Recommender Systems: Concepts, Techniques, and Applications

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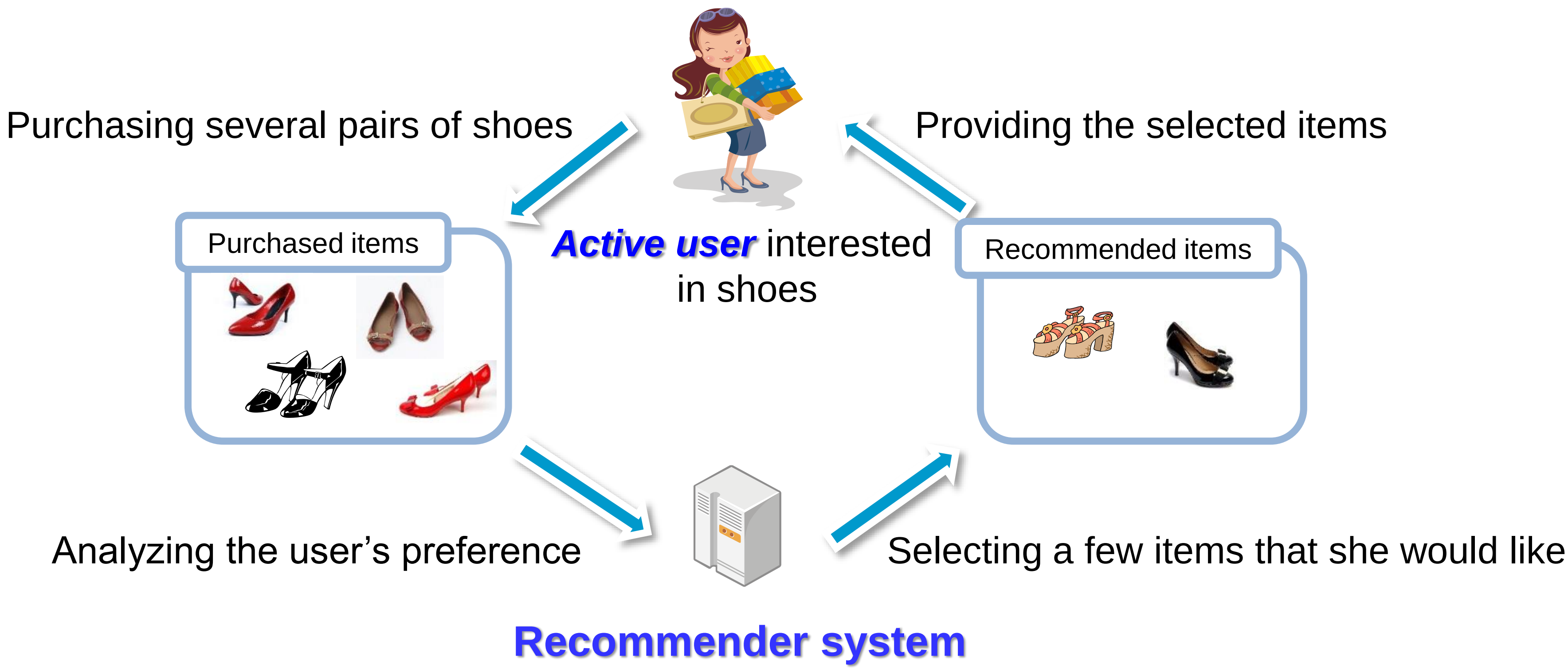
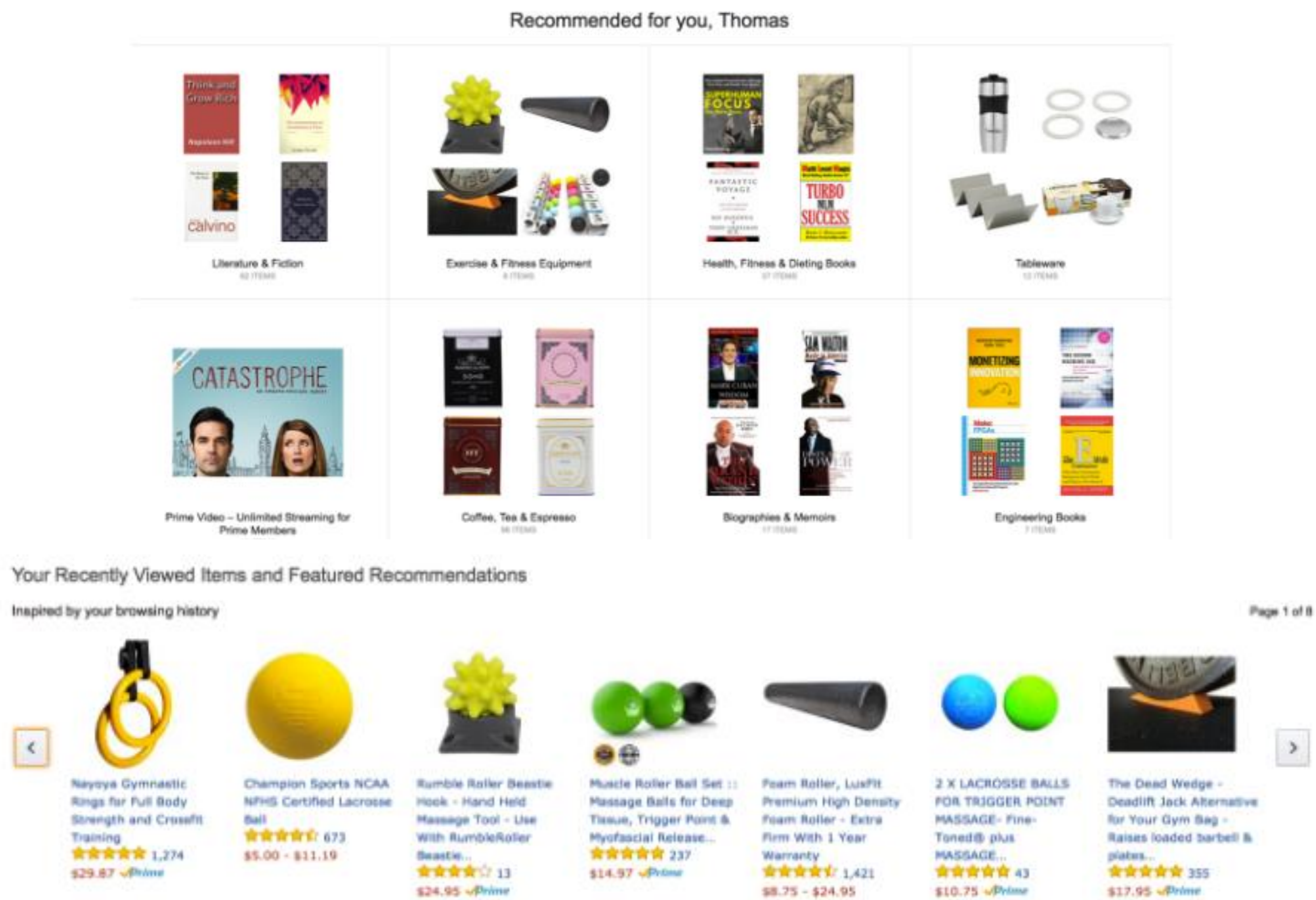
Contents

Recommendation Systems

- Provide a user with a few items that she would like
  - Using her history of evaluating, purchasing, and browsing

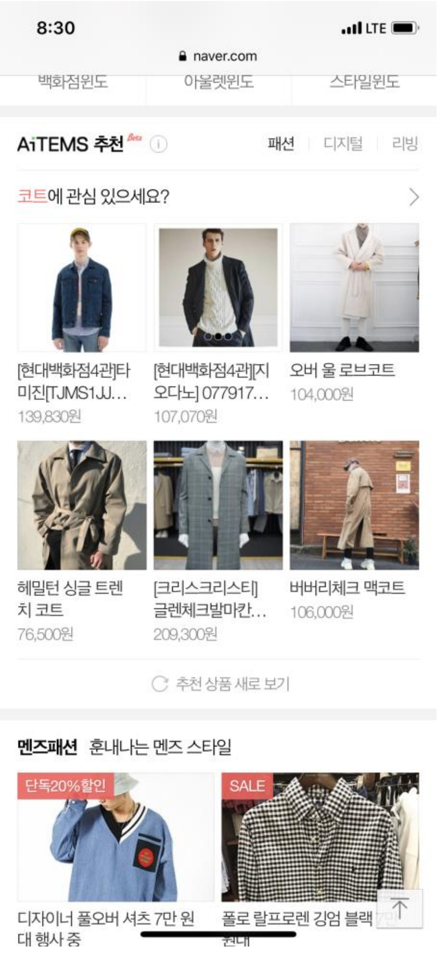


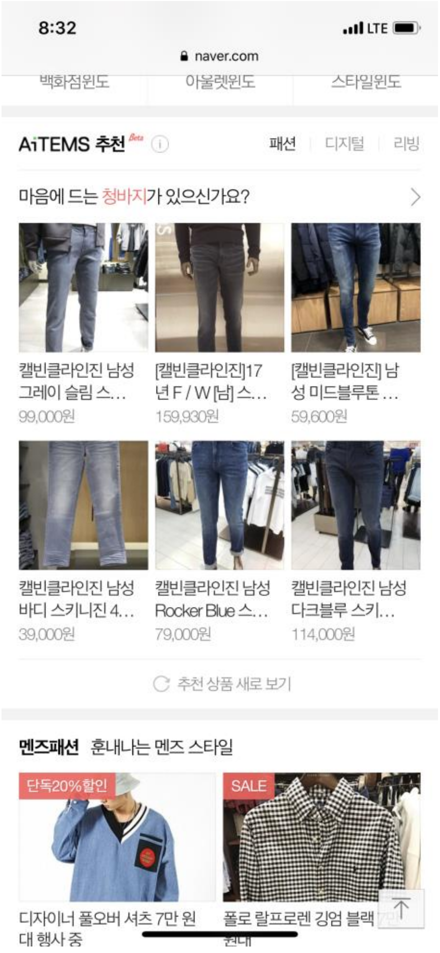
Amazon



http://rejoiner.com/resources/amazon-recommendations-secret-selling-online/

Naver Shopping



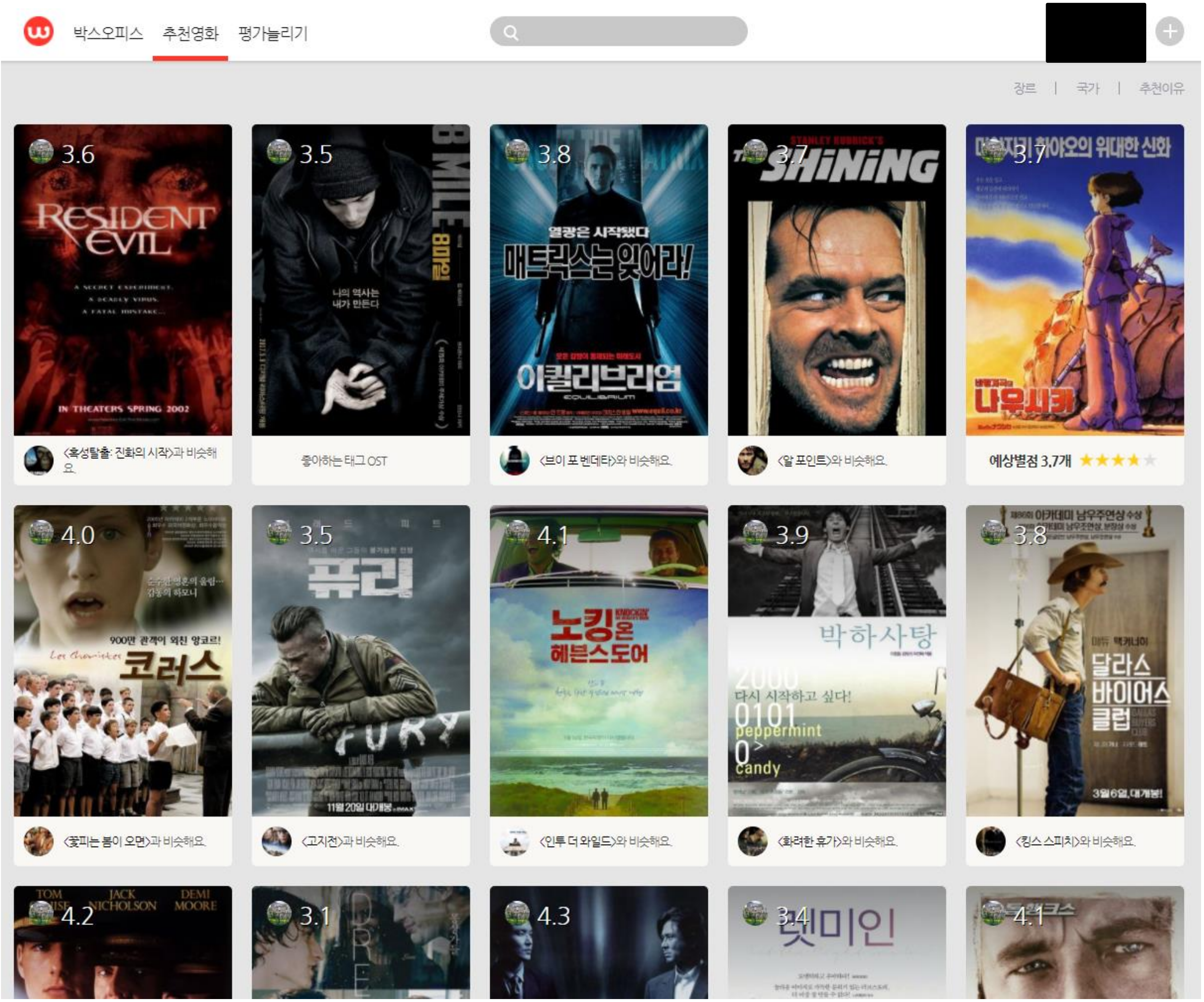


http://pc.shopping2.naver.com/

Netflix

https://www.netflix.com/

Watcha



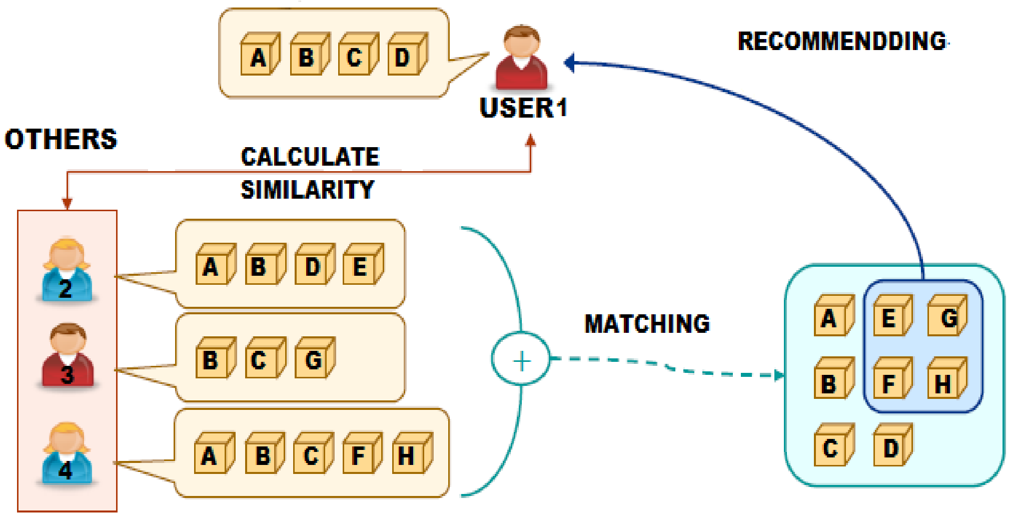
https://watcha.net/recommendation

Classification of Recommendation Systems

- Content-based approach
  - Recommending those items that have similar contents to those of the active user's favorite items
- **Collaborative filtering (CF) approach (our focus)**
  - Recommending items rated high by neighbors who have preferences similar to that of the active user
- Trust-based approach
  - Recommending items based on trust relationships among users
- Hybrid approach
  - Recommending items by combining the approaches above

Collaborative Filtering (CF) Approach

- Recommend such items rated high by neighbors who have preferences similar to that of the active user
  - Step 1: *Finding a group of users (neighbors)* whose preferences are similar to that of an active user *c*
  - Step 2: *Estimating $r_{c,s}$, the rating of item s for active user c,* based on the ratings given to item *s* by *c*'s neighbors
  - Step 3: Recommending *a few items with the ratings estimated high*



Collaborative Filtering (CF)

- Data: rating matrix

Items

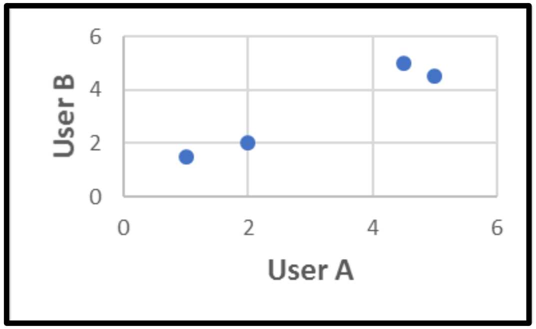
Users	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}	i_{11}	i_{12}
u_1		1		1		5	3			5		
u_2	1	3		4		4				2	4	
u_3												5
u_4		3		4		4		4	3			
u_5			4									
u_6	1			3	5	1		4			3	

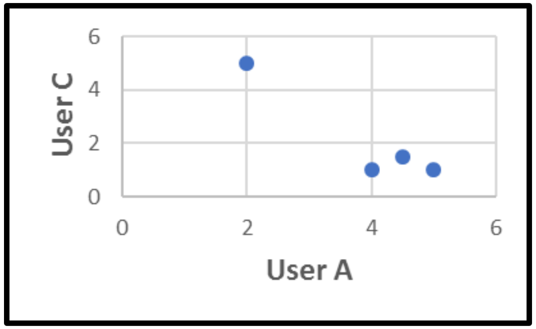
A rating on i_1 given by user u_6

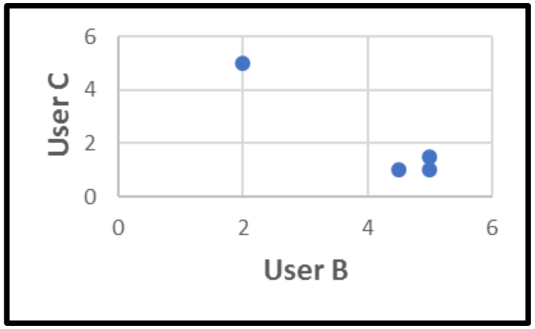
Heuristic-based Method in CF: Step 1

- Similarity measure for users a and i (used in finding neighbors)
  - Example: three users' ratings for six movies
    - User A = <4.0, 1.0, 4.5, 5.0, 2.0, _>
    - User B = < _, 1.5, 5.0, 4.5, 2.0, 5.0>
    - User C = <1.0, _, 1.5, 1.0, 5.0, 1.0>
  - Pearson correlation coefficient (PCC)

$$w(a,i) = \frac{\sum_j (v_{a,j} - \bar{v}_a)(v_{i,j} - \bar{v}_i)}{\sqrt{\sum_j (v_{a,j} - \bar{v}_a)^2 \sum_j (v_{i,j} - \bar{v}_i)^2}}$$







Heuristic-based Method in CF: Step 2

- Aggregation of ratings on a target item given by the neighbors

$$r_{c,s} = \operatorname*{aggr}_{c' \in \hat{C}} r_{c',s}$$

  - $r_{c,s}$: Estimated rating on item s for user c
  - $\hat{C}$: Set of neighbors for user c
  - Different methods for aggregation

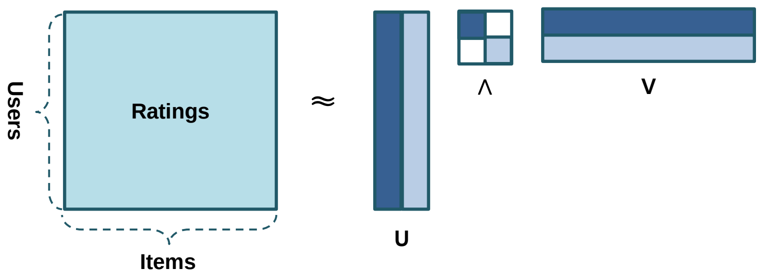
$$(a)\ r_{c,s} = \frac{1}{N} \sum_{c' \in \hat{C}} r_{c',s}$$

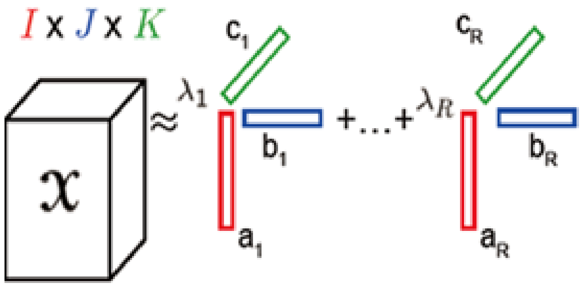
$$(b)\ r_{c,s} = k \sum_{c' \in \hat{C}} sim(c,c') \times r_{c',s}$$

$$(c)\ r_{c,s} = \bar{r}_c + k \sum_{c' \in \hat{C}} sim(c,c') \times (r_{c',s} - \bar{r}_{c'})$$

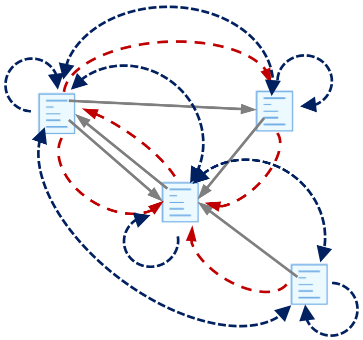
Machine-Learning Based CF Techniques

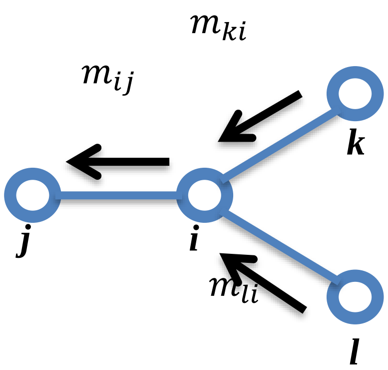
- Matrix/Tensor Factorization



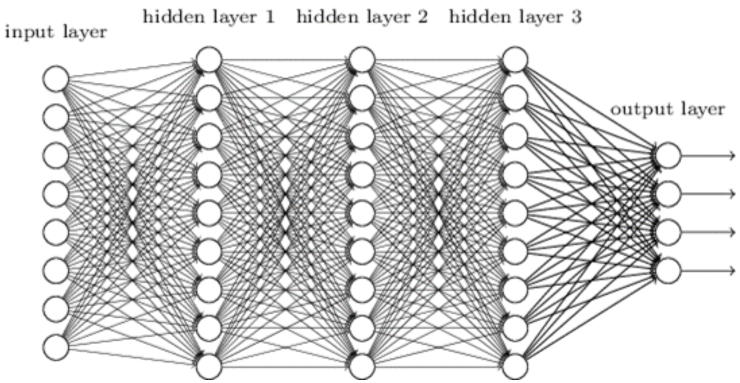


- Social Network Analysis

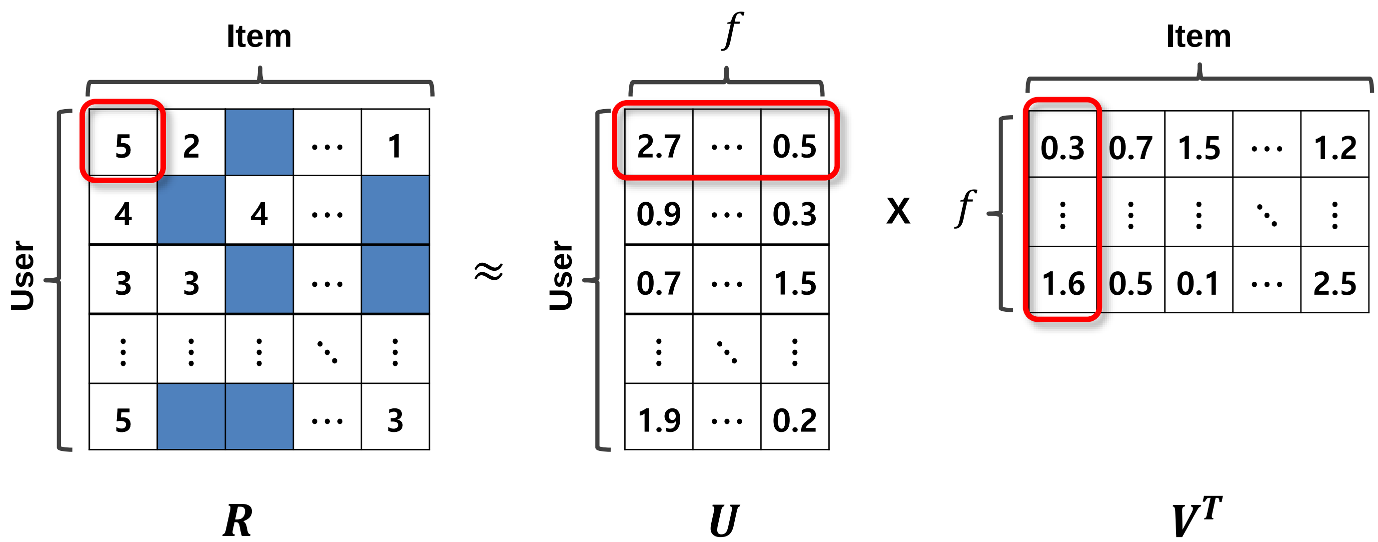




- Deep Learning



Matrix Factorization (MF)

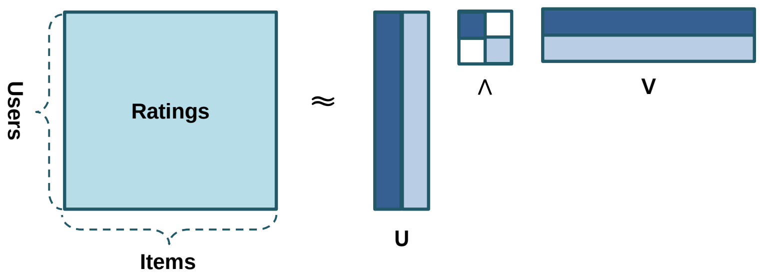


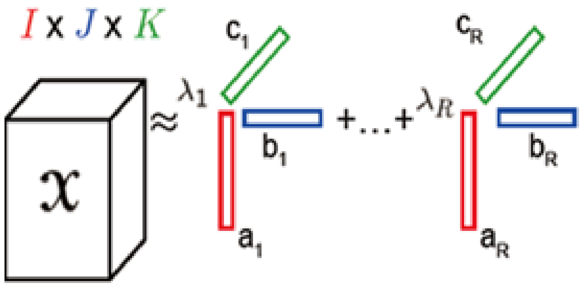
Matrix Factorization (MF)

$$
\underbrace{\text{User}\left\{\overbrace{\begin{bmatrix} 2.7 & \cdots & 0.5 \\ 0.9 & \cdots & 0.3 \\ 0.7 & \cdots & 1.5 \\ \vdots & \ddots & \vdots \\ 1.9 & \cdots & 0.2 \end{bmatrix}}^{f}\right.}_{\boldsymbol{U}}
\times
\underbrace{f\left\{\overbrace{\begin{bmatrix} 0.3 & 0.7 & 1.5 & \cdots & 1.2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1.6 & 0.5 & 0.1 & \cdots & 2.5 \end{bmatrix}}^{\text{Item}}\right.}_{\boldsymbol{V}^{T}}
=
\underbrace{\text{User}\left\{\overbrace{\begin{bmatrix} 4.9 & 1.5 & 3.5 & \cdots & 1.2 \\ 3.5 & 2.4 & 4.0 & \cdots & 1.9 \\ 3.0 & 3.5 & 4.5 & \cdots & 0.5 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 4.8 & 1.3 & 3.4 & \cdots & 3.2 \end{bmatrix}}^{\text{Item}}\right.}_{\hat{\boldsymbol{R}}}
$$

Machine-Learning Based CF Techniques

- Matrix/Tensor Factorization





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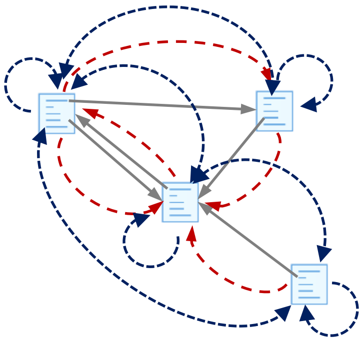
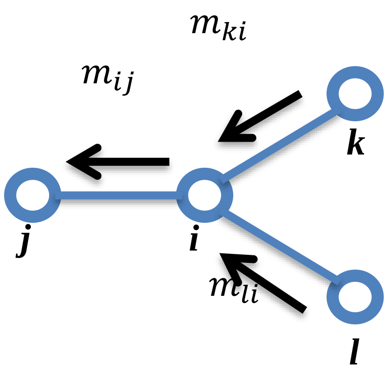
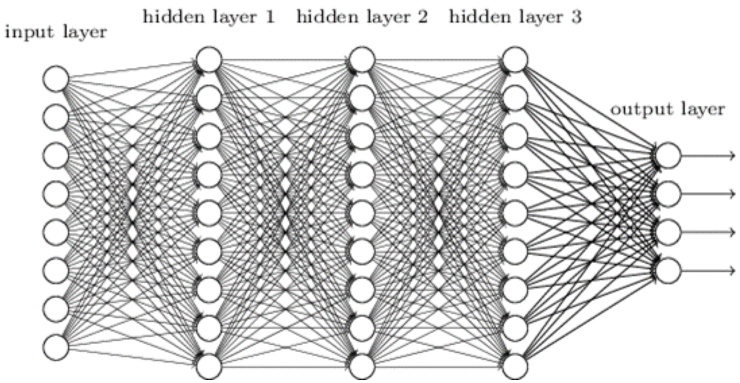




- Deep Learning



Contents

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- Extensions
  - To data imputation
  - To one-class settings
- Conclusions

"Told You I Didn't Like It": Exploiting Uninteresting Items for Effective Collaborative Filtering

(IEEE ICDE'16 / IEEE TKDE'19)

Motivation

- CF approaches focus on *only the ratings given by users*
  - Data sparsity problem: most users have evaluated *only a few items*
  - There are only a few ratings in a rating matrix (< 4%)
- CF approaches suffer from *low accuracy and coverage*

Items

Users	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}	i_{11}	i_{12}
u_1		1		1		5	3			5		
u_2	1	3		4		4				2	4	
u_3												5
u_4		3		4		4		4	3			
u_5			4									
u_6	1			3	5	1		4			3	

A rating on i_1 given by user u_6

A Rating Matrix

Our Idea: Using Unrated Items

- Exploit uncharted unrated items
  - A fraction of rated items in a rating matrix R is extremely small (< 4%)
  - Exploiting the vast number of "unrated" items in R can lead to a significant improvement in CF approaches

Items

Users	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}	i_{11}	i_{12}
u_1		1		1		5	3			5		
u_2	1	3		4		4				2	4	
u_3												5
u_4		3		4		4		4	3			
u_5			4									
u_6	1			3	5	1		4			3	

unrated items

Our Idea: Uninteresting Items (ICDE’16 / TKDE’19)

- Unrated items
  - Users were not aware of their existence
    - Candidates for recommendation
  - Users knew but did not like and thus did not purchase
    - ***Uninteresting items***
- Uninteresting items (of a user)
  - Items on which the user has “negative” preferences

Users' Preferences: Two New Notions

- **Pre-use preferences**
  - User's impression on items before purchasing and using them
  - Determined via meta data of items (known before purchasing)
- **Post-use preferences**
  - User's impression on items after purchasing and using them
  - Determined via real content of items (unknown before purchasing)

Pre-Use/Post-Use Preferences and Ratings

- A user has high pre-use preference for Movie #1 and Movie #2
  - The user likes Movie #1 but is disappointed at Movie #2
- A user has low pre-use preference for Movie #3

Movie	Pre-use preference	Post-use preference	Rating
Movie#1	High	High	5
Movie#2	High	Low	1
Movie#3	Not high	Unknown	Unrated

- In this case
  - Uninteresting items: Movie #3
  - Interesting items: Movie #1 (preferred) and Movie #2 (not preferred)

Pre-Use Preference and Uninteresting Items

- Challenge: To identify uninteresting items among unrated items
- A user's uninteresting items
  - Her pre-use preferences on them are relatively low
- How to know a user's pre-use preferences
  - For all "rated" items: highest pre-use preferences
    - Otherwise, users would not have bought them in the first place
  - For unrated items: pre-use preferences need to be inferred
    - Based on pre-use preferences on rated items

Zero-Injection (IEEE ICDE'16 / IEEE TKDE'19)

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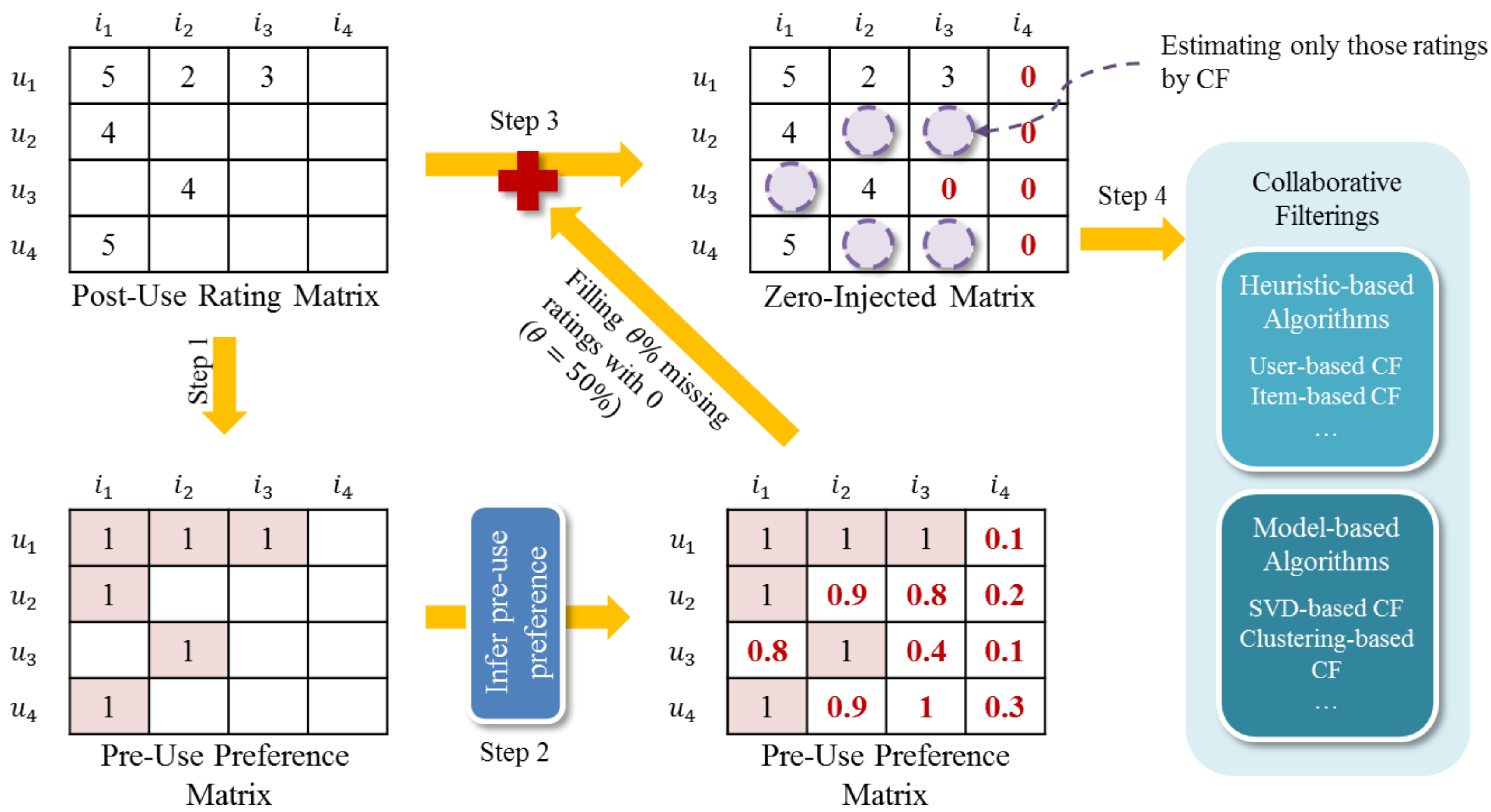
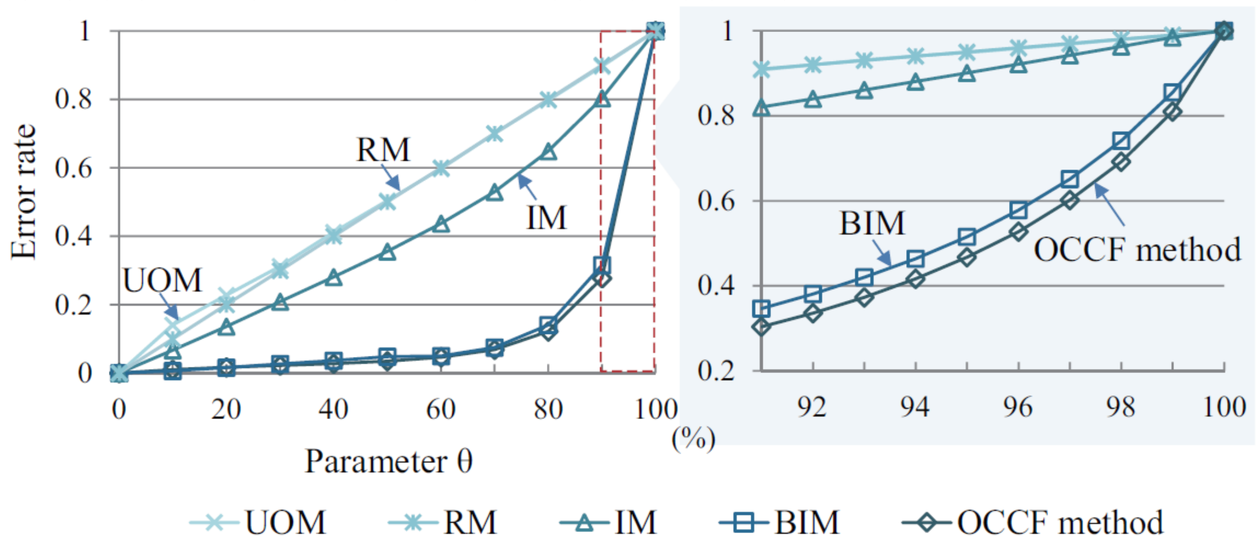


Exploiting Uninteresting items

- Two strategies with uninteresting items
  - Strategy 1: to exclude uninteresting items from the final recommendation list
  - Strategy 2: to exploit both uninteresting items and ratings in CF

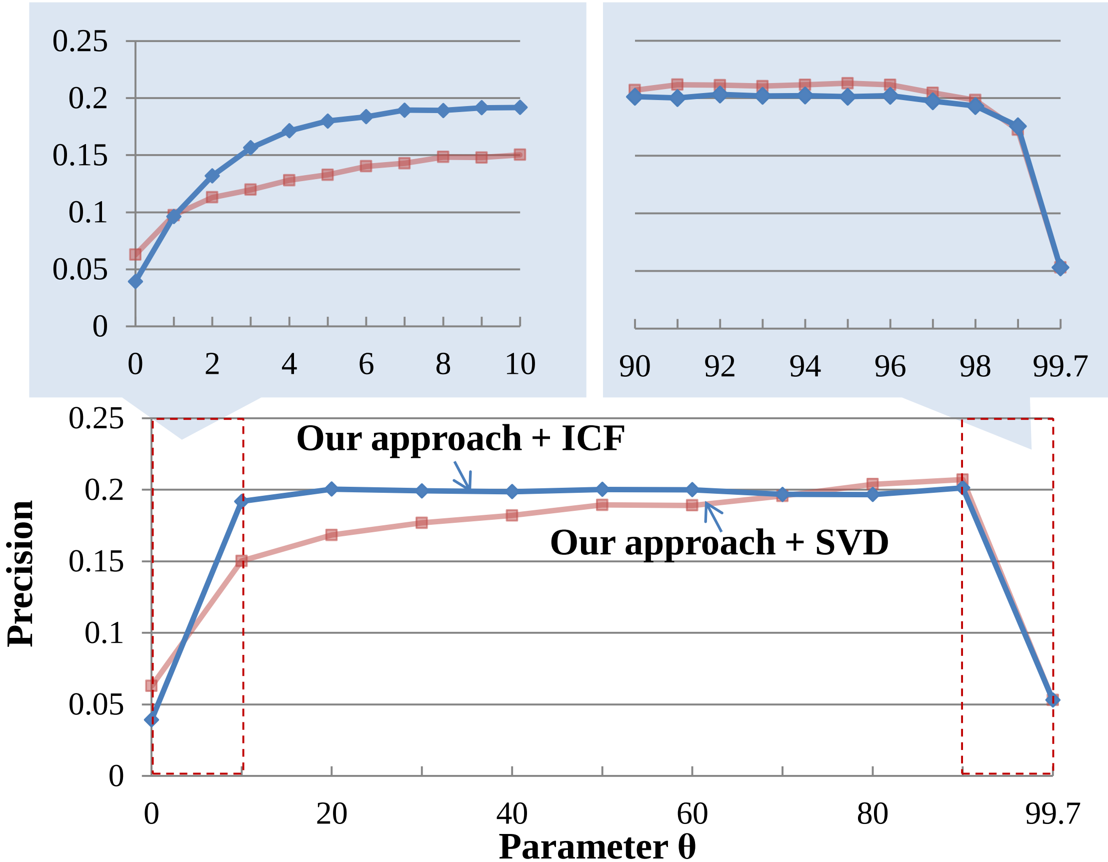
Accuracy in Finding Uninteresting items

- Error rate comparison of five inference methods
  - A user *u*'s error rate (with 5 cross validation)
    - How many *rated items* (in the test set) are selected as uninteresting items (*i.e.*, mis-classified) for *u*
    - $err_u^\theta = \frac{|I_u^{un}(\theta) \cap I_u^{test}|}{|I_u^{test}|}$
  - The OCCF method is the most effective

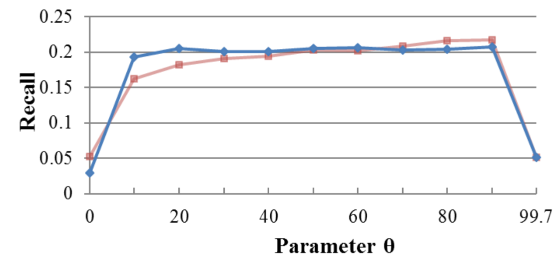


Effectiveness (IEEE ICDE'16 / IEEE TKDE'19)

- Accuracy of ICF and SVD equipped with our zero-injection under varying parameter θ



<Precision>



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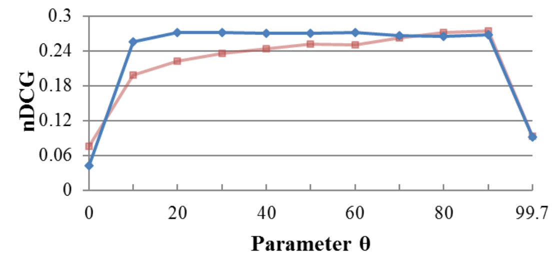
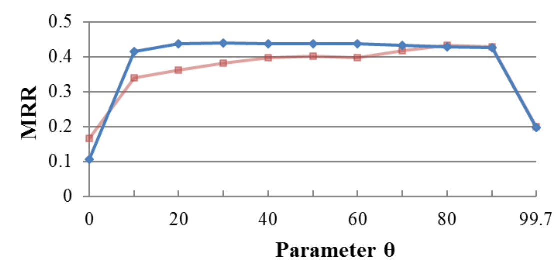


<nDCG>



<MRR>

Effectiveness (IEEE ICDE'16 / IEEE TKDE'19)

- Accuracy of four CF methods equipped with zero-injection ($\theta = 90\%$)

Metric		ICF			SVD			SVD++			PureSVD		
		Orginal	Ours	Gain	Orginal	Ours	Gain	Orginal	Ours	Gain	Orginal	Ours	Gain
Precision	@5	0.039	0.201	413.8%	0.063	0.207	229.7%	0.076	0.193	153.3%	0.100	0.106	16.7%
	@10	0.041	0.161	292.6%	0.056	0.166	196.9%	0.069	0.154	123.9%	0.082	0.089	19.1%
	@15	0.040	0.137	243.7%	0.053	0.142	169.9%	0.063	0.134	112.0%	0.071	0.078	11.3%
	@20	0.039	0.121	211.7%	0.048	0.125	159.1%	0.058	0.118	102.3%	0.063	0.071	13.7%
Recall	@5	0.030	0.207	600.3%	0.052	0.218	316.0%	0.063	0.194	209.6%	0.112	0.120	16.9%
	@10	0.059	0.305	412.7%	0.089	0.325	265.9%	0.109	0.288	163.1%	0.175	0.191	19.3%
	@15	0.085	0.375	341.4%	0.121	0.394	226.3%	0.150	0.361	141.2%	0.220	0.245	11.4%
	@20	0.111	0.428	285.4%	0.144	0.450	213.5%	0.184	0.415	125.3%	0.254	0.293	15.4%
nDCG	@5	0.043	0.268	527.9%	0.076	0.274	260.7%	0.087	0.256	196.0%	0.135	0.143	16.0%
	@10	0.053	0.285	436.0%	0.084	0.297	252.0%	0.099	0.272	175.6%	0.151	0.162	17.6%
	@15	0.062	0.303	390.7%	0.094	0.315	234.8%	0.110	0.291	163.7%	0.164	0.178	18.9%
	@20	0.071	0.319	351.7%	0.101	0.332	227.3%	0.121	0.306	153.5%	0.174	0.193	10.9%
MRR		0.106	0.426	303.0%	0.165	0.428	159.2%	0.181	0.416	129.3%	0.262	0.274	14.7%

Contents

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gOCCF: Graph-Theoretic One-Class Collaborative Filtering Based on Uninteresting Items

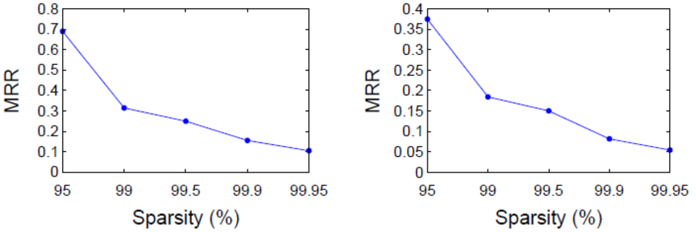
(AAAI'18)

Motivation

- ***One-Class*** Collaborative Filtering (OCCF)
  - To handle implicit feedback (*i.e.*, one-class setting, rather than ratings setting)
    - Example: Click, bookmark, and purchase
  - Challenges
    - *Less information to capture a user's taste* than in ratings setting
    - *Sparser datasets* than in ratings setting

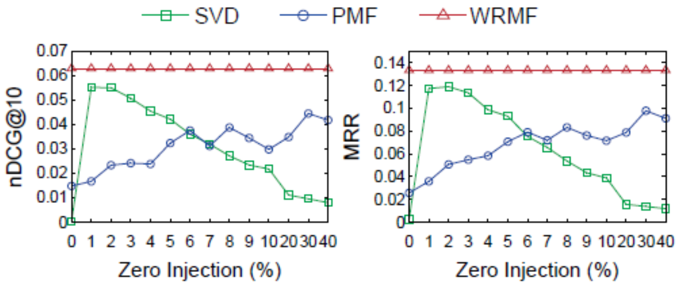
Motivation

- Existing OCCF approaches
  - Less effective in dealing with sparser datasets with many unrated items



(a) MovieLens 100K (b) Watcha

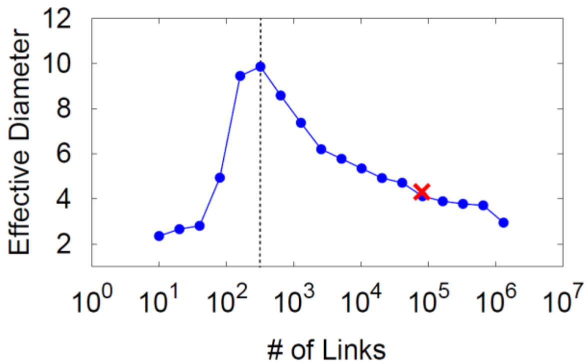
- A naïve application of zero-injection in one-class setting
  - Lower accuracy than existing OCCF approaches
  - Sensitivity to the number of uninteresting items



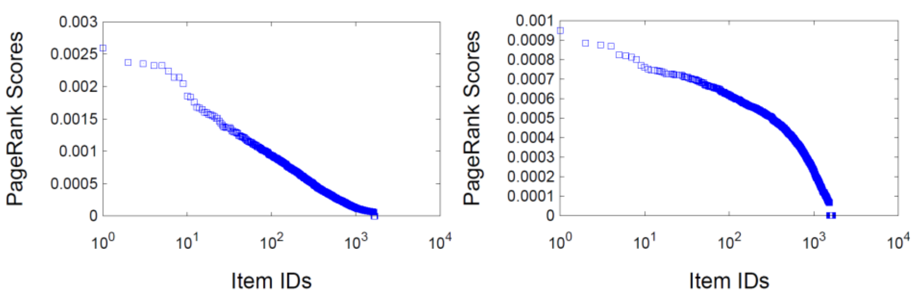
Our Idea: Exploiting Graph Properties (AAAI'18)

- Challenge: To determine *a right number of uninteresting items* with the best accuracy

- Analyze properties of negative graphs constructed by user-uninteresting item pairs
  - Topological properties
    - Use *graph shattering theory*
  - Information propagation
    - Use PageRank scores



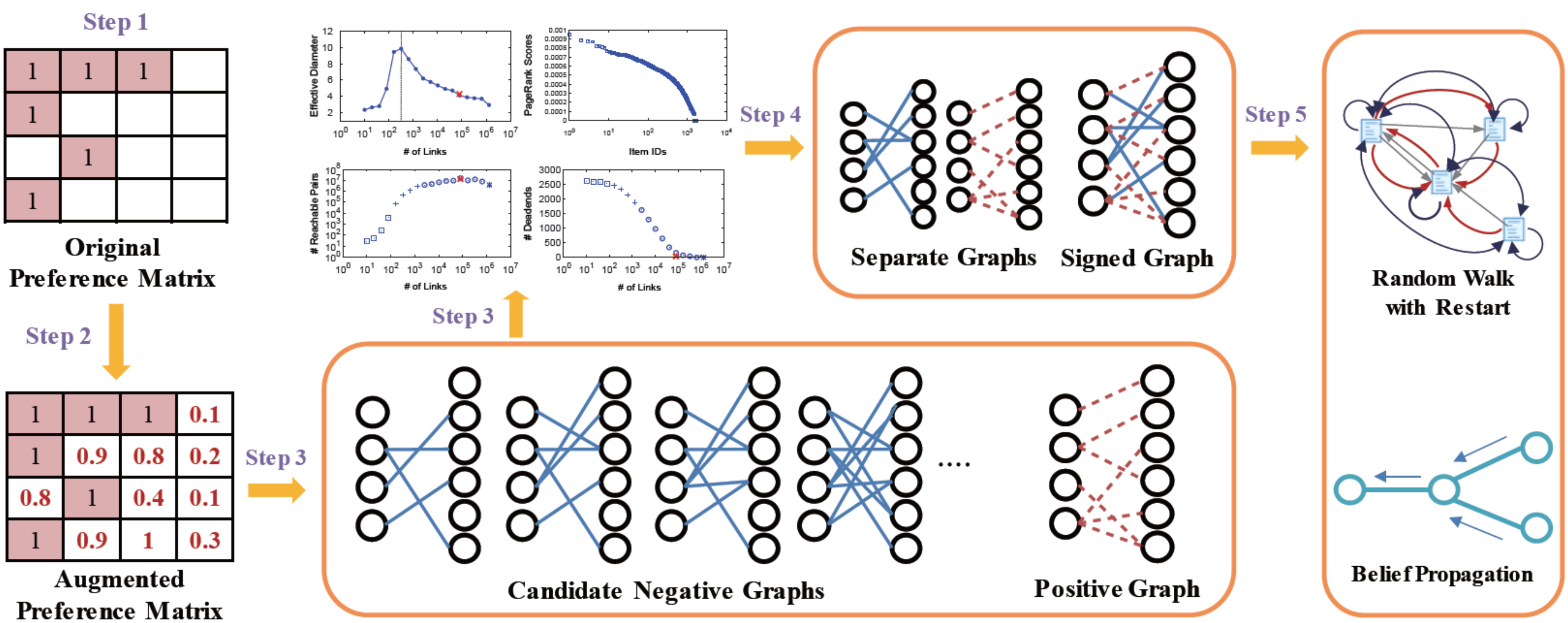
(1) ShatterPlot



(a) Real Positive Graph (b) Negative Graph

(2) PageRank Scores

Overview of Our Approach: gOCCF (AAAI'18)



Effectiveness of gOCCF (AAAI'18)

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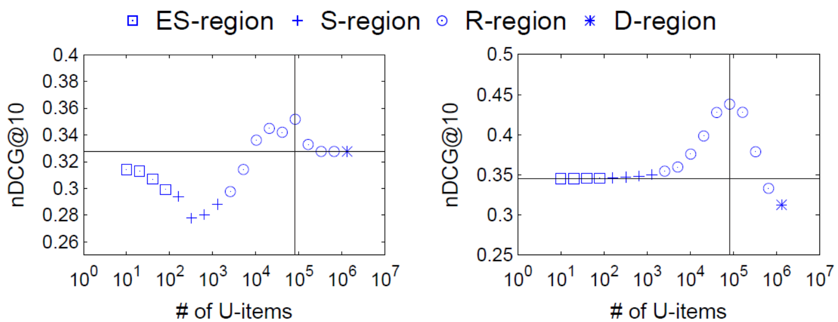
- Accuracy according to the number of uninteresting items



(a) separateRWR (b) signedBP

  – Best accuracy when having the same number of negative links as that of positive links

- Accuracy before and after exploiting uninteresting items

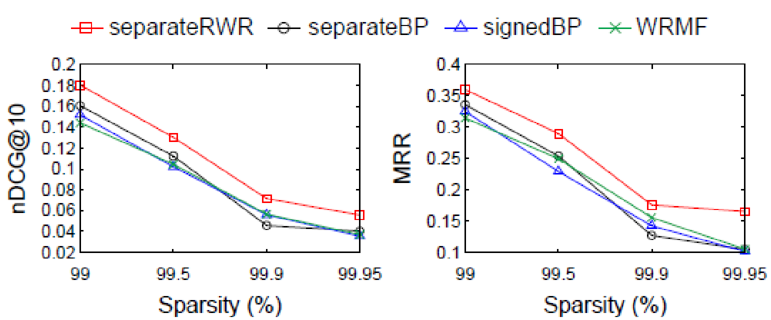
Metrics	MovieLens		
	separateRWR	separateBP	signedBP
P@10	0.302 (**9.2%**)	0.309 (**7.2%**)	0.370 (**28.2%**)
R@10	0.171 (**8.2%**)	0.164 (**10.9%**)	0.210 (**42.1%**)
nDCG@10	0.352 (**7.3%**)	0.365 (**5.7%**)	0.438 (**27.0%**)
MRR	0.584 (**2.5%**)	0.604 (**1.9%**)	0.679 (**14.6%**)
HLU	43.894 (**2.8%**)	47.195 (**1.4%**)	55.980 (**20.3%**)
	Watcha		
	separateRWR	separateBP	signedBP
P@10	0.113 (**10.8%**)	0.124 (**13.2%**)	0.151 (**38.3%**)
R@10	0.107 (**9.6%**)	0.113 (**13.4%**)	0.142 (**41.9%**)
nDCG@10	0.136 (**9.9%**)	0.152 (**13.2%**)	0.190 (**41.8%**)
MRR	0.295 (**7.1%**)	0.329 (**10.8%**)	0.391 (**32.0%**)
HLU	14.288 (**7.7%**)	17.448 (**20.4%**)	23.012 (**58.8%**)
	CiteULike		
	separateRWR	separateBP	signedBP
P@10	0.122 (**21.0%**)	0.112 (**26.9%**)	0.091 (**2.9%**)
R@10	0.199 (**13.5%**)	0.162 (**26.4%**)	0.131 (**2.4%**)
nDCG@10	0.202 (**18.2%**)	0.175 (**29.9%**)	0.138 (**2.3%**)
MRR	0.326 (**14.0%**)	0.295 (**21.0%**)	0.247 (**1.3%**)
HLU	21.257 (**23.0%**)	19.323 (**33.3%**)	14.680 (**1.2%**)

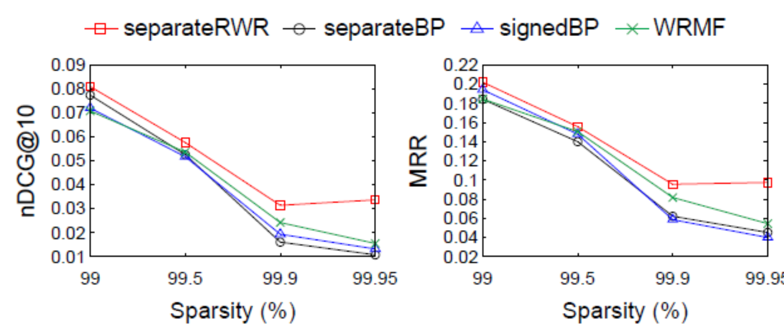
Effectiveness of gOCCF (AAAI'18)

- Accuracy of competing methods and our approach
  - CiteULike dataset

	MostPopular	SVD_ZI	PMF_ZI	WRMF	BPRMF	GBPRMF	SLIM	**separateRWR**	**separateBP**	**signedBP**
P@10	0.012	0.043	0.034	0.045	0.092	0.049	-	**0.122**	0.112	0.091
R@10	0.029	0.044	0.037	0.049	0.140	0.078	-	**0.199**	0.162	0.131
nDCG@10	0.023	0.055	0.044	0.062	0.136	0.066	-	**0.202**	0.175	0.138
MRR	0.050	0.117	0.073	0.133	0.240	0.132	-	**0.326**	0.295	0.247
HLU	1.527	5.899	4.489	7.198	12.754	4.005	-	**21.257**	19.323	14.680

- Accuracy of WRMF and our approach per sparsity
  - MovieLens 100K dataset
  - Watcha dataset





Summary

- We propose a *new concept of uninteresting items* to make more accurate CF for both *ratings and one-class settings*
- Our approach
  - To identify uninteresting items
  - To apply them to existing CF methods
  - To exclude them from the final recommendation list
- Strengths of our approach
  - *Orthogonal to* CF methods
  - *Parameter-free* for both *ratings and one-class settings*
  - *Consistently and universally improves* existing CF and OCCF methods

How to Impute Missing Ratings? Claims, Solution, and Its Application to Collaborative Filtering

(WWW'18)

CFGAN: A Generic Collaborative Filtering Framework based on GAN

(ACM CIKM'18)

RAGAN: Rating Augmentation with GAN towards Accurate Collaborative Filtering

(WWW’19)

No, That’s Not My Feedback: TV Show Recommendation Using Watchable Interval

(IEEE ICDE’19)

RealGraph: A Graph Engine Leveraging the Power-Law Distribution of Real-World Graphs

(WWW'19)

Conclusions

- Background
  - Recommendation systems
  - Collaborative filtering (CF)
- Exploiting Uninteresting Items for Effective CF
  - Motivation
  - Proposed method
  - Evaluation
- Extensions
  - To data imputation
  - To one-class settings
- Conclusions

Thank You !