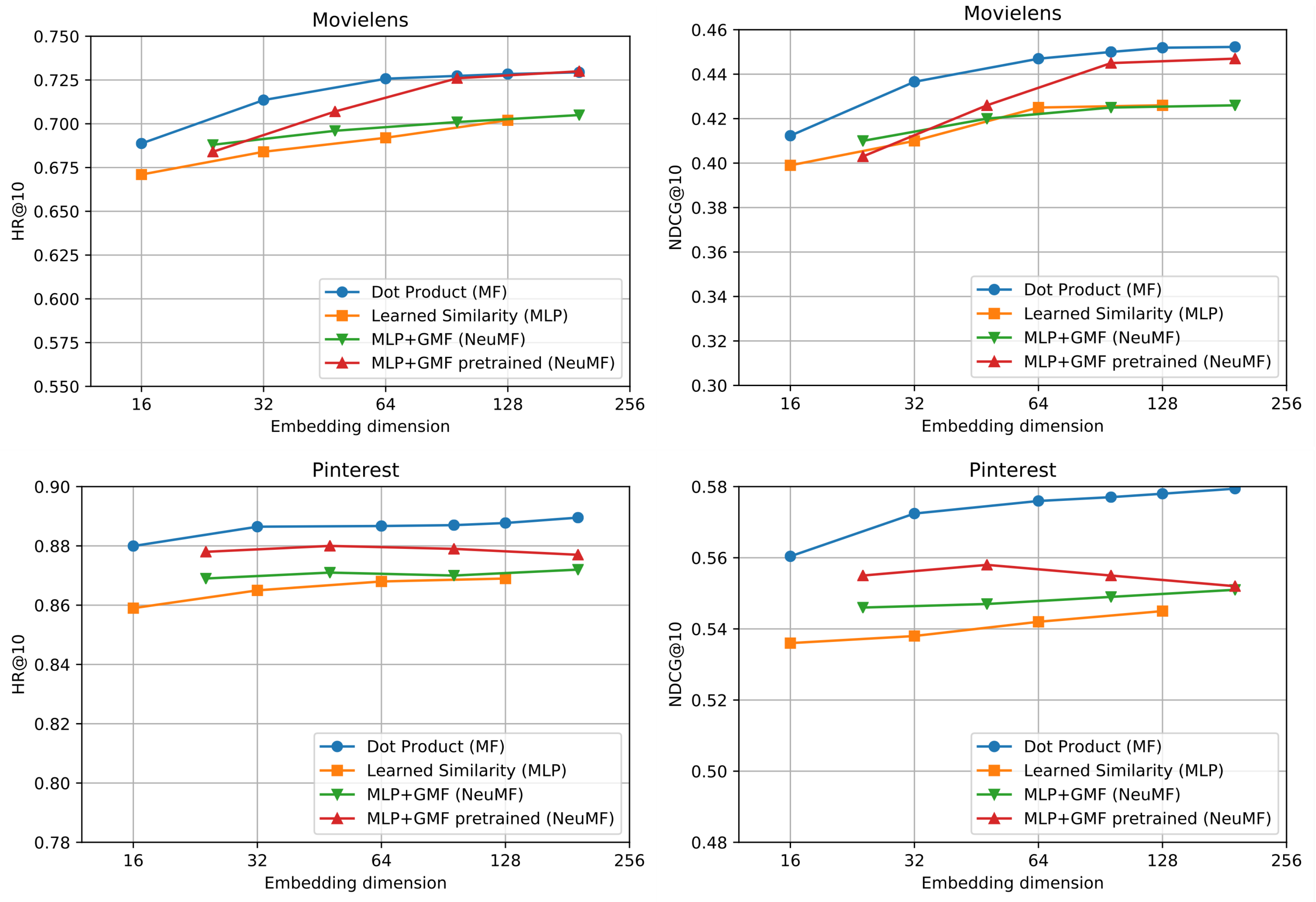
Embedding based models have been the state of the art in collaborative filtering for over a decade. A core operation of most of these embedding based models is to combine two or more embeddings. For example, combining a user embedding with an item embedding to obtain a single score that indicates the preference of the user for the item. This can be viewed as a *similarity function* in the embedding space. Traditionally, a dot product or higher order products have been used for the similarity. Recently, it has become popular to learn the similarity function with a neural network. Most

Performance Revisited

- Motivation: Learning similarity functions (e.g., Neural Collaborative Filtering) has typically been regarded as the de facto standard in academic studies and is considered a strong baseline

- Experimental Setup
  - Follows the Neural Collaborative Filtering paper
  - Datasets: MovieLens 1M and Pinterest
  - Compared Methods: Matrix Factorization (MF) and Neural Collaborative Filtering variants

Results

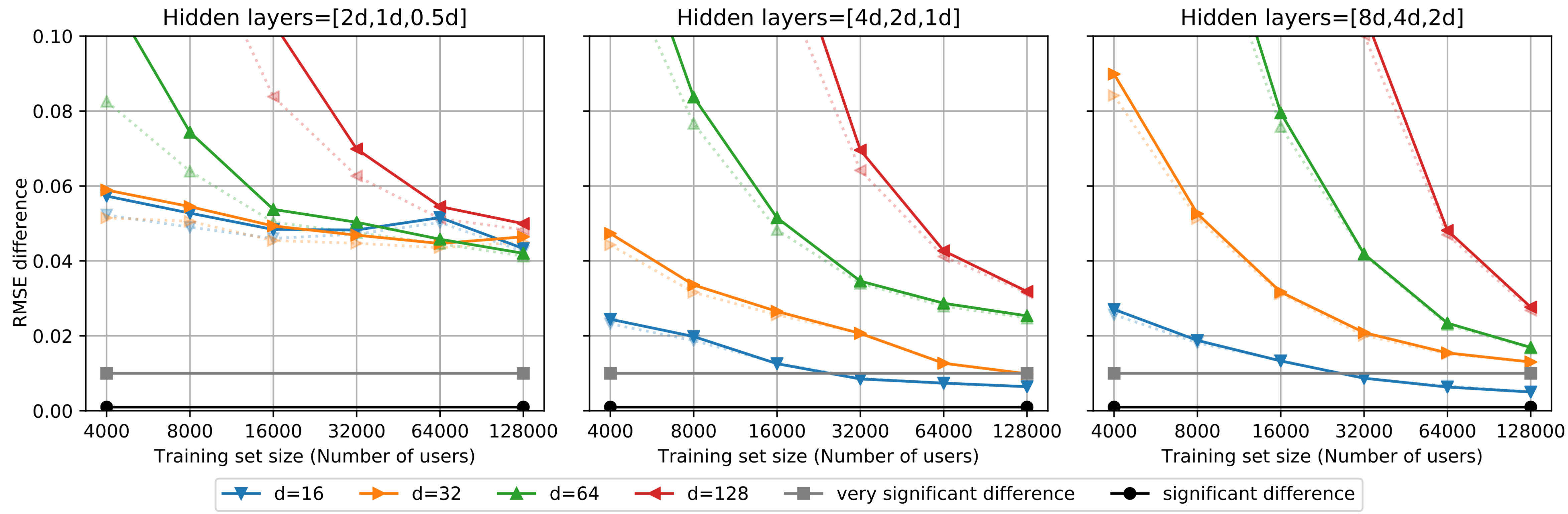


- MF substantially outperforms Neural Collaborative Filtering variants (MLP and NeuMF) on all datasets, evaluation metrics and embedding dimensions.

Why does this happen?

- Why did we believe Neural Collaborative Filtering could be better than MF?
  - Since MLPs can approximate any continuous function under certain conditions (known as the Universal Approximation Theorem), we expect MLPs to capture more complex user-item similarity patterns than a simple inner product
- But how much training data does Neural Collaborative Filtering need to capture complex user-item similarity patterns?
- Let's further simplify the learning problem: how much training data does Neural Collaborative Filtering need to capture even the simple inner product similarity?

MLPs require massive data even to learn an inner product!

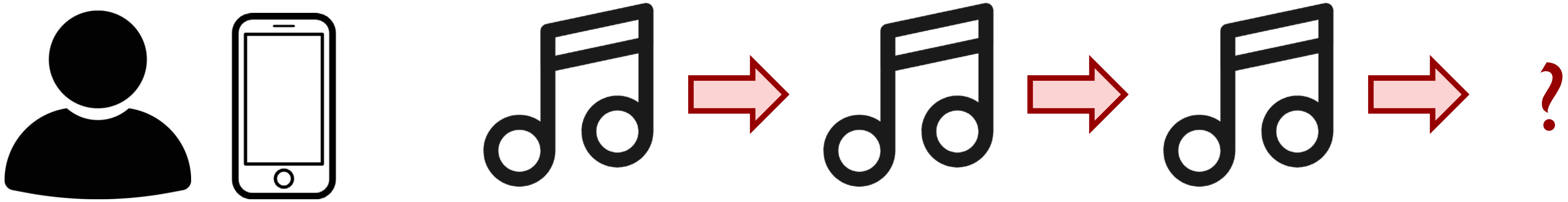


- As models become more complex, we need more training data (for example, the entire Wikipedia and BookCorpus used for BERT). However, in recommender systems, we rarely have access to such large amounts of data.

Sequential Recommendation

We are adding streaming to our record store!

- What is the next track to stream to a user?



We are adding streaming to our record store!

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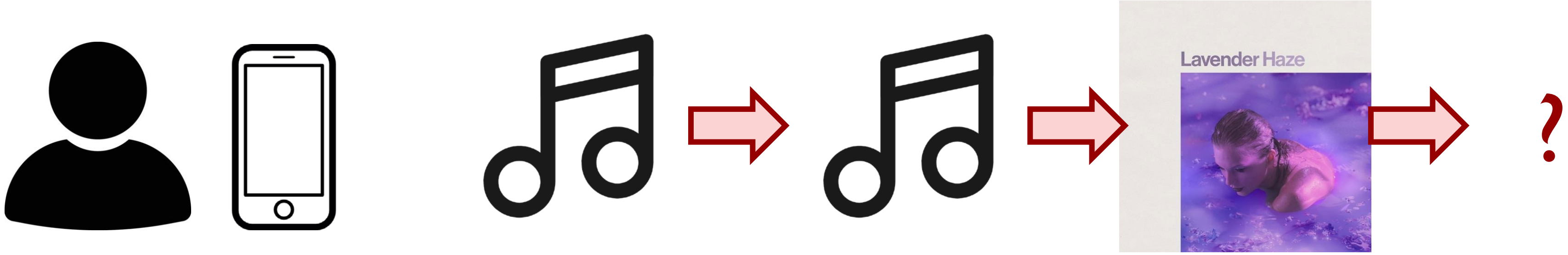


- Our user just listened to Taylor Swift's *Lavender Haze*
  - What should we do next?
  - Play more songs by Taylor Swift?
  - Play more color-themed songs?
  - Play more modern pop songs?
  - Play it again?

- Question 1: What do these options have in common?
- Question 2: What other factors should I consider in choosing among these options?

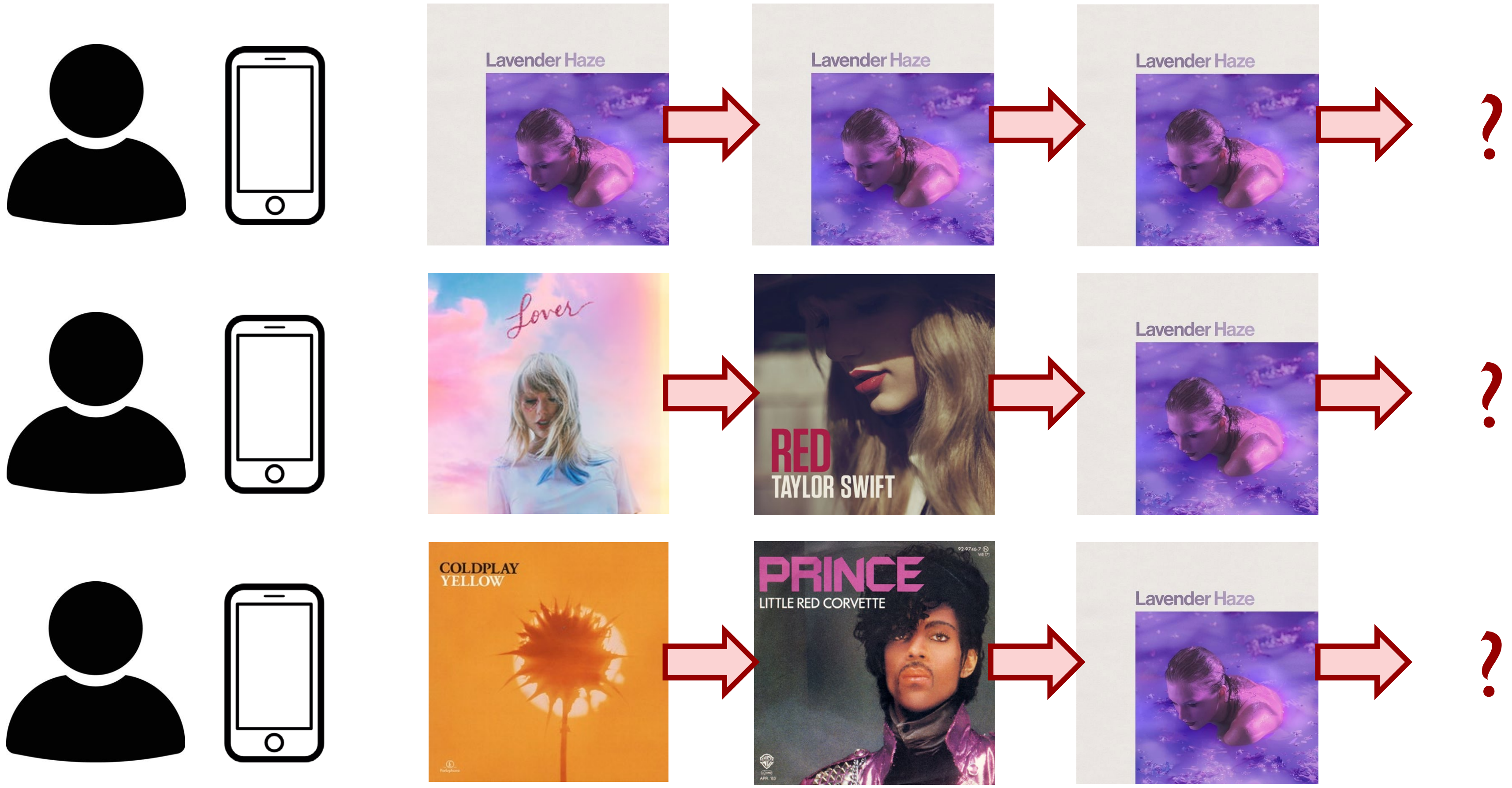
What RecSys techniques have we already learned?

- Content-Based Approach: Recommend items that are similar to those previously viewed
  - Here, the definition of similarity is based on attributes (e.g., lyrics)
- Item-Item Collaborative Filtering: Given a candidate item, first identify its similar items, and then check whether the user has viewed any of them
  - Here, the definition of similarity is based on the columns corresponding to the two items in the user-item matrix
- Matrix Factorization: Find the item in the embedding space that are closest to the user and have not yet been viewed
  - A user's embedding should be close to the embeddings of the items they have already viewed
- Neural Collaborative Filtering: More sophisticated similarity computation methods, but still based on embeddings

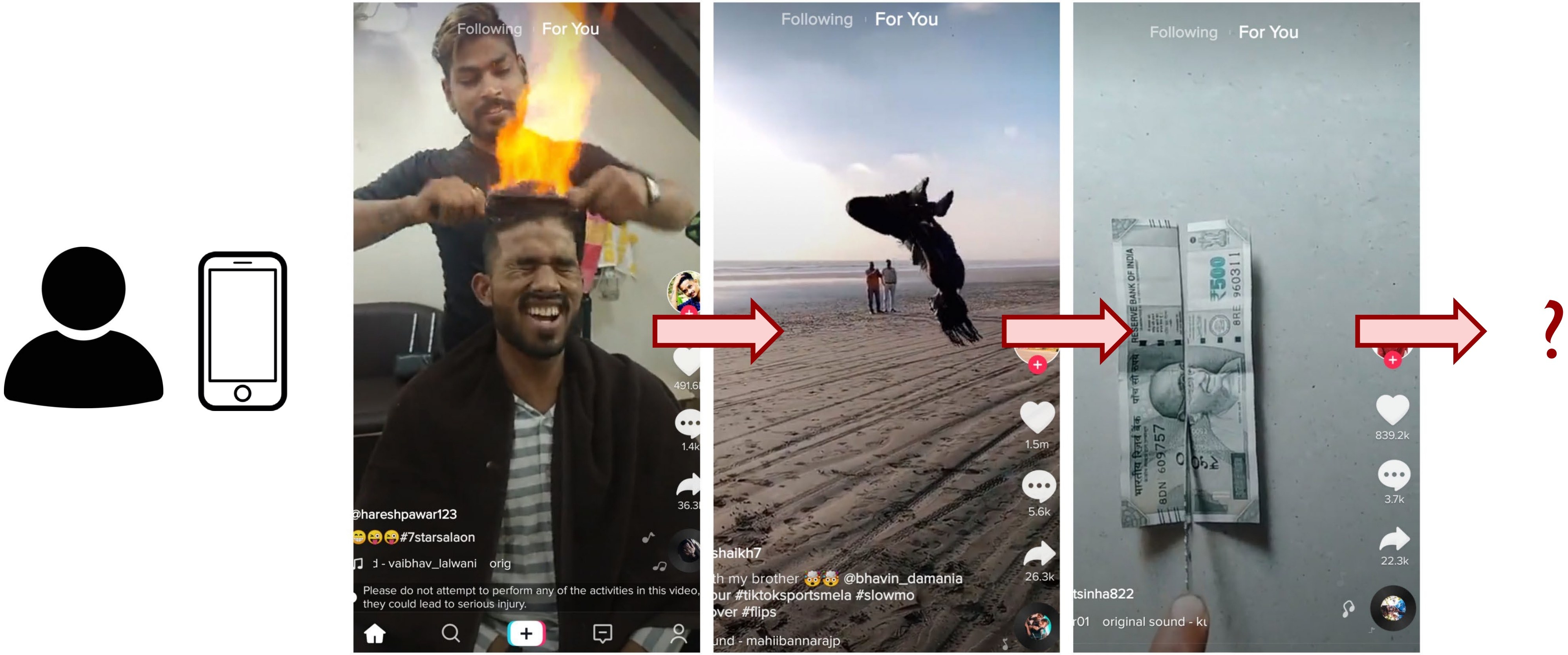
- Summary: Find items similar to those a user has already viewed. The only difference lies in how similarity is defined

What are we missing?

- Understanding dynamic user intent from sequential interactions

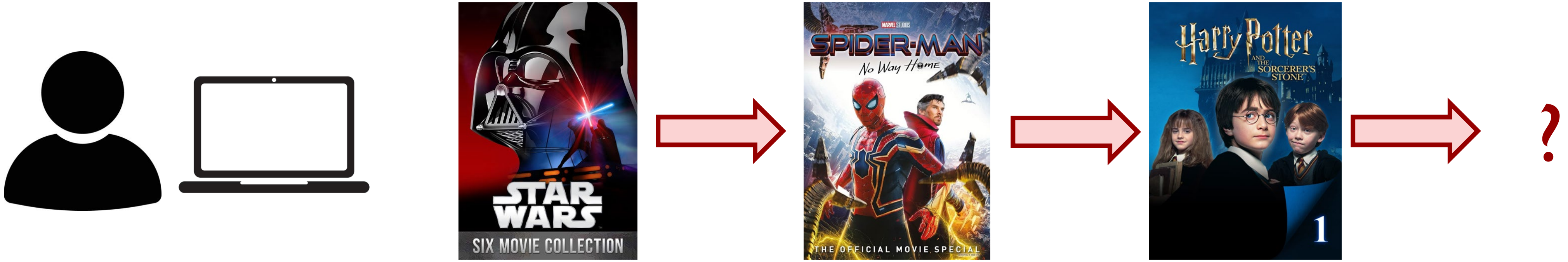


Other Sequential RecSys Examples: TikTok



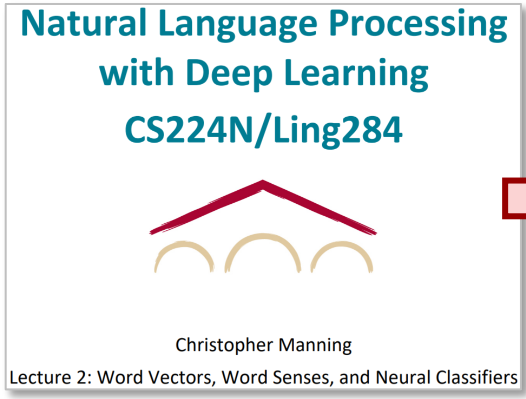
Please do not attempt to perform any of the activities in this video, they could lead to serious injury.

Other Sequential RecSys Examples: Netflix



- For certain products, the order can be crucial!
  - [movies and books] Suppose I just watched *Harry Potter 2*. Would it make sense to recommend *Harry Potter 1*?
  - [lecture videos] Suppose I just watched the video for Lecture 3 of Stanford's CS224N. Would it make sense to recommend the video for Lecture 2?
  - [electronic devices] Suppose I just bought an iPhone XR. Would it make sense to recommend an iPhone 8?

Other Sequential RecSys Examples: YouTube and Amazon

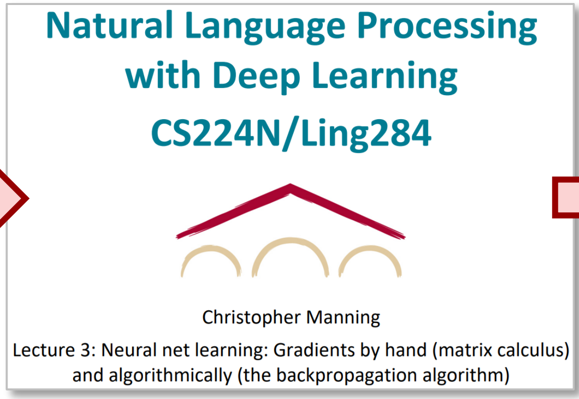


Natural Language Processing with Deep Learning

CS224N/Ling284

Christopher Manning

Lecture 2: Word Vectors, Word Senses, and Neural Classifiers



Natural Language Processing with Deep Learning

CS224N/Ling284

Christopher Manning

Lecture 3: Neural net learning: Gradients by hand (matrix calculus) and algorithmically (the backpropagation algorithm)

?

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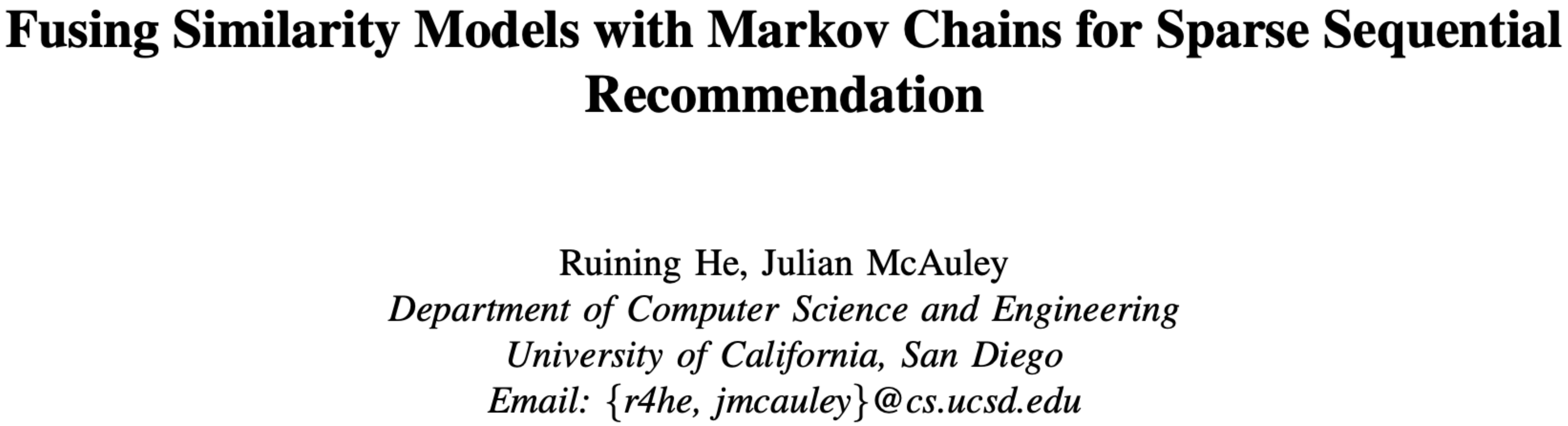
What are we missing?

- Embedding similarity is symmetric.
    - If the user has just viewed item i, whether the model will recommend item j as the next item fully depends on $\text{score}(i, j) = \boldsymbol{e}_i^T \boldsymbol{e}_j$ or $\cos(\boldsymbol{e}_i, \boldsymbol{e}_j)$
    - If the user has just viewed item j, whether the model will recommend item i as the next item fully depends on $\text{score}(j, i) = \text{score}(i, j)$
- Sequential recommendation is asymmetric.
    - When your model recommends item j as the next item after item i, it does NOT necessarily mean that i should be recommended as the next item after j.
    - We should model something like $\text{score}(j \mid i) \neq \text{score}(i \mid j)$

Transition matrix is asymmetric!

Fossil [He and McAuley, ICDM 2016]



Fusing Similarity Models with Markov Chains for Sparse Sequential Recommendation

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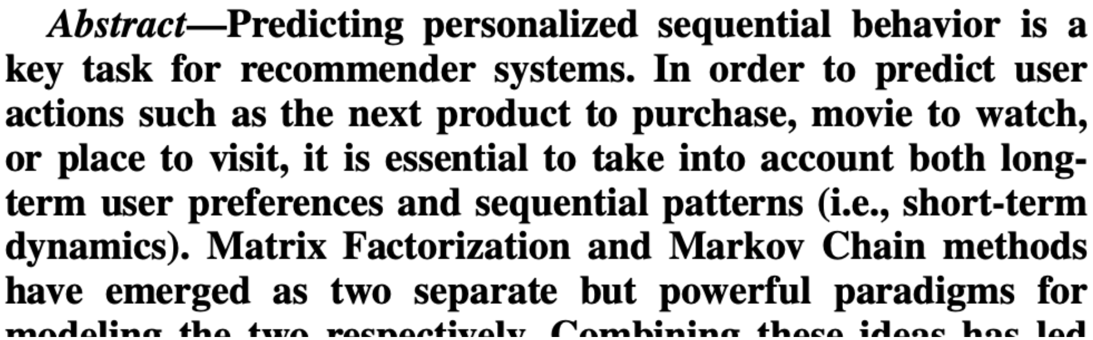
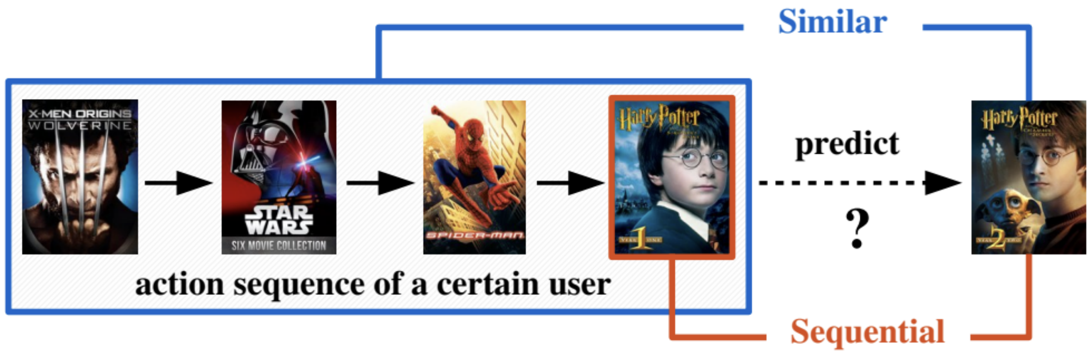
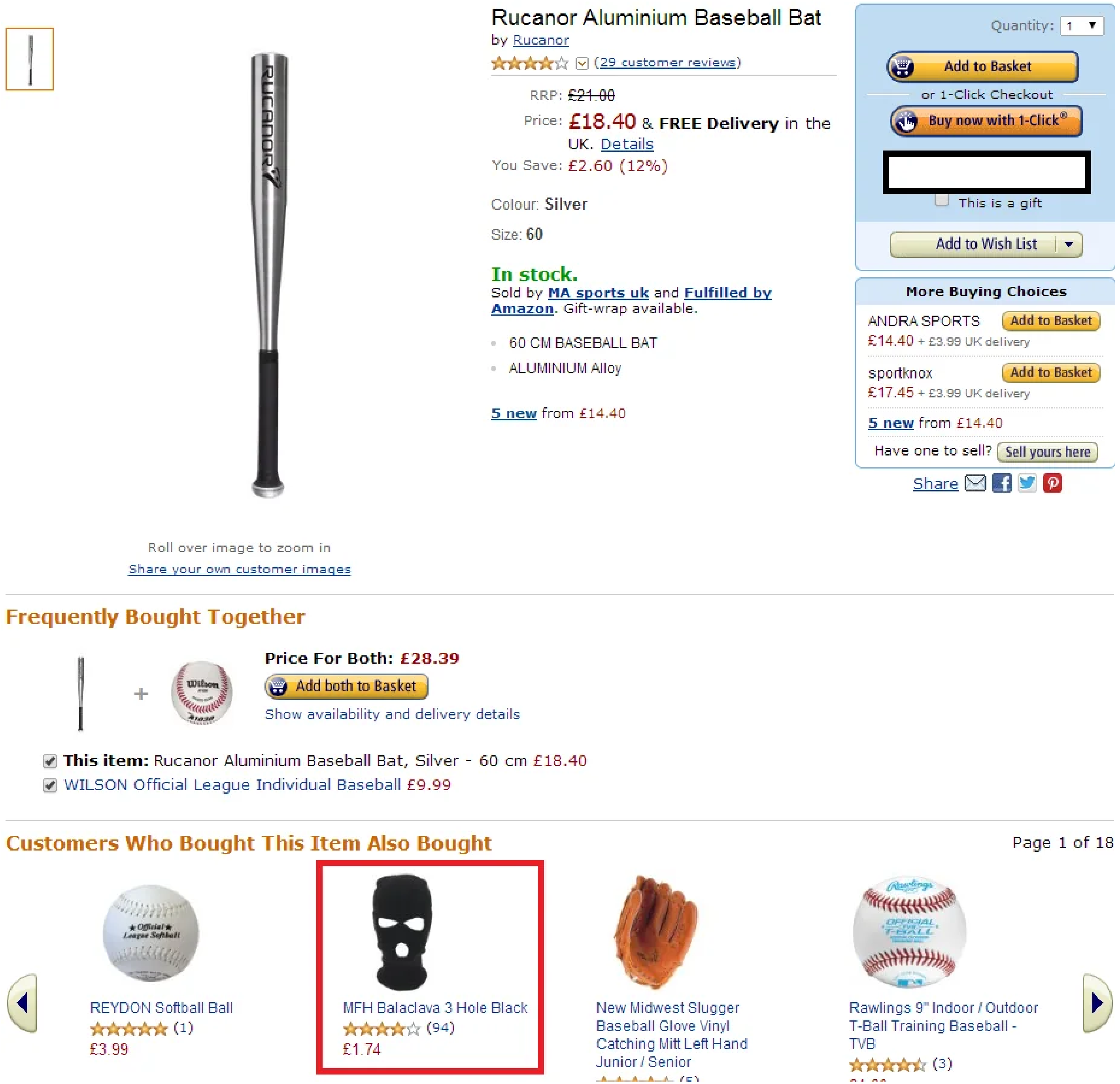


***Abstract*—Predicting personalized sequential behavior is a key task for recommender systems. In order to predict user actions such as the next product to purchase, movie to watch, or place to visit, it is essential to take into account both long-term user preferences and sequential patterns (i.e., short-term dynamics). Matrix Factorization and Markov Chain methods have emerged as two separate but powerful paradigms for modeling the two respectively. Combining these ideas has led**





Rucanor Aluminium Baseball Bat

by Rucanor

★★★★☆ (29 customer reviews)

RRP: ~~£21.00~~

Price: £18.40 & FREE Delivery in the UK. Details

You Save: £2.60 (12%)

Colour: Silver

Size: 60

In stock.

Sold by MA sports uk and Fulfilled by Amazon. Gift-wrap available.

- 60 CM BASEBALL BAT
- ALUMINIUM Alloy

5 new from £14.40

Roll over image to zoom in

Share your own customer images

More Buying Choices

ANDRA SPORTS	£14.40 + £3.99 UK delivery	Add to Basket
sportknox	£17.45 + £3.99 UK delivery	Add to Basket

5 new from £14.40

Have one to sell? Sell yours here

Share

Frequently Bought Together

Price For Both: £28.39

Add both to Basket

Show availability and delivery details

☑ **This item:** Rucanor Aluminium Baseball Bat, Silver - 60 cm £18.40

☑ WILSON Official League Individual Baseball £9.99

Customers Who Bought This Item Also Bought

Page 1 of 18

REYDON Softball Ball ★★★★★ (1) £3.99

MFH Balaclava 3 Hole Black ★★★★☆ (94) £1.74

New Midwest Slugger Baseball Glove Vinyl Catching Mitt Left Hand Junior / Senior

Rawlings 9" Indoor / Outdoor T-Ball Training Baseball - TVB ★★★★☆ (3)

- Predict a user's next step based on the next-step behavior patterns of the overall population
- Amazon's "*Customer Who Bought This Item Also Bought*"

Markov Chain to Model Sequential Dynamics

- Historical user-item interactions

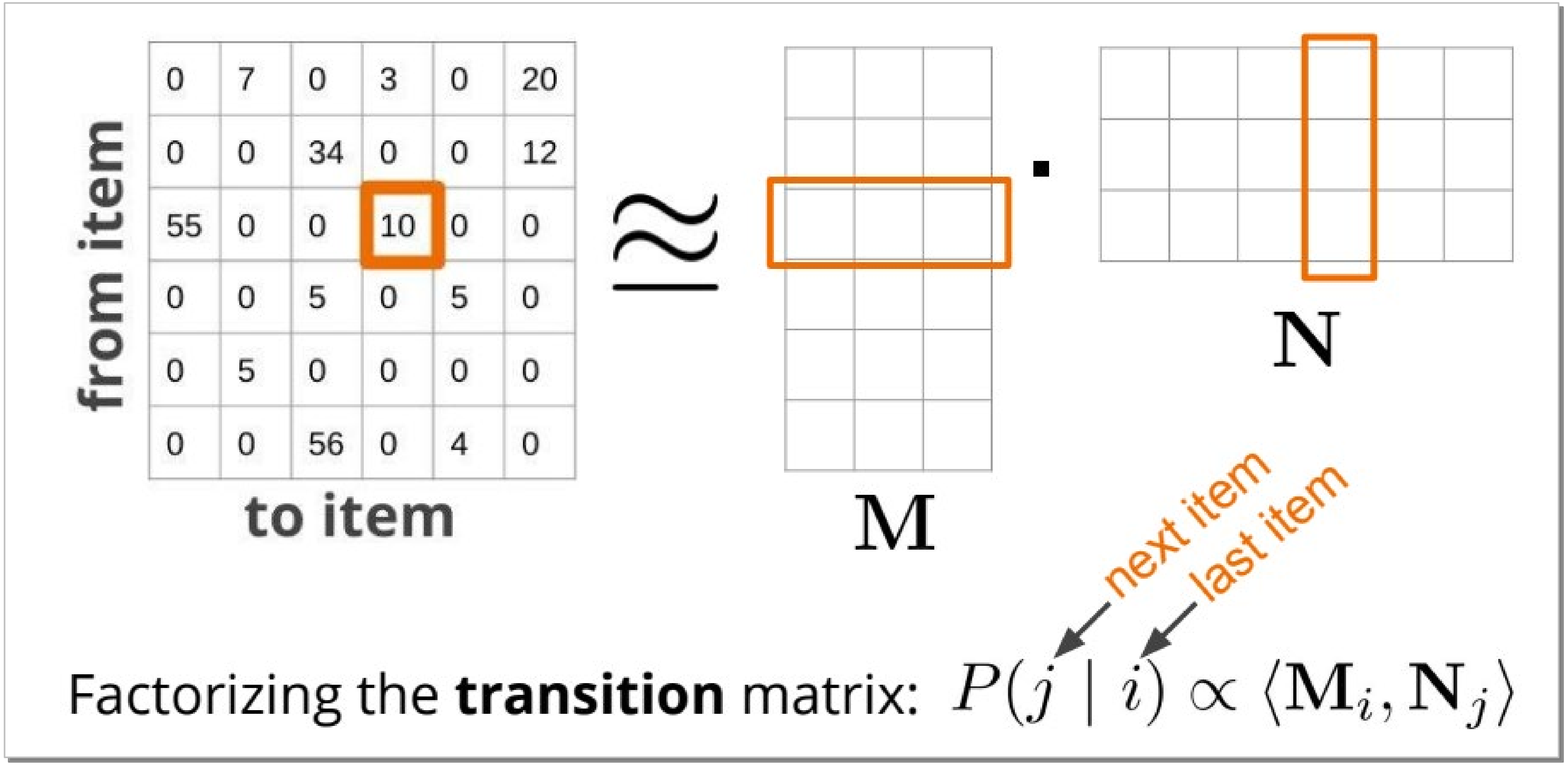
User								
$u1$	$\rightarrow$	$i1$	$\rightarrow$	$i2$	$\rightarrow$	$i4$		
$u2$	$\rightarrow$	$i3$	$\rightarrow$	$i4$				
$u3$	$\rightarrow$	$i1$	$\rightarrow$	$i2$	$\rightarrow$	$i4$	$\rightarrow$	$i3$
$u4$	$\rightarrow$	$i3$	$\rightarrow$	$i1$	$\rightarrow$	$i2$		

- Step 1: Construct a transition matrix

	$i1$	$i2$	$i3$	$i4$
$i1$	0	3	0	0
$i2$	0	0	0	2
$i3$	1	0	0	1
$i4$	0	0	1	0

Markov Chain to Model Sequential Dynamics

- Step 2: Factorize the transition matrix



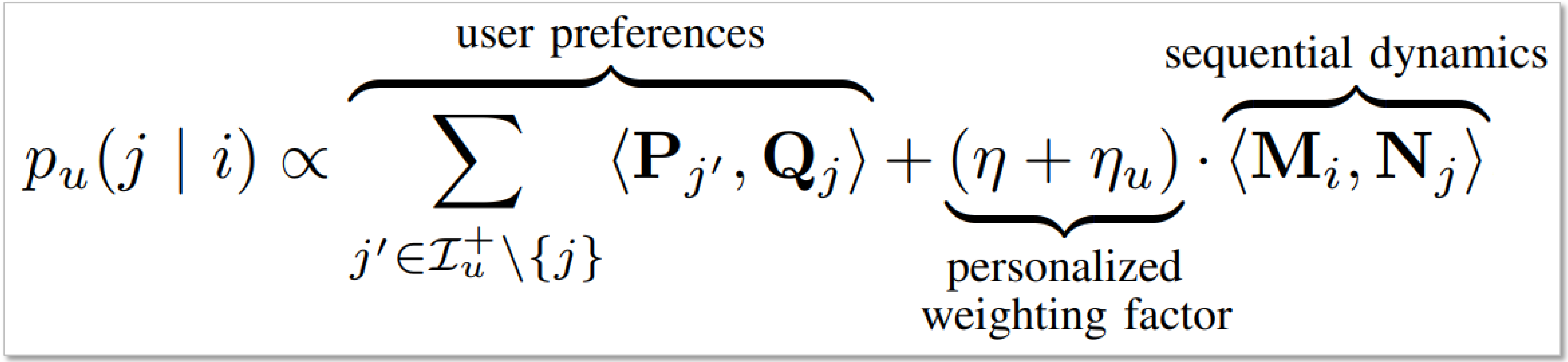
0	7	0	3	0	20
0	0	34	0	0	12
55	0	0	10	0	0
0	0	5	0	5	0
0	5	0	0	0	0
0	0	56	0	4	0

Factorizing the **transition** matrix: $P(j \mid i) \propto \langle \mathbf{M}_i, \mathbf{N}_j \rangle$

Markov Chain to Model Sequential Dynamics

- Problems with this approach?
  - NOT personalized!
  - Regardless of which user the model is considering, $\mathrm{score}(j \mid i) \propto \boldsymbol{M}_i^T \boldsymbol{N}_j$
  - But $\boldsymbol{M}_i$ and $\boldsymbol{N}_j$ are the same for all users

- How to make the model personalized?



$$p_u(j \mid i) \propto \overbrace{\sum_{j' \in \mathcal{I}_u^+ \setminus \{j\}} \langle \mathbf{P}_{j'}, \mathbf{Q}_j \rangle}^{\text{user preferences}} + \underbrace{(\eta + \eta_u)}_{\substack{\text{personalized} \\ \text{weighting factor}}} \cdot \overbrace{\langle \mathbf{M}_i, \mathbf{N}_j \rangle}^{\text{sequential dynamics}}$$

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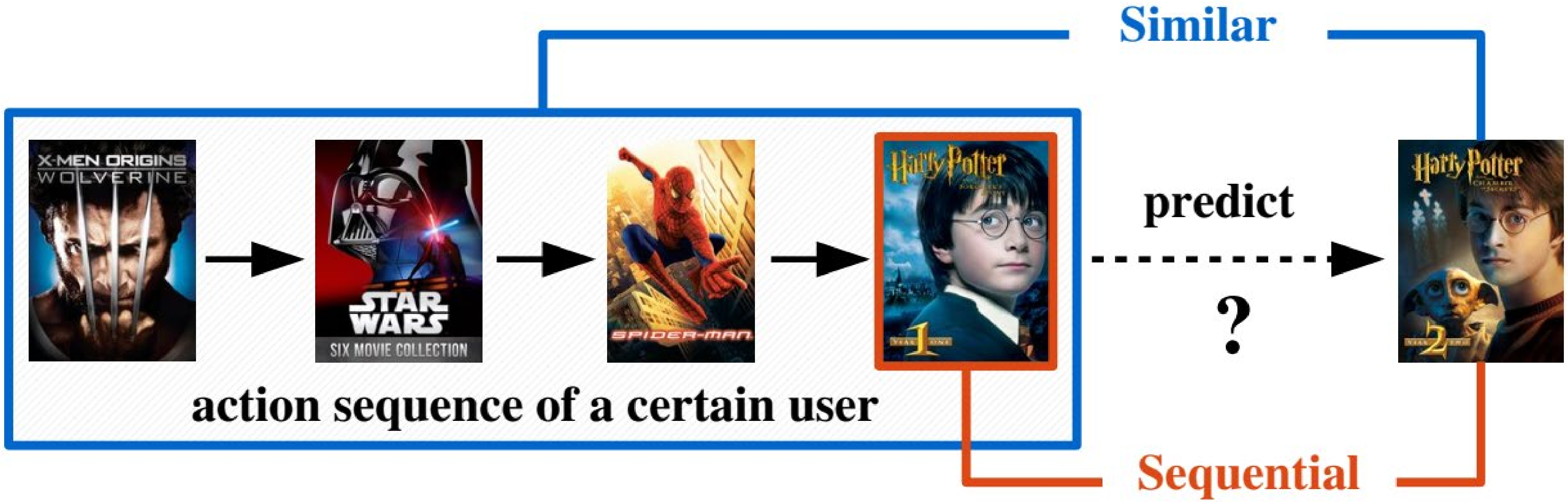
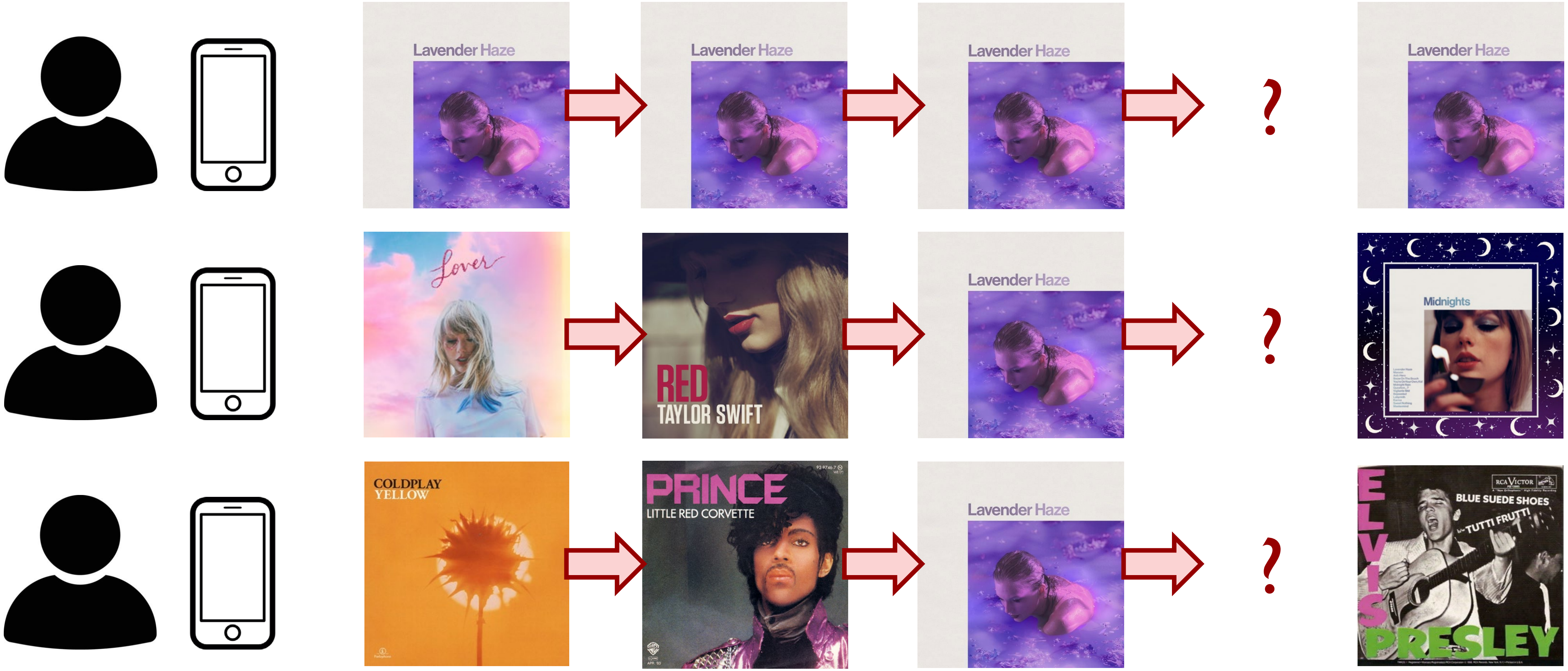


Back to Motivating Example

- Play *Lavender Haze* again? Play more songs by Taylor Swift? Play more color-themed songs?
    - Might all be likely according to the transition matrix. But if you consider user preference …



Higher-Order Markov Chain

User								
$u1$	→	$i1$	→	$i2$	→	$i4$		
$u2$	→	$i3$	→	$i4$				
$u3$	→	$i1$	→	$i2$	→	$i4$	→	$i3$
$u4$	→	$i3$	→	$i1$	→	$i2$		

- Transition matrix:

	$i1$	$i2$	$i3$	$i4$
$i1 \rightarrow i2$	0	0	0	2
$i1 \rightarrow i3$	0	0	0	0
$i1 \rightarrow i4$	0	0	0	0
$i2 \rightarrow i1$	0	0	0	0
…	…	…	…	…

- Sparse
- # of rows increases exponentially with the order of the Markov chain
- Similar to the n-gram language model
- Can we use a neural language model to alleviate sparsity?

Performance

- Fossil outperforms BPR-MF (and other static baselines) because it models sequential dynamics
- Small orders seem to be enough to achieve good performance

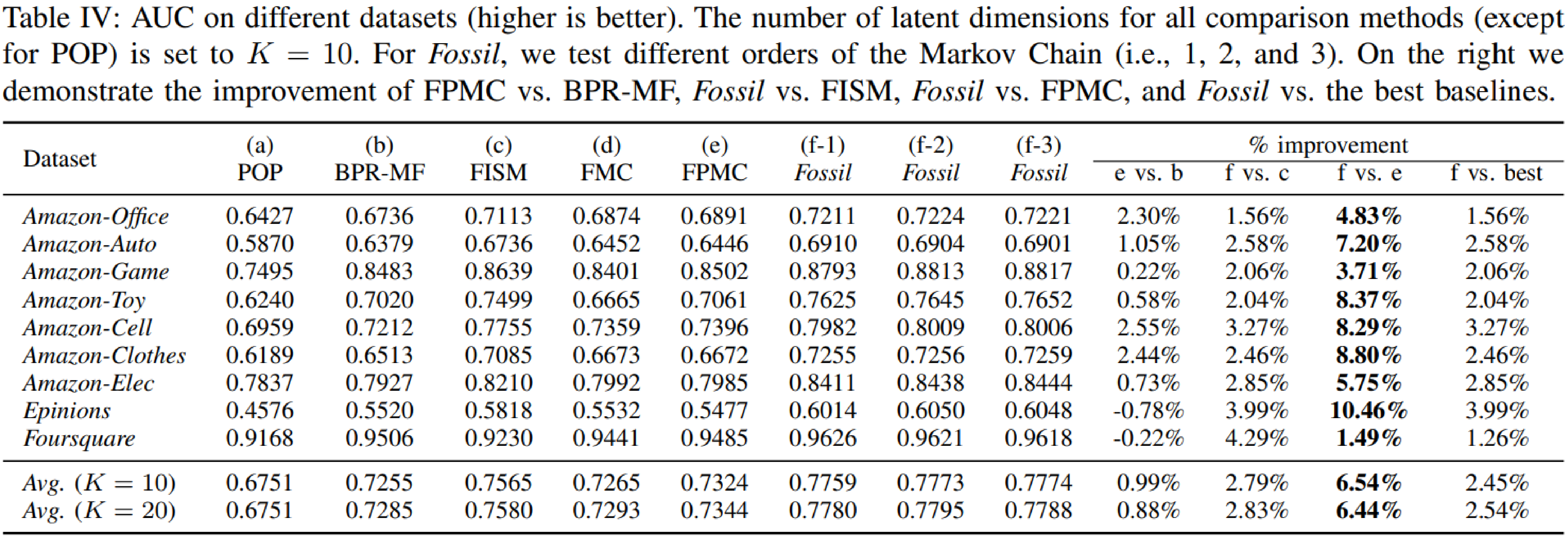
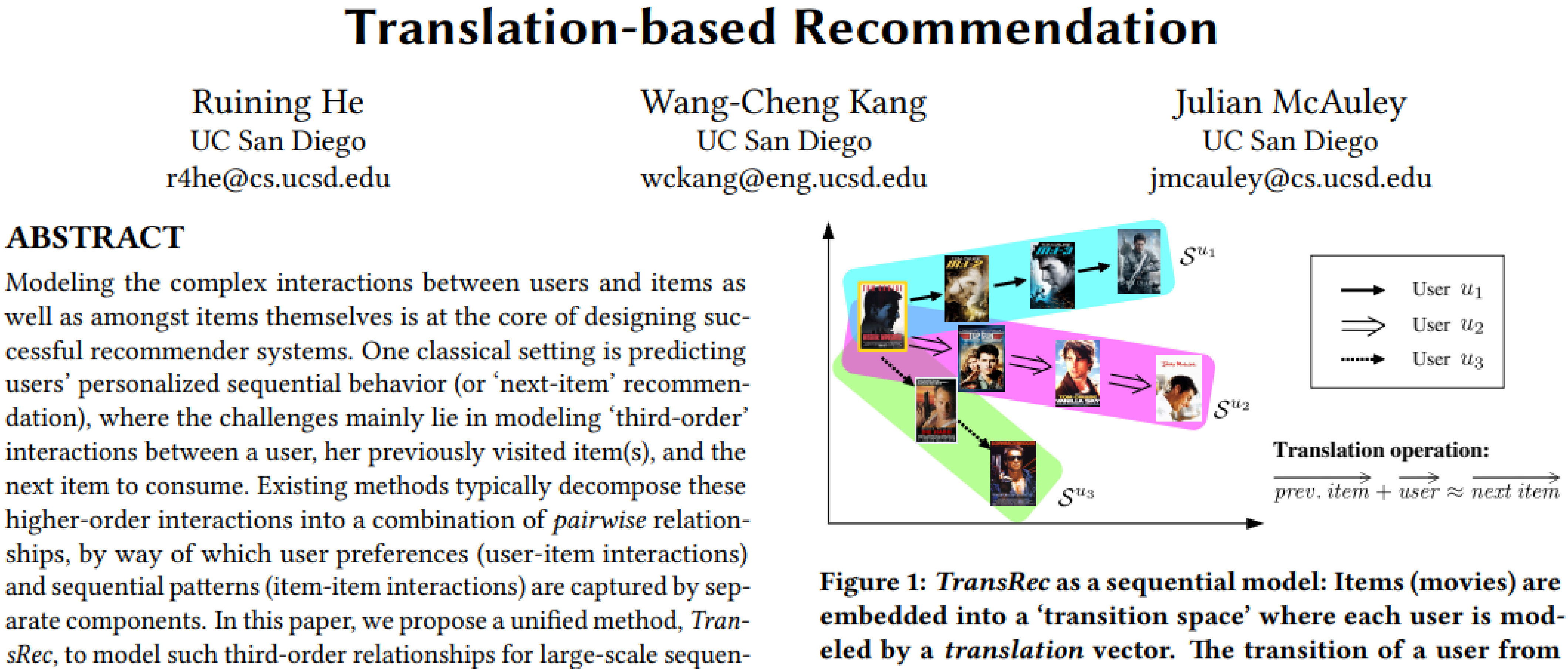


Table IV: AUC on different datasets (higher is better). The number of latent dimensions for all comparison methods (except for POP) is set to $K = 10$. For *Fossil*, we test different orders of the Markov Chain (i.e., 1, 2, and 3). On the right we demonstrate the improvement of FPMC vs. BPR-MF, *Fossil* vs. FISM, *Fossil* vs. FPMC, and *Fossil* vs. the best baselines.

Dataset	(a)	(b)	(c)	(d)	(e)	(f-1)	(f-2)	(f-3)	% improvement			
	POP	BPR-MF	FISM	FMC	FPMC	*Fossil*	*Fossil*	*Fossil*	e vs. b	f vs. c	f vs. e	f vs. best
Amazon-Office	0.6427	0.6736	0.7113	0.6874	0.6891	0.7211	0.7224	0.7221	2.30%	1.56%	**4.83%**	1.56%
Amazon-Auto	0.5870	0.6379	0.6736	0.6452	0.6446	0.6910	0.6904	0.6901	1.05%	2.58%	**7.20%**	2.58%
Amazon-Game	0.7495	0.8483	0.8639	0.8401	0.8502	0.8793	0.8813	0.8817	0.22%	2.06%	**3.71%**	2.06%
Amazon-Toy	0.6240	0.7020	0.7499	0.6665	0.7061	0.7625	0.7645	0.7652	0.58%	2.04%	**8.37%**	2.04%
Amazon-Cell	0.6959	0.7212	0.7755	0.7359	0.7396	0.7982	0.8009	0.8006	2.55%	3.27%	**8.29%**	3.27%
Amazon-Clothes	0.6189	0.6513	0.7085	0.6673	0.6672	0.7255	0.7256	0.7259	2.44%	2.46%	**8.80%**	2.46%
Amazon-Elec	0.7837	0.7927	0.8210	0.7992	0.7985	0.8411	0.8438	0.8444	0.73%	2.85%	**5.75%**	2.85%
Epinions	0.4576	0.5520	0.5818	0.5532	0.5477	0.6014	0.6050	0.6048	-0.78%	3.99%	**10.46%**	3.99%
Foursquare	0.9168	0.9506	0.9230	0.9441	0.9485	0.9626	0.9621	0.9618	-0.22%	4.29%	**1.49%**	1.26%
Avg. ($K = 10$)	0.6751	0.7255	0.7565	0.7265	0.7324	0.7759	0.7773	0.7774	0.99%	2.79%	**6.54%**	2.45%
Avg. ($K = 20$)	0.6751	0.7285	0.7580	0.7293	0.7344	0.7780	0.7795	0.7788	0.88%	2.83%	**6.44%**	2.54%

Translation is asymmetric!

TransRec [He et al., RecSys 2017]



Translation-based Recommendation

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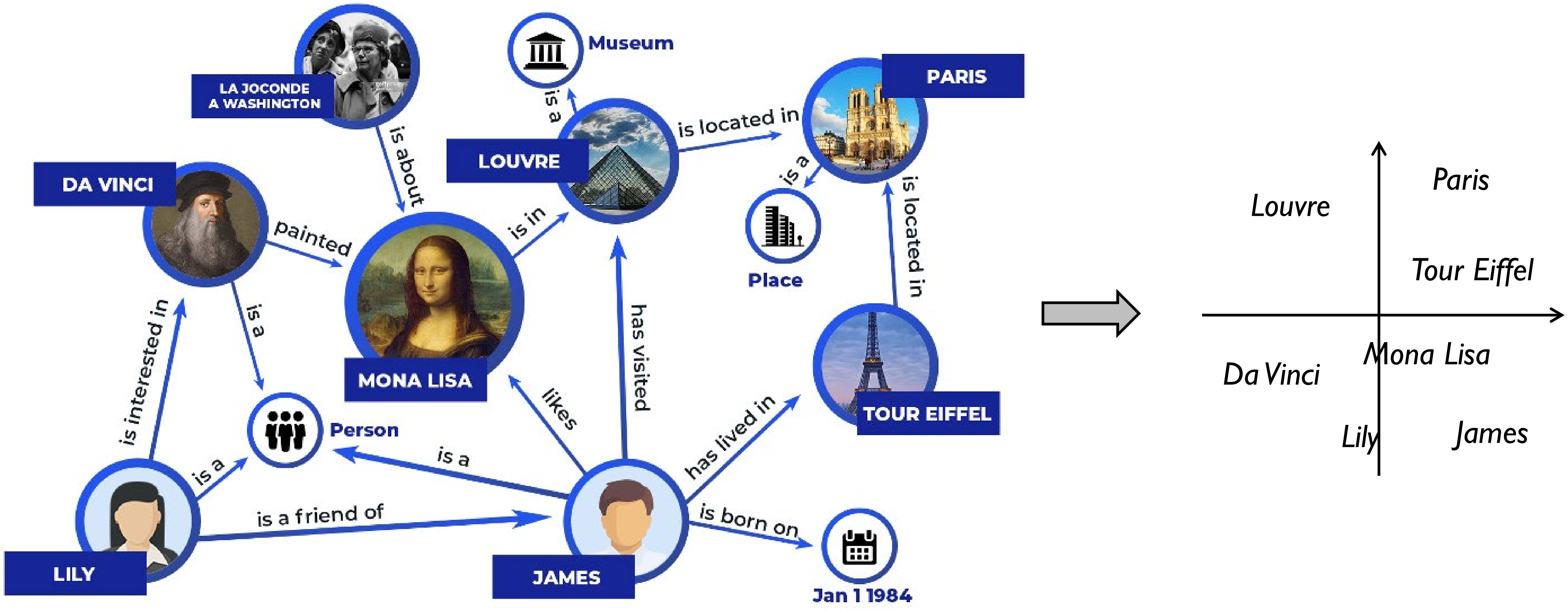
ABSTRACT

Modeling the complex interactions between users and items as well as amongst items themselves is at the core of designing successful recommender systems. One classical setting is predicting users' personalized sequential behavior (or 'next-item' recommendation), where the challenges mainly lie in modeling 'third-order' interactions between a user, her previously visited item(s), and the next item to consume. Existing methods typically decompose these higher-order interactions into a combination of *pairwise* relationships, by way of which user preferences (user-item interactions) and sequential patterns (item-item interactions) are captured by separate components. In this paper, we propose a unified method, *TransRec*, to model such third-order relationships for large-scale sequen-

Figure 1: *TransRec* as a sequential model: Items (movies) are embedded into a 'transition space' where each user is modeled by a *translation* vector. The transition of a user from

Background: Translation-Based Embedding

- You have a knowledge graph, and you want to embed all the nodes into a vector space



Background: Translation-Based Embedding

- Each edge can be represented as a triplet (h, r, t)

head entity h	relation r	tail entity t
Tour Eiffel	is located in	*Paris*
Da Vinci	painted	*Mona Lisa*
Lily	is a friend of	*James*
…	…	…

- A simple (but suboptimal) solution: Each node should be close to its neighbors

$$\max_{\boldsymbol{e}_h, \boldsymbol{e}_t} \sum_{(h,r,t)\in\mathcal{G}} \frac{\exp(\boldsymbol{e}_h^T \boldsymbol{e}_t)}{\sum_{t'} \exp(\boldsymbol{e}_h^T \boldsymbol{e}_{t'})}$$

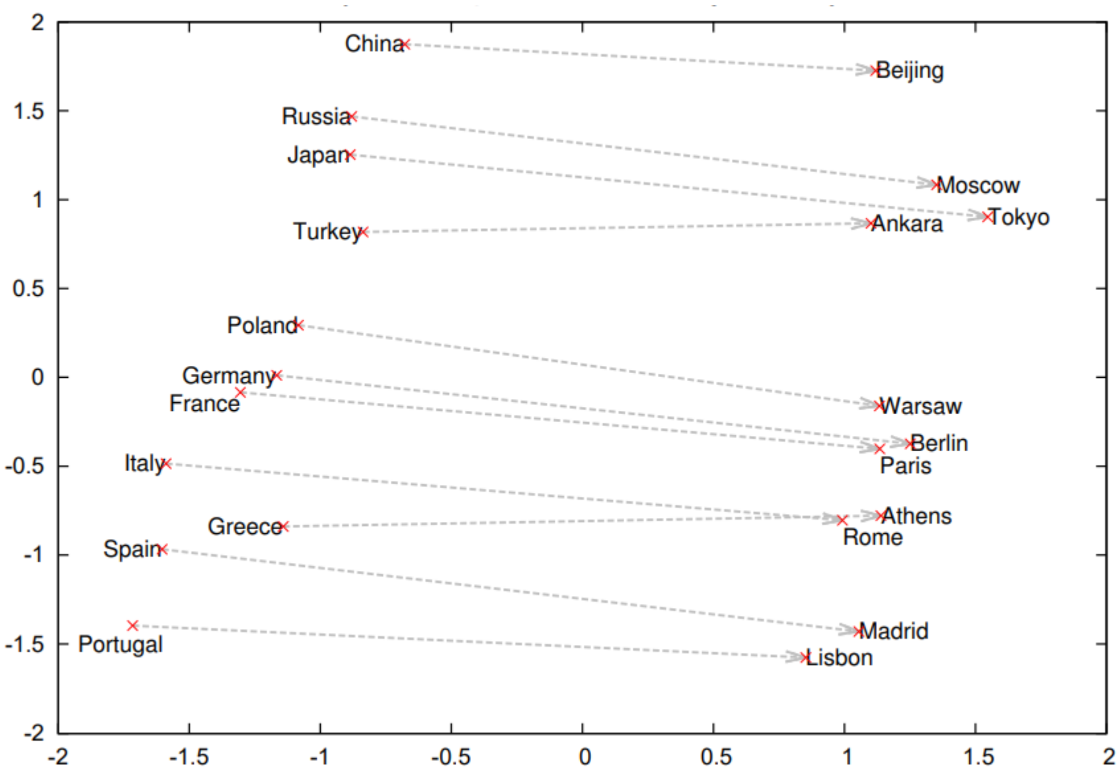
  - Limitation: It ignores different relations

TransE [Bordes et al., NIPS 2013]

- Idea: Model relations as translations

head entity h	relation r	tail entity t
Paris	is capital of	*France*

$$e_h + e_r \approx e_t$$



TransE [Bordes et al., NIPS 2013]

- Idea: Model relations as translations
- Training:

head entity h	relation r	tail entity t
Paris	is capital of	*France*

Minimize $\|\boldsymbol{e}_h + \boldsymbol{e}_r - \boldsymbol{e}_t\|$

head entity h	relation r	“corrupted” tail entity t'
Paris	is capital of	*UK*

Maximize $\|\boldsymbol{e}_h + \boldsymbol{e}_r - \boldsymbol{e}_{t'}\|$

(but stop when it becomes sufficiently larger than $\|\boldsymbol{e}_h + \boldsymbol{e}_r - \boldsymbol{e}_t\|$)

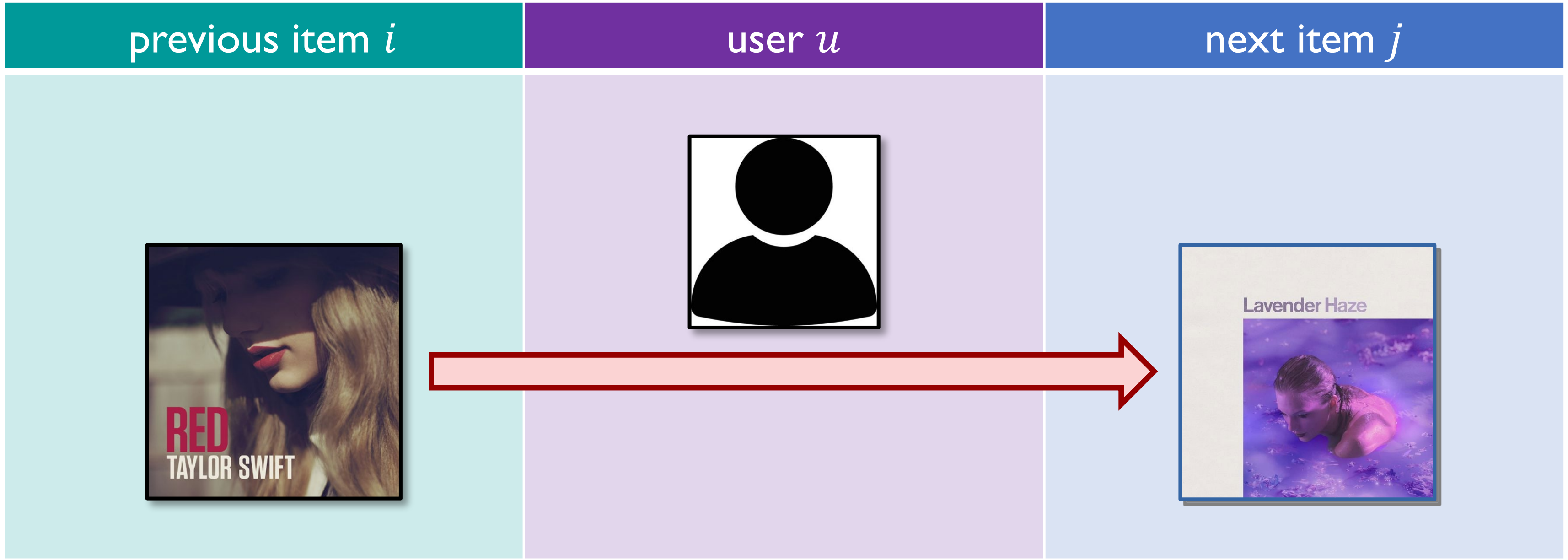
- Testing:

head entity h	relation r	tail entity t
Ottawa	is capital of	*?*

Find the nearest neighbor of $\boldsymbol{e}_h + \boldsymbol{e}_r$

Translation-Based Recommendation

- Items as points
- Users as translational vectors



previous item i

user u

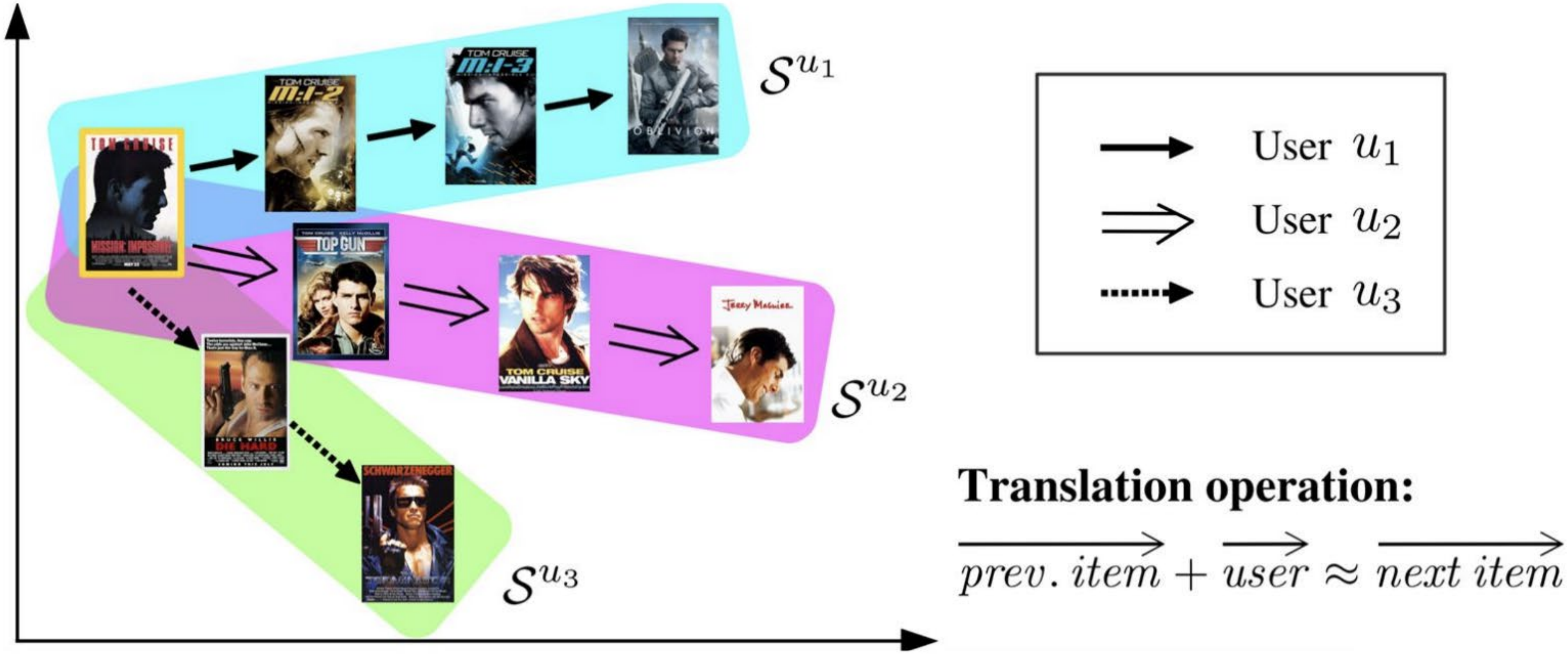
next item j

$$\boldsymbol{e}_i + \boldsymbol{e}_u \approx \boldsymbol{e}_j$$

Translation-Based Recommendation

- Items as points
- Users as translational vectors
  - E.g., the songs progressively become more up-tempo, as the user is at a party
    - $\boldsymbol{e}_u$:“the next song is more up-tempo than the previous song”
  - E.g., the songs gradually become more relaxing, as the user is going to sleep
    - $\boldsymbol{e}_u$:“the next song is more relaxing than the previous song”

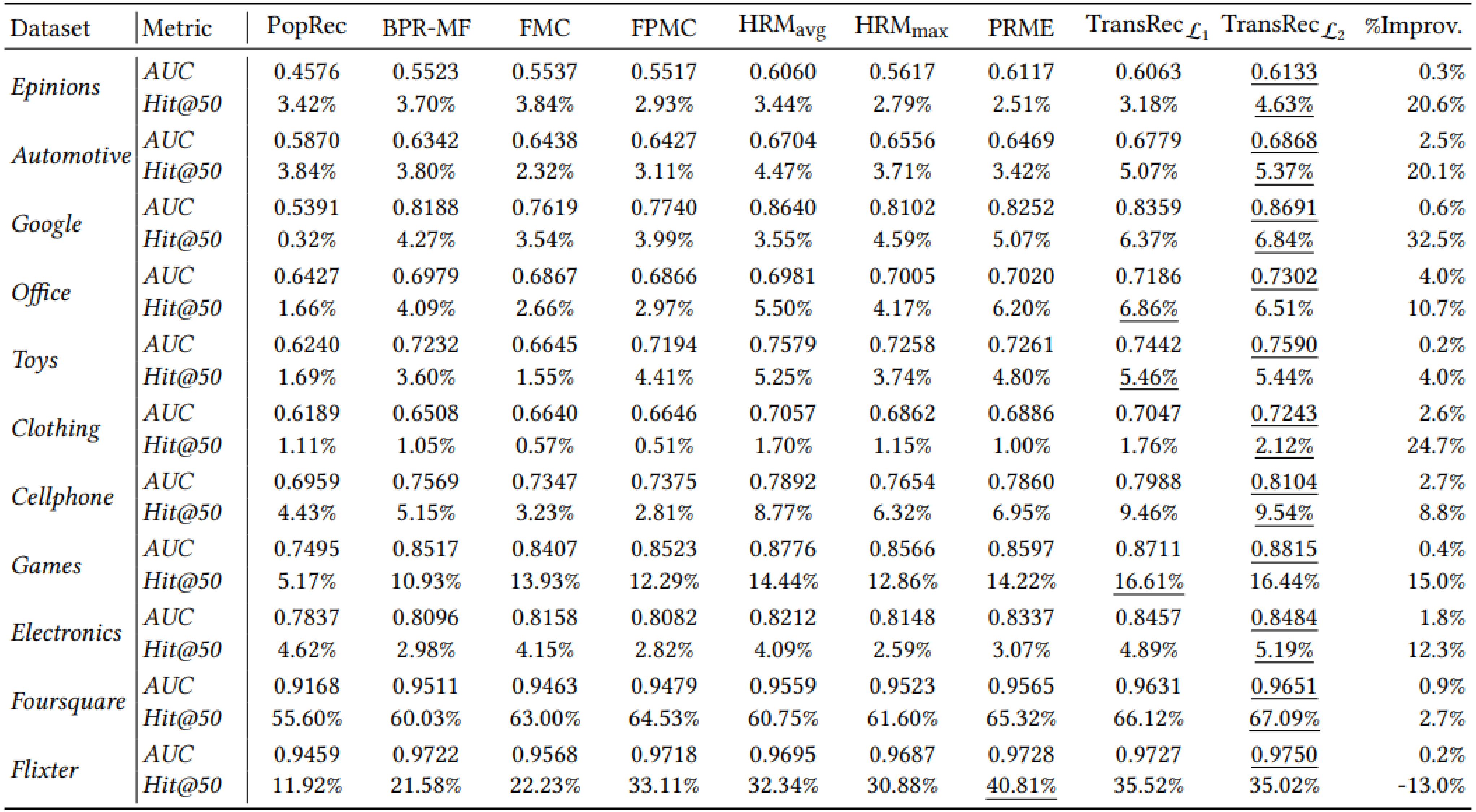
Translation-Based Recommendation



- Testing time: Find the nearest neighbor of $\boldsymbol{e}_i + \boldsymbol{e}_u$

Performance

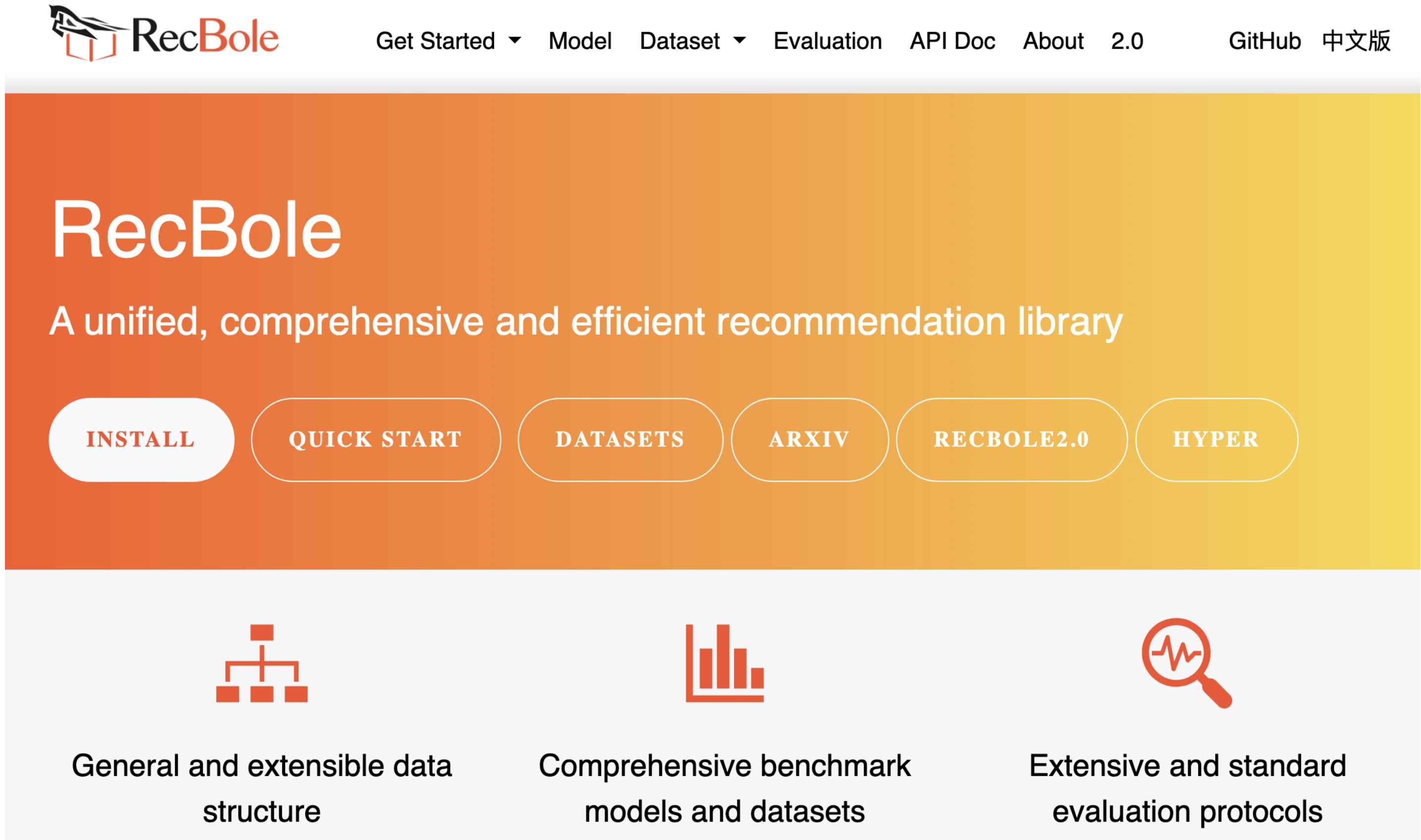
- Outperforms BPR-MF
- No comparisons with Fossil



Dataset	Metric	PopRec	BPR-MF	FMC	FPMC	HRM$_{avg}$	HRM$_{max}$	PRME	TransRec$_{\mathcal{L}_1}$	TransRec$_{\mathcal{L}_2}$	%Improv.
Epinions	*AUC*	0.4576	0.5523	0.5537	0.5517	0.6060	0.5617	0.6117	0.6063	0.6133	0.3%
	Hit@50	3.42%	3.70%	3.84%	2.93%	3.44%	2.79%	2.51%	3.18%	4.63%	20.6%
Automotive	*AUC*	0.5870	0.6342	0.6438	0.6427	0.6704	0.6556	0.6469	0.6779	0.6868	2.5%
	Hit@50	3.84%	3.80%	2.32%	3.11%	4.47%	3.71%	3.42%	5.07%	5.37%	20.1%
Google	*AUC*	0.5391	0.8188	0.7619	0.7740	0.8640	0.8102	0.8252	0.8359	0.8691	0.6%
	Hit@50	0.32%	4.27%	3.54%	3.99%	3.55%	4.59%	5.07%	6.37%	6.84%	32.5%
Office	*AUC*	0.6427	0.6979	0.6867	0.6866	0.6981	0.7005	0.7020	0.7186	0.7302	4.0%
	Hit@50	1.66%	4.09%	2.66%	2.97%	5.50%	4.17%	6.20%	6.86%	6.51%	10.7%
Toys	*AUC*	0.6240	0.7232	0.6645	0.7194	0.7579	0.7258	0.7261	0.7442	0.7590	0.2%
	Hit@50	1.69%	3.60%	1.55%	4.41%	5.25%	3.74%	4.80%	5.46%	5.44%	4.0%
Clothing	*AUC*	0.6189	0.6508	0.6640	0.6646	0.7057	0.6862	0.6886	0.7047	0.7243	2.6%
	Hit@50	1.11%	1.05%	0.57%	0.51%	1.70%	1.15%	1.00%	1.76%	2.12%	24.7%
Cellphone	*AUC*	0.6959	0.7569	0.7347	0.7375	0.7892	0.7654	0.7860	0.7988	0.8104	2.7%
	Hit@50	4.43%	5.15%	3.23%	2.81%	8.77%	6.32%	6.95%	9.46%	9.54%	8.8%
Games	*AUC*	0.7495	0.8517	0.8407	0.8523	0.8776	0.8566	0.8597	0.8711	0.8815	0.4%
	Hit@50	5.17%	10.93%	13.93%	12.29%	14.44%	12.86%	14.22%	16.61%	16.44%	15.0%
Electronics	*AUC*	0.7837	0.8096	0.8158	0.8082	0.8212	0.8148	0.8337	0.8457	0.8484	1.8%
	Hit@50	4.62%	2.98%	4.15%	2.82%	4.09%	2.59%	3.07%	4.89%	5.19%	12.3%
Foursquare	*AUC*	0.9168	0.9511	0.9463	0.9479	0.9559	0.9523	0.9565	0.9631	0.9651	0.9%
	Hit@50	55.60%	60.03%	63.00%	64.53%	60.75%	61.60%	65.32%	66.12%	67.09%	2.7%
Flixter	*AUC*	0.9459	0.9722	0.9568	0.9718	0.9695	0.9687	0.9728	0.9727	0.9750	0.2%
	Hit@50	11.92%	21.58%	22.23%	33.11%	32.34%	30.88%	40.81%	35.52%	35.02%	-13.0%

Homework 4 (Part 1): Compare Fossil and TransRec

- No need to implement them yourself!
- The RecBole library: https://recbole.io/



RecBole

A unified, comprehensive and efficient recommendation library

General and extensible data structure

Comprehensive benchmark models and datasets

Extensive and standard evaluation protocols

Thank You!

Course Website: https://yuzhang-teaching.github.io/CSCE670-F25.html