大数据驱动智能+
BDTC 2019 中国大数据技术大会
Big Data Technology Conference 2019
主办单位：中国计算机学会（CCF）
承办单位：CCF大数据专家委员会
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结合知识的推荐系统

谢　幸
微软亚洲研究院

Recommendation Everywhere

Our Research

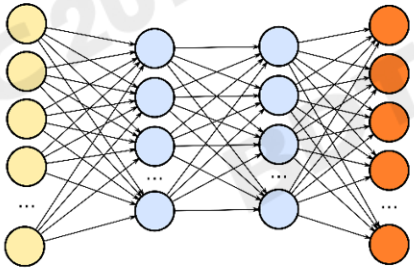
Deep learning based user modeling

user

Item

Knowledge enhanced recommendation

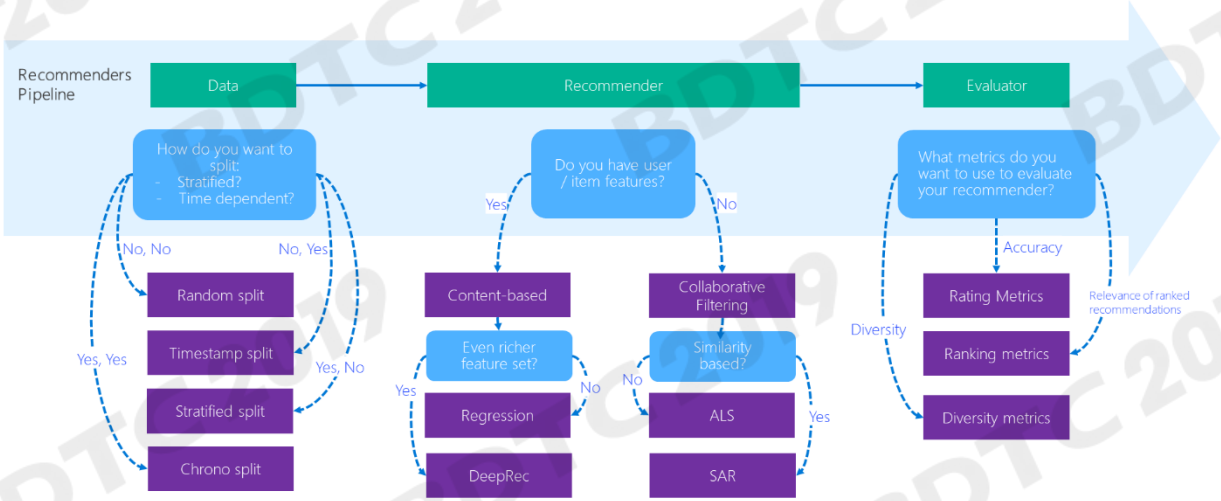
Deep learning based recommendation



Explainable recommendation

Microsoft Recommenders

- Providing examples and best practices for helping Azure developers to build their user representation and recommender algorithms https://github.com/microsoft/recommenders
- 6000+ stars, top 1 GitHub repository in this area
- KDD 2019 hands-on tutorial

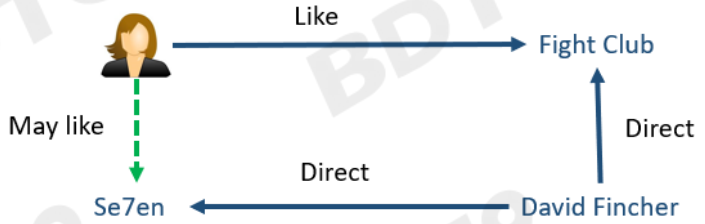


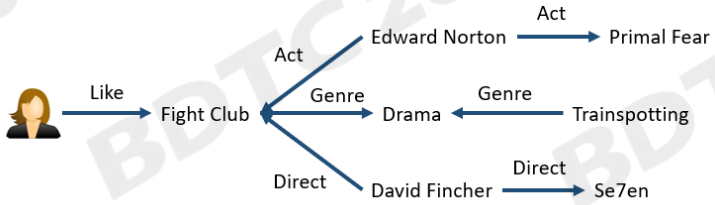
Knowledge Graph

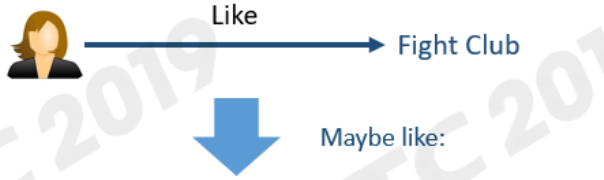
- A kind of semantic network, where node indicates entity or concept, edge indicates the semantic relation between entity/concept

Knowledge Enhanced Recommendation

- Precision
  - More semantic content about items
  - Deep user interest
- Diversity
  - Different types of relations in knowledge graph
  - Extend user's interest in different paths
- Explainability
  - Connect user interest and recommendation results
  - Improve user satisfaction, boost user trust







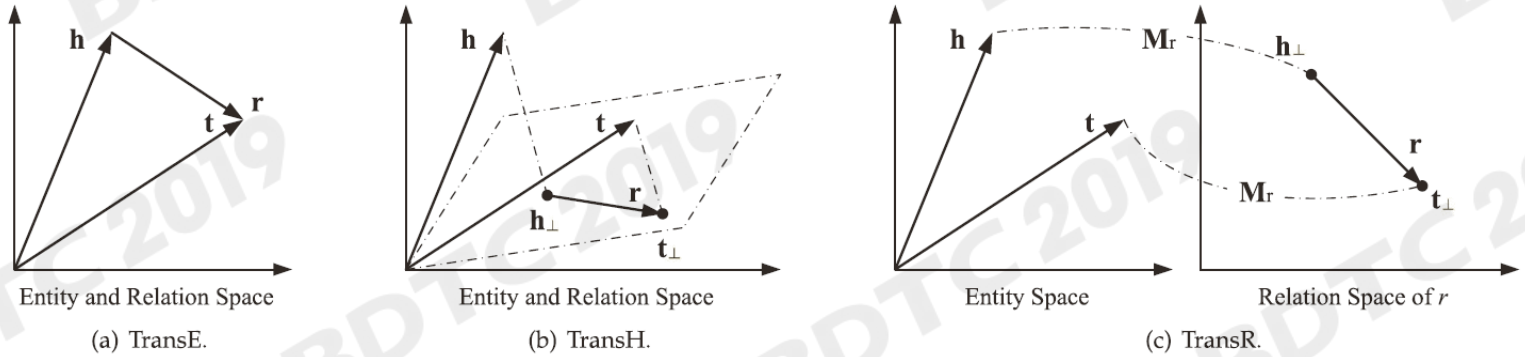
Primal Fear, because they share the same actor
Trainspotting, because they share the same genre
Se7en, because they share the same director

Knowledge Graph Embedding

- Learns a low-dimensional vector for each entity and relation in KG, which can keep the structural and semantic knowledge

Distance-based Models

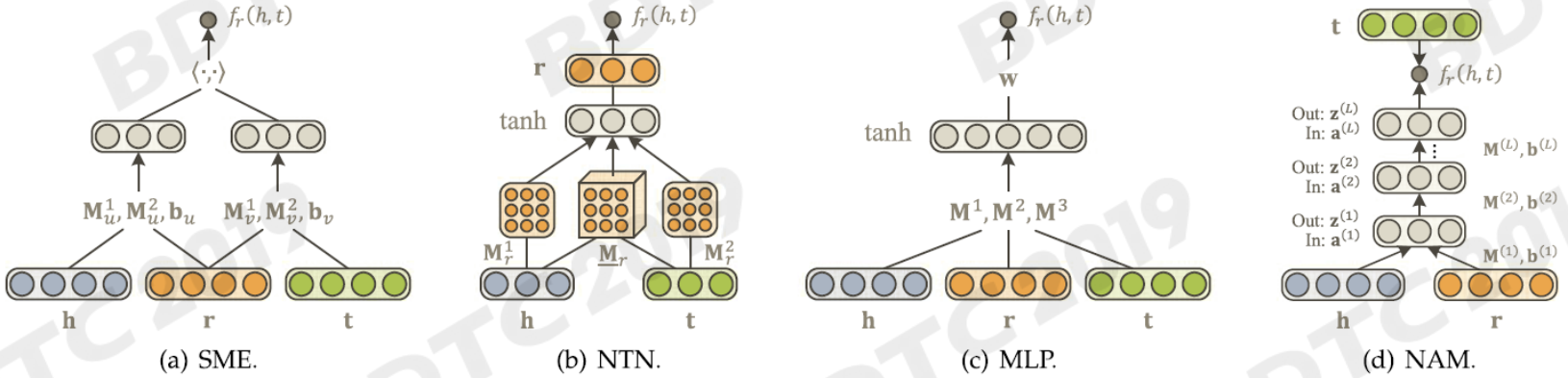
- Apply distance-based score function to estimate the triple probability
- TransE, TransH, TransR, etc.



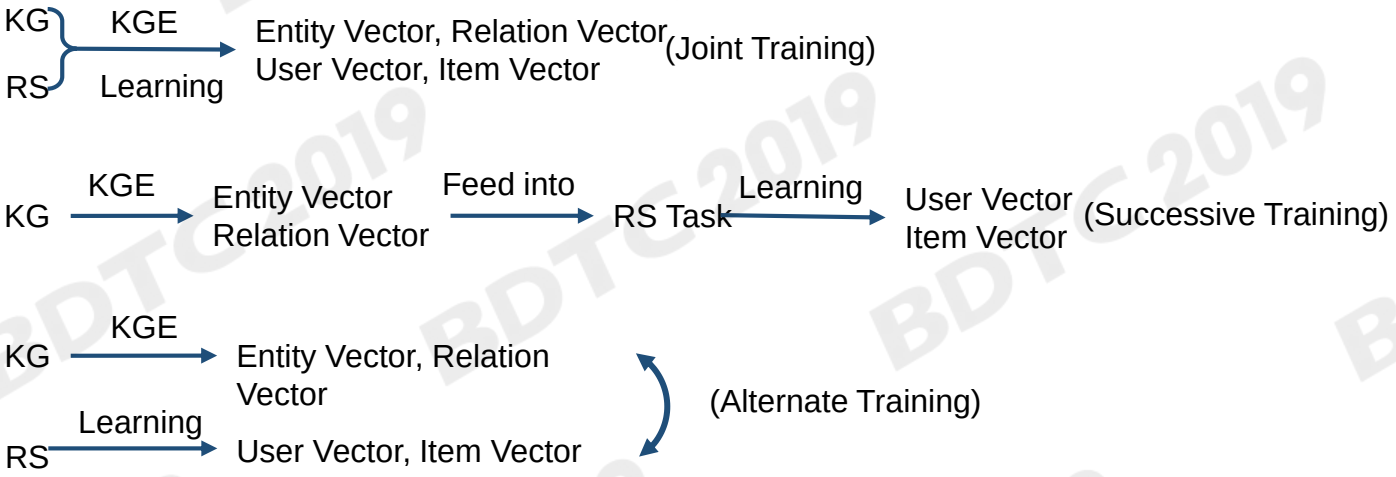
Knowledge Graph Embedding

Matching-based Models

- Apply similarity-based score function to estimate the triple probability
- SME, NTN, MLP, NAM, etc.

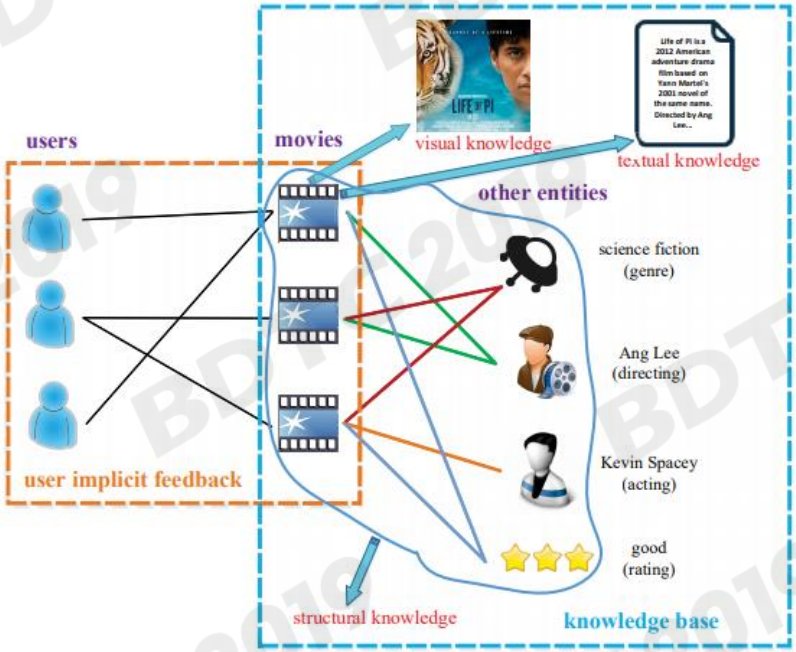


Knowledge Graph Embedding



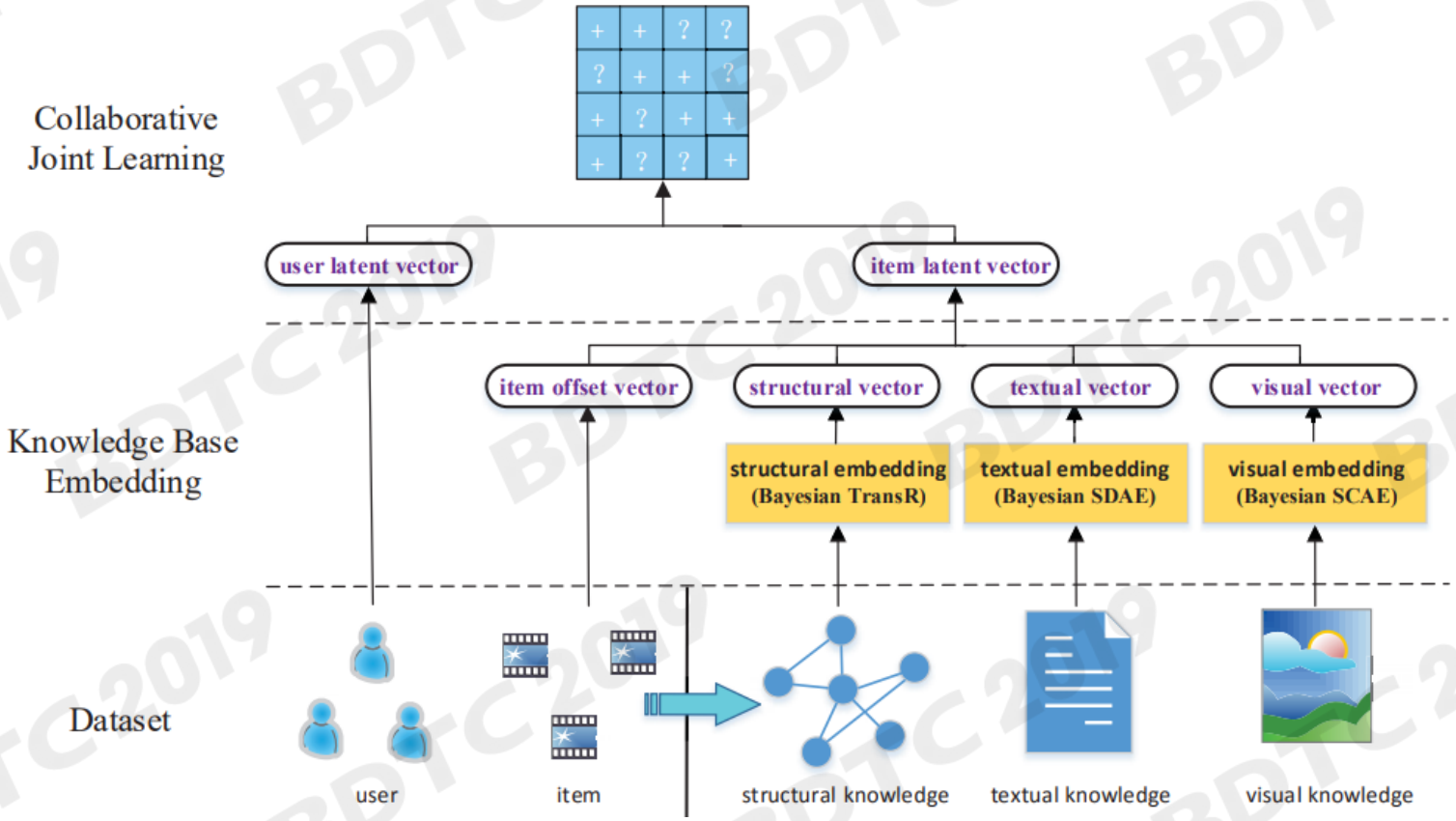
Collaborative Knowledge Embedding

- Structural knowledge
  - Direct, act, etc.
- Visual knowledge
  - Movie poster, book cover image, etc.
- Textual knowledge
  - Movie description, reviews, etc.



Fuzheng Zhang, Nicholas Jing Yuan, Defu Lian, Xing Xie, Wei-Ying Ma, Collaborative Knowledge Base Embedding for Recommender Systems, KDD 2016

Collaborative Knowledge Embedding



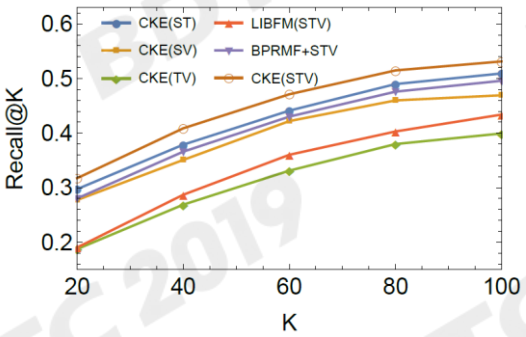
Data

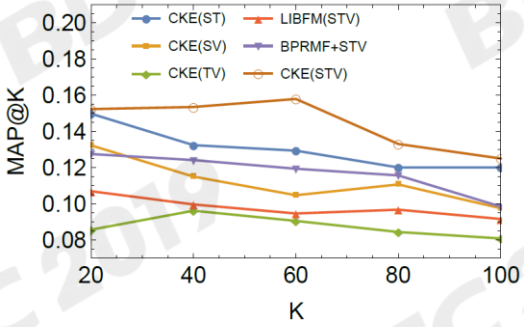
- MovieLens-1M
  - 1-step subgraph includes category, director, writer, actors, language, country, production date, rating, nominated awards, and received awards
- IntentBooks
  - 9-month Bing query logs, apply entity linking to find out book entity
  - 1-step subgraph includes category, author, publish date, belonged series, language, and rating

	MovieLens-1M	IntentBooks
#user	5,883	92,564
#item	3,230	18,475
#interactions	226,101	897,871
#sk nodes	84,011	26,337
#sk edges	169,368	57,408
#sk edge types	10	6
#tk items	2,752	17,331
#vk items	2,958	16,719

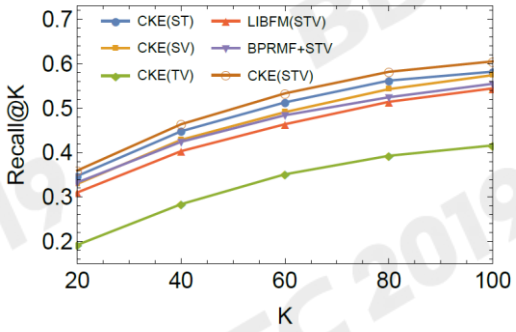
Results

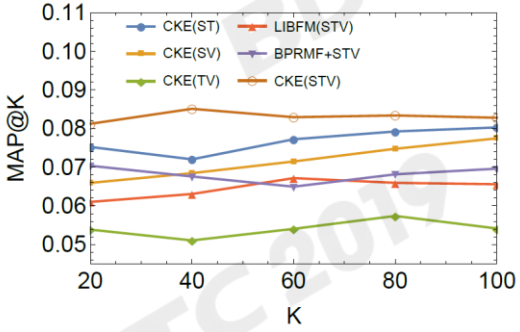
- Baselines
  - CKE(ST), CKE(SV), CKE(TV): only two types of knowledge
  - LIBFM(STV): all knowledge as raw features
  - BPRMF+STV: not joint-learning





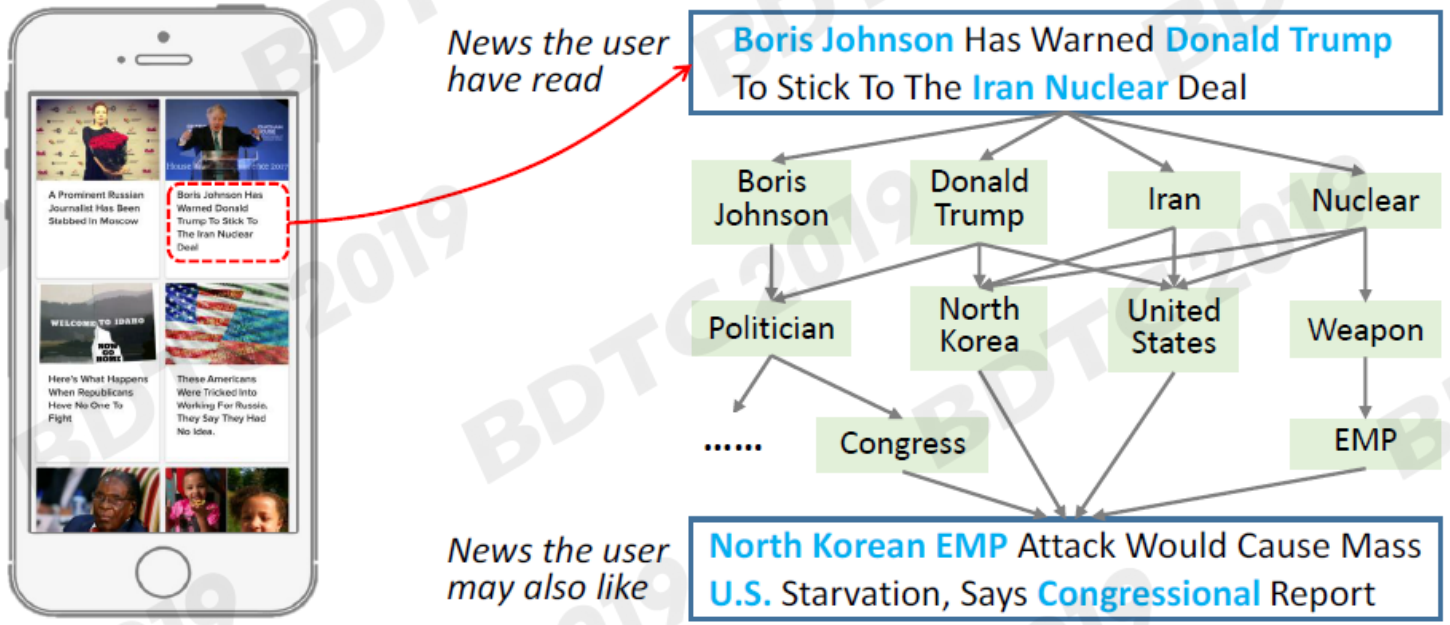
MovieLens-1M





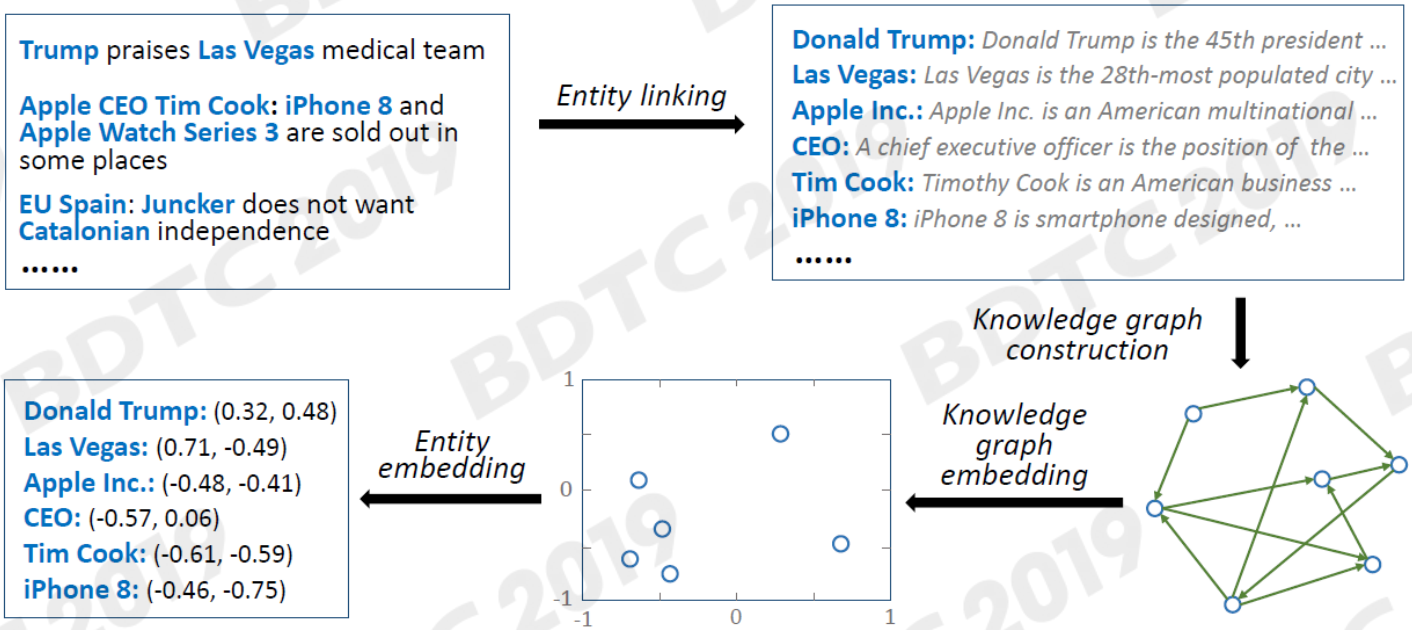
IntentBooks

Deep Knowledge-aware Network



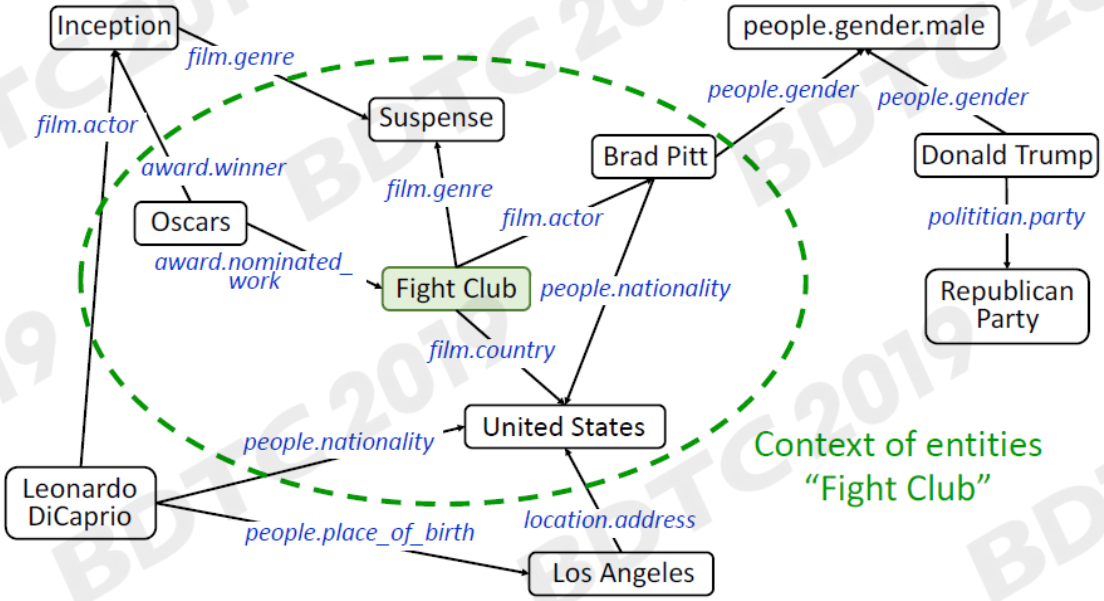
Hongwei Wang, Fuzheng Zhang, Xing Xie, Minyi Guo, DKN: Deep Knowledge-Aware Network for News Recommendation, WWW 2018

Deep Knowledge-aware Network

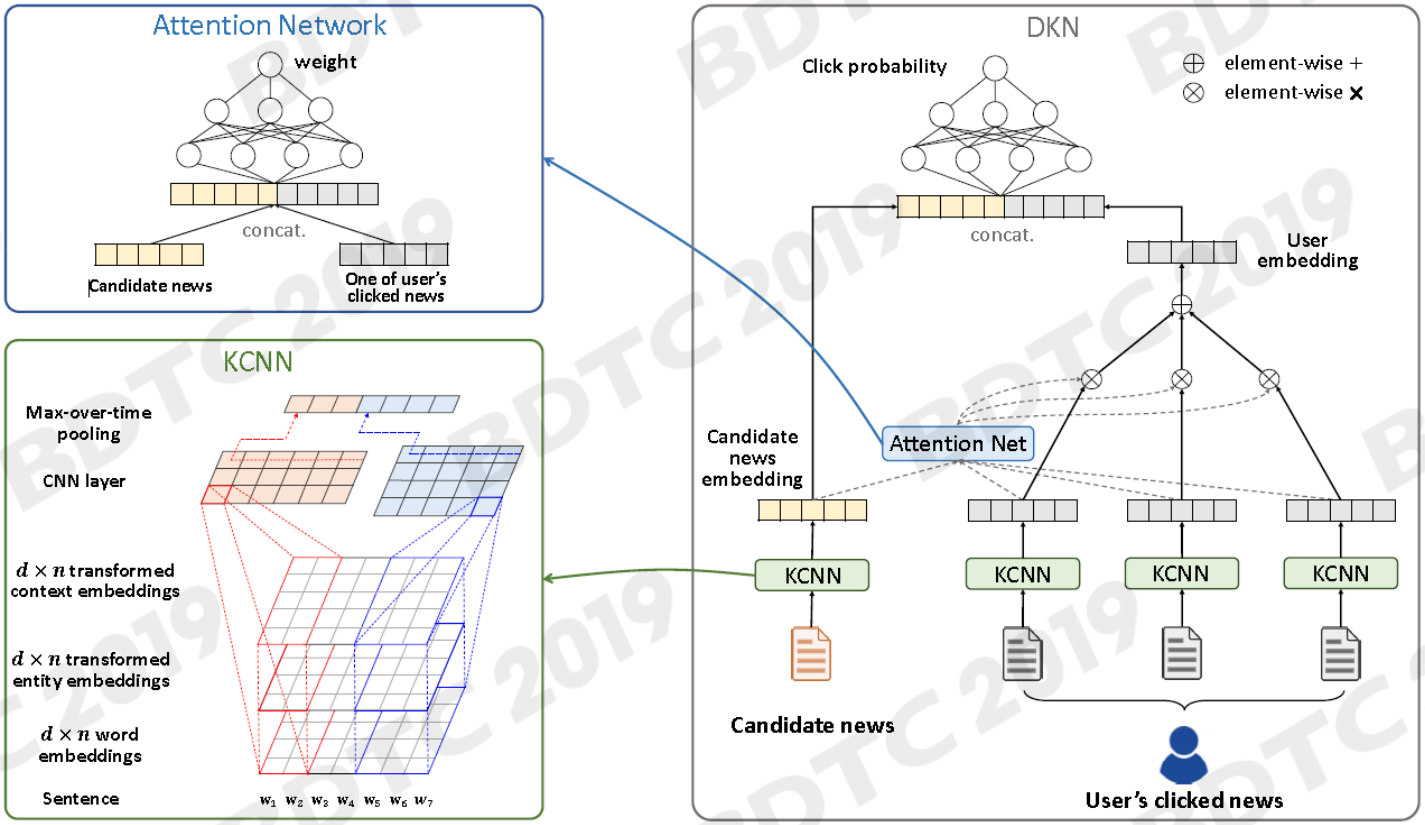


Extract Knowledge Representations

- Additionally use contextual entity embeddings to include structural information
- Context implies one-step neighbor



Deep Knowledge-aware Network

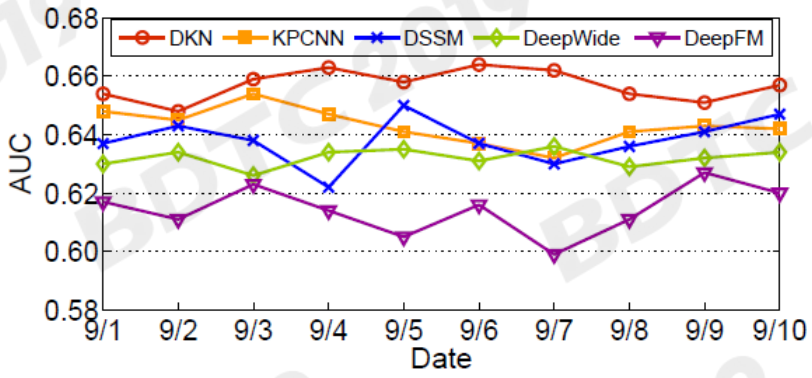


Experiments

Models*	F1	AUC	*p*-value**
DKN	**68.9 ± 1.5**	**65.9 ± 1.2**	–
LibFM	61.8 ± 2.1 (-10.3%)	59.7 ± 1.8 (-9.4%)	$< 10^{-3}$
LibFM(-)	61.1 ± 1.9 (-11.3%)	58.9 ± 1.7 (-10.6%)	$< 10^{-3}$
KPCNN	67.0 ± 1.6 (-2.8%)	64.2 ± 1.4 (-2.6%)	0.098
KPCNN(-)	65.8 ± 1.4 (-4.5%)	63.1 ± 1.5 (-4.2%)	0.036
DSSM	66.7 ± 1.8 (-3.2%)	63.6 ± 2.0 (-3.5%)	0.063
DSSM(-)	66.1 ± 1.6 (-4.1%)	63.2 ± 1.8 (-4.1%)	0.045
DeepWide	66.0 ±1.2 (-4.2%)	63.3 ± 1.5 (-3.9%)	0.039
DeepWide(-)	63.7 ± 0.9 (-7.5%)	61.5 ± 1.1 (-6.7%)	0.004
DeepFM	63.8 ± 1.5 (-7.4%)	61.2 ± 2.3 (-7.1%)	0.014
DeepFM(-)	64.0 ± 1.9 (-7.1%)	61.1 ± 1.8 (-7.3%)	0.007
YouTubeNet	65.5 ± 1.2 (-4.9%)	63.0 ± 1.4 (-4.4%)	0.025
YouTubeNet(-)	65.1 ± 0.7 (-5.5%)	62.1 ± 1.3 (-5.8%)	0.011
DMF	57.2 ± 1.2 (-17.0%)	55.3 ± 1.0 (-16.1%)	$< 10^{-3}$

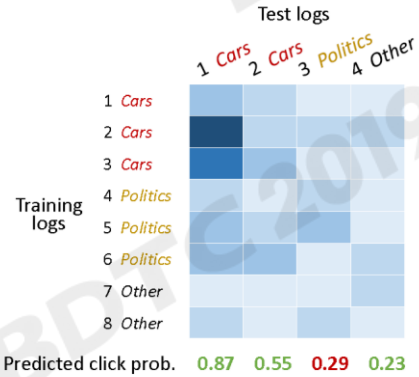
* "(-)" denotes "without input of entity embeddings".

** *p*-value is the probability of no significant difference with DKN on AUC by *t*-test.

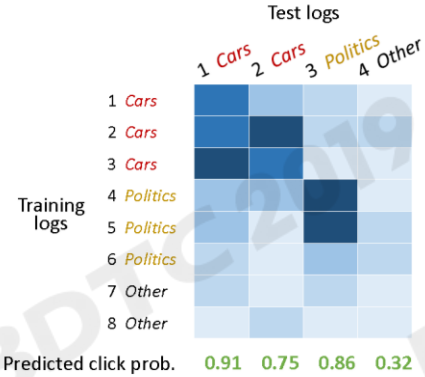


Examples

	No.	Date	News title	Entities	Label	Category
training	1	12/25/2016	Elon Musk teases huge upgrades for Tesla's supercharger network	Elon Musk; Tesla Inc.	1	Cars
	2	03/25/2017	Elon Musk offers Tesla Model 3 sneak peek	Elon Musk; Tesla Model 3	1	Cars
	3	12/14/2016	Google fumbles while Tesla sprints toward a driverless future	Google Inc.; Tesla Inc.	1	Cars
	4	12/15/2016	Trump pledges aid to Silicon Valley during tech meeting	Donald Trump; Silicon Valley	1	Politics
	5	03/26/2017	Donald Trump is a big reason why the GOP kept the Montana House seat	Donald Trump; GOP; Montana	1	Politics
	6	05/03/2017	North Korea threat: Kim could use nuclear weapons as "blackmail"	North Korea; Kim Jong-un	1	Politics
	7	12/22/2016	Microsoft sells out of unlocked Lumia 950 and Lumia 950 XL in the US	Microsoft; Lumia; United States	1	Other
	8	12/08/2017	6.5 magnitude earthquake recorded off the coast of California	earthquake; California	1	Other
			.....			
test	1	07/08/2017	Tesla makes its first Model 3	Tesla Inc; Tesla Model 3	1	Cars
	2	08/13/2017	General Motors is ramping up its self-driving car: Ford should be nervous	General Motors; Ford Inc.	1	Cars
	3	06/21/2017	Jeh Johnson testifies on Russian interference in 2016 election	Jeh Johnson; Russian	1	Politics
	4	07/16/2017	"Game of Thrones" season 7 premiere: how you can watch	Game of Thrones	0	Other



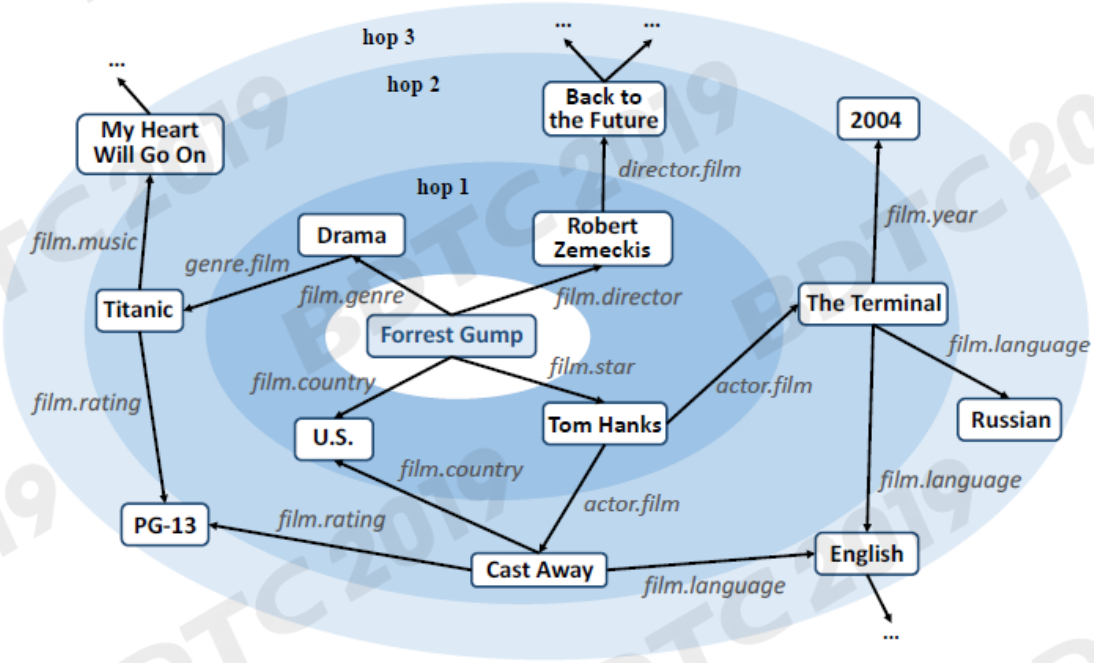
(a) without knowledge graph



(b) with knowledge graph

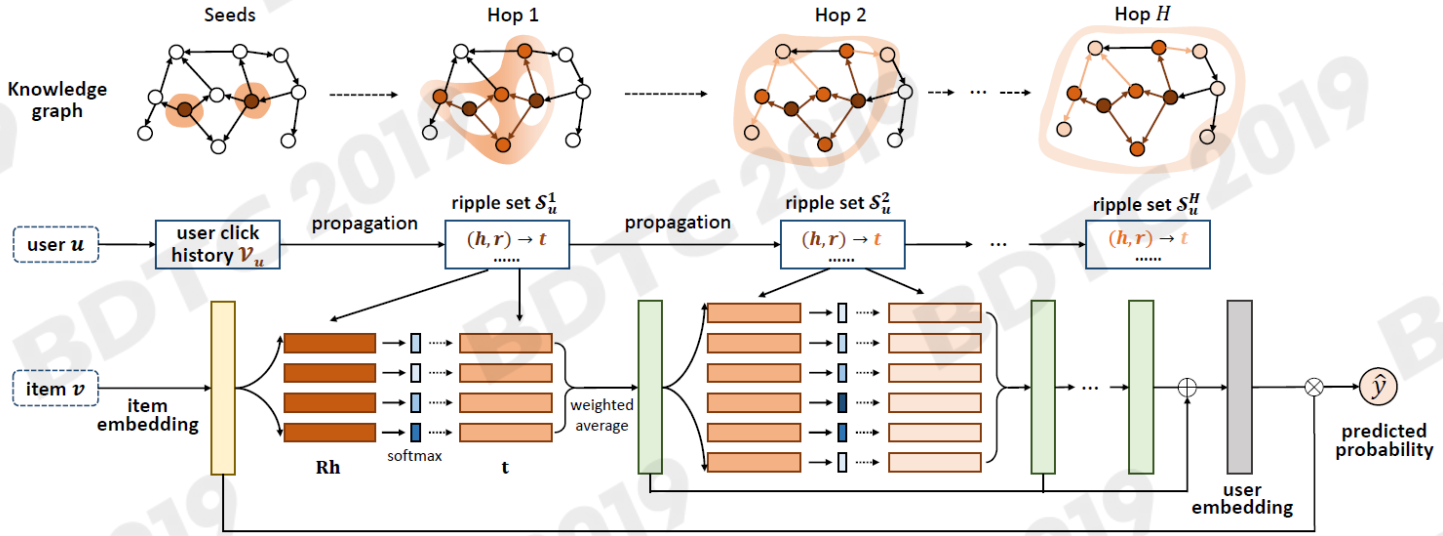
Ripple Network

- Users interests as seed entity, propagates in the graph step by step
- Decay in the propagating process



Hongwei Wang, etc. Ripple Network: Propagating User Preferences on the Knowledge Graph for Recommender Systems, CIKM 2018

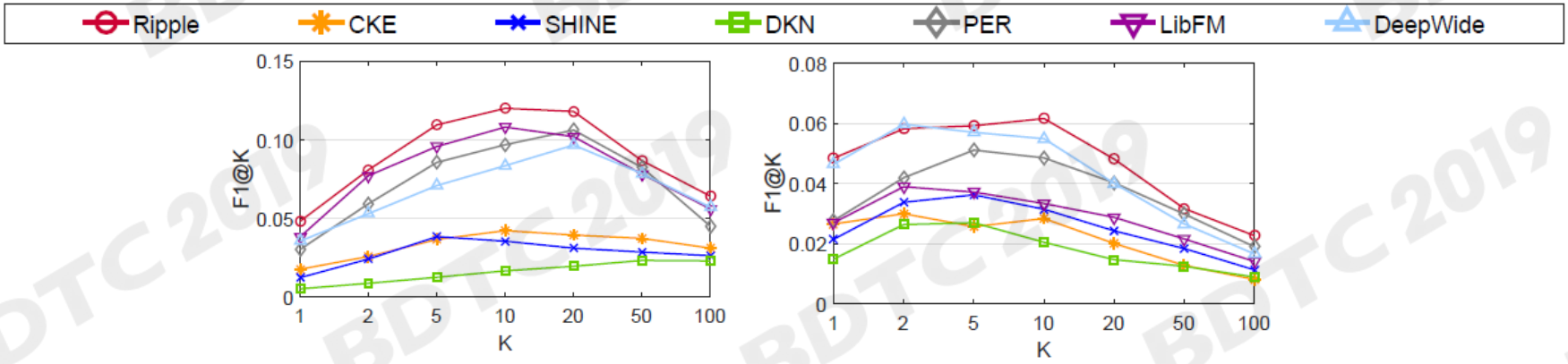
Ripple Network



Experiments

Model	MovieLens-1M		Book-Crossing		Bing-News	
	AUC	*ACC*	*AUC*	*ACC*	*AUC*	*ACC*
Ripple*	**0.913**	**0.835**	**0.840**	**0.775**	**0.778**	**0.732**
CKE	0.796	0.739	0.634	0.606	0.660	0.617
SHINE	0.778	0.732	0.668	0.636	0.614	0.587
DKN	0.655	0.589	0.621	0.598	0.761	0.704
PER	0.901	0.826	0.814	0.735	-	-
LibFM	0.892	0.812	0.763	0.705	0.744	0.688
DeepWide	0.903	0.822	0.806	0.731	0.754	0.695

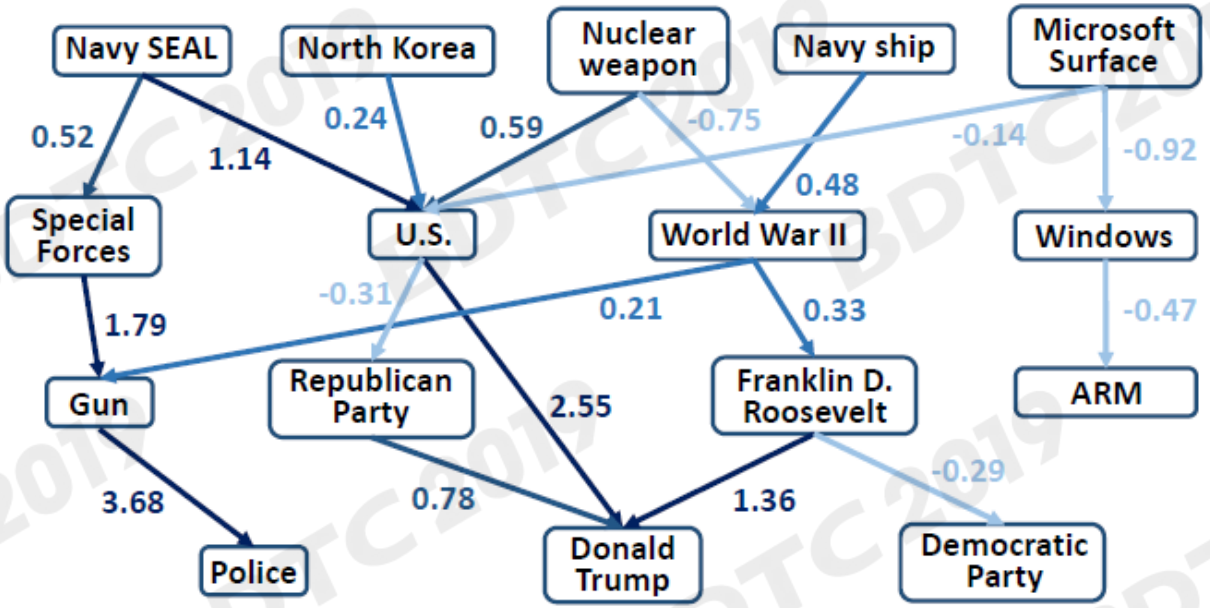
* Statistically significant improvements by t-test.



Example

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*

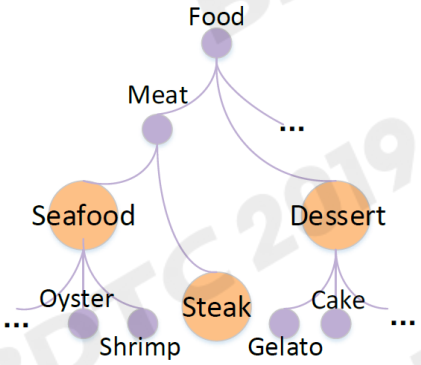


Candidate news: *Trump Announces Gunman Dead, Credits 'Heroic Actions' of Police*

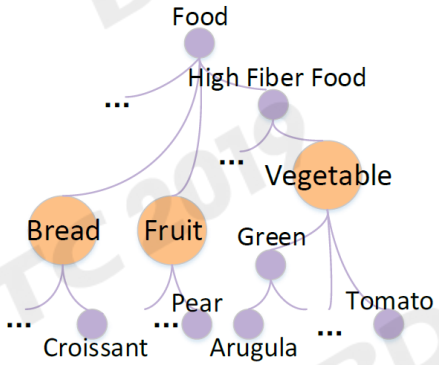
Explainable Recommendation Through Attentive Multi-View Learning

- Existing methods are either “deep but unexplainable” or “explainable but shallow”
- We want to develop an explainable deep model which
  - Achieves the state-of-art accuracy and is also explainable
  - Models multi-level user interest in an unsupervised manner

26-year-old female user

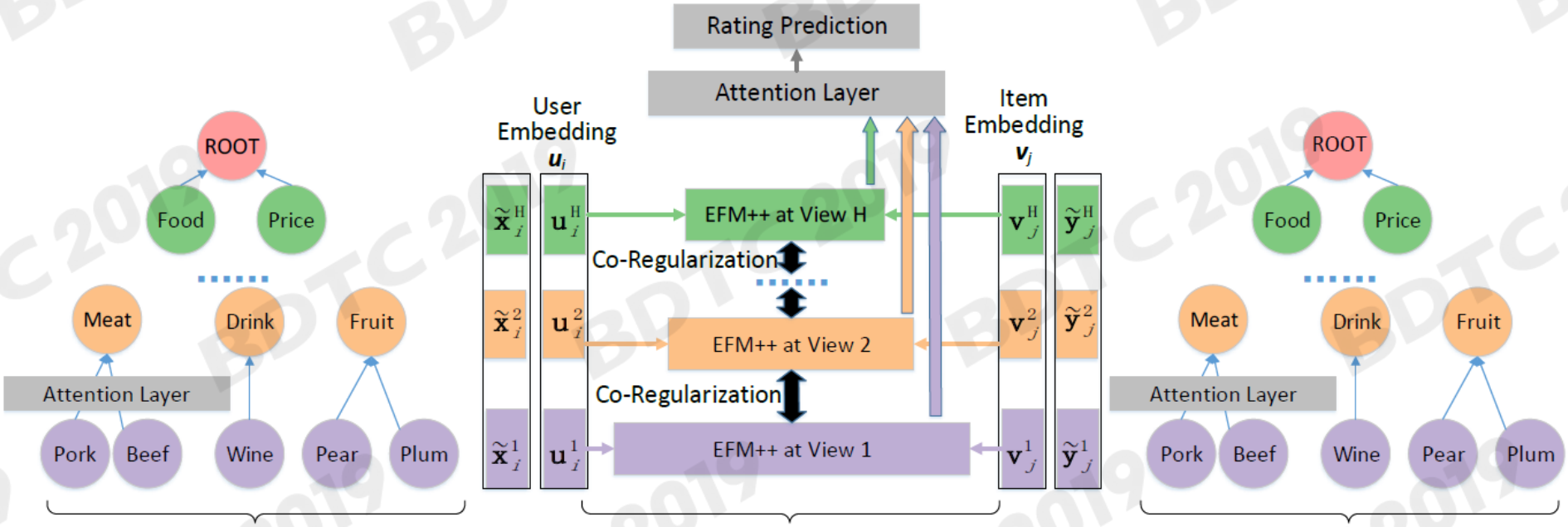


30-year-old male user



Model

You might be interested in [features in E], on which this item performs well



Hierarchical Propagation (User-Feature Interest)

Attentive Multi-View Learning

Hierarchical Propagation (Item-Feature Quality)

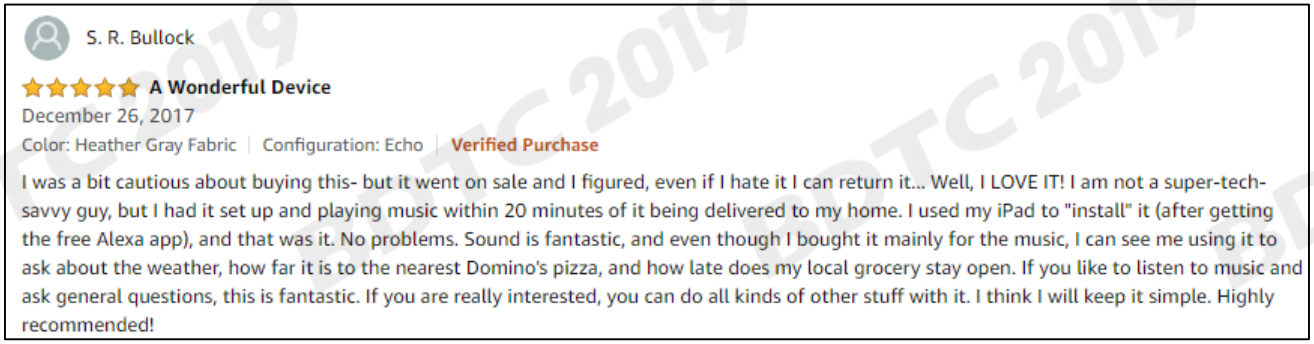
Data

Amazon

Dataset	#Users	#Items	#Reviews
Toys and Games	19,412	11,924	167,597
Digital Music	5,541	3,568	64,706
Yelp	8,744	14,082	212,922

Review: user, item, rating, review text, timestamp

Amazon


S. R. Bullock

A Wonderful Device

December 26, 2017

Color: Heather Gray Fabric | Configuration: Echo | Verified Purchase

I was a bit cautious about buying this- but it went on sale and I figured, even if I hate it I can return it... Well, I LOVE IT! I am not a super-tech-savvy guy, but I had it set up and playing music within 20 minutes of it being delivered to my home. I used my iPad to "install" it (after getting the free Alexa app), and that was it. No problems. Sound is fantastic, and even though I bought it mainly for the music, I can see me using it to ask about the weather, how far it is to the nearest Domino's pizza, and how late does my local grocery stay open. If you like to listen to music and ask general questions, this is fantastic. If you are really interested, you can do all kinds of other stuff with it. I think I will keep it simple. Highly recommended!

Yelp


Adrian R.

Manhattan, NY

2 friends

5 reviews

1 photo

Share review

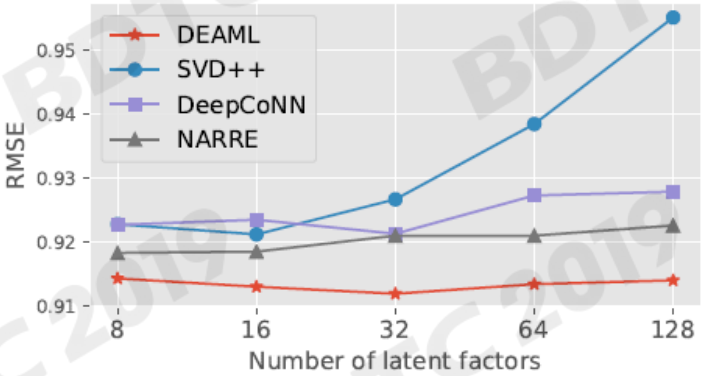
10/19/2018

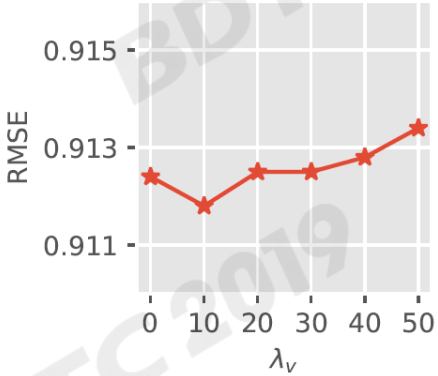
I freaking love Square Pie Guys. The pizza is so good that you'll spend your days yearning for another slice. Very few places can live up to Square Pie Guys and their quality ingredients, inventive toppings, and consistent execution. FEED ME!!!!

Accuracy

RMSE comparison with baselines on three datasets. Best results are highlighted in bold.

	G1			G2	G3				Ours	
	NMF	PMF	SVD++	CKE	HFT	EFM	DeepCoNN	NARRE	DEAML-V	DEAML
Toys and Games	1.1489	1.1832	0.9071	0.9923	0.9958	0.9534	0.9199	0.9084	0.9062	**0.9040**
Digital Music	1.1520	1.2619	0.9211	0.9849	1.0910	0.9696	0.9212	0.9209	0.9190	**0.9118**
Yelp	1.2678	1.2413	1.1561	1.2279	1.2738	1.2019	1.1503	1.1348	1.1343	**1.1333**





λ_v: weight for the co-regularization term

Explainability

- 20 participants, all Yelp users
- Collect their Yelp reviews and generate personalized explanations
- Ask them to rate the usefulness of each explanation

Average score on explanation usefulness. <30 and ≥ 30 refer to two age groups.

	Male	Female	<30	≥ 30	Overall
PAV	1.35	1.51	1.65	1.11	1.41
EFM	3.18	3.13	3.03	3.32	3.16
DEAML	**3.69**	**3.52**	**3.58**	**3.68**	**3.63**

Conclusions and Future Work

- Knowledge graph expands the amount of information of each item and strengthens the connection between them; leads to additional diversity and explainability of recommendation results

- Integrate graph reasoning with recommendation systems
- Jointly design and optimize recommendation algorithms and underlying architectures
- Deal with temporal evolvement of knowledge

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