- Overview of multidomain recommender systems (Liang Hu, 25 mins)
- Multi-item domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-user domain recommender systems (Qi Zhang, 20 mins)
- Multi-data domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-spatial domain recommender systems (Qi Zhang 20 mins)
- Multi-temporal domain recommender systems (Z. Y. Lai, 20 mins)
- **Multi-goal domain recommender systems (Liang Hu, 20 mins)**
- Summary (Liang Hu, 5 mins)

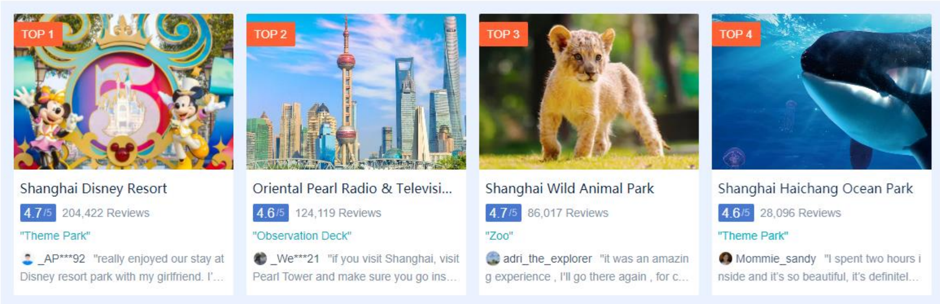
Multi-goal domain recommender systems

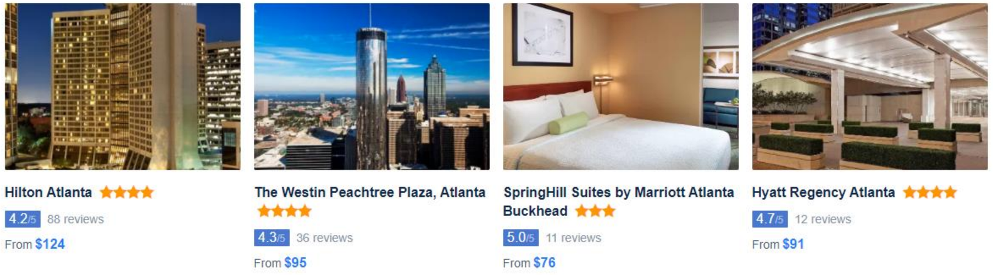
- Preliminary of multi-goal domain recommender systems
- Multi-intention modeling for multidomain recommendation
- Multi-objective modeling for multidomain recommendation

Multi-goal domain recommender systems

- Multi-goal domain RSs aims to make comprehensive recommendations by jointly modeling multiple goals, like user intentions and objectives.

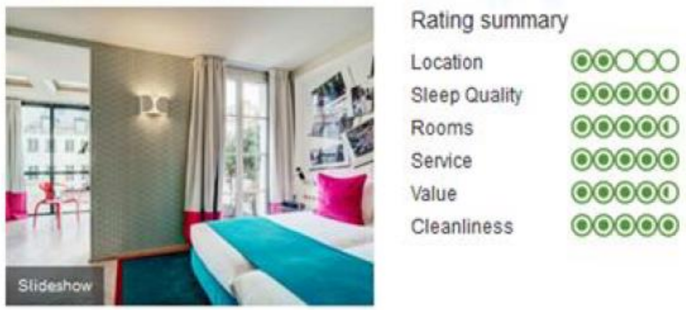
- Recommendation via modeling multiple intentions:
  - E.g. A travel recommendation needs to consider multiple intentions, such as visiting attractions and enjoying local food.



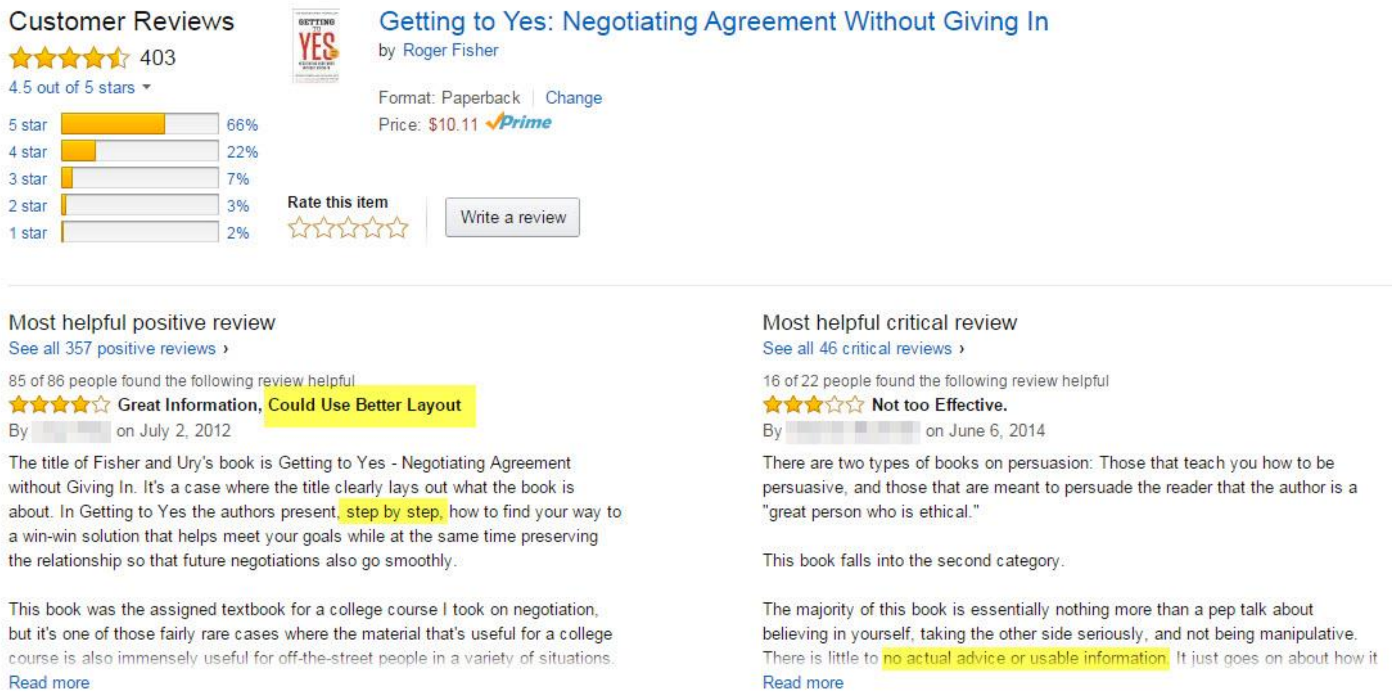


Multi-goal domain recommender systems

- Recommendation via modeling multiple objectives:
  - E.g. A hotel recommendation needs to consider multiple criteria, such as location, cleanliness, services.



  - E.g. The evaluation of hotel recommendation needs to consider not only accuracy but also helpfulness.



Multi-goal domain recommender systems

- Preliminary of multi-goal domain recommender systems
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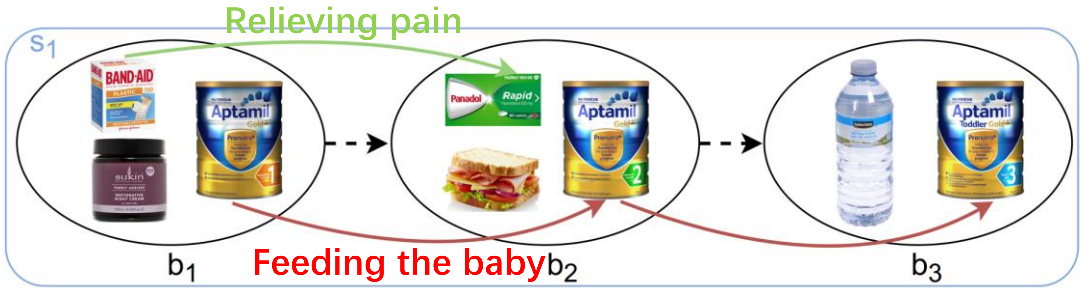
User action is driven by multiple intentions

- Human behaviors are **complex**, which are often observed as a sequence of **heterogeneous** actions.
- Although happening together as a sequence, human actions are usually driven by different **intentions**, e.g., feeding the baby or relieving pain, from the Psychological perspective.



A sequence shopping actions driven by different intentions

- We take a typical case to study the composite of intentions for shopping basket recommendation .

Modeling composite of multiple intentions

- **Traditional session-based recommendation methods** simply model the transitions between baskets without considering intentions behind.
- **Intention nets** model the intentions embedded in a sequence of baskets and capture the action transitions for each intention independently.

Figure 2: An example of a sequence of three baskets (b_1, b_2, b_3).

Wang S, Hu L, Wang Y, Sheng QZ, Orgun MA, Cao L. Intention2Basket: A Neural Intention-driven Approach for Dynamic Next-basket Planning. In IJCAI 2020

Intention Nets

- Two main modules:
  - Intention recognition nets (IRNs), Parallel action chain nets (PACN)

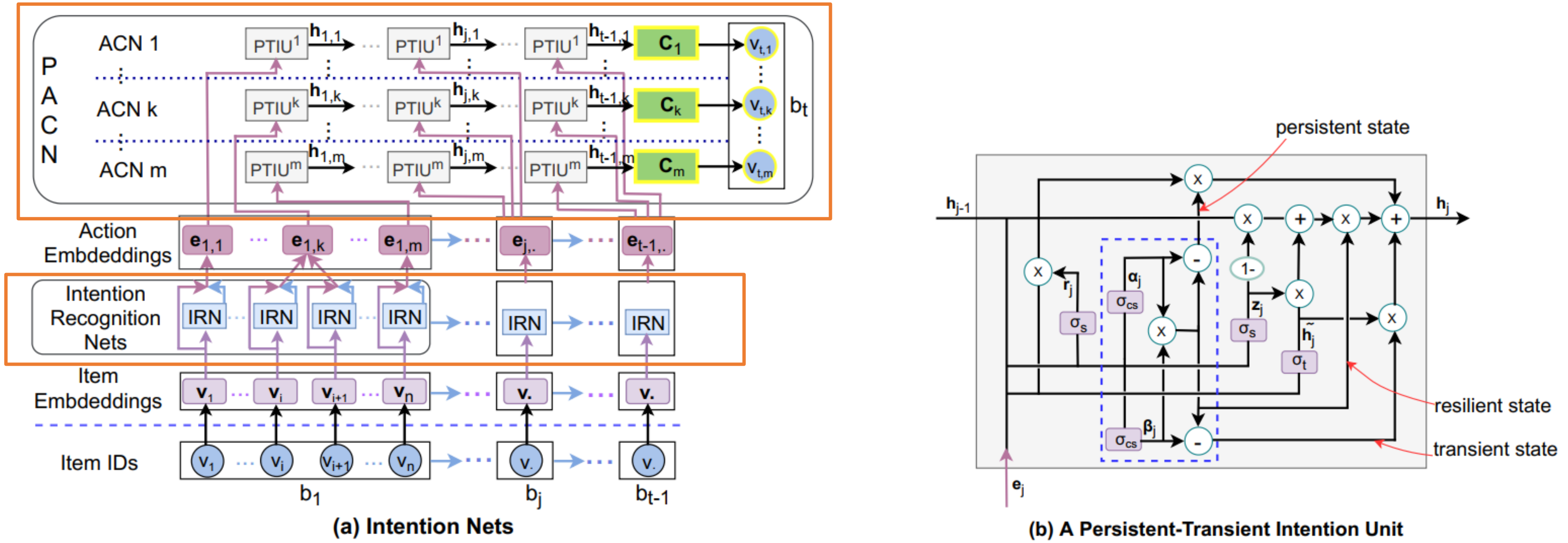


Figure 2: (a) The Intention Nets model consist of two main components: Intention Recognition Nets and Parallel Action Chain Nets (PACN); (b) The Persistent-Transient Intention Unit (PTIU) introduces a persistent gate and transient gate (see the blue dash line square) to respectively determine the persistent part and transient part of the intention state and update them accordingly.

Wang S, Hu L, Wang Y, Sheng QZ, Orgun MA, Cao L. Intention2Basket: A Neural Intention-driven Approach for Dynamic Next-basket Planning. In IJCAI 2020

Datasets

- **Tmall**: recorded the purchased baskets from each anonymous user on Tmall platform (The Chinese version of Amazon) in six months.
- **Tafang**: contained the transactional data of a Chinese grocery store generated in four months.

Table 2: Statistics of datasets

Statistics	**Tmall**	**Tafeng**
#Sequences	135,014	10,453
#Baskets	399,008	60,392
#Items	98,727	11,207
Avg. sequence length	2.96	5.78
Avg. basket size	3.08	8.42

Wang S, Hu L, Wang Y, Sheng QZ, Orgun MA, Cao L. Intention2Basket: A Neural Intention-driven Approach for Dynamic Next-basket Planning. In IJCAI 2020

Experimental Results

- IntNet achieves 3% to 19.89% improvements over the best performing baseline w.r.t. all the three metrics (F1-score (F1), Hit ratio (HR) and Normalized discounted cumulative gain (nDCG)) on both datasets.

	Tmall						**Tafeng**					
	F1@5	**F1@20**	**HR@5**	**HR@20**	**nDCG@5**	**nDCG@20**	**F1@5**	**F1@20**	**HR@5**	**HR@20**	**nDCG@5**	**nDCG@20**
TBP	0.0282	0.0312	0.0210	0.0488	0.0642	0.1002	0.0252	0.0310	0.0187	0.0379	0.0842	0.1000
FPMC	0.0614	0.0538	0.0876	0.2068	0.0645	0.1088	0.0618	0.0565	0.0668	0.1468	0.0564	0.1012
HRM	0.0848	0.0788	0.1010	0.2322	0.0854	0.1362	0.0847	0.0785	0.0800	0.1788	0.0786	0.1326
DERAM	0.1080	0.0816	0.1226	0.2551	0.1028	0.1600	0.1038	0.0824	0.0906	0.1956	0.1312	0.1628
NAM	0.1088	0.0819	0.1224	0.2498	0.1148	0.1715	0.1108	0.0736	0.0978	0.1739	0.1301	0.1507
Beacon	0.1200	0.0880	0.1268	0.2746	0.1262	0.1876	0.1100	0.0897	0.0988	0.2012	0.1304	0.1626
MCPRN	0.1202	0.0882	0.1224	0.2755	0.1267	0.1892	0.1090	0.0897	0.1014	0.2137	0.1328	0.1669
IntNet-S	0.1182	0.0787	0.1309	0.2449	0.1237	0.1613	0.1102	0.0810	0.0942	0.1920	0.1315	0.1623
IntNet-GRU	0.1202	0.0880	0.1220	0.2752	0.1263	0.1888	0.1104	0.0824	0.0946	0.1956	0.1316	0.1625
IntNet	**0.1238**	**0.0934**	**0.1378**	**0.2857**	**0.1416**	**0.2018**	**0.1161**	**0.0971**	**0.1078**	**0.2283**	**0.1395**	**0.2001**
Improve (%)[4]	3.00	5.87	5.30	3.70	11.76	6.66	4.78	8.25	6.31	6.83	5.05	19.89

Wang S, Hu L, Wang Y, Sheng QZ, Orgun MA, Cao L. Intention2Basket: A Neural Intention-driven Approach for Dynamic Next-basket Planning. In IJCAI 2020

Experimental Results

- IntNet achieves the highest recall.

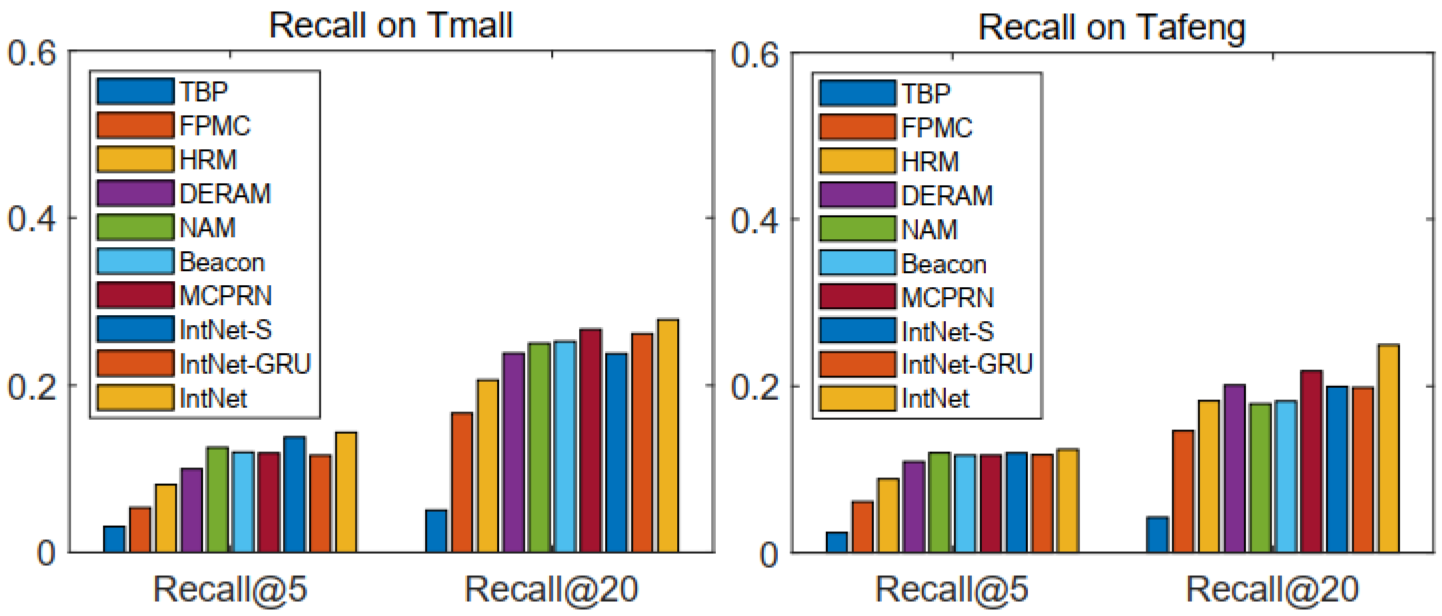


Figure 3: Recalls of Intention Nets and other compared methods.

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IntNet Work Mechanism Visualization

- The choices on different items (e.g., v_1; v_2; v_6) in one basket (e.g., b_1) are commonly driven by different intentions (e.g., intentions 1, 2 and 3) .

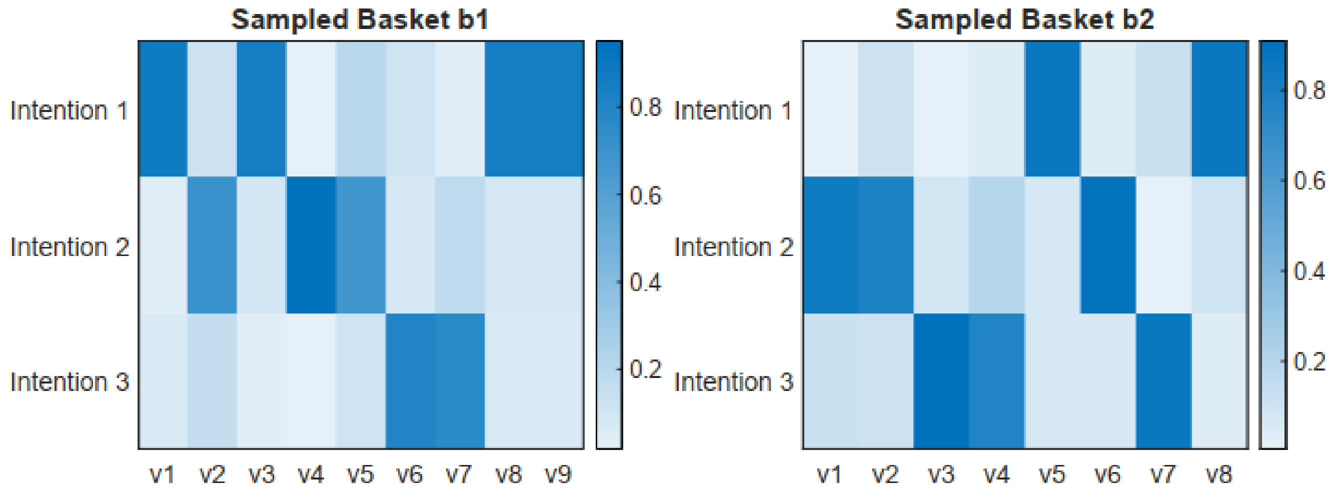

Figure 4: Intention assignment visualization of the items in two sampled baskets on Tafeng.

Wang S, Hu L, Wang Y, Sheng QZ, Orgun MA, Cao L. Intention2Basket: A Neural Intention-driven Approach for Dynamic Next-basket Planning. In IJCAI 2020

Multi-goal domain recommender systems

- Preliminary of multi-goal domain recommender systems
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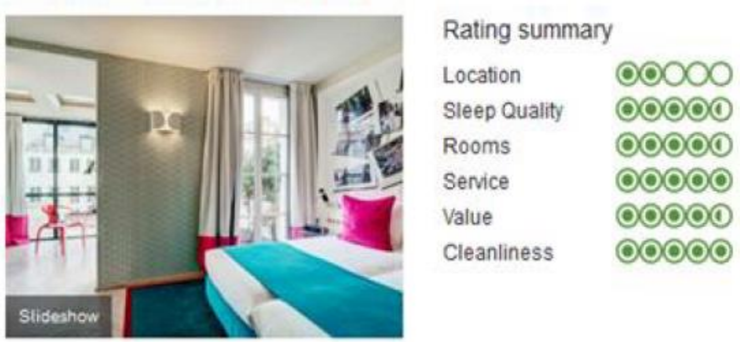
- Multi-objective modeling for multidomain recommendation

Multiple objectives in recommendation

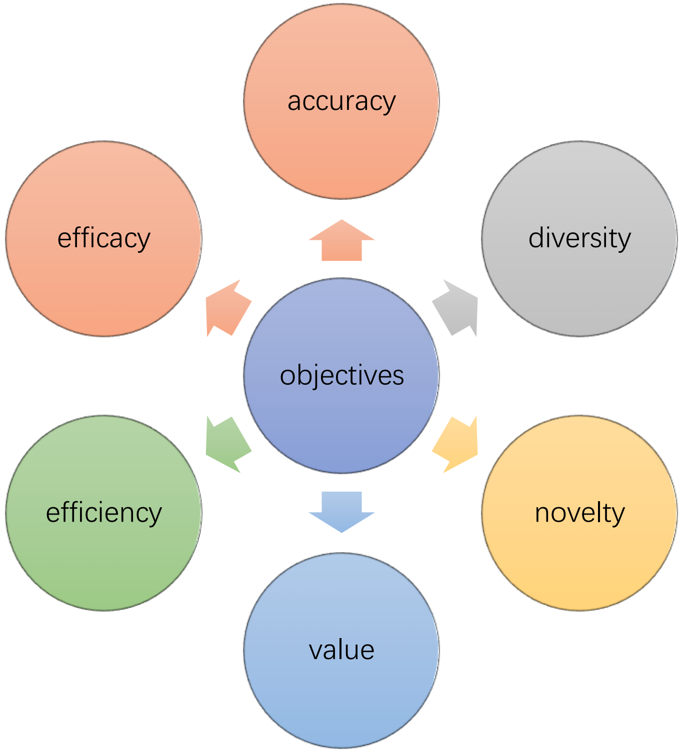
- Traditional RSs are built on single objective

- Users' choices are often jointly determined by multiple aspects



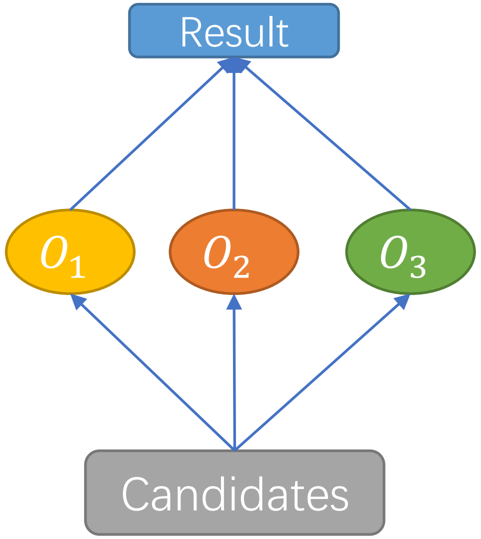
Modeling composite of multiple objectives

- To provide comprehensive views for recommendation, we model the ***composite of multiple objectives***

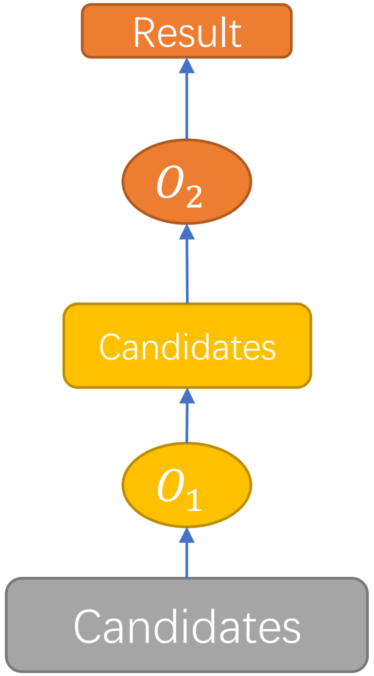


Three multi-objective learning schemes for recommendation

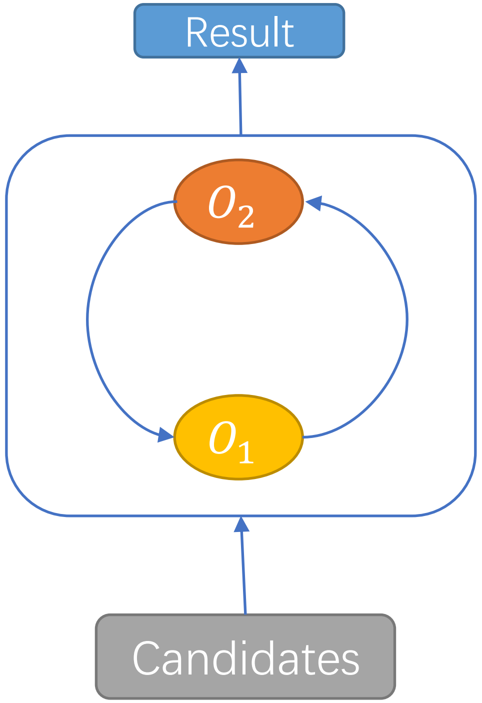
- Parallel



- Cascade

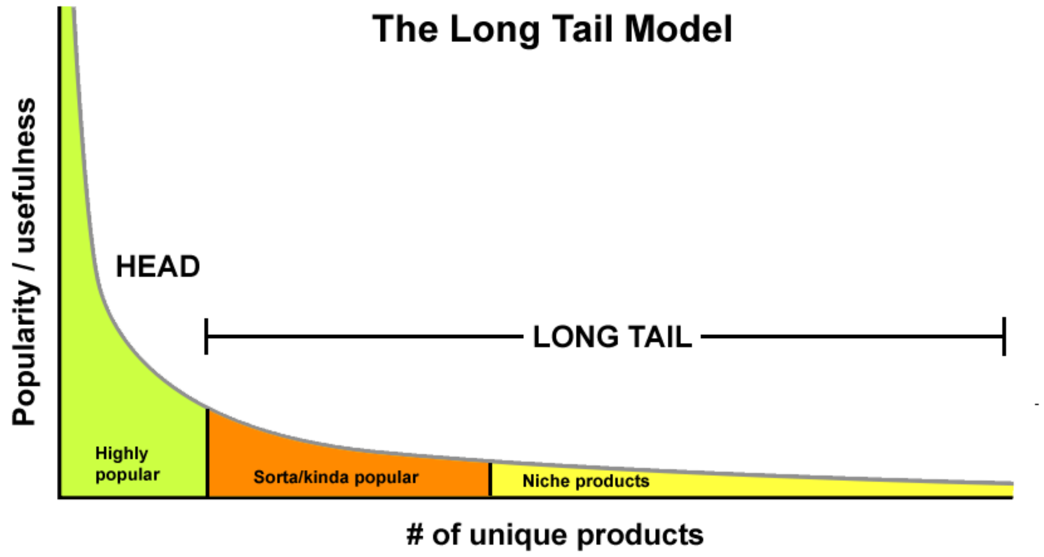


- Iterative



Specialty and credibility modeling for recommendation

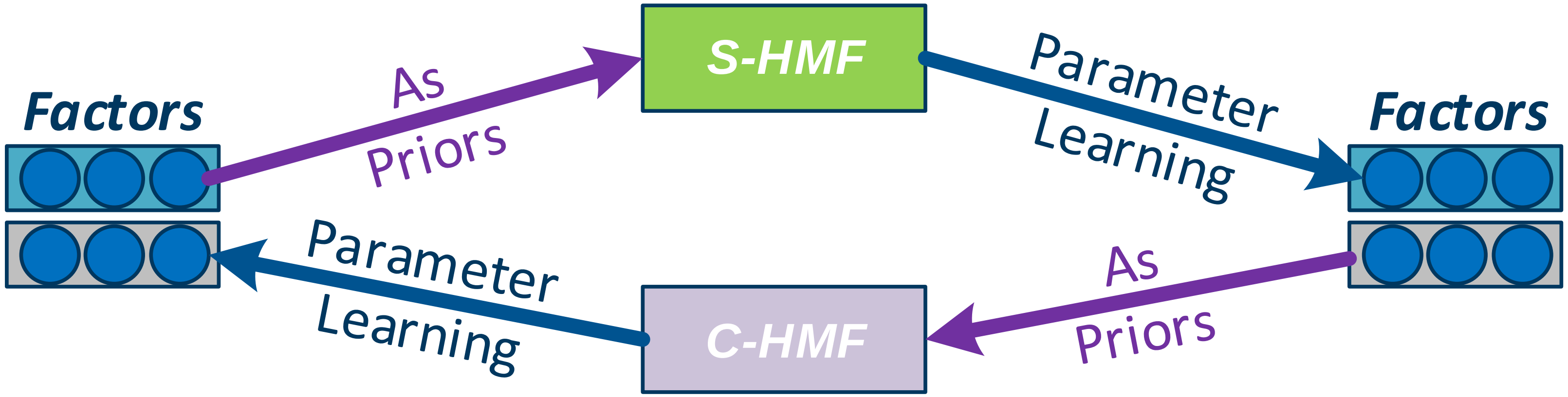
- Popularity Bias
  - Short-head users and items account for the majority of data, and models tend to fit these users and items.
  - Specialty modeling is desirable
- Shilling Attack
  - Long-tail items have few data and they are more vulnerable to shilling attack.
  - Credibility modeling is desirable



Hu, L., Cao, L., Cao, J., Gu, Z., Xu, G., and Wang, J. Improving the Quality of Recommendations for Users and Items in the Tail of Distribution. ACM Trans. Inf. Syst., 2017

Iterative optimizing credibility and specialty

- Recurrent Mutual Regularization Model (RMRM) consists of two main components
  - C-HMF models user choices by emphasizing credibility
  - S-HMF models user choices by emphasizing specialty
- Each component leads to a different objective for optimization, so RMRM is a multi-objective recommenders systems



Hu, L., Cao, L., Cao, J., Gu, Z., Xu, G., and Wang, J. Improving the Quality of Recommendations for Users and Items in the Tail of Distribution. ACM Trans. Inf. Syst., 2017

Heteroscedastic MF

- $P(\boldsymbol{U}_i) = N(\boldsymbol{U}_i | \boldsymbol{\mu}_U, \sigma_U^2 \boldsymbol{I})$
- $P(\boldsymbol{V}_j) = N(\boldsymbol{V}_j | \boldsymbol{\mu}_V, \sigma_V^2 \boldsymbol{I})$
- $P(Y_{ij} | \boldsymbol{U}_i, \boldsymbol{V}_j) = N(Y_{ij} | \boldsymbol{U}_i^{\mathrm{T}} \boldsymbol{V}_j, \sigma_{ij}^2)$

$$P(\boldsymbol{U}, \boldsymbol{V} | \boldsymbol{Y}) \propto P(\boldsymbol{Y}, \boldsymbol{U}, \boldsymbol{V}) = \prod_{ij \in \boldsymbol{O}} P(Y_{ij} | \boldsymbol{U}_i, \boldsymbol{V}_j) \prod_i P(\boldsymbol{U}_i) \prod_j P(\boldsymbol{V}_j)$$

- *Loss function:*
  - $-\log P(Y_{ij}, \boldsymbol{U}_i, \boldsymbol{V}_j) =$
  - $\underset{\boldsymbol{U},\boldsymbol{V}}{argmin} \left[\underbrace{\sum_{ij} w_{ij} (Y_{ij} - \boldsymbol{U}_i^{\mathrm{T}} \boldsymbol{V}_j)^2}_{weighted\ loss} + \underbrace{\lambda_U \sum_i \|\boldsymbol{U}_i - \boldsymbol{\mu}_i\|^2 + \lambda_V \sum_j \|\boldsymbol{V}_j - \boldsymbol{\mu}_j\|^2}_{regularization} \right]$

  - model variance, i.e. weight on the loss : $w_{ij} = f(\sigma_{ij}^{-2})$

Popularity Bias

Shilling Attack

Hu, L., Cao, L., Cao, J., Gu, Z., Xu, G., and Wang, J. Improving the Quality of Recommendations for Users and Items in the Tail of Distribution. ACM Trans. Inf. Syst., 2017

Specialty enhancement

- S-HMF (Specialty-specific Heteroscedastic MF) **Popularity Bias**
  - $\sigma_{ij}^2 = f^S(Y_{ij}) \propto {\psi_j}^{-1}$, i.e., $w_{ij} \propto \psi_j$, scores the *specialty* of user choice, which tightly fits the choices over long-tail items

- Given all observed choices, the ***specialty score*** of a choice on an item j is measured by the *self-information*:
  - $\psi_j = -\log \bar{p}(j|\alpha)$

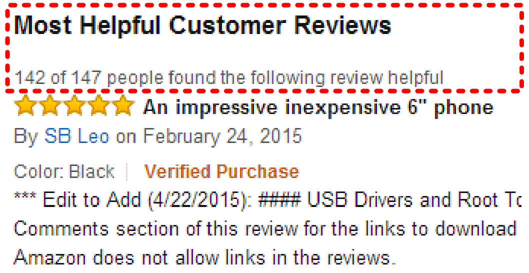
Hu, L., Cao, L., Cao, J., Gu, Z., Xu, G., and Wang, J. Improving the Quality of Recommendations for Users and Items in the Tail of Distribution. ACM Trans. Inf. Syst., 2017

Credibility enhancement

Shilling Attack

- C-HMF (Credibility-specific Heteroscedastic MF)
  - $\sigma_{ij}^2 = f^C(Y_{ij}) \propto \varphi_i^{-1}$, i.e., $w_{ij} \propto \varphi_i$, scores the *credibility* of each review
- Bayesian Reputation Modeling
  - *Reputation Score: Given the helpfulness scores $\boldsymbol{h}_i$ of a user $\boldsymbol{i}$, the reputation score on this user is defined by:*

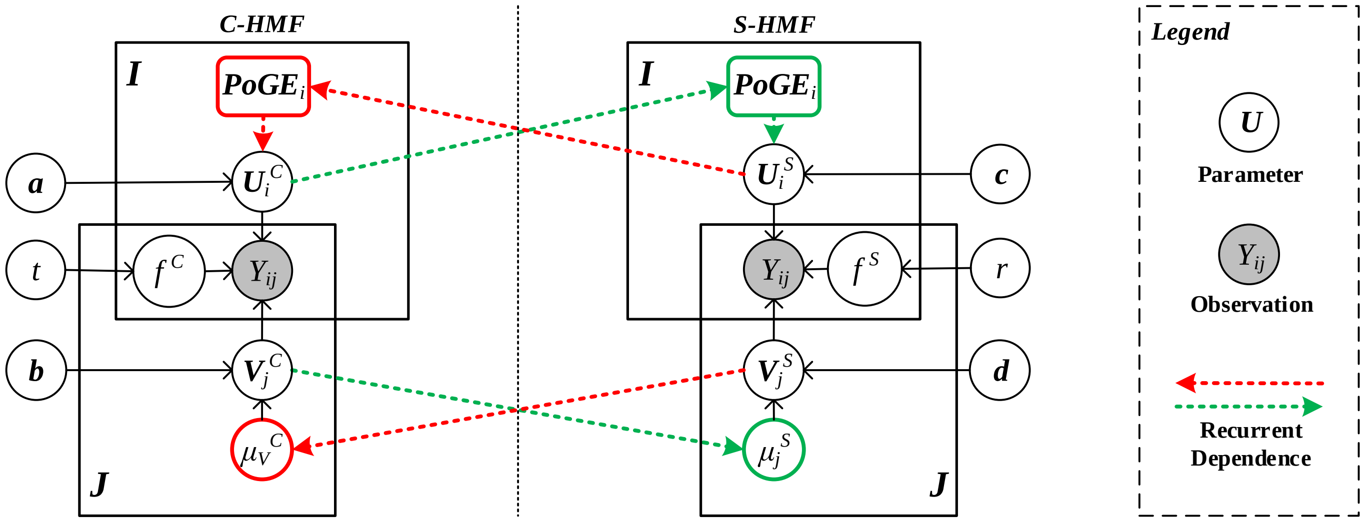
$$\varphi_i = \mathcal{R}(\boldsymbol{e}_i|\boldsymbol{h}_i) \stackrel{\text{def}}{=} \frac{r+\alpha}{r+s+\alpha+\beta}$$



Hu, L., Cao, L., Cao, J., Gu, Z., Xu, G., and Wang, J. Improving the Quality of Recommendations for Users and Items in the Tail of Distribution. ACM Trans. Inf. Syst., 2017

Recurrent Mutual Regularization

- A **recurrent mutual regularization process** couples S-HMF and C-HMF using the user and items factors learned from each other as the **empirical priors**



Graphical model of RMRM framework

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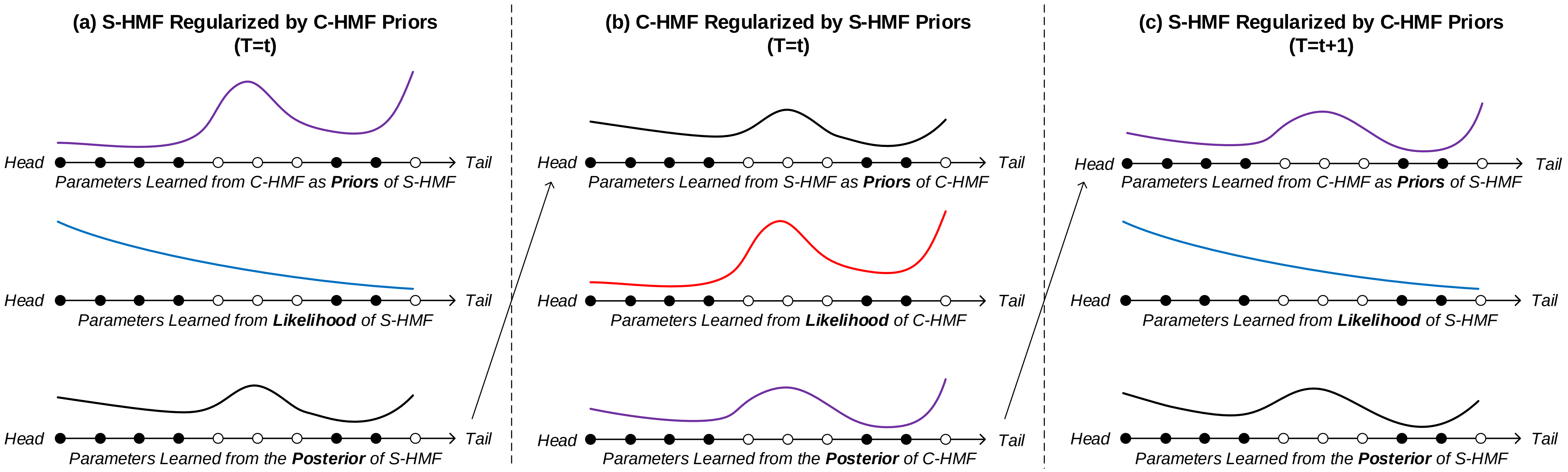
Demonstration of the recurrent mutual regularization process



$$\underset{U^C,V^C}{argmin}\left[\underbrace{\sum_{ij} w_{ij}\left(Y_{ij}-U_i^{C\,\mathrm{T}}V_j^C\right)^2}_{weighted\ loss}+\underbrace{\lambda_U\sum_i\left\|U_i^C-U_i^S\right\|^2+\lambda_V\sum_j\left\|V_j^C-V_j^S\right\|^2}_{regularization}\right]$$

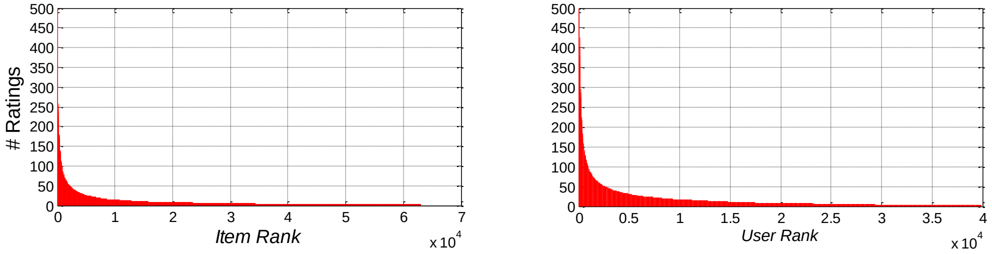
$$\underset{U^S,V^S}{argmin}\left[\underbrace{\sum_{ij} w_{ij}\left(Y_{ij}-U_i^{S\,\mathrm{T}}V_j^S\right)^2}_{weighted\ loss}+\underbrace{\lambda_U\sum_i\left\|U_i^S-U_i^C\right\|^2+\lambda_V\sum_j\left\|V_j^S-V_j^C\right\|^2}_{regularization}\right]$$

Mutual Regularization

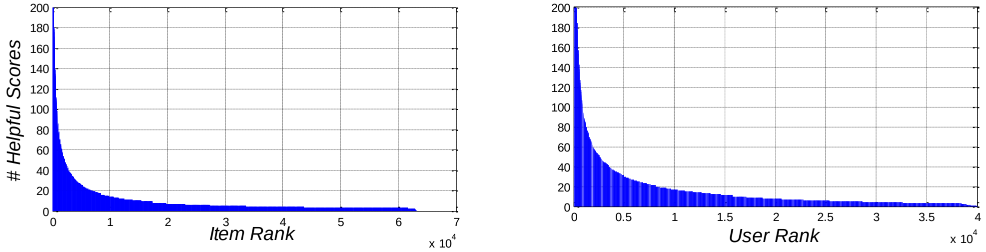
Hu, L., Cao, L., Cao, J., Gu, Z., Xu, G., and Wang, J. Improving the Quality of Recommendations for Users and Items in the Tail of Distribution. ACM Trans. Inf. Syst., 2017

Dataset: Epinions

# users: 39,902	# items: 63,027
# trust links: 43,8965	# trusters / users: 11
max # of trusters: 1,713	# users with zero truster: 14,202
# ratings: 734,441	density: 0.029%
# ratings / users: 18	# ratings / items: 11
max # ratings of user: 1,809	max # ratings of item: 2,112

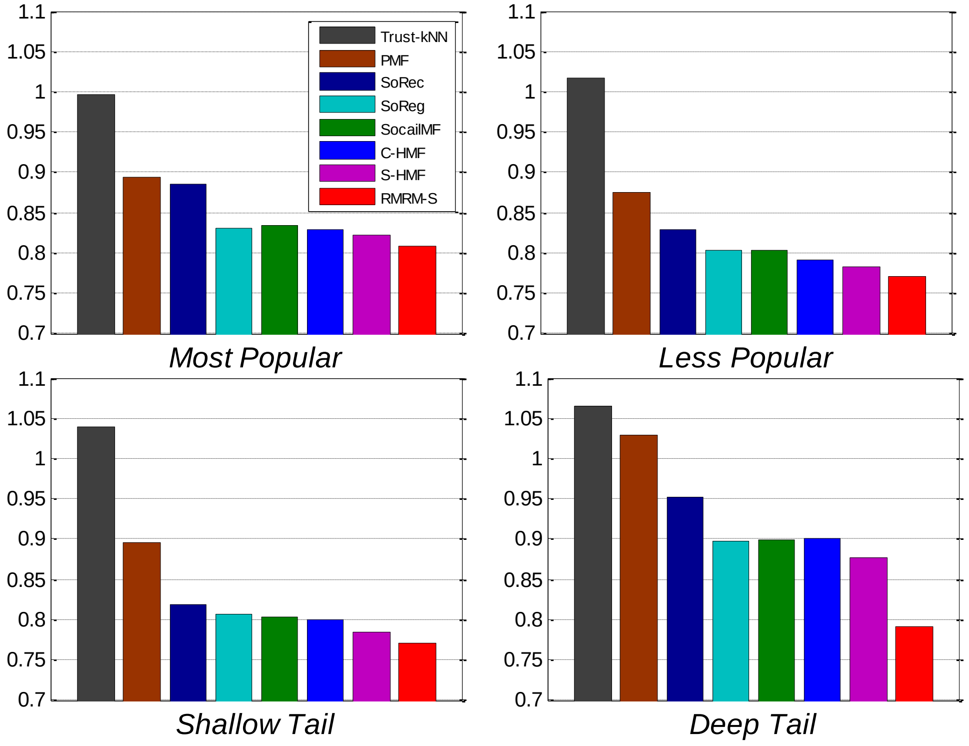


Long-tail distributions for the number of ratings of items and users (truncated from 0 to 500)

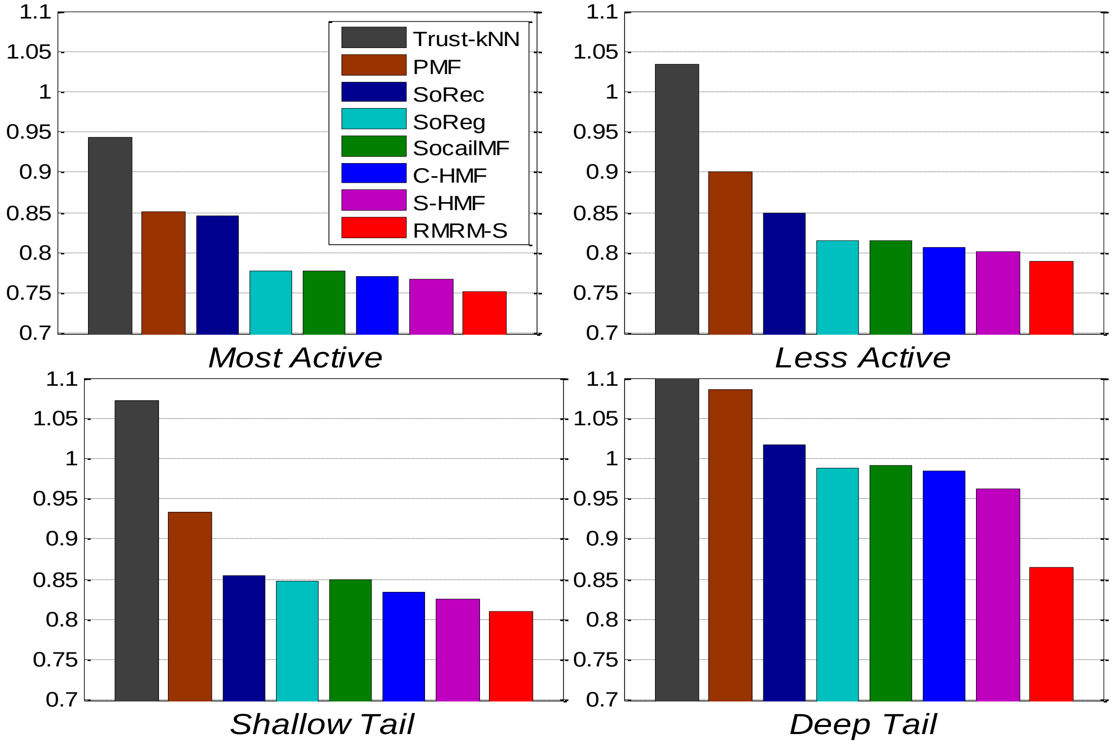


The distributions for the number of helpful scores w.r.t. items and users (truncated from 0 to 200)

Rating Prediction on Long-tail Distributed Items and Users



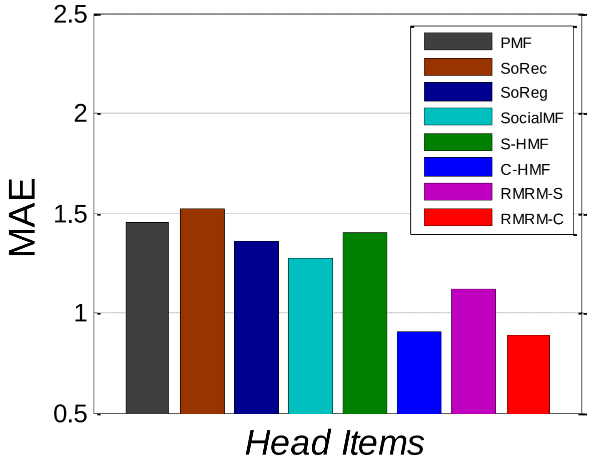
MAEs of rating prediction for the long-tail item distribution

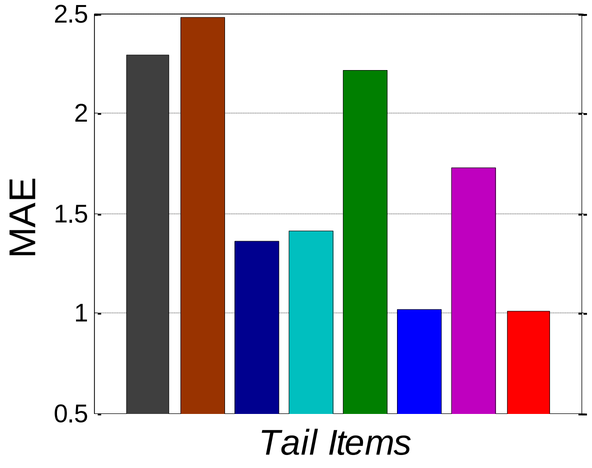


MAEs of rating prediction for the long-tail user distribution

Shilling Attack Simulation

- To simulate such an environment
  - We created 1,000 virtual spam users to conduct the attack
  - We selected 100 items from the head (0%~20%) and the tail (20%~100%) as the attack targets.
- Nuke attack in the case of the average attack model





Next chapter

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- Multi-temporal domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-goal domain recommender systems (Liang Hu, 20 mins)
- **Summary (Liang Hu, 5 mins)**