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RippleNet: Propagating User Preferences on the Knowledge Graph for Recommender Systems

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Recommender Systems

Recommender systems (RS) intend to address the information explosion by finding a small set of items for users to meet their personalized interests

Movie (IMDb)

Recommender Systems

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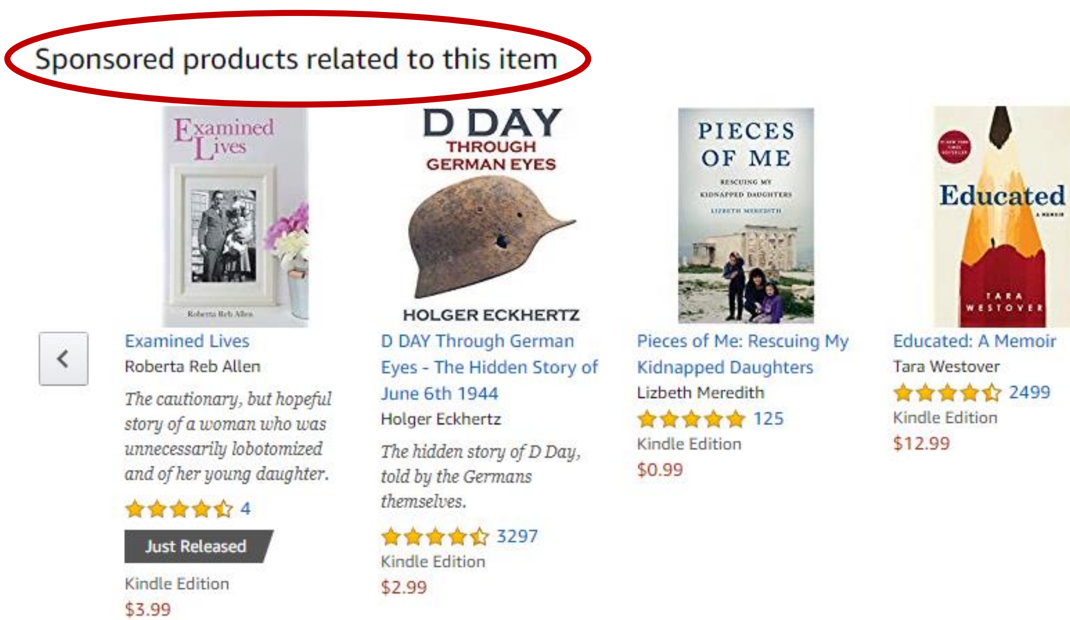
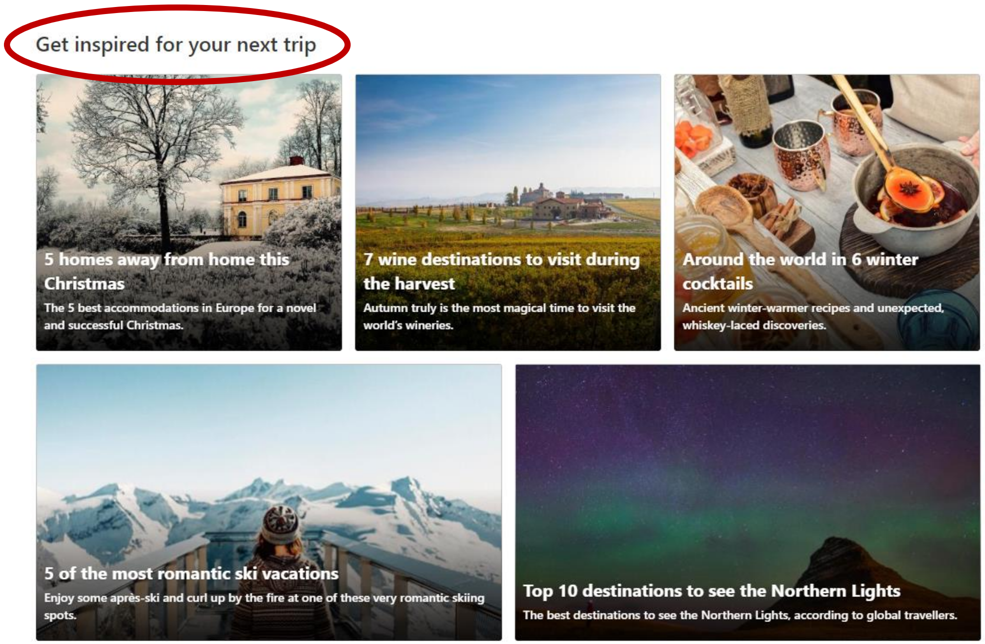


Book (Amazon)

Recommender Systems

Recommender systems (RS) intend to address the information explosion by finding a small set of items for users to meet their personalized interests



Trip (Booking)

Rating/CTR Prediction

Explicit feedback

2	?	3	?
?	?	4	?
?	5	?	2
3	1	4	?

Rating prediction

Implicit feedback

1	?	0	?
?	?	1	?
?	0	?	1
0	1	0	?

Click-through rate
(CTR) prediction

Collaborative Filtering

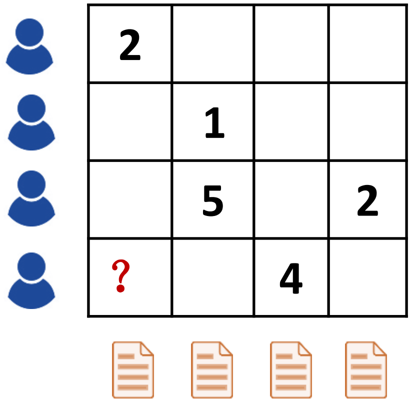
- Collaborative filtering (CF) assumes that similar uses (with respect to their historical records) have similar preferences
  - Matrix factorization

$$R_{pq} = \mathbf{p}^\top \mathbf{q}$$

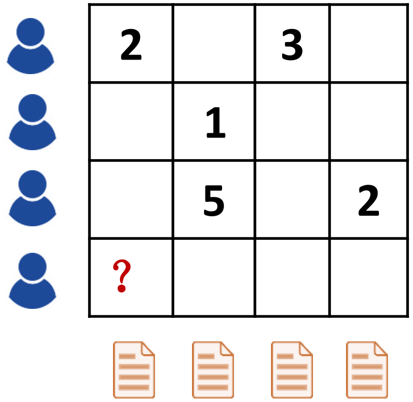
$$L = \| \boldsymbol{R} - \boldsymbol{P}^{\mathrm{T}} \boldsymbol{Q} \|_2^2 + \| \boldsymbol{P} \|_2^2 + \| \boldsymbol{Q} \|_2^2$$

CF Fails To Address …

- Sparsity of user-item interactions
- Cold start problem

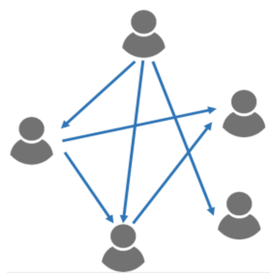


Sparsity



Cold start

CF + Side Information



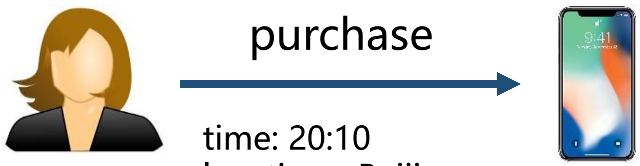
Social network

Alice
Female
California
…

iPhone X
2017
5.8 inch
$999
…

User/item attributes

Multimedia (image, text, video, audio …)



time: 20:10
location: Beijing
What else in carts: …

Context

Knowledge Graph

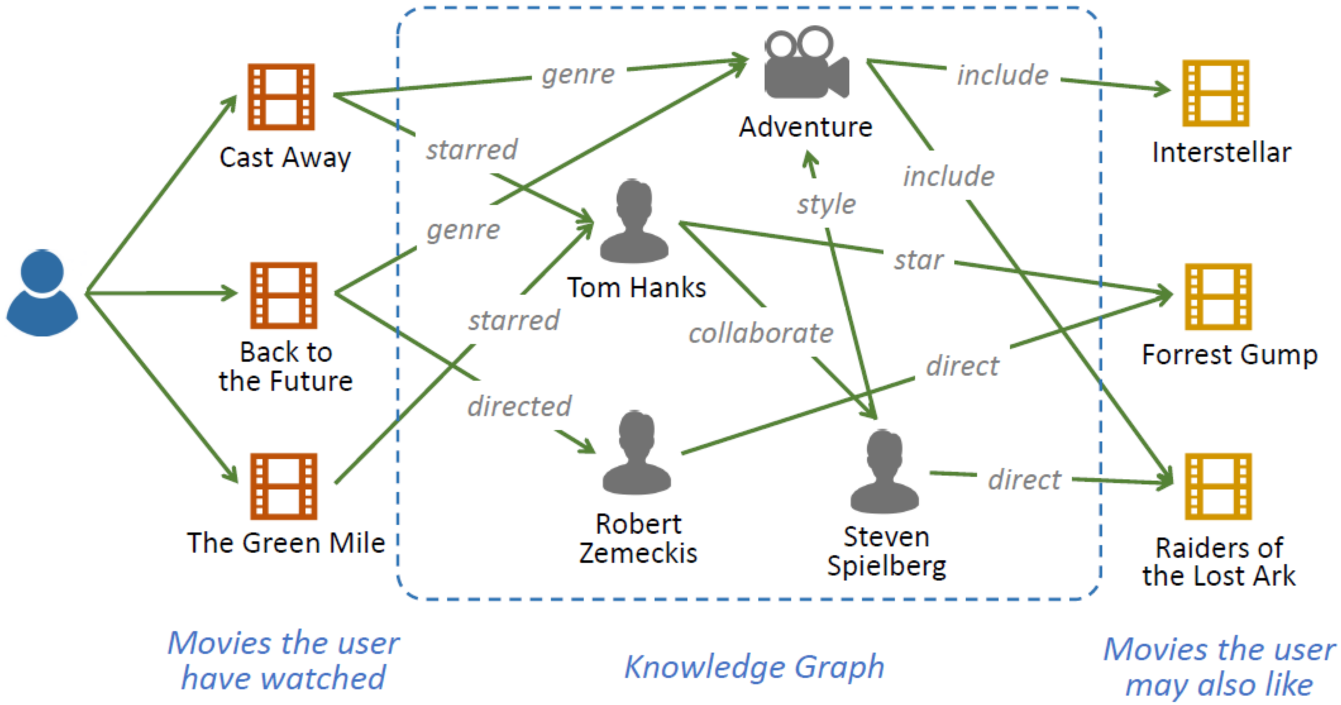
- A **knowledge graph** (KG) is a type of directed heterogeneous graph in which nodes correspond to **entities** and edges correspond to **relations**
- A KG usually consists of massive triples **(head, relation, tail)**

Forrest Gump —*film.film.star*→ Tom Hanks

Tom Hanks —*people.people.date_of_brith*→ July 7, 1956

Knowledge Graph

A snippet of knowledge graph in movie recommendation



KG-aware RS

- **Embedding-based methods** pre-process a KG with knowledge graph embedding (KGE) algorithms, then incorporate the learned entity embeddings into a recommendation framework
  - Collaborative Knowledge base Embedding (CKE) [KDD 16]
  - Deep Knowledge-aware Network (DKN) [WWW 18]
  - Signed Heterogeneous Information Network Embedding (SHINE) [WSDM 18]
  - Knowledge-enhanced Sequential Recommender (KSR) [SIGIR 18]

KG-aware RS

- **Path-based methods** explore the various patterns of connections among items in KG to provide additional guidance for recommendations
  - Personalized Entity Recommendation (PER) [WSDM 14]
  - Factorization Machine with Group lasso (FMG) [KDD 17]

Pros and Cons

- **Embedding-based methods**
  - have high flexibility, but …
  - the adopted KGE algorithms focus more on modeling rigorous semantic relatedness
- **Path-based methods**
  - make use of KG in a more natural and intuitive way, but …
  - they rely heavily on manually designed meta-paths/meta-graphs

Our Work

- We propose **RippleNet**, an end-to-end framework for KG-aware recommendation
- The key idea of RippleNet is **preference propagation**
- RippleNet combines the advantages of the two types of methods:
  - RippleNet incorporates the KGE methods into RS by preference propagation
  - RippleNet can automatically discover possible meta-paths

Problem Formulation

- Users: $\mathcal{U} = \{u_1, u_2, \dots\}$, items: $\mathcal{V} = \{v_1, v_2, \dots\}$
- User-item interaction (implicit feedback):

$$\mathrm{Y} = \{y_{uv} \in \{0,1\} \mid u \in \mathcal{U}, v \in \mathcal{V}\}$$

- Knowledge graph $\mathcal{G} = (\mathcal{E}, \mathcal{R})$:
  - $\mathcal{G} = \{(h, r, t) \mid h \in \mathcal{E},\ r \in \mathcal{R},\ t \in \mathcal{E}\}$
  - $\mathcal{V} \subseteq \mathcal{E}$ (each item in $\mathcal{V}$ associates with an entity in $\mathcal{E}$)

- Goal: learning a prediction function

$$\hat{y}_{uv} = \mathcal{F}(u, v;\ \Theta) \in [0,1]$$

Relevant Entity

- **Definition 1 (relevant entity):** Given interaction matrix Y and knowledge graph $\mathcal{G}$, the set of k-hop relevant entities for user u is (recursively) defined as

$$\mathcal{E}_u^k = \{t \mid (h, r, t) \in \mathcal{G} \text{ and } h \in \mathcal{E}_u^{k-1}\}, \quad k = 1, 2, ..., H,$$

  - $\mathcal{E}_u^0 = \mathcal{V}_u = \{v \mid y_{uv} = 1\}$ is the set of the user's clicked items in the past

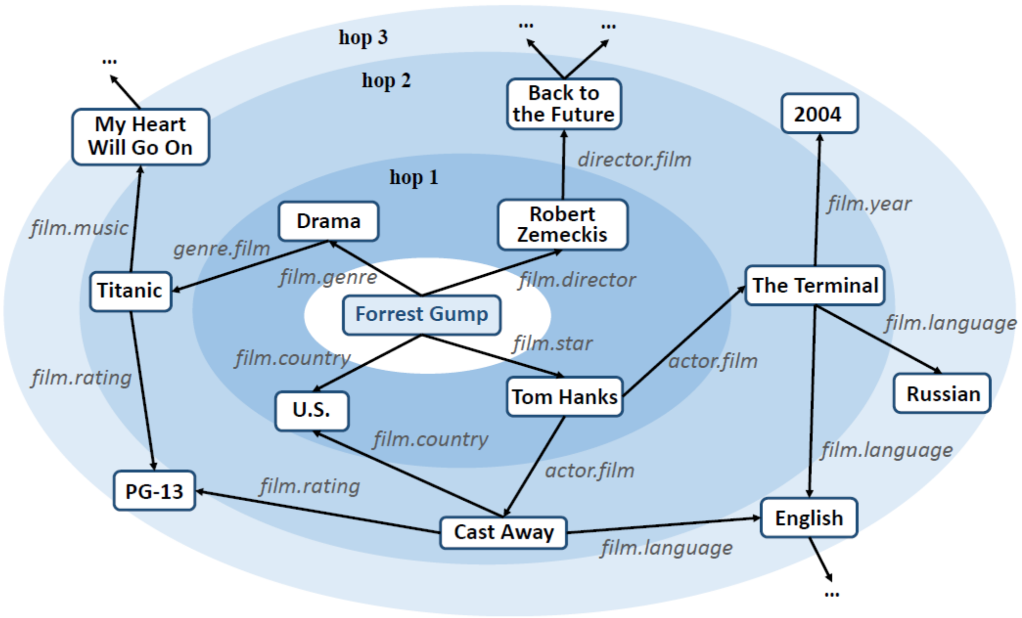
Ripple Set

- **Definition 2 (ripple set):** The k-hop ripple set of user u is defined as the set of knowledge triples starting from $\mathcal{E}_u^{k-1}$:

$$\mathcal{S}_u^k = \{(h, r, t) \mid (h, r, t) \in \mathcal{G} \; and \; h \in \mathcal{E}_u^{k-1}\}, \quad k = 1, 2, ..., H.$$

Ripple Set

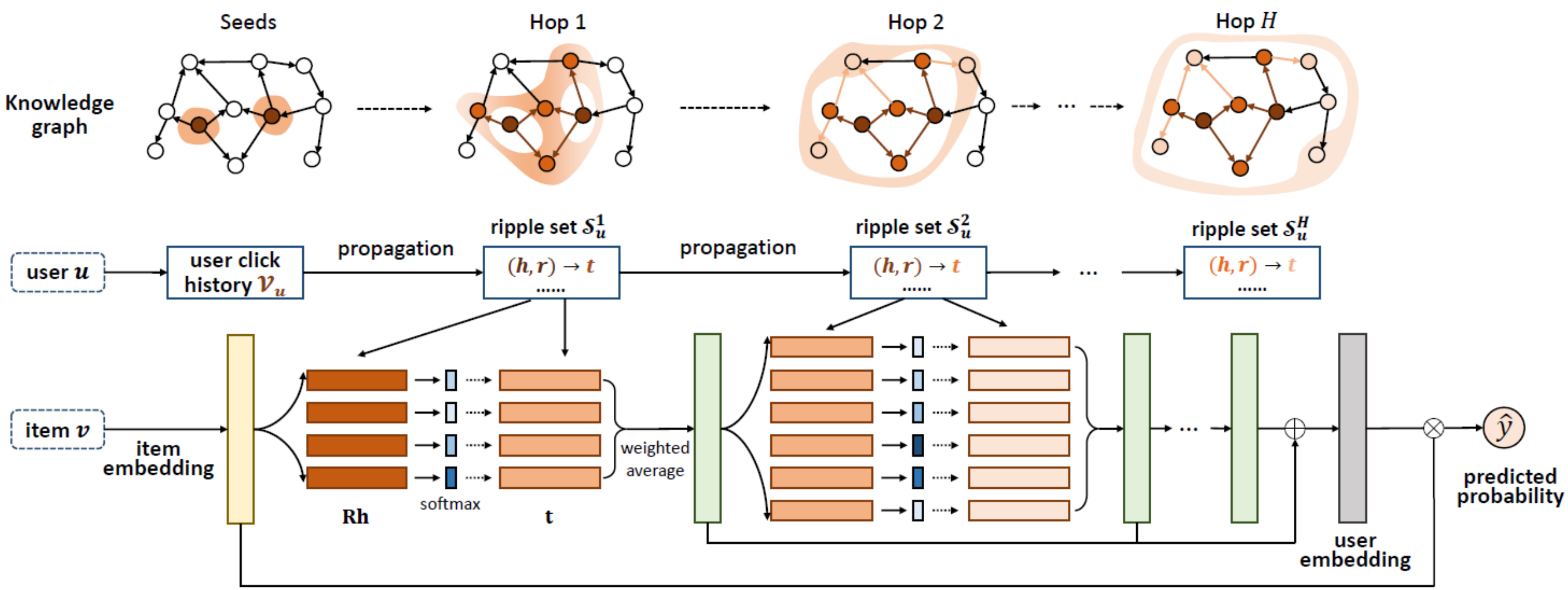
$$\mathcal{S}_u^k = \{(h, r, t) \mid (h, r, t) \in \mathcal{G} \text{ and } h \in \mathcal{E}_u^{k-1}\}, \quad k = 1, 2, \ldots, H.$$



Ripple set of "Forrest Gump" in the knowledge graph

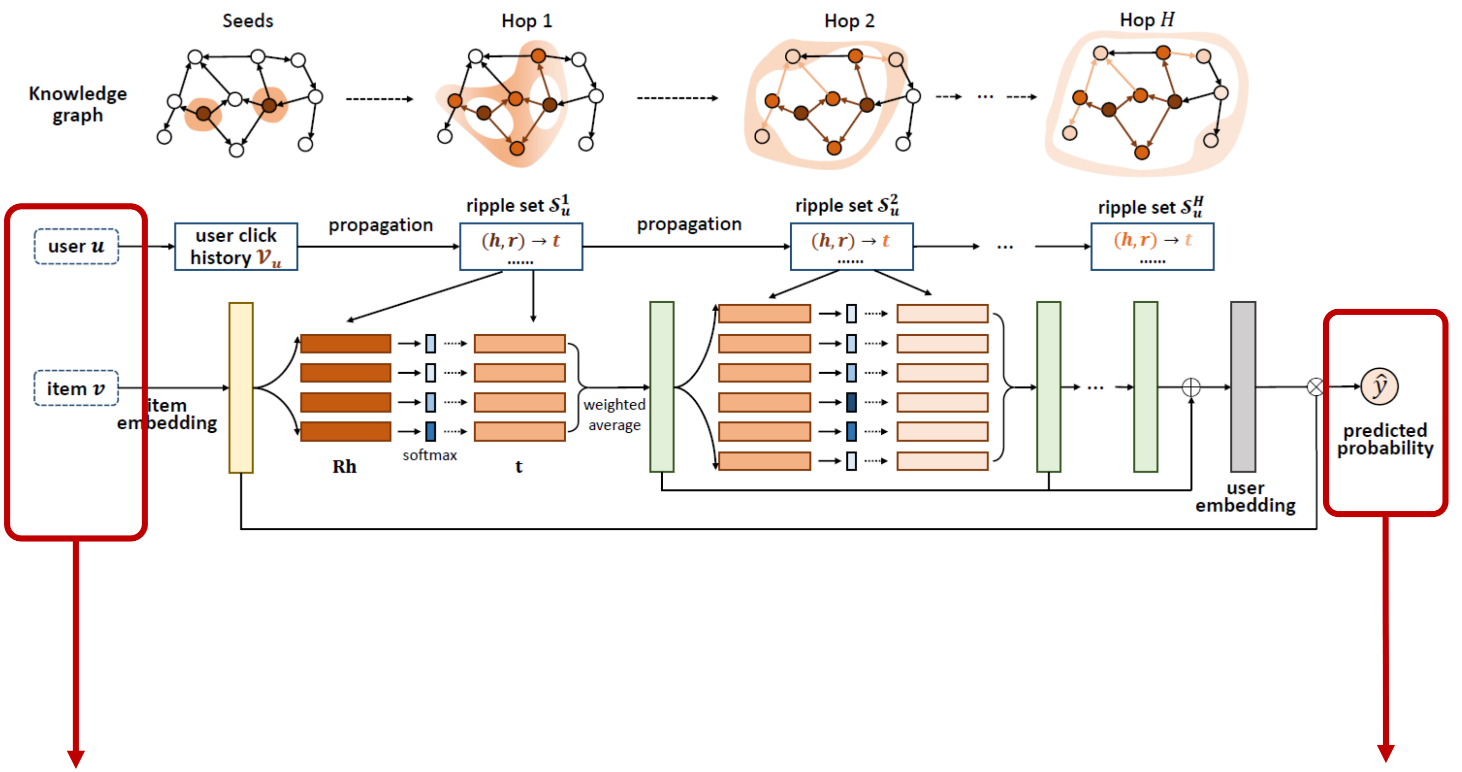
Ripples created by water droplet

Framework



Framework of RippleNet

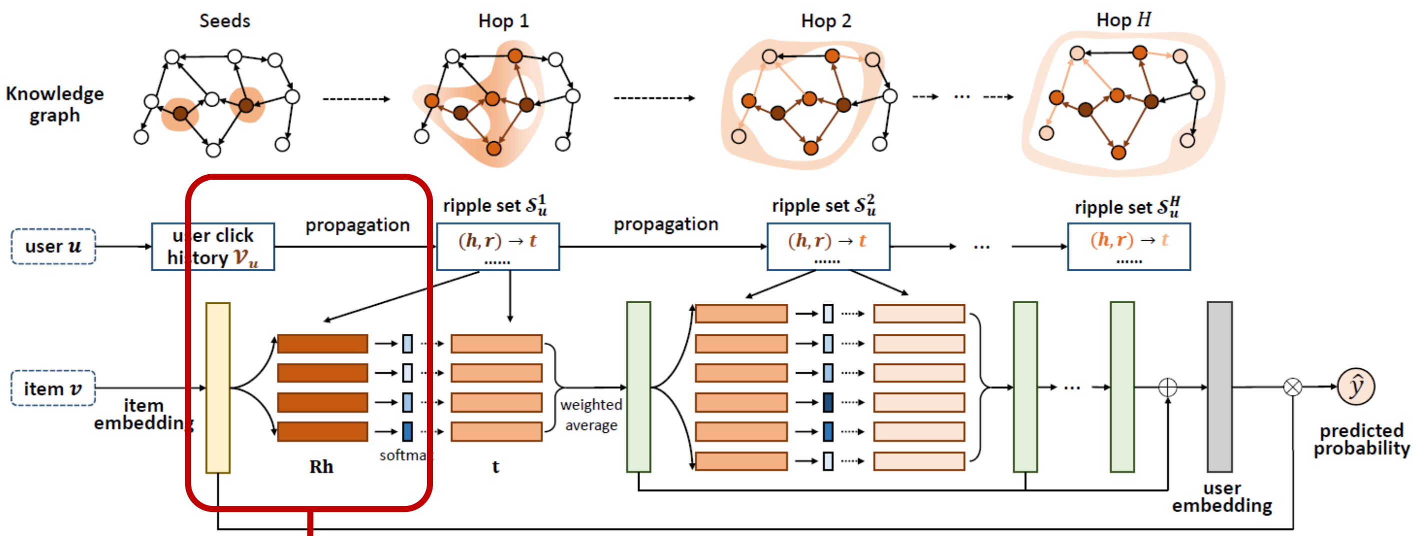
Preference Propagation



input

output

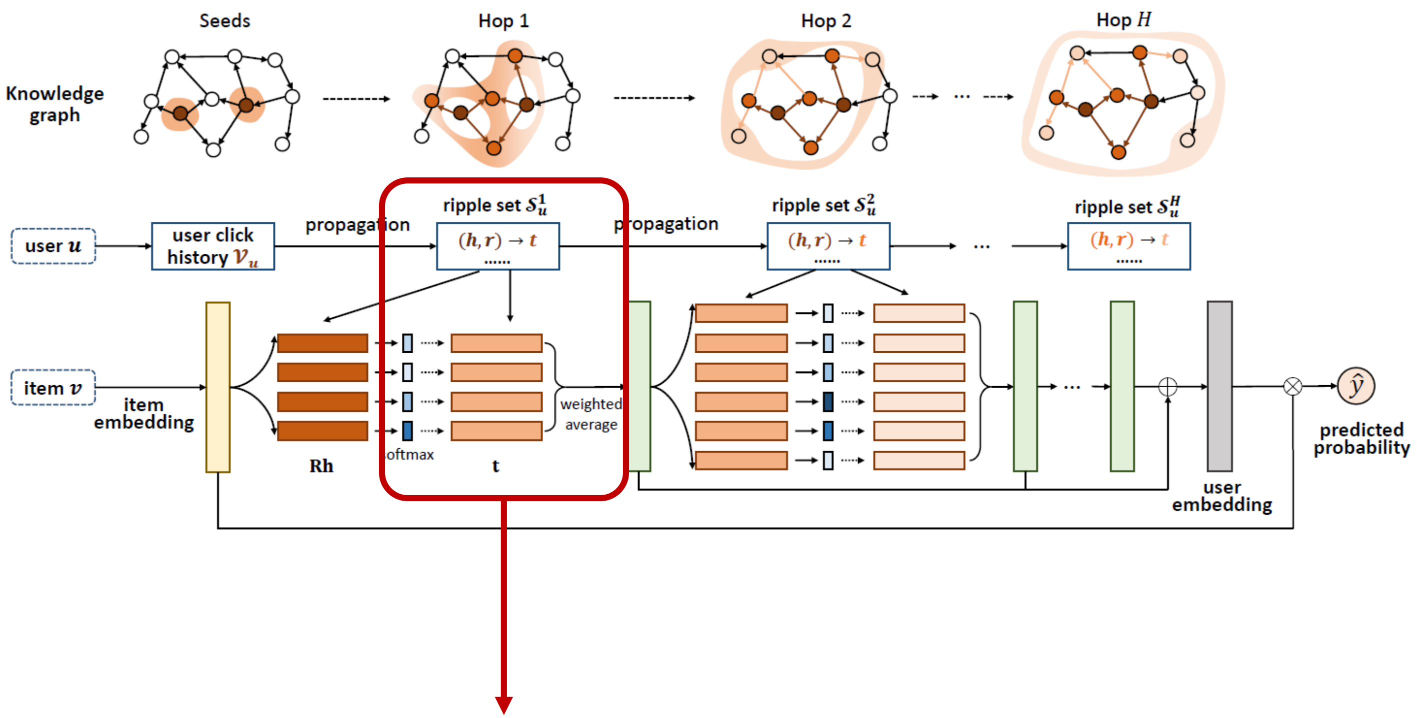
Preference Propagation



$$p_i = \mathrm{softmax}\left(\mathbf{v}^{\mathrm{T}}\mathbf{R}_i\mathbf{h}_i\right) = \frac{\exp\left(\mathbf{v}^{\mathrm{T}}\mathbf{R}_i\mathbf{h}_i\right)}{\sum_{(h,r,t)\in\mathcal{S}_u^1}\exp\left(\mathbf{v}^{\mathrm{T}}\mathbf{R}\mathbf{h}\right)}$$

Relevance probability

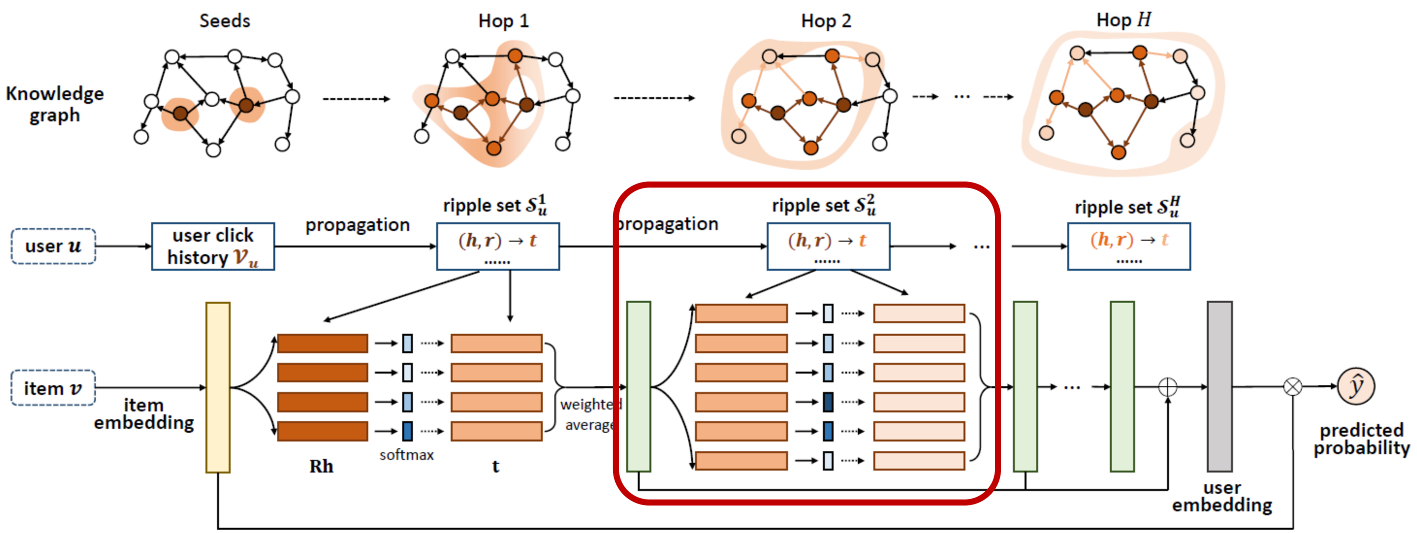
Preference Propagation



$$\mathbf{o}_u^1 = \sum_{(h_i, r_i, t_i) \in \mathcal{S}_u^1} p_i \mathbf{t}_i$$

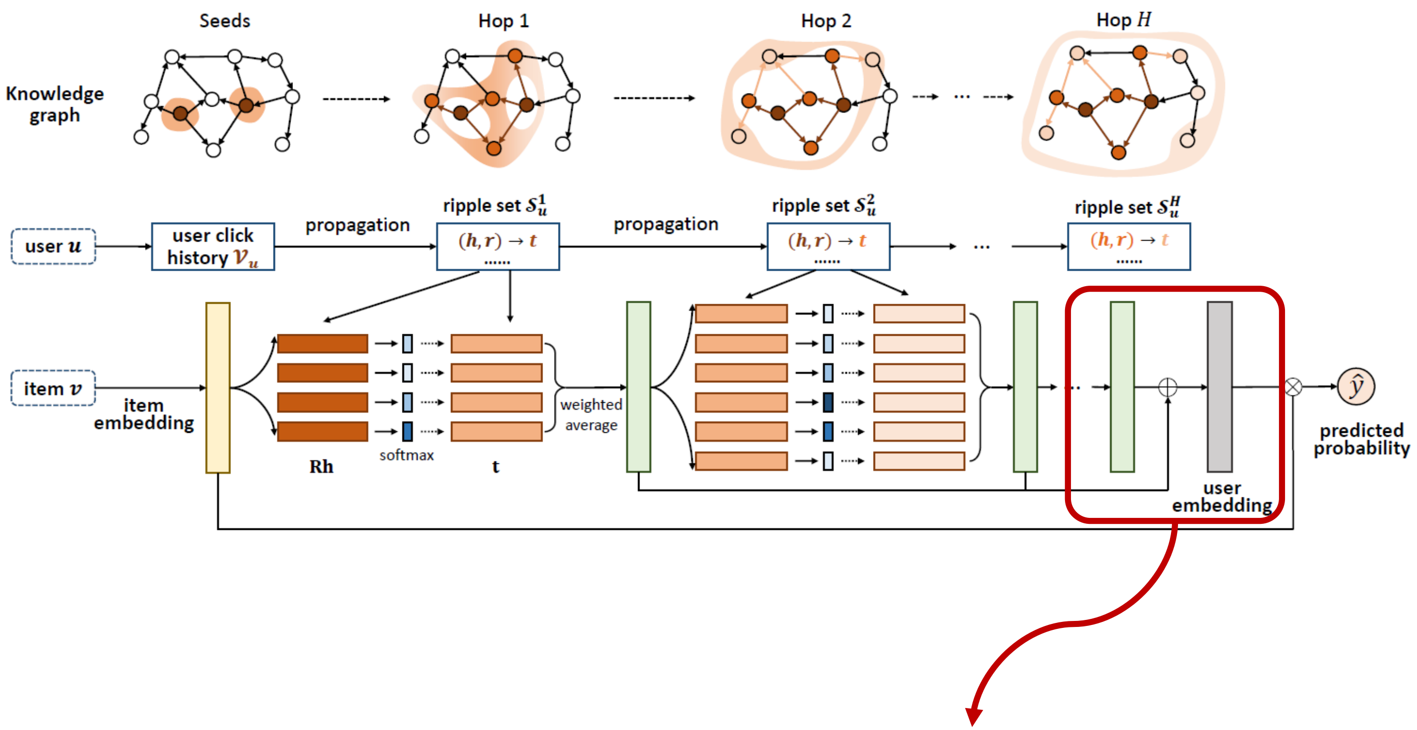
User's 1-order response

Preference Propagation



Repeat the propagation …

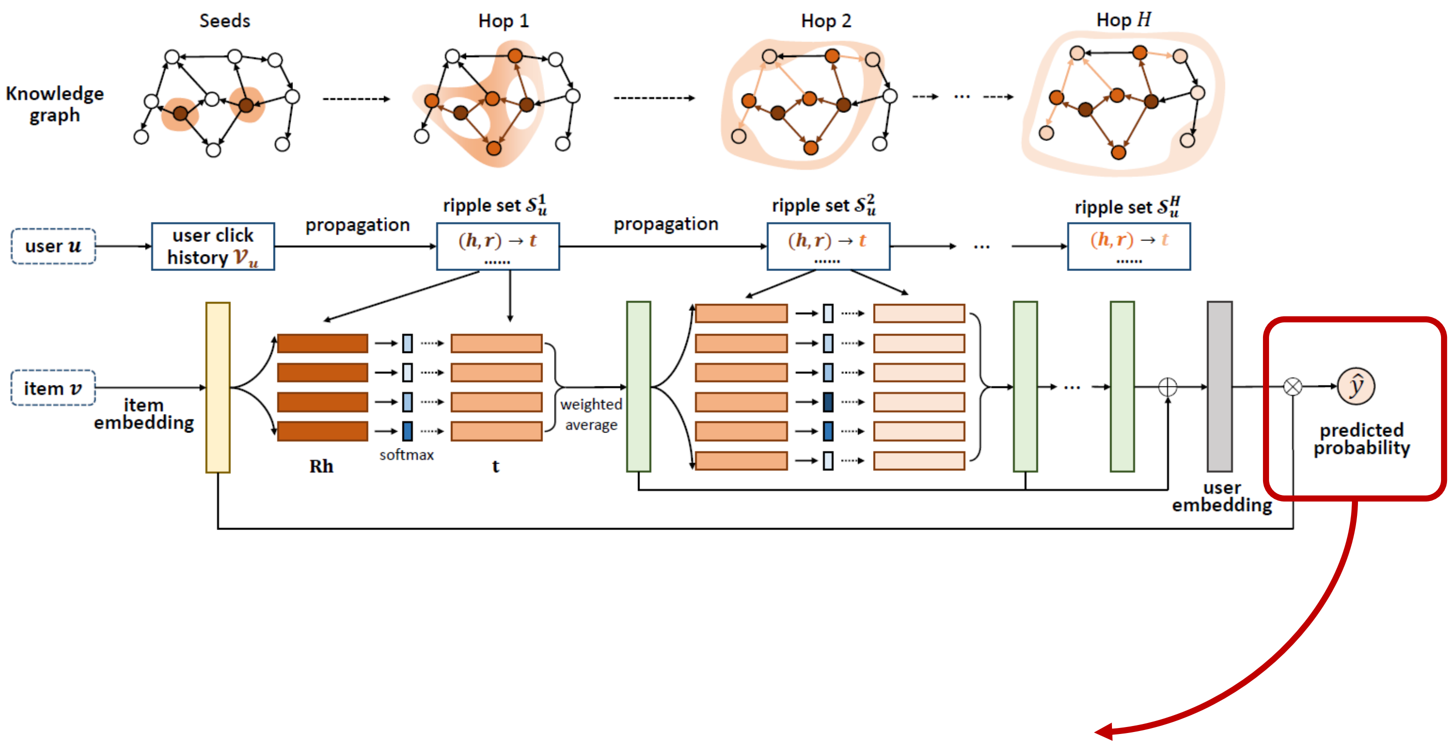
Preference Propagation



$$\mathbf{u} = \mathbf{o}_u^1 + \mathbf{o}_u^2 + \ldots + \mathbf{o}_u^H$$

User embedding

Preference Propagation



$$\hat{y}_{uv} = \sigma(\mathbf{u}^{\mathrm{T}}\mathbf{v})$$

Predicted probability

Learning Algorithm

- Maximizing the posterior probability

$$\max p(\Theta|\mathcal{G}, \mathrm{Y})$$

$$p(\Theta|\mathcal{G}, \mathrm{Y}) = \frac{p(\Theta, \mathcal{G}, \mathrm{Y})}{p(\mathcal{G}, \mathrm{Y})} \propto \boxed{p(\Theta)} \cdot p(\mathcal{G}|\Theta) \cdot p(\mathrm{Y}|\Theta, \mathcal{G})$$

- The priori probability of model parameters Θ:

$$p(\Theta) = \mathcal{N}(\mathbf{0},\ \lambda_1^{-1}\mathbf{I})$$

Learning Algorithm

- Maximizing the posterior probability

$$\max p(\Theta|\mathcal{G}, \mathrm{Y})$$

$$p(\Theta|\mathcal{G}, \mathrm{Y}) = \frac{p(\Theta, \mathcal{G}, \mathrm{Y})}{p(\mathcal{G}, \mathrm{Y})} \propto p(\Theta) \cdot \boxed{p(\mathcal{G}|\Theta)} \cdot p(\mathrm{Y}|\Theta, \mathcal{G})$$

- The likelihood function of the observed knowledge graph $\mathcal{G}$ given Θ (knowledge graph embedding):

$$\begin{aligned} p(\mathcal{G}|\Theta) &= \prod_{(h,r,t)\in\mathcal{E}\times\mathcal{R}\times\mathcal{E}} p\big((h,r,t)|\Theta\big) \\ &= \prod_{(h,r,t)\in\mathcal{E}\times\mathcal{R}\times\mathcal{E}} \mathcal{N}\big(I_{h,r,t} - \mathbf{h}^{\mathrm{T}}\mathbf{R}\mathbf{t},\ \lambda_2^{-1}\big) \end{aligned}$$

Learning Algorithm

- Maximizing the posterior probability

$$\max p(\Theta|\mathcal{G}, \mathrm{Y})$$

$$p(\Theta|\mathcal{G}, \mathrm{Y}) = \frac{p(\Theta, \mathcal{G}, \mathrm{Y})}{p(\mathcal{G}, \mathrm{Y})} \propto p(\Theta) \cdot p(\mathcal{G}|\Theta) \cdot \boxed{p(\mathrm{Y}|\Theta, \mathcal{G})}$$

- The likelihood function of the observed implicit feedback given Θ and $\mathcal{G}$ (Bernouli distributions)

$$p(\mathrm{Y}|\Theta, \mathcal{G}) = \prod_{(u,v)\in \mathrm{Y}} \sigma(\mathbf{u}^{\mathrm{T}}\mathbf{v})^{y_{uv}} \cdot \left(1 - \sigma(\mathbf{u}^{\mathrm{T}}\mathbf{v})\right)^{1-y_{uv}}$$

Learning Algorithm

- Maximizing the posterior probability

$$\max p(\Theta|\mathcal{G}, \mathrm{Y})$$

$$p(\Theta|\mathcal{G}, \mathrm{Y}) = \frac{p(\Theta, \mathcal{G}, \mathrm{Y})}{p(\mathcal{G}, \mathrm{Y})} \propto p(\Theta) \cdot p(\mathcal{G}|\Theta) \cdot p(\mathrm{Y}|\Theta, \mathcal{G})$$

- Loss function

$$\begin{aligned}
\min \mathcal{L} &= -\log\left(p(\mathrm{Y}|\Theta, \mathcal{G}) \cdot p(\mathcal{G}|\Theta) \cdot p(\Theta)\right) \\
&= \sum_{(u,v)\in \mathrm{Y}} -\left(y_{uv} \log \sigma(\mathbf{u}^{\mathrm{T}}\mathbf{v}) + (1 - y_{uv}) \log\left(1 - \sigma(\mathbf{u}^{\mathrm{T}}\mathbf{v})\right)\right) \\
&\quad + \frac{\lambda_2}{2} \sum_{r\in\mathcal{R}} ||\mathbf{I}_r - \mathbf{E}^{\mathrm{T}}\mathbf{R}\mathbf{E}||_2^2 + \frac{\lambda_1}{2}\left(||\mathbf{V}||_2^2 + ||\mathbf{E}||_2^2 + \sum_{r\in\mathcal{R}} ||\mathbf{R}||_2^2\right)
\end{aligned}$$

Datasets

- MovieLens-1M (movie recommendation)
- Book-Crossing (book recommendation)
- Bing-News (news recommendation)

Table 1: Basic statistics of the three datasets.

	MovieLens-1M	Book-Crossing	Bing-News
# users	6,036	17,860	141,487
# items	2,445	14,967	535,145
# interactions	753,772	139,746	1,025,192
# 1-hop triples	20,782	19,876	503,112
# 2-hop triples	178,049	65,360	1,748,562
# 3-hop triples	318,266	84,299	3,997,736
# 4-hop triples	923,718	71,628	6,322,548

Experiment Setup

- Explicit feedback -> implicit feedback
- Source of the knowledge graph: **Microsoft Satori**
- Entity linking
- Constructing knowledge sub-graph for each dataset

Table 2: Hyper-parameter settings for the three datasets.

MovieLens-1M	$d = 16, H = 2, \lambda_1 = 10^{-7}, \lambda_2 = 0.01, \eta = 0.02$
Book-Crossing	$d = 4, H = 3, \lambda_1 = 10^{-5}, \lambda_2 = 0.01, \eta = 0.001$
Bing-News	$d = 32, H = 3, \lambda_1 = 10^{-5}, \lambda_2 = 0.05, \eta = 0.005$

Baselines

KG-aware methods

- **CKE** [KDD 16]: Collaborative filtering + TransR
- **SHINE** [WSDM 18]: Autoencoder
- **DKN** [WWW 18]: Convolutional neural networks
- **PER** [WSDM 14]: Meta-path

Generic methods

- **LibFM**: Factorization machines
- **Wide&Deep**: deep neural network for RS

Results —— CTR Prediction

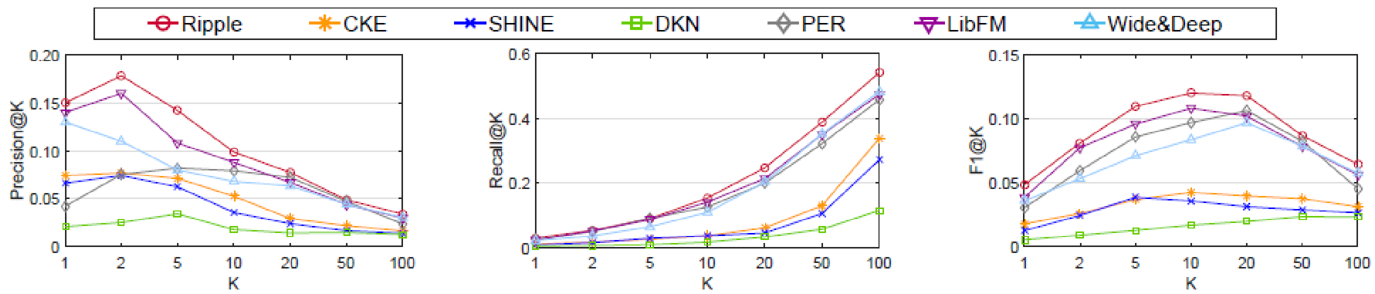
Table 3: The results of *AUC* and *Accuracy* in CTR prediction.

Model	MovieLens-1M		Book-Crossing		Bing-News	
	AUC	*ACC*	*AUC*	*ACC*	*AUC*	*ACC*
RippleNet*	**0.921**	**0.844**	**0.729**	**0.662**	**0.678**	**0.632**
CKE	0.796	0.739	0.674	0.635	0.560	0.517
SHINE	0.778	0.732	0.668	0.631	0.554	0.537
DKN	0.655	0.589	0.621	0.598	0.661	0.604
PER	0.712	0.667	0.623	0.588	-	-
LibFM	0.892	0.812	0.685	0.639	0.644	0.588
Wide&Deep	0.903	0.822	0.711	0.623	0.654	0.595

* Statistically significant improvements by unpaired two-sample t-test with $p = 0.1$.

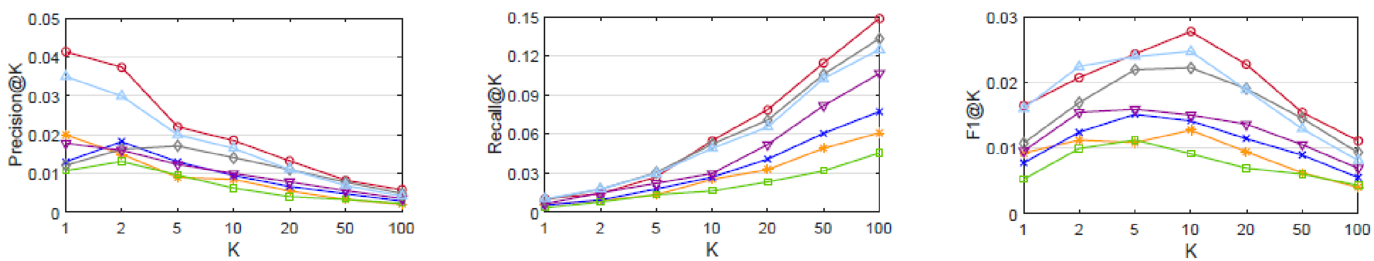
Improvements on AUC	2.0% ~ 40.6%	2.5% ~ 17.4%	2.6% ~ 22.4%

Results —— Top-K Recommendation



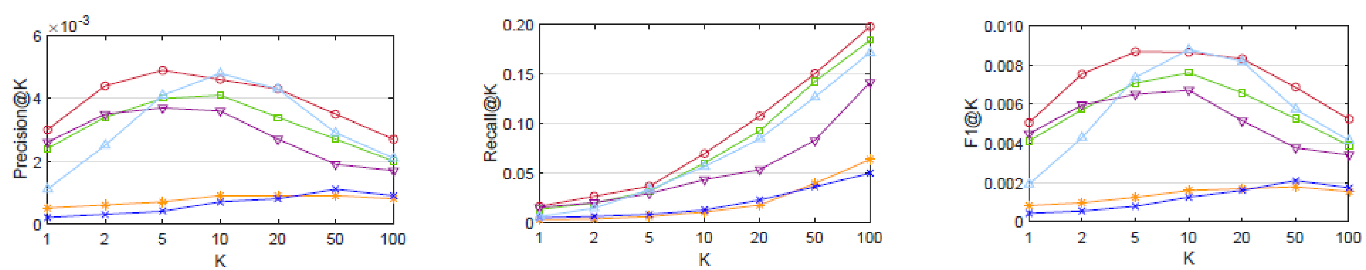
(a) *Precision@K* (b) *Recall@K* (c) *F1@K*

Figure 5: *Precision@K*, *Recall@K*, and *F1@K* in top-*K* recommendation for MovieLens-1M.



(a) *Precision@K* (b) *Recall@K* (c) *F1@K*

Figure 6: *Precision@K*, *Recall@K*, and *F1@K* in top-*K* recommendation for Book-Crossing.



(a) *Precision@K* (b) *Recall@K* (c) *F1@K*

Figure 7: *Precision@K*, *Recall@K*, and *F1@K* in top-*K* recommendation for Bing-News.

Results —— Parameter Sensitivity

Size of ripple set

Table 4: The results of *AUC* w.r.t. different sizes of a user's ripple set.

Size of ripple set	2	4	8	16	32	64
MovieLens-1M	0.903	0.908	0.911	0.918	**0.920**	0.919
Book-Crossing	0.694	0.696	0.708	**0.726**	0.706	0.711
Bing-News	0.659	0.672	0.670	0.673	**0.678**	0.671

Hop number

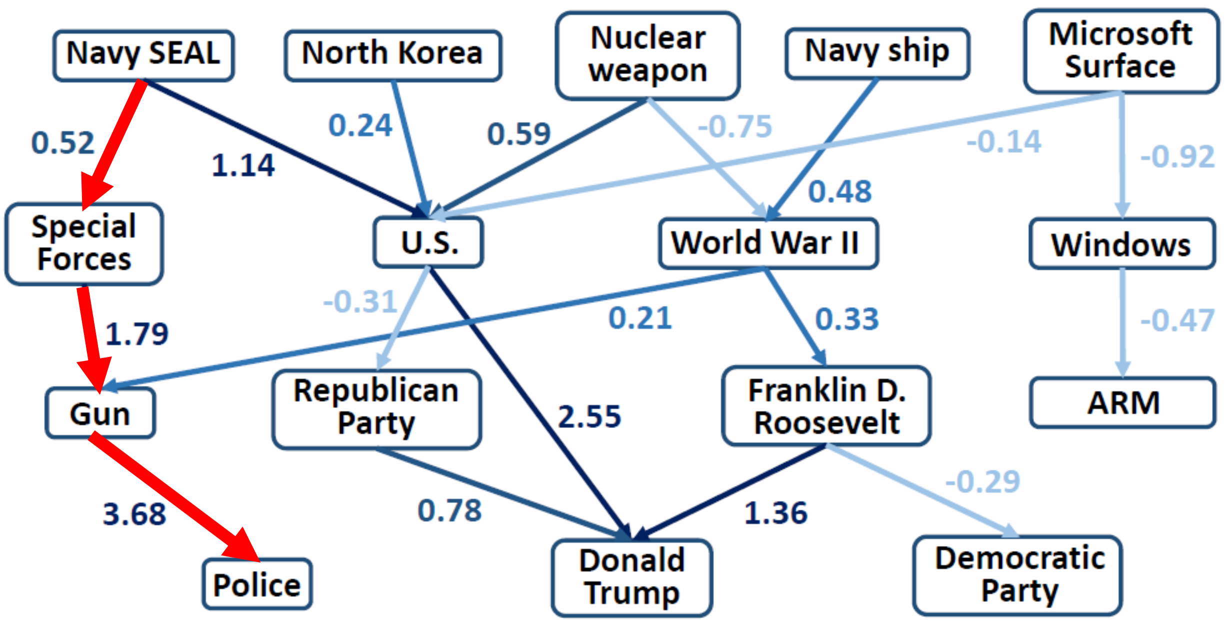
Table 5: The results of *AUC* w.r.t. different hop numbers.

Hop number H	1	2	3	4
MovieLens-1M	0.916	**0.919**	0.915	0.918
Book-Crossing	0.727	0.722	**0.730**	0.702
Bing-News	0.662	0.676	**0.679**	0.674

Results —— Explainability

Click history:

1. *Family of **Navy SEAL** Trainee Who Died During Pool Exercise Plans to Take Legal Action*
2. ***North Korea** Vows to Strengthen **Nuclear Weapons***
3. ***North Korea** Threatens 'Toughest Counteraction' After **U.S.** Moves **Navy Ships***
4. *Consumer Reports Pulls Recommendation for **Microsoft Surface** Laptops*



Candidate news: ***Trump** Announces Gunman Dead, Credits 'Heroic Actions' of **Police***

Summary

- We propose **RippleNet**, an end-to-end framework for KG-aware recommendation
- The key idea of RippleNet is **preference propagation**, which automatically propagates users’ preferences and explores their hierarchical interests in the KG
- RippleNet **combines the advantages** of embedding-based and path-based methods
- Experiment results demonstrate the **efficacy** and **explainability** of RippleNet

Q & A

Thanks !

- This work was partially sponsored by National Basic Research 973 Program of China (2015CB352403), National Natural Science Foundation of China (61272291), and SIGIR Student Travel Grant.
- The code is available at https://github.com/hwwang55/RippleNet.