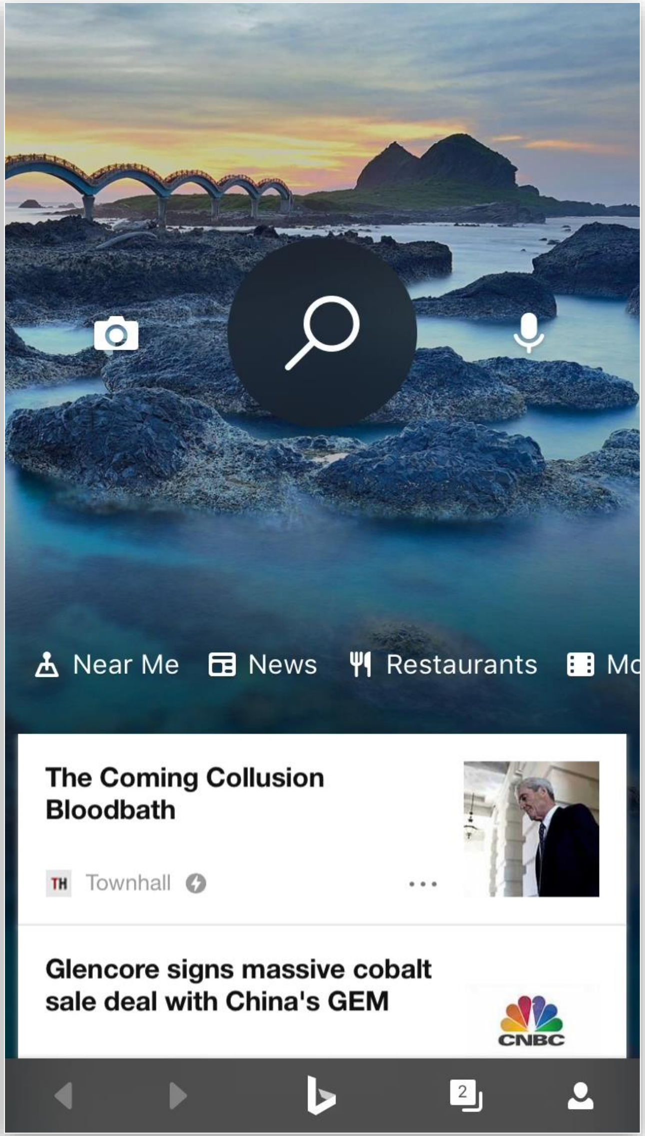
Future of Personalized Recommendation Systems

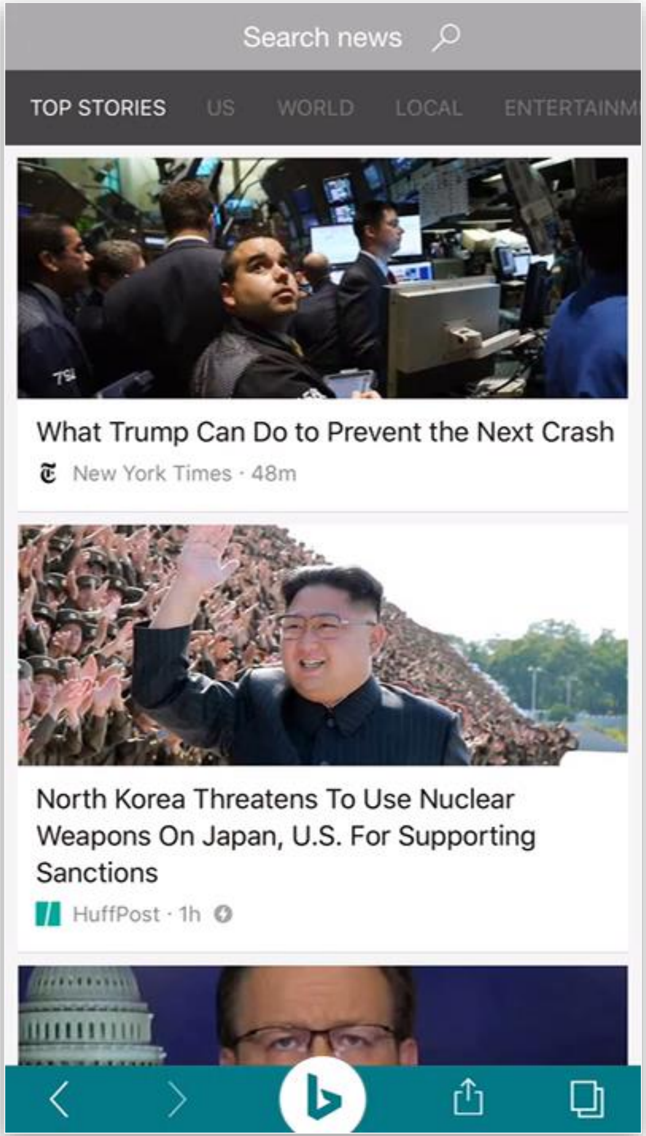
Xing Xie

Microsoft Research Asia

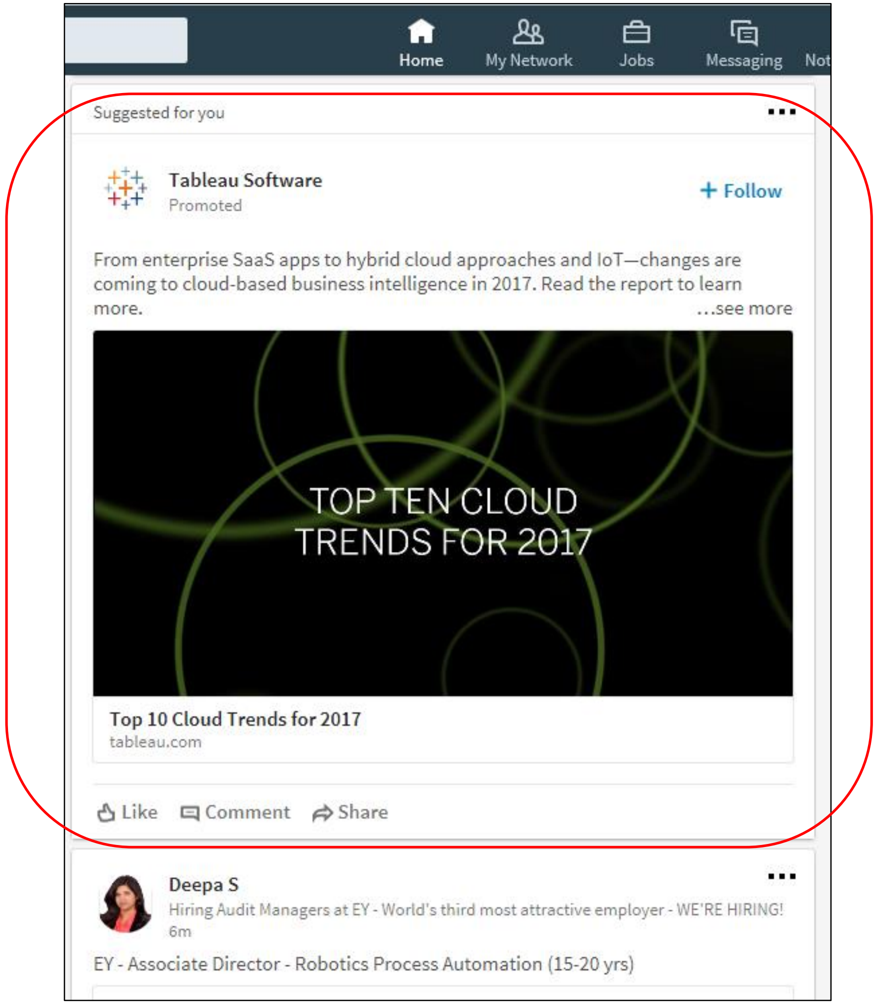
Recommendation Everywhere

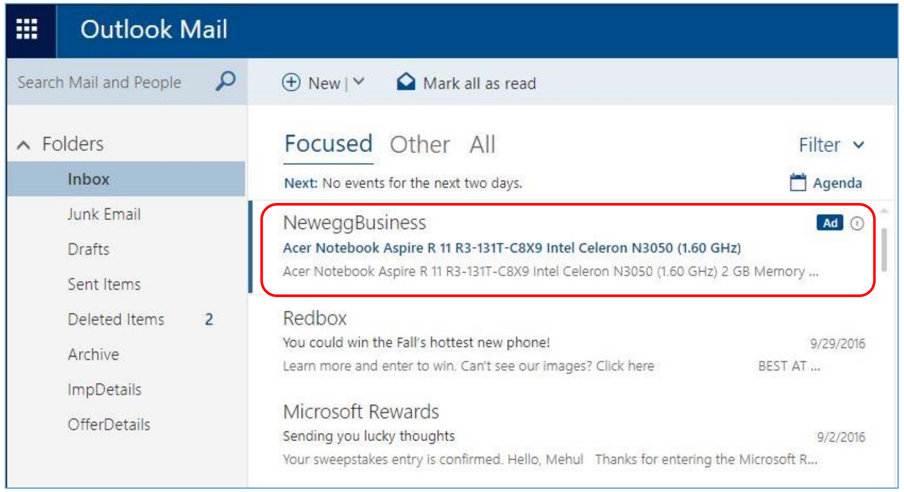
Personalized News Feed

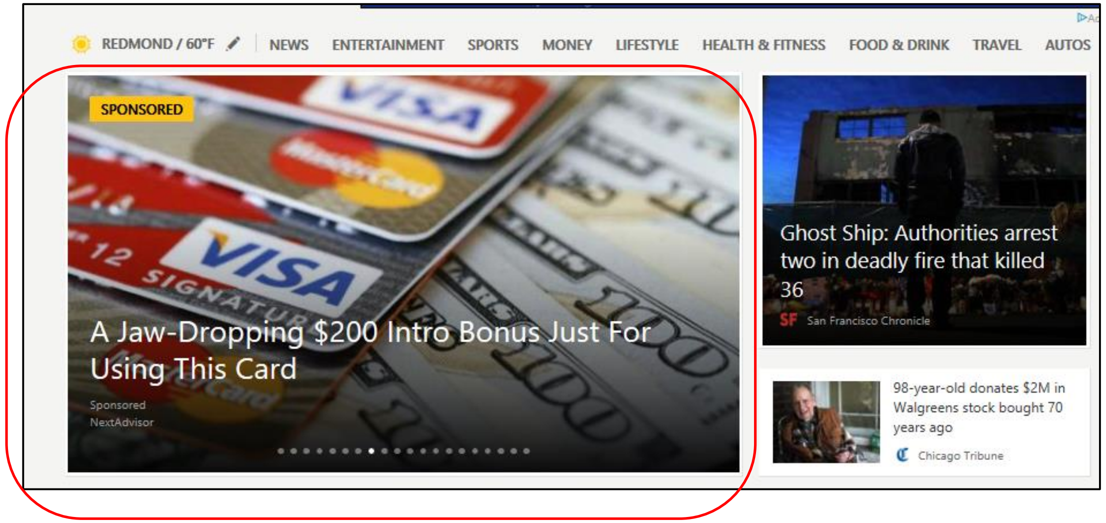




Online Advertising



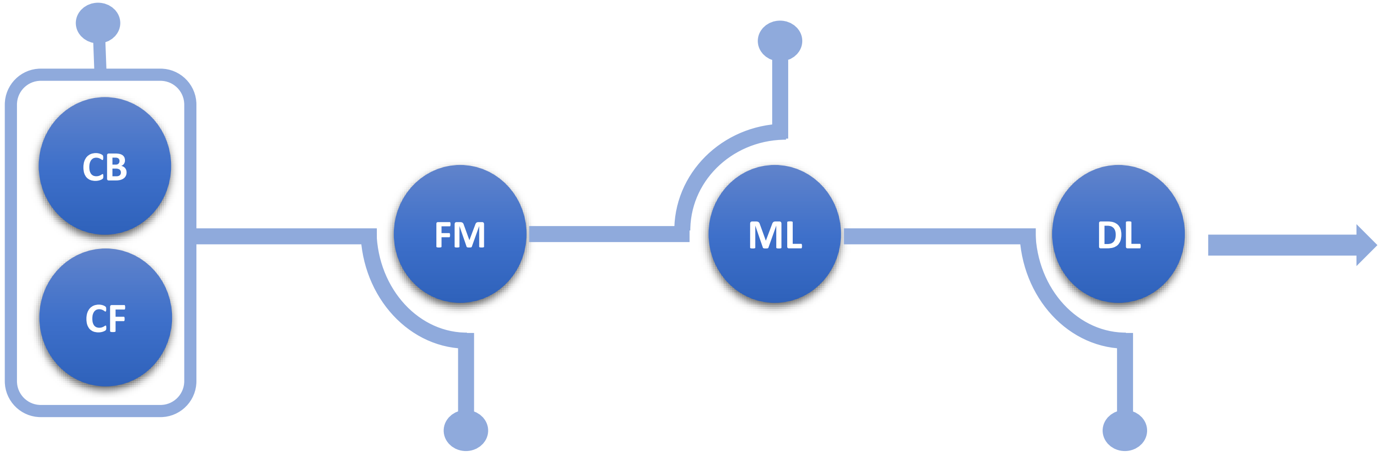




History

1990s (Tapestry, GroupLens)
Content based filtering
Collaborative filtering

2010 (Various data competitions)
Hybrid models with machine learning
LR, FM, GBDT, etc.
Pair-wise ranking

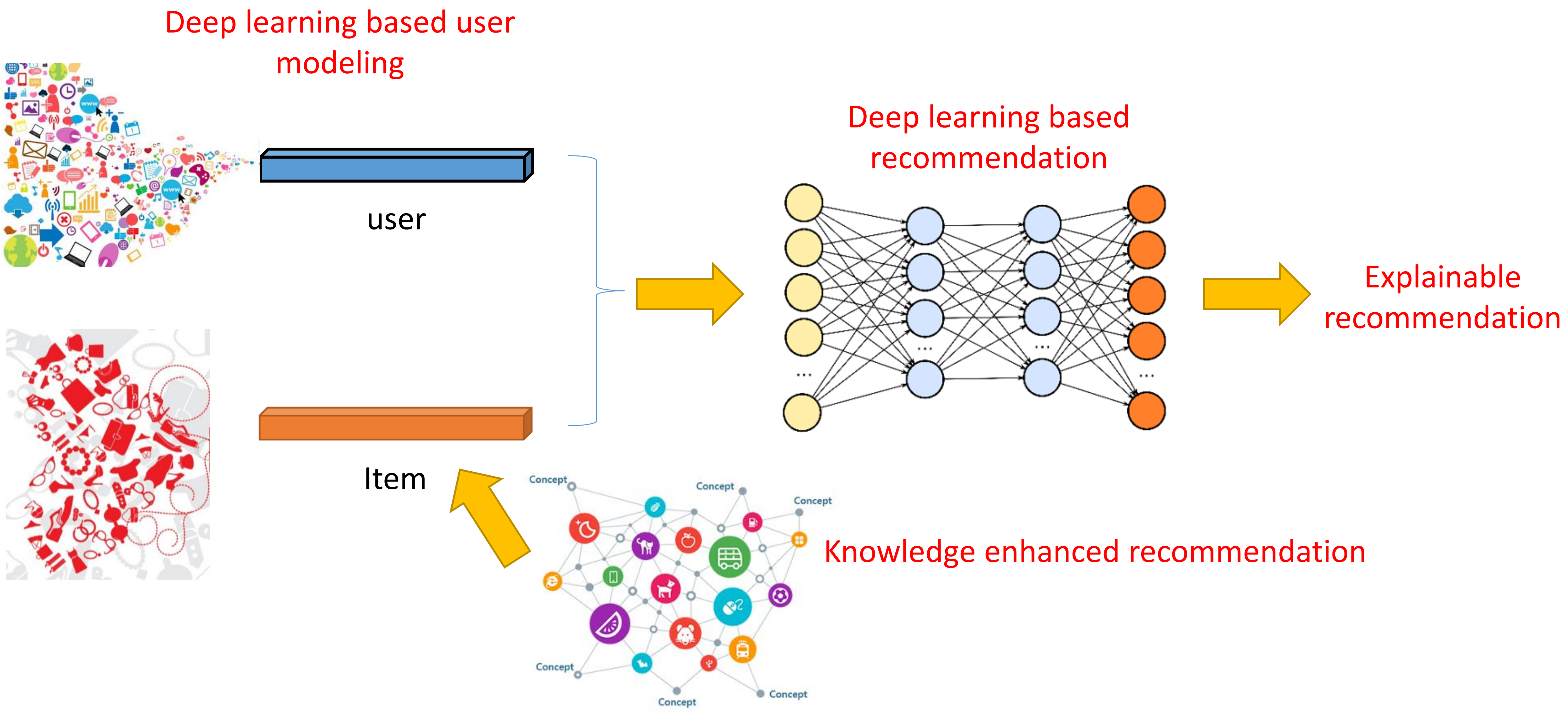


Explainable recommendation
Knowledge enhanced recommendation
Reinforcement learning
Transfer learning
...

2006 (Netflix prize)
Factorization-based Models
SVD++

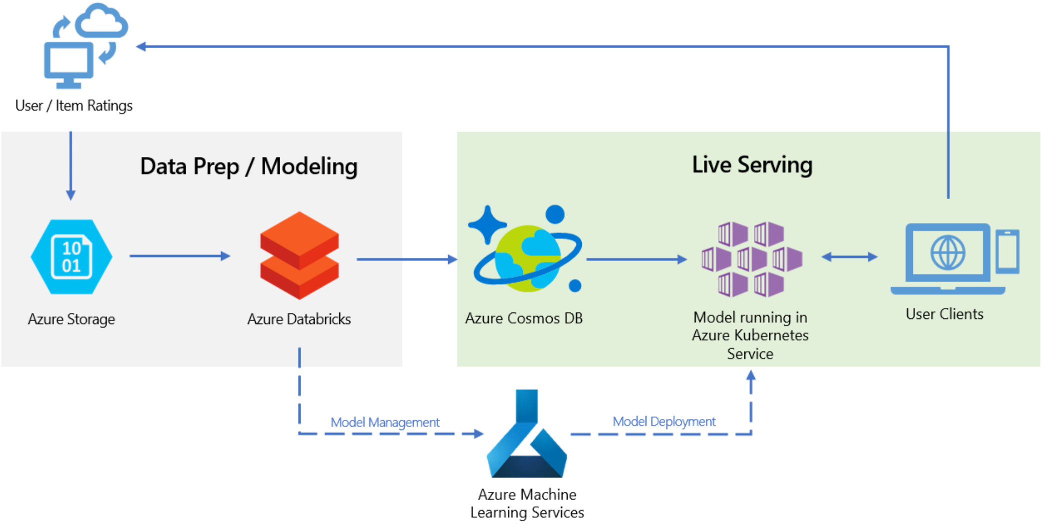
2015 (Deep learning)
Flourish with neural models
PNN, Wide&Deep, DeepFM, xDeepFM, etc.

Our Research



Microsoft Recommenders

- Helping researchers and developers to quickly select, prototype, demonstrate, and productionize a recommender system
- Accelerating enterprise-grade development and deployment of a recommender system into production
- https://github.com/microsoft/recommenders



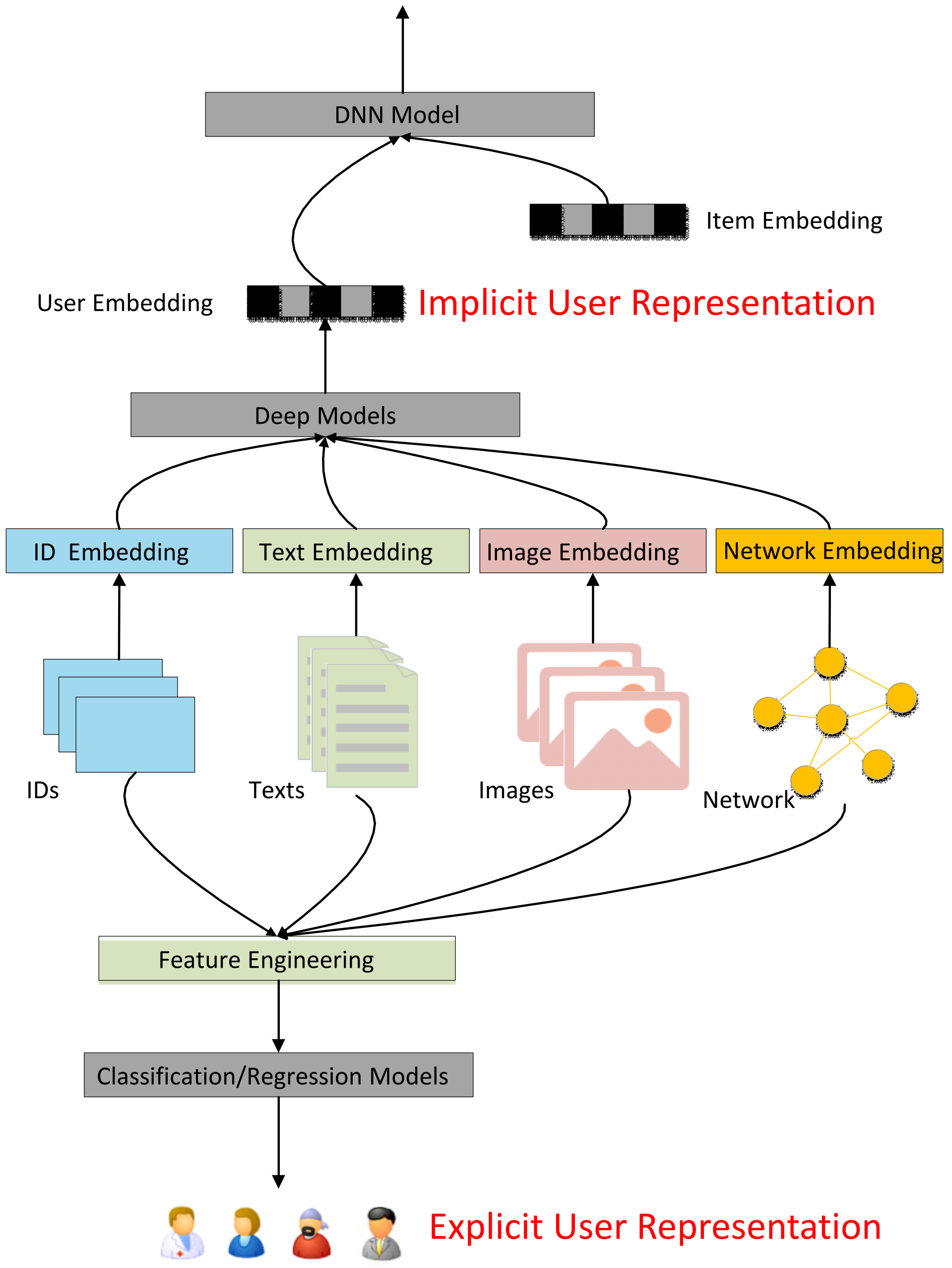
User Behavioral Data

Explicit User Representation

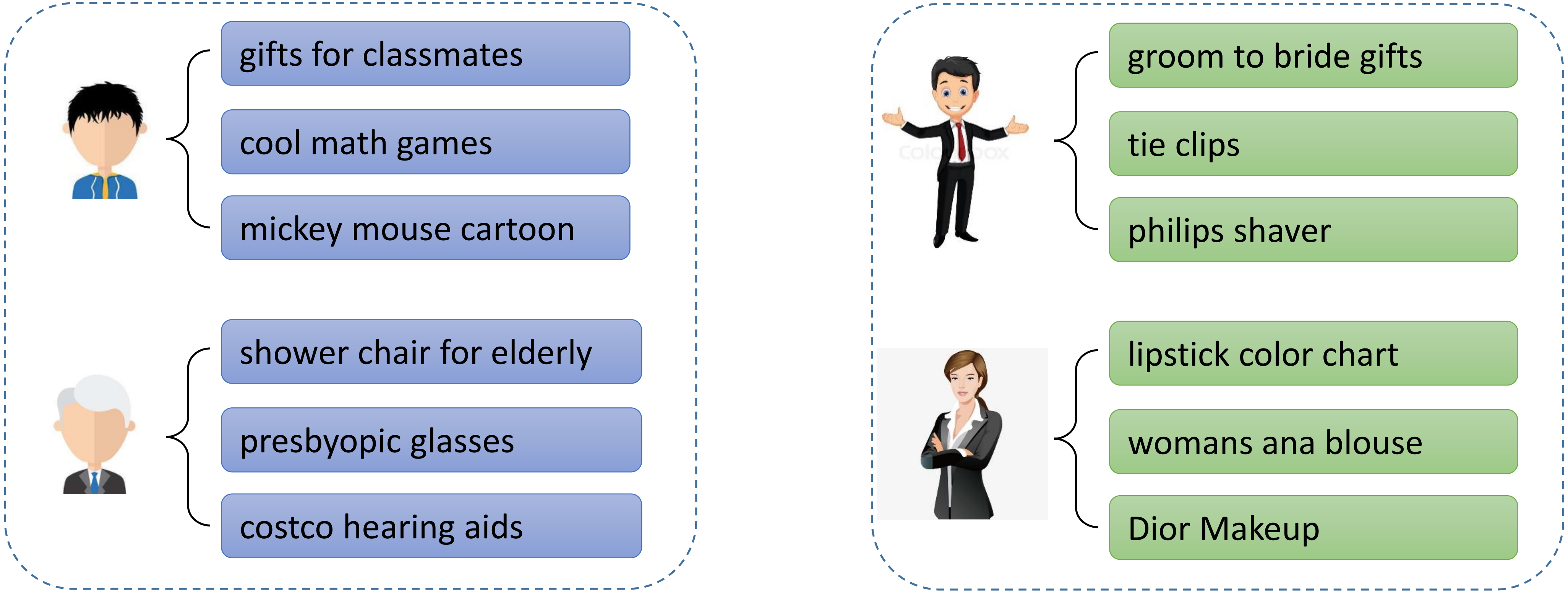
- Demographic
  - Age
  - Gender
  - Life stage
  - Marital status
  - Residence
  - Education
  - Vocation
- Personality
  - Openness
  - Conscientiousness
  - Extraversion
  - Agreeableness
  - Neuroticism
  - Impulsivity
  - Novelty-seeking
  - Indecisiveness
- Interests
  - Food
  - Book
  - Movie
  - Music
  - Sport
  - Restaurant
- Status
  - Emotion
  - Event
  - Health
  - Wealth
  - Device
- Social
  - Friend
  - Coworker
  - Spouse
  - Children
  - Other relatives
  - Tie strength
- Schedule
  - Task
  - Driving route
  - Metro/bus line
  - Appointment
  - Vacation

Explicit vs Implicit

Representation	Pros	Cons
Explicit	• Easy to understand; • Can be directly bidden by advertisers	• Hard to obtain training data; • Difficult to satisfy complex and global needs;
Implicit	• Unified and heterogenous user representation; • End-to-end learning	• Difficult to explain; • Need to fine-tune in each task



Query Log based User Modeling



Chuhan Wu, Fangzhao Wu, Junxin Liu, Shaojian He, Yongfeng Huang, Xing Xie, Neural Demographic Prediction using Search Query, WSDM 2019

Query Log based User Modeling

Different words may have different importance

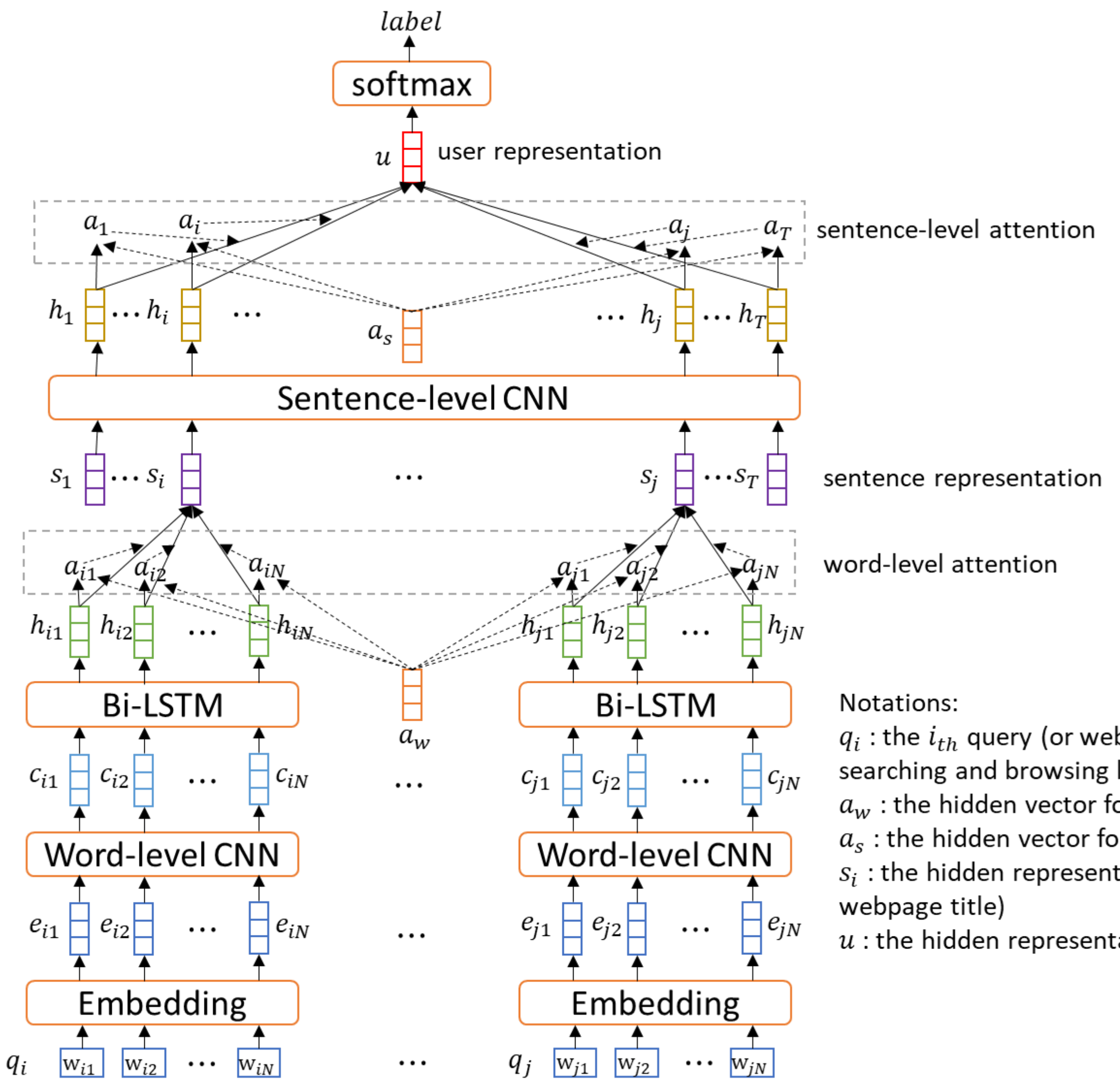
Different records have different informativeness

Neighboring records may have relatedness, while far ones usually not

birthday gift for grandson
central garden street
google
my health plan
medicaid new York
medicaid for elderly in new York
alcohol treatment
amazon.com
documentary grandson
youtube

The same word may have different importance in different contexts

Query Log based User Modeling



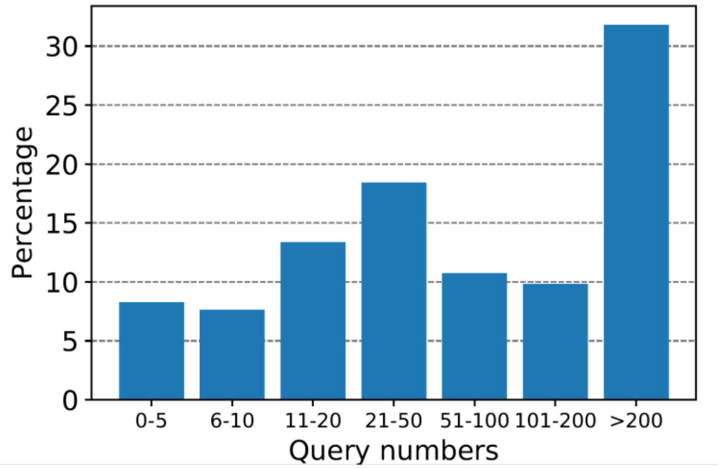
Notations:
q_i : the i_{th} query (or webpage title) from user's searching and browsing log
a_w : the hidden vector for word-level attention
a_s : the hidden vector for sentence-level attention
s_i : the hidden representation of the i_{th} query (or webpage title)
u : the hidden representation of the user

Experiments

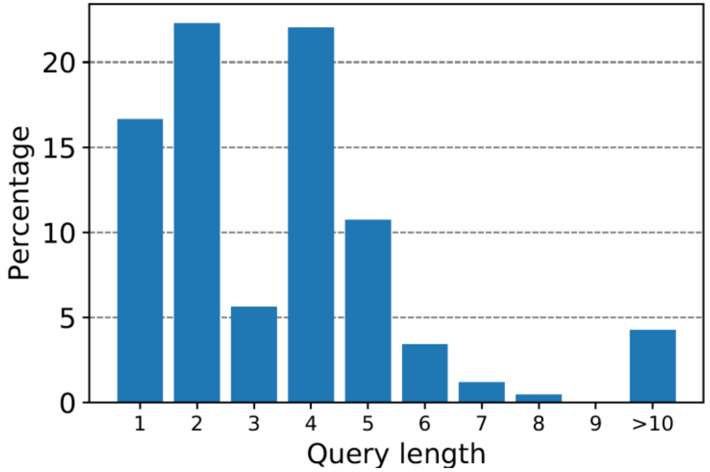
Mapping between age category and age range

Age category	1	2	3	4	5	6
Age range	< 18	$[18, 24]$	$[25, 34]$	$[35, 49]$	$[50, 64]$	> 64

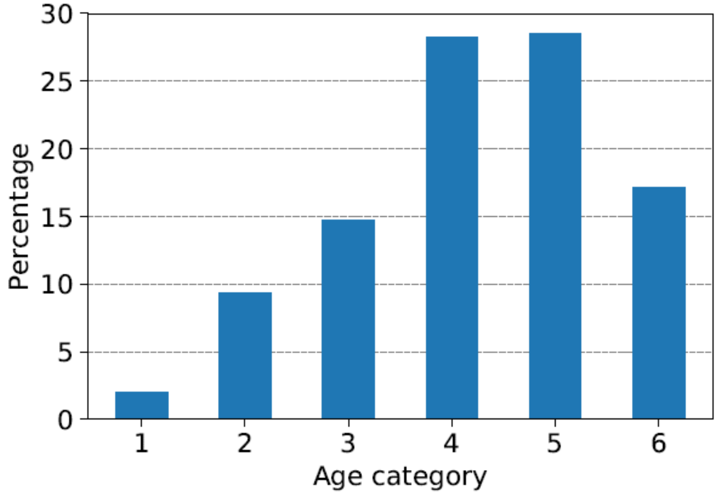
- Dataset:
  - 15,346,617 users in total with age category labels
    - Randomly sampled 10,000 users for experiments
    - Search queries posted from October 1, 2017 to March 31, 2018



Distribution of query number per user



Distribution of query length

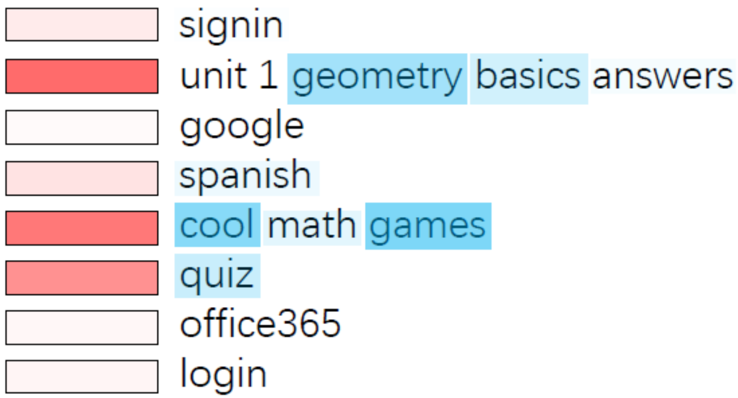


Distribution of age category

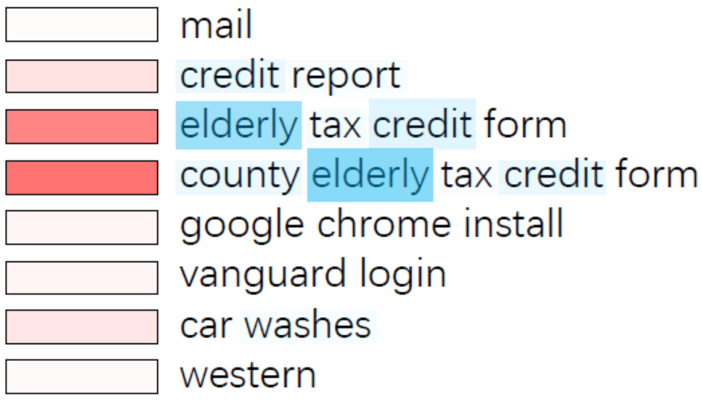
Experiments

	10%		50%		100%		
	Accuracy	Fscore	Accuracy	Fscore	Accuracy	Fscore	
SVM	31.97	21.96	34.20	26.32	34.53	27.44	discrete feature, linear model
LR	31.61	21.55	33.09	25.94	33.91	26.92	
LinReg	27.12	17.38	29.64	22.48	30.34	23.52	
FastText	28.65	21.09	30.40	23.55	30.90	24.01	continuous feature, linear model
CNN	30.08	19.66	35.58	26.17	37.31	26.96	flat DNN models
LSTM	30.15	20.46	36.11	24.67	37.96	25.28	
HAN	32.06	22.58	37.04	25.88	39.86	29.79	hierarchical LSTM model
HURA	34.07	24.16	39.68	28.68	41.22	31.18	

User Age Inference



Queries from a young user



Queries from an elder user

Car / Pet Segment

2018 mazda cx9 reliability
mathway math problem solver
open the dvd or cd drive in windows 10
lowes van & truck rental
facebook log in or sign up
buying high quality cars at a low price
plot summary imdb
how can i block a phone number from my home phone

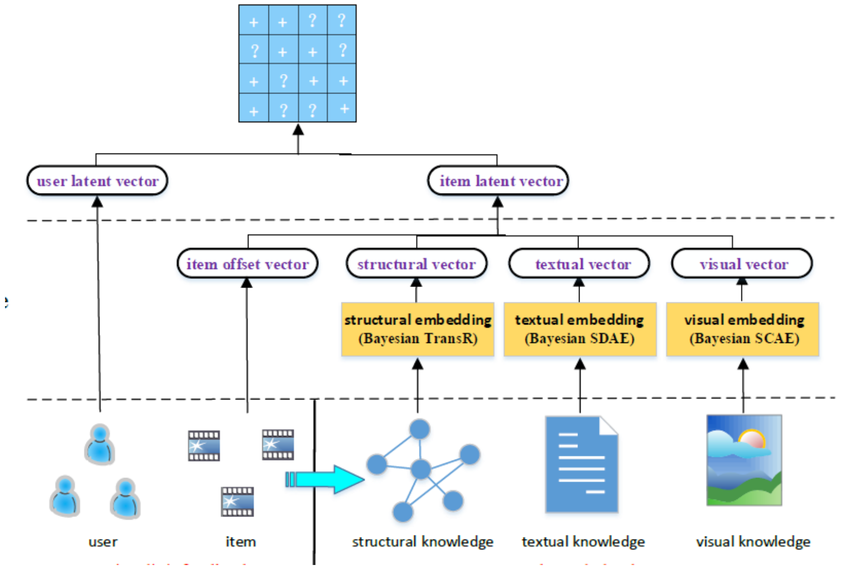
dog food, cat food, and treats
the denver post official site
easybib: free bibliography generator
chords crowder guitar video
akc golden retriever pet adoption northern California
among large uk newspapers, which are considered
gmail email from google
heritage animal hospital care.com

Universal User Representation

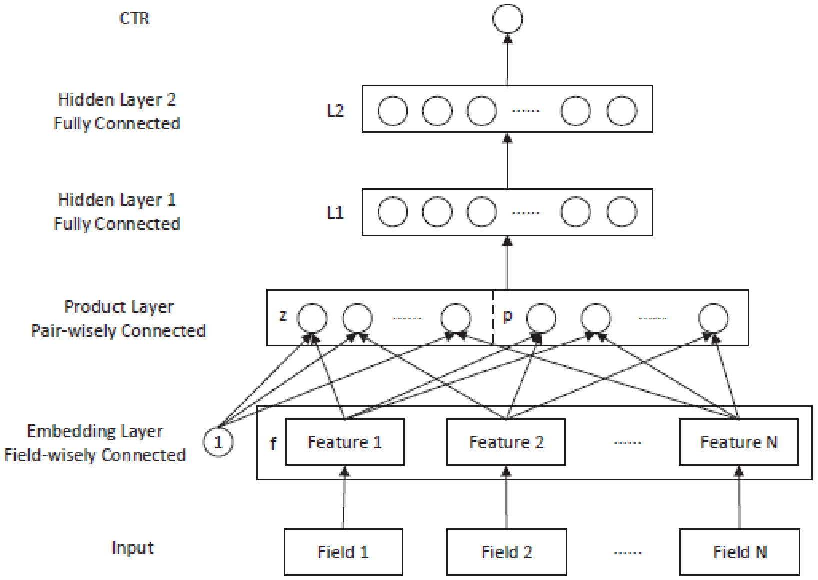
- Existing user representation learning are task-specific
  - Difficult to generalize to other tasks
  - Highly rely on labeled data
  - Costly to exploit heterogenous unlabeled user behavior data
- Learn universal user representations from heterogenous and multi-source user data
  - Capture global patterns of online users
  - Easily applied to different tasks as additional user features
  - Do not rely on manually labeled data

Deep Learning Based Recommender System

Learning latent representations



Learning feature interactions



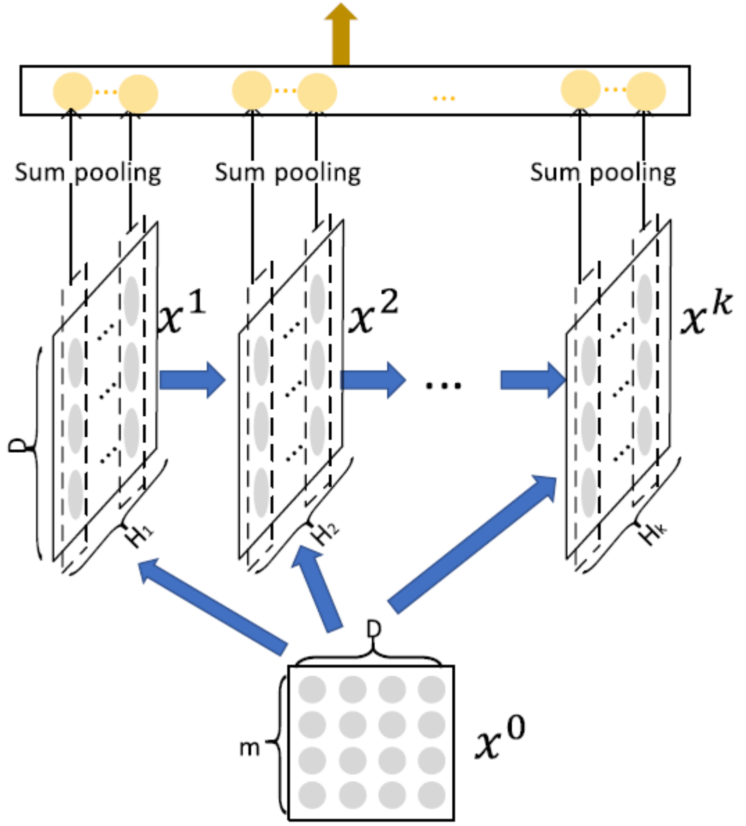
Motivations

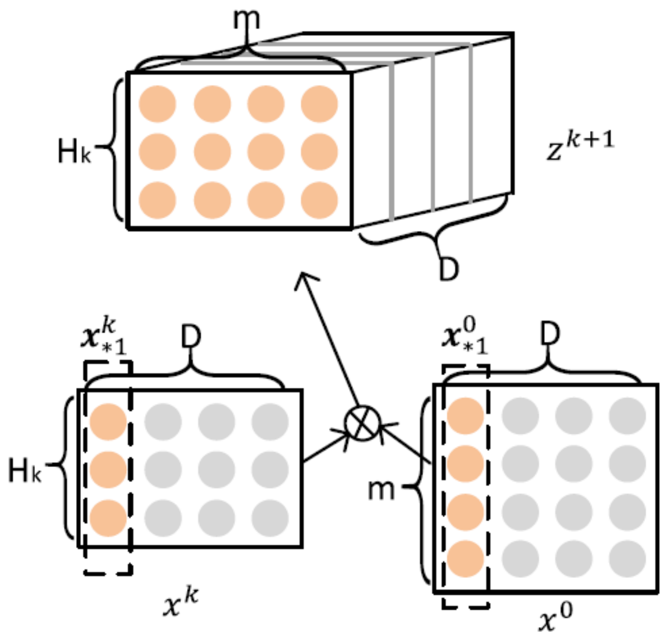
- We try to design a new neural structure that
  - Automatically learns explicit high-order interactions
  - Vector-wise interaction, rather than bit-wise
  - Different types of feature interactions can be combined easily

- Goals
  - Higher accuracy
  - Reducing manual feature engineering work

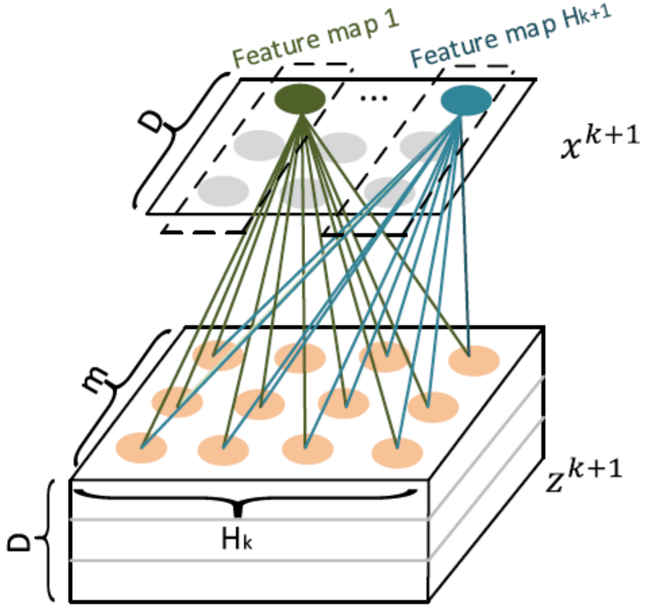
Jianxun Lian, Xiaohuan Zhou, Fuzheng Zhang, Zhongxia Chen, Xing Xie, Guangzhong Sun, xDeepFM: Combining Explicit and Implicit Feature Interactions for Recommender Systems, KDD 2018

Compressed Interaction Network (CIN)



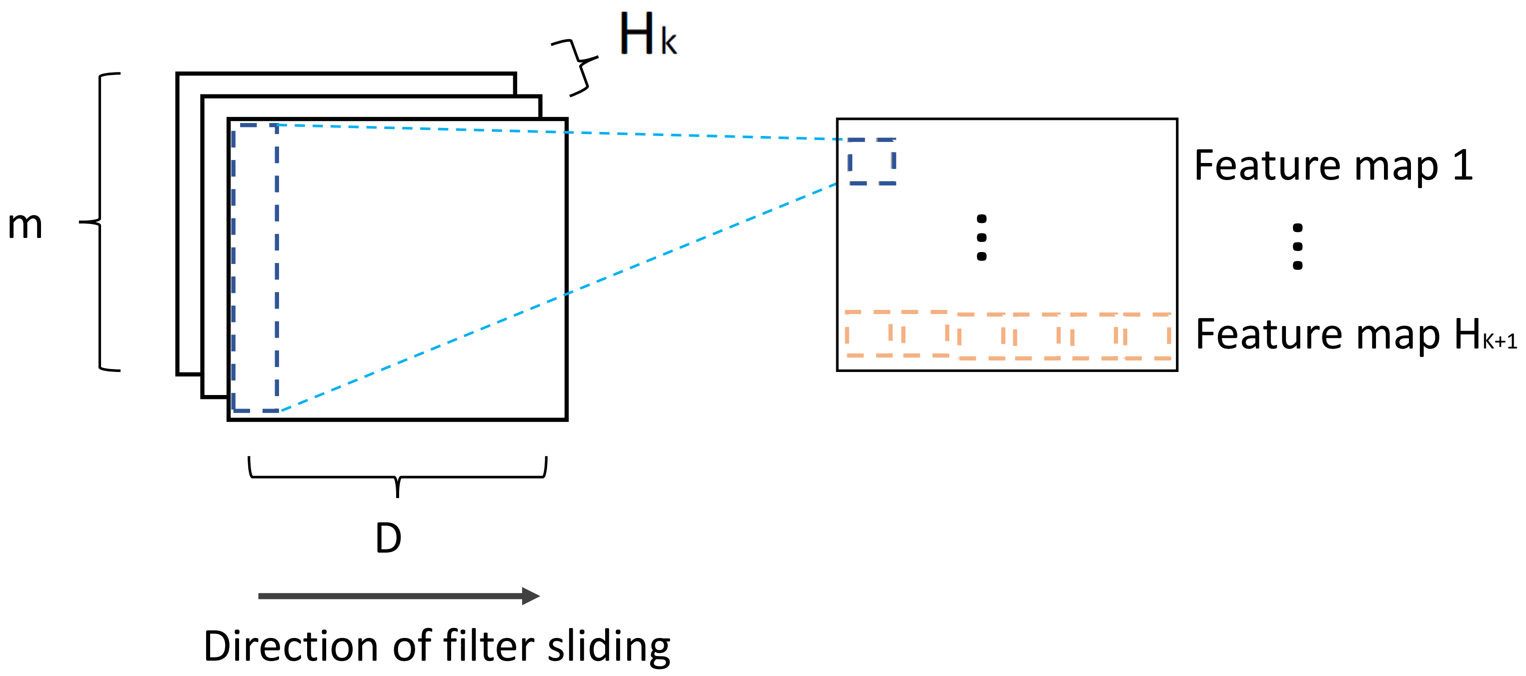


(a) Outer products along each dimension for feature interactions. The tensor Z^{k+1} is an intermediate result for further learning.

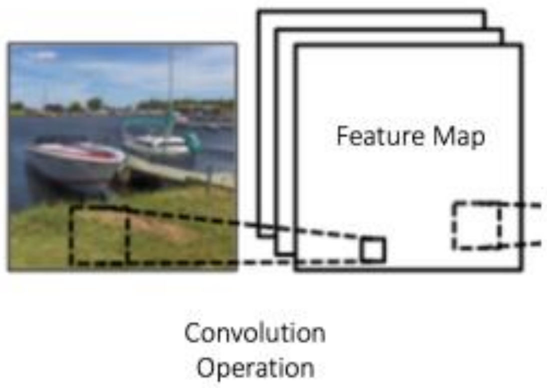


(b) The k-th layer of CIN. It compresses the intermediate tensor Z^{k+1} to H_{k+1} embedding vectors (aslo known as *feature maps*).

Relation with CNN

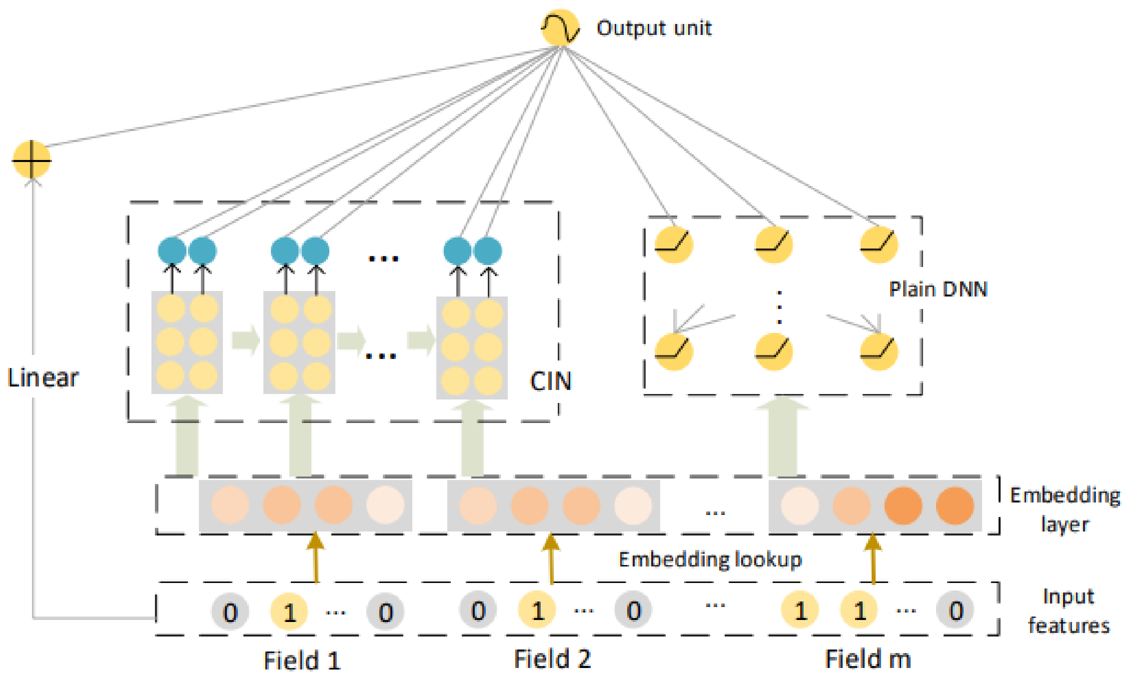


An example of image CNN



Extreme Deep Factorization Machine (xDeepFM)

- Combining explicit and implicit feature interaction network
- Integrate both memorization and generalization



Data

- Criteo: ads click-through-rate prediction
- Dianping: restaurant recommendation
- Bing News: news recommendation

Datasest	#instances	#fields	#features (sparse)
Criteo	45M	39	2.3M
Dianping	1.2M	18	230K
Bing News	5M	45	17K

Experiments

	Criteo			Dianping			Bing News		
Model name	AUC	Logloss	Depth	AUC	Logloss	Depth	AUC	Logloss	Depth
LR	0.7577	0.4854	-,-	0.8018	0.3608	-,-	0.7988	0.2950	-,-
FM	0.7900	0.4592	-,-	0.8165	0.3558	-,-	0.8223	0.2779	-,-
DNN	0.7993	0.4491	-,2	0.8318	0.3382	-,3	0.8366	0.2730	-,2
DCN	0.8026	0.4467	2,2	0.8391	0.3379	4,3	0.8379	0.2677	2,2
Wide&Deep	0.8000	0.4490	-,3	0.8361	0.3364	-,2	0.8377	0.2668	-,2
PNN	0.8038	0.4927	-,2	0.8445	0.3424	-,3	0.8321	0.2775	-,3
DeepFM	0.8025	0.4468	-,2	0.8481	0.3333	-,2	0.8376	0.2671	-,3
xDeepFM	**0.8052**	**0.4418**	3,2	**0.8639**	**0.3156**	3,3	**0.8400**	**0.2649**	3,2

Experiments

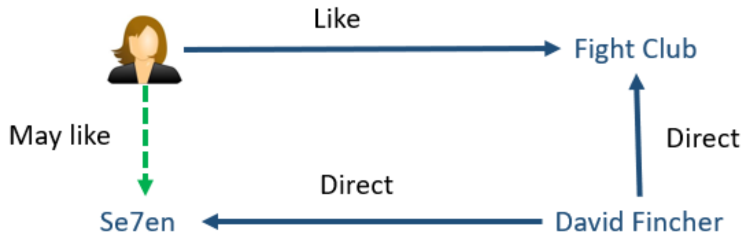
Model name	AUC	Logloss	Depth
Criteo			
FM	0.7900	0.4592	-
DNN	0.7993	0.4491	2
CrossNet	0.7961	0.4508	3
CIN	**0.8012**	0.4493	3
Dianping			
FM	0.8165	0.3558	-
DNN	0.8318	0.3382	3
CrossNet	0.8283	0.3404	2
CIN	**0.8576**	**0.3225**	2
Bing News			
FM	0.8223	0.2779	-
DNN	0.8366	0.273	2
CrossNet	0.8304	0.2765	6
CIN	**0.8377**	**0.2662**	5

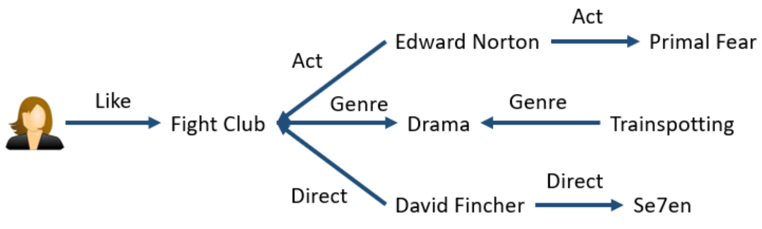
Knowledge Graph

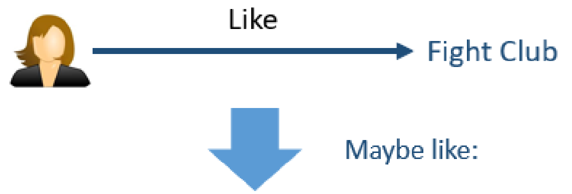
- A kind of semantic network, where node indicates entity or concept, edge indicates the semantic relation between entity/concept

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







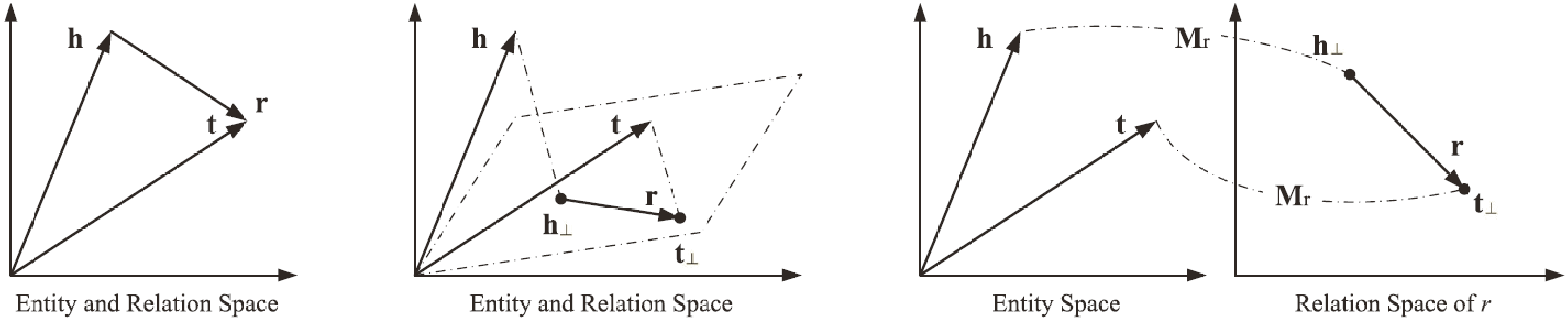
Primal Fear, because they share the same actor
Trainspotting, because they share the same genre
Se7en, because they share the same director

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.

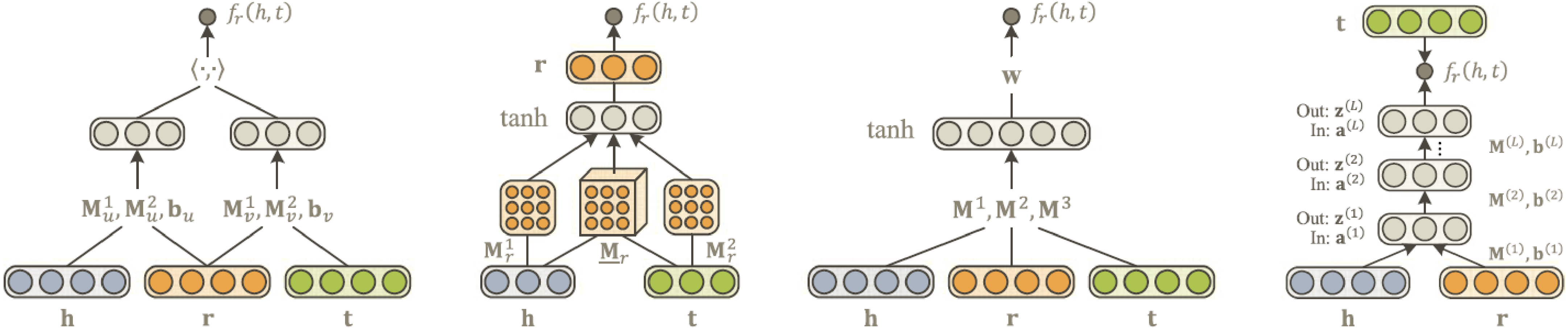


(a) TransE. (b) TransH. (c) TransR.

Knowledge Graph Embedding

Matching-based Models

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



(a) SME. (b) NTN. (c) MLP. (d) NAM.

Knowledge Graph Embedding

KG, RS $\xrightarrow[\text{Learning}]{\text{KGE}}$ Entity Vector, Relation Vector; User Vector, Item Vector (Joint Training)

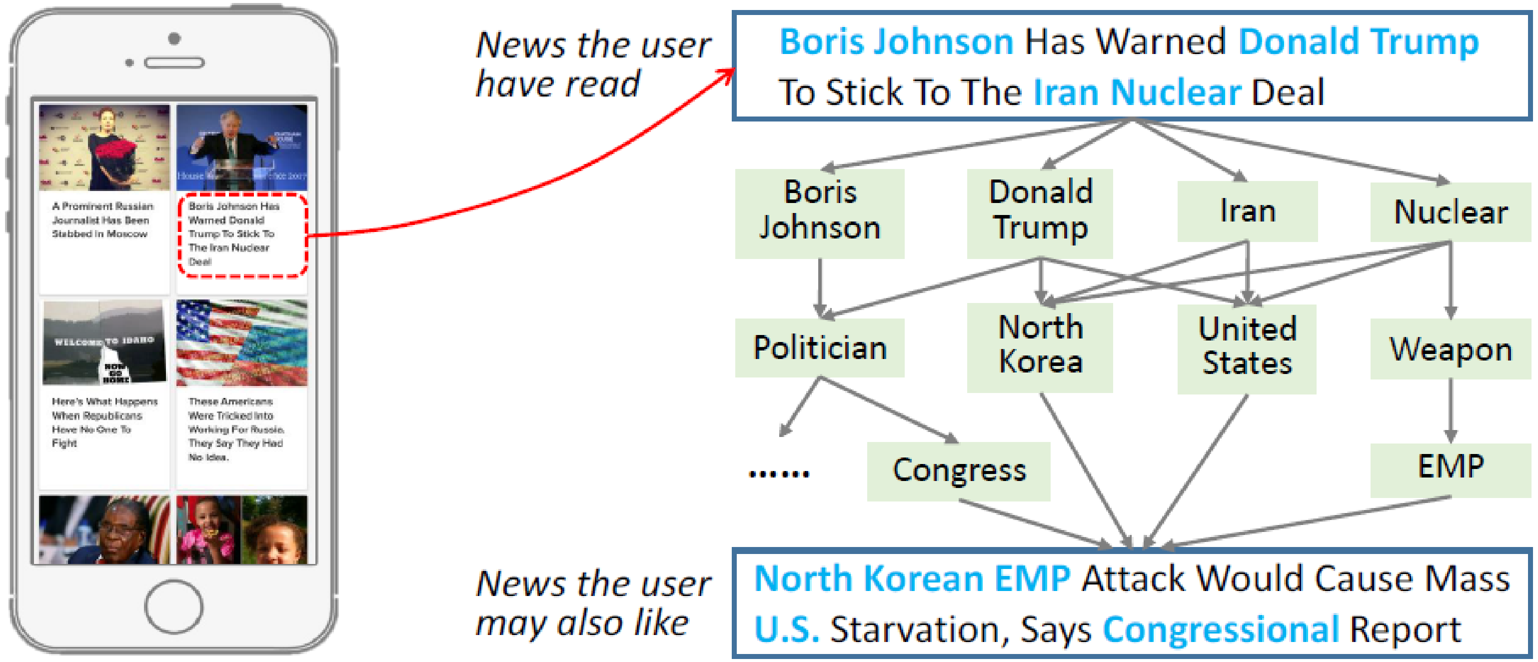
KG $\xrightarrow{\text{KGE}}$ Entity Vector, Relation Vector $\xrightarrow{\text{Feed into}}$ RS Task $\xrightarrow{\text{Learning}}$ User Vector, Item Vector (Successive Training)

KG $\xrightarrow{\text{KGE}}$ Entity Vector, Relation Vector

RS $\xrightarrow{\text{Learning}}$ User Vector, Item Vector

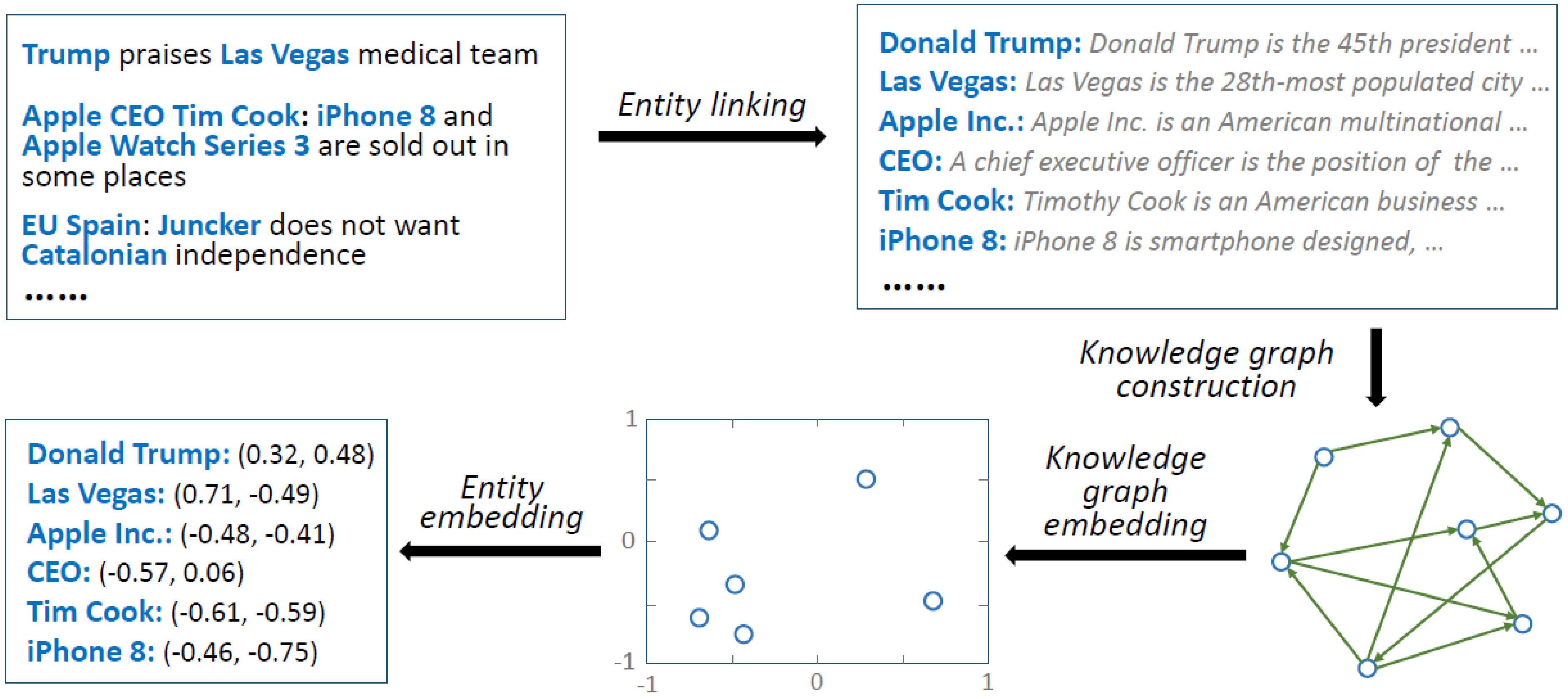
(Alternate Training)

Deep Knowledge-aware Network



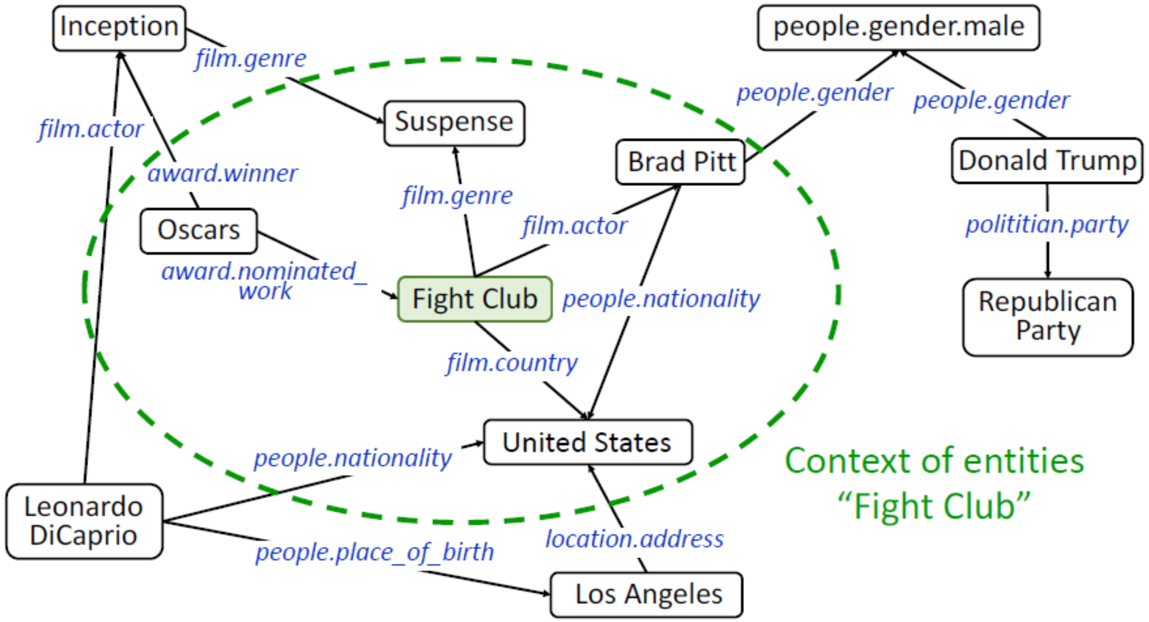
Hongwei Wang, Fuzheng Zhang, Xing Xie, Minyi Guo, DKN: Deep Knowledge-Aware Network for News Recommendation, WWW 2018

Deep Knowledge-aware Network

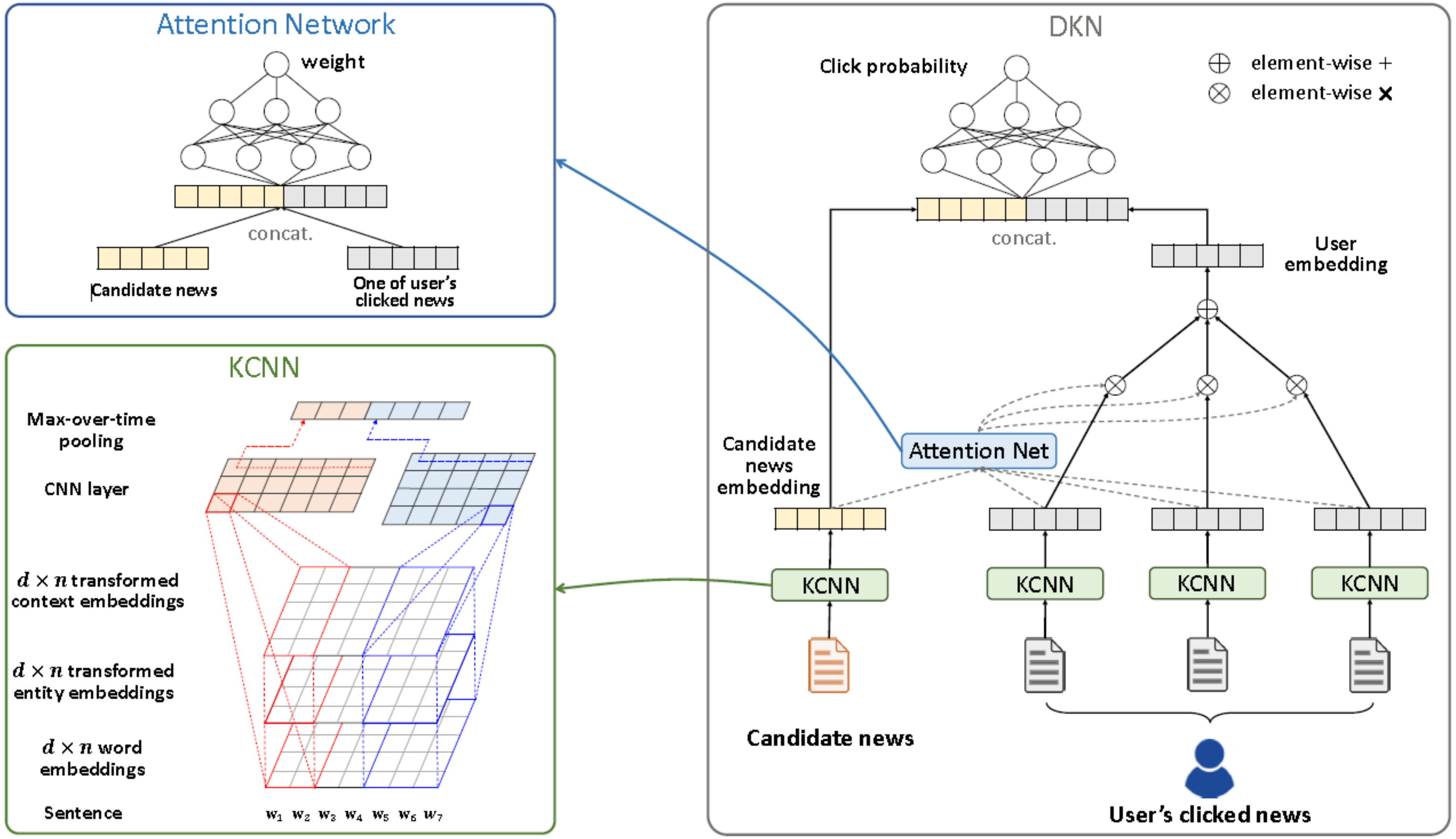


Extract Knowledge Representations

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



Deep Knowledge-aware Network

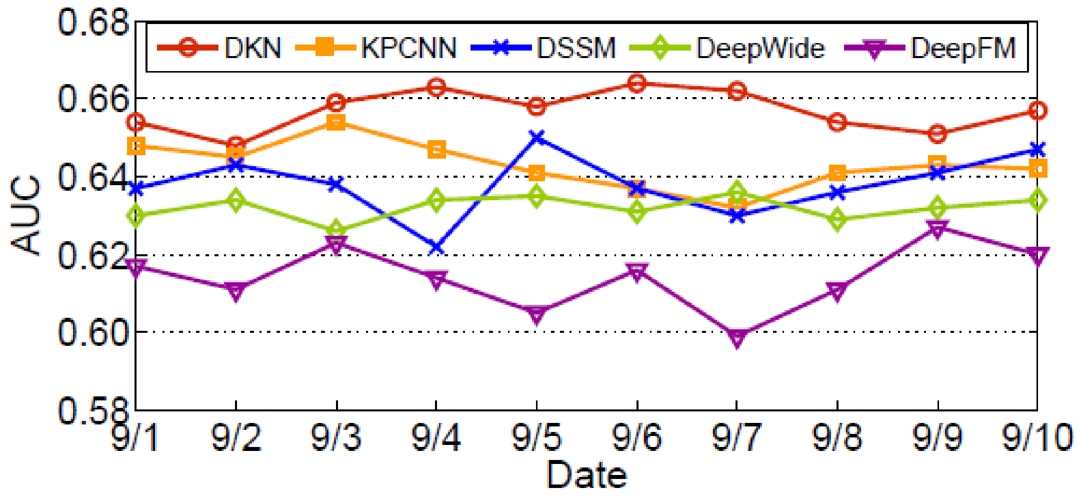


Experiments

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%)	$< 10^{-3}$

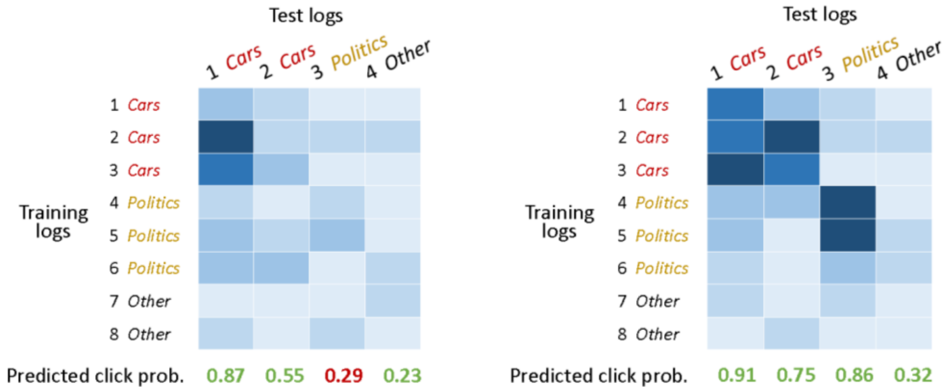
* "(-)" denotes "without input of entity embeddings".

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



Examples

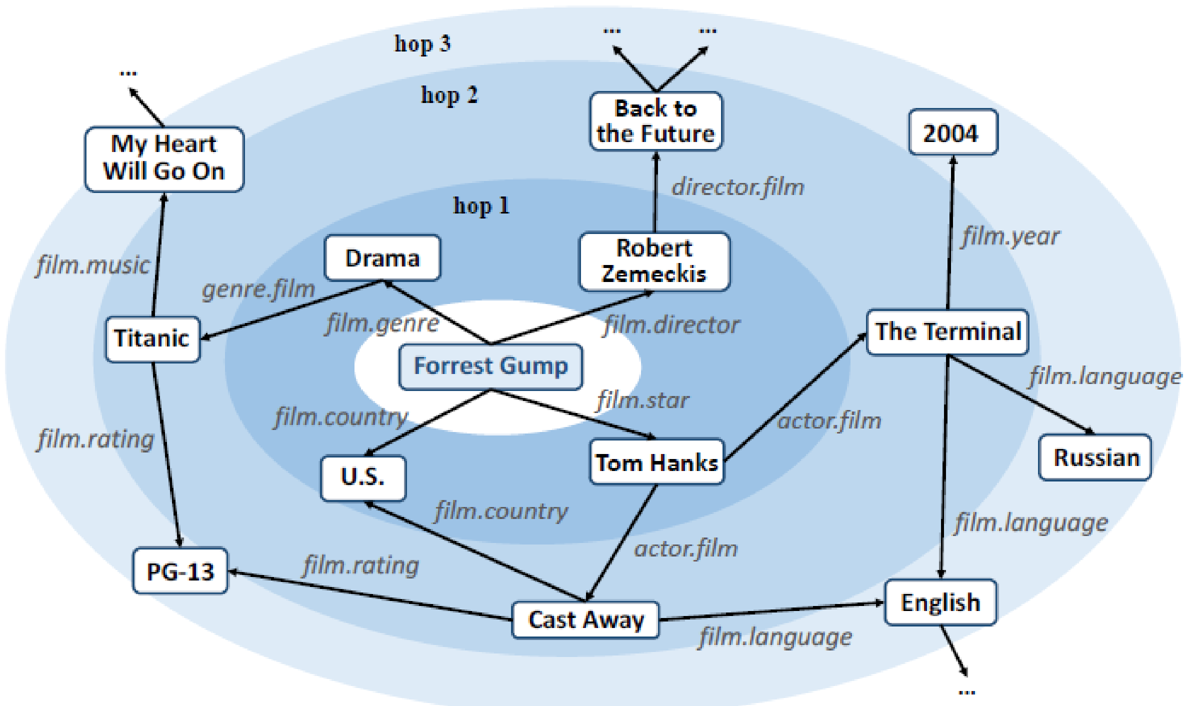
	No.	Date	News title	Entities	Label	Category
training	1	12/25/2016	Elon Musk teases huge upgrades for Tesla's supercharger network	Elon Musk; Tesla Inc.	1	Cars
	2	03/25/2017	Elon Musk offers Tesla Model 3 sneak peek	Elon Musk; Tesla Model 3	1	Cars
	3	12/14/2016	Google fumbles while Tesla sprints toward 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**

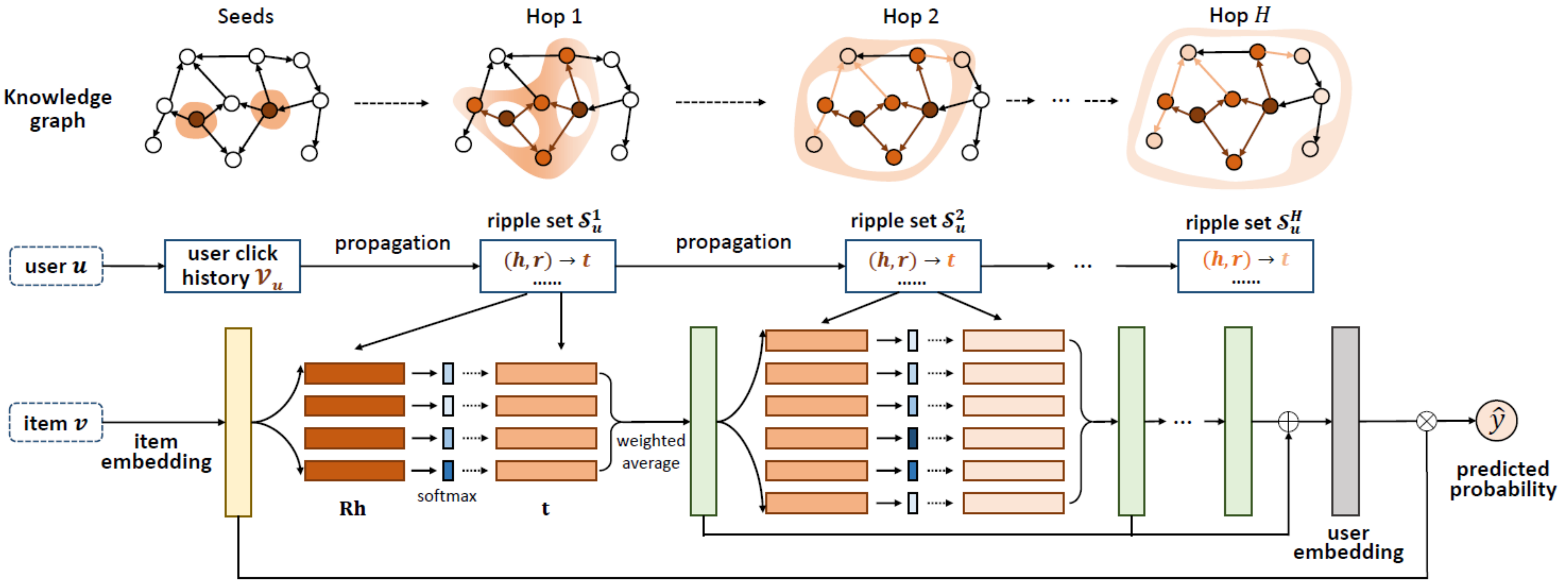
Ripple Network

- 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

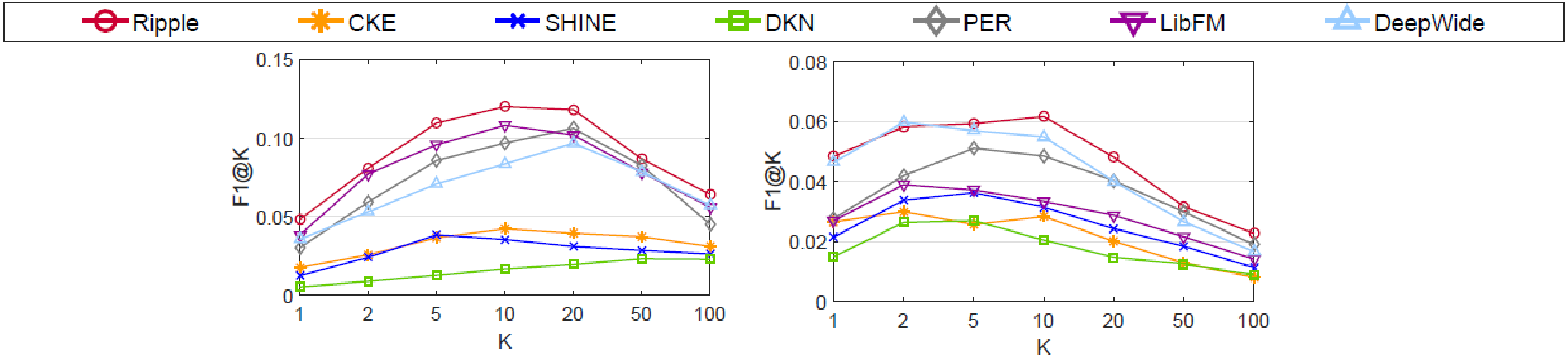
Ripple Network



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

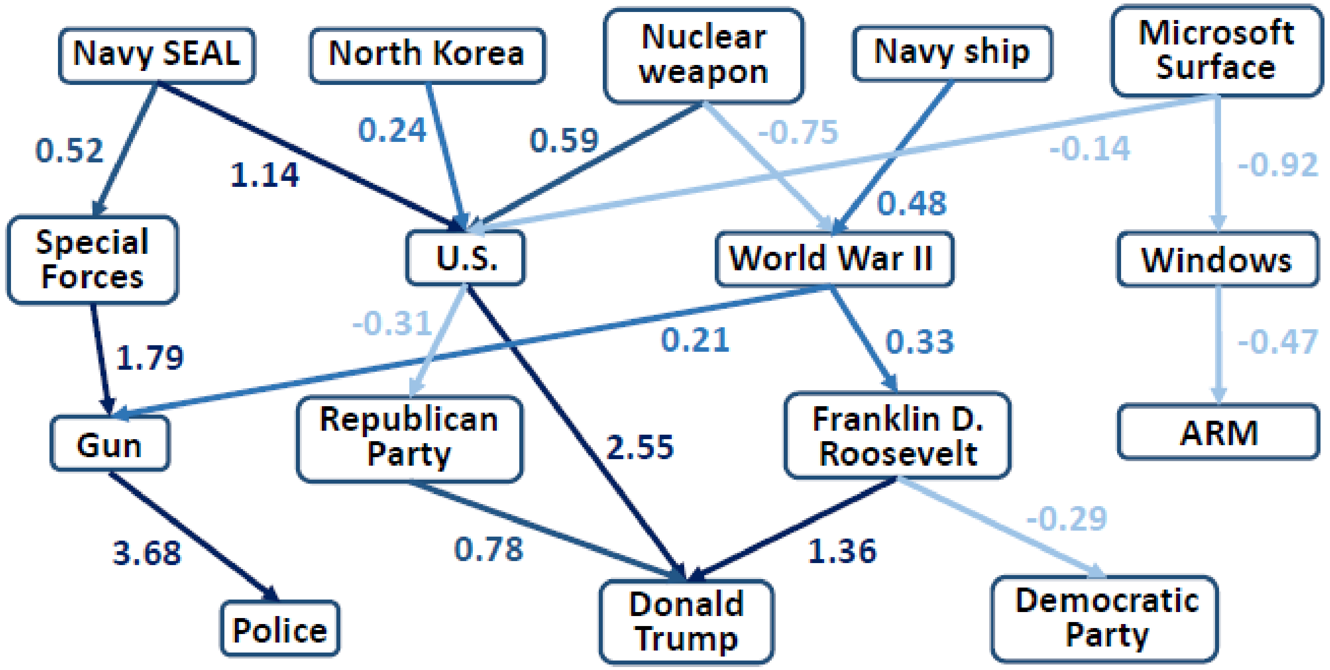
* Statistically significant improvements by t-test.



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*

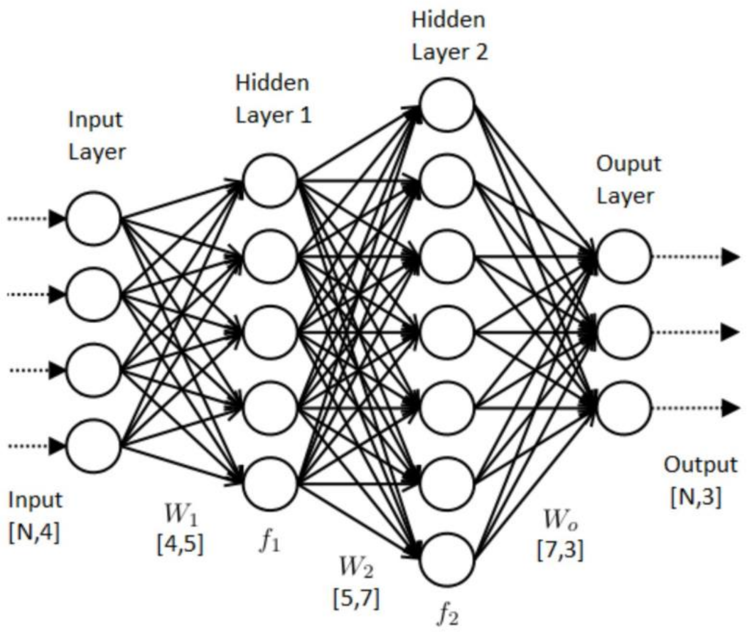


Candidate news: *Trump Announces Gunman Dead, Credits 'Heroic Actions' of Police*

Explainable Recommendation Systems

Model Explainability — Transparency, Trust

Effectiveness, Persuasiveness, Readability — Presentation Quality



Explainable Recommendation Systems

Fog Harbor Fish House

4703 reviews

Their **tan tan noodles** are made of magic. The chili oil is really appetizing.

However, **prices** are on the high side.

1-800-FLOWERS.COM – Elegant Flowers for Lovers

Ad · 1800Flowers.com · 40,100+ followers on Twitter
Ratings: Product Selection 4.5/5 - Price 4/5 - Customer Service 4/5

1800flowers.com has been visited by 10K+ users in the past month
1800flowers.com is rated ★★★★★ (321,968 reviews)

Model Explainability { Transparency, Trust

Effectiveness, Persuasiveness, Readability } Presentation Quality

Problem Definition

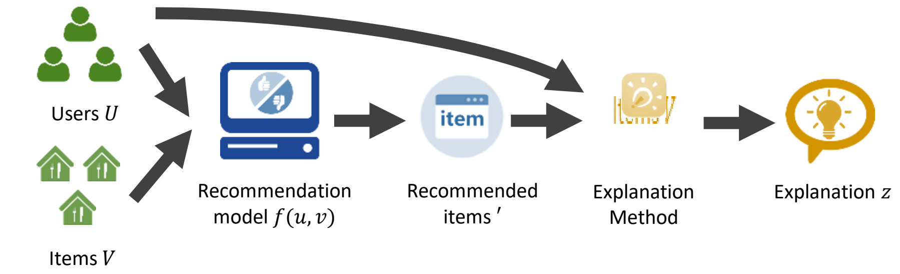
- Input
  - User set U, $u \in U$ is a user -------------------- u: user ID and user attributes
  - Item set V, $v \in V$ is an item -------------------- $\boldsymbol{v} = (i, \boldsymbol{l}_1, \boldsymbol{l}_2, ..., \boldsymbol{l}_m)$

    i: item ID l_j: interpretable component
  - A recommendation model to be explained $f(u, v)$
- Output
  - *z* is generated based on the selected components
  - Explanation $z =$ *expgen* $(z_1, z_2, ...z_m)$

$z_j = 1$ The jth interpretable component is selected

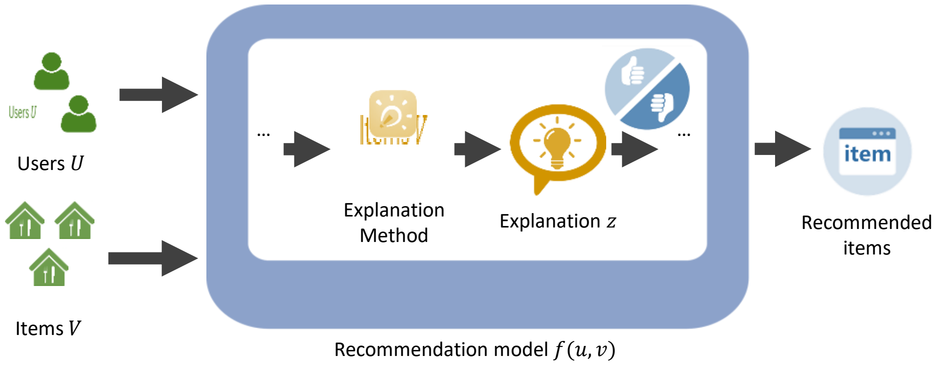
$z_j = 0$ The jth interpretable component is not selected

Outline



Can we enhance persuasiveness (presentation quality) in a data-driven way?

*Feedback Aware Generative Model, Shipped to **Bing Ads**, revenue increased by 0.5%*



Can we build an explainable deep model (enhance model explainability)?

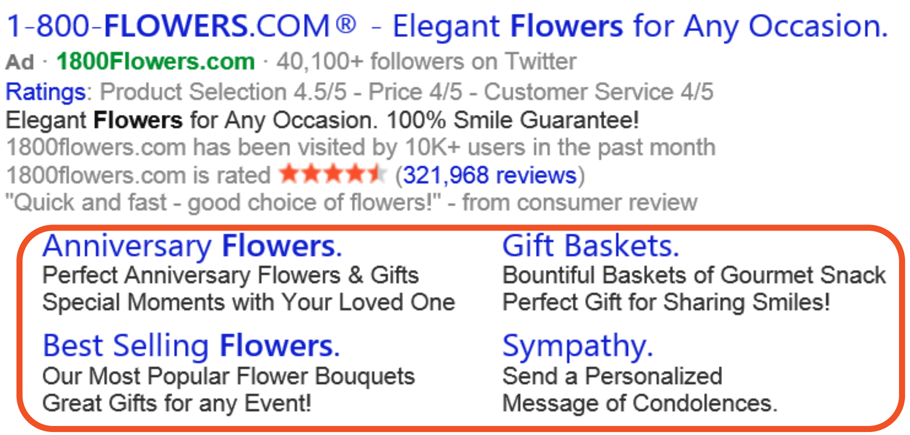
*Explainable Recommendation Through Attentive Multi-View Learning, **AAAI 2019***

Can we design a pipeline which better balances presentation quality and model explainability?

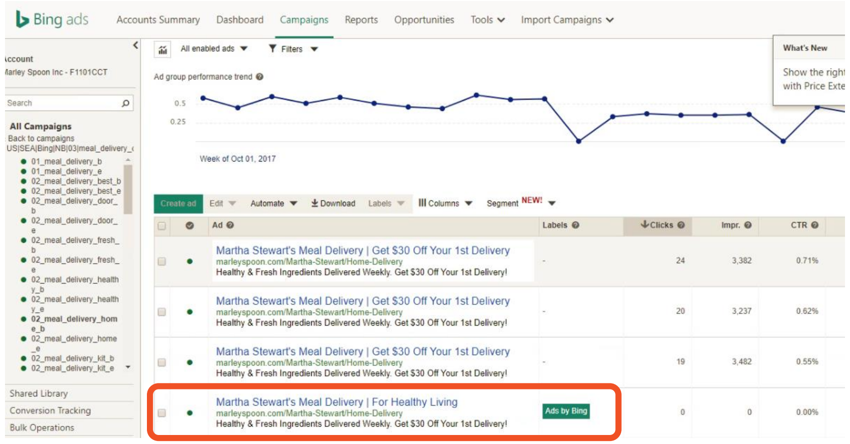
*A Reinforcement Learning Framework for Explainable Recommendation, **ICDM 2018***

Explainable Recommendation for Ads

Search Ads

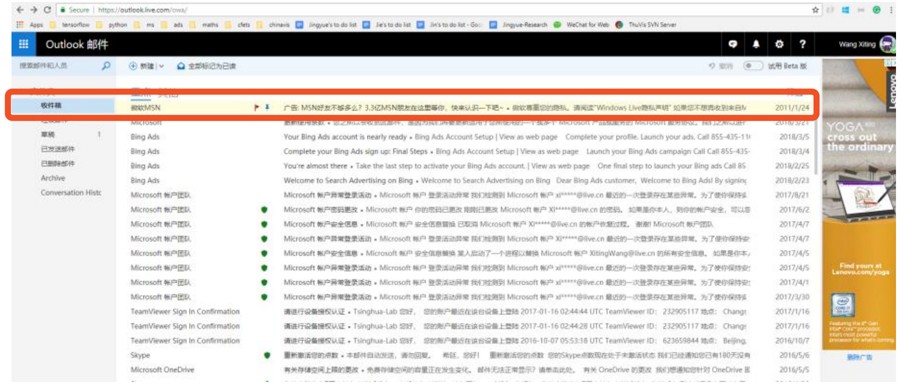


Advertiser Platform



Native Ads / MSN

Native Ads / Outlook.com



Feedback Aware Generative Model

- Traditional Seq2Seq model

$$\underset{\theta}{argmax} \prod_i p(y_i|x_i;\theta)$$

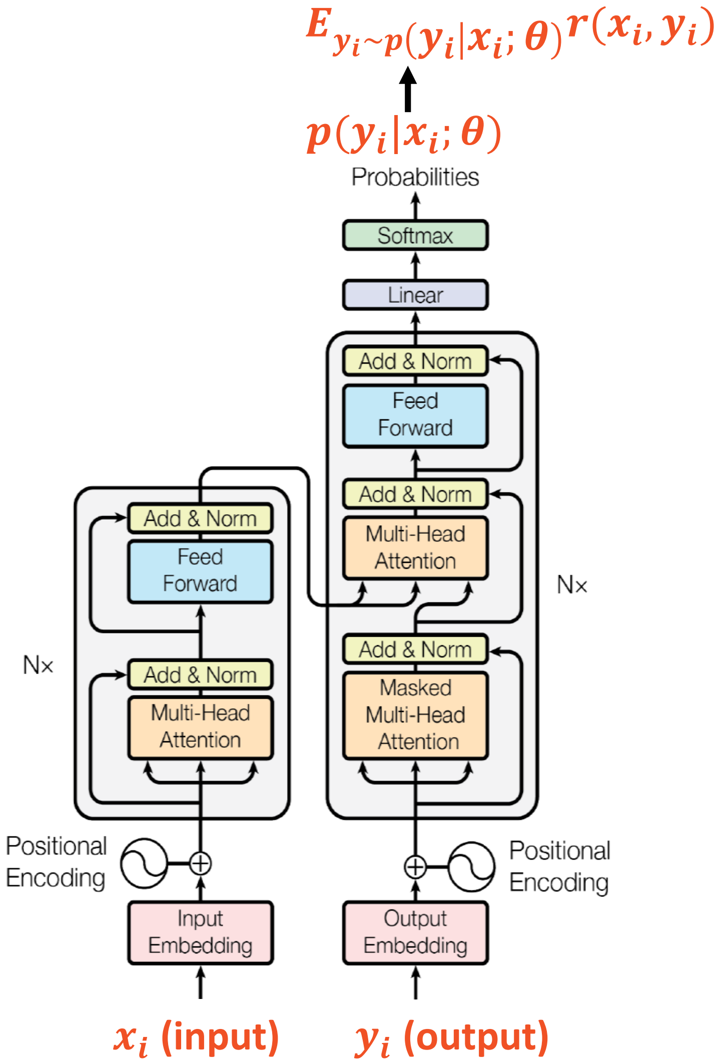
- Feedback aware model

$$\underset{\theta}{argmax} \sum_i E_{y_i \sim p(y_i|x_i;\theta)} r(x_i, y_i)$$

Input x_i	**Output y_i**	**Reward $r(\cdot)$**
Ad title, category, keyword, sitelink title	Ad title, Ad description, sitelink description	CTR

Ad title: *Flowers delivered today*
Category: *Occasions & Gifts*

Elegant flowers for any occasion.
100% smile guarantee!



Example Results

The model has the ability to generate persuasive phrases

The model can differentiate similar inputs

Diversified results

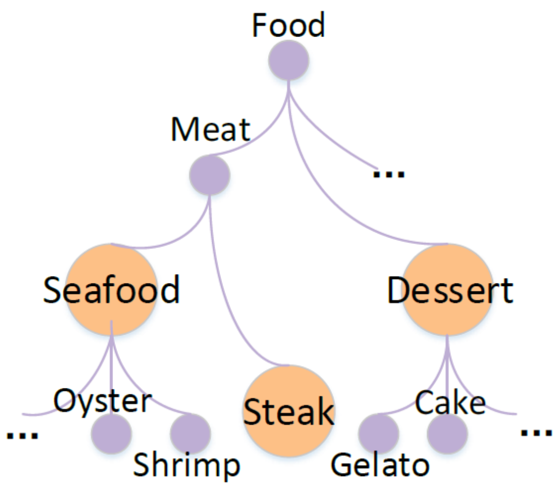
Input AdTitle	job applications online
Output AdDescriptions	New: job application online. Apply today & find your perfect job!
	Now hiring - submit an application. Browse full & part time positions.
	3 open positions left -- apply now! Jobs in your area
	Open positions left -- apply now! Job application online.
	7 open positions left -- apply now! Jobs in your area
	Sales positions open. Hiring now - apply today!

Input AdTitle	US passport application
Output AdDescriptions	Find US passport application and related articles. Search now!
	Quick & easy application. Apply for your passport online today!
	Quick & easy application. Find government passport application and related articles.
	Government passport application. Quick and easy to search results!
	Start your passport online today. Apply now & find the best results!
	Open your passport online today. 100% free tool!

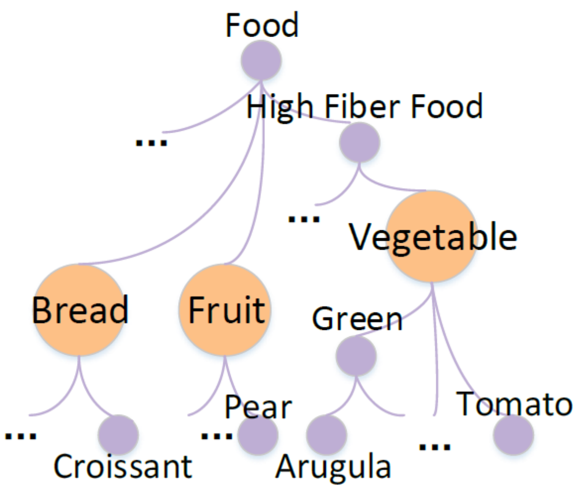
Explainable Recommendation Through Attentive Multi-View Learning

- 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

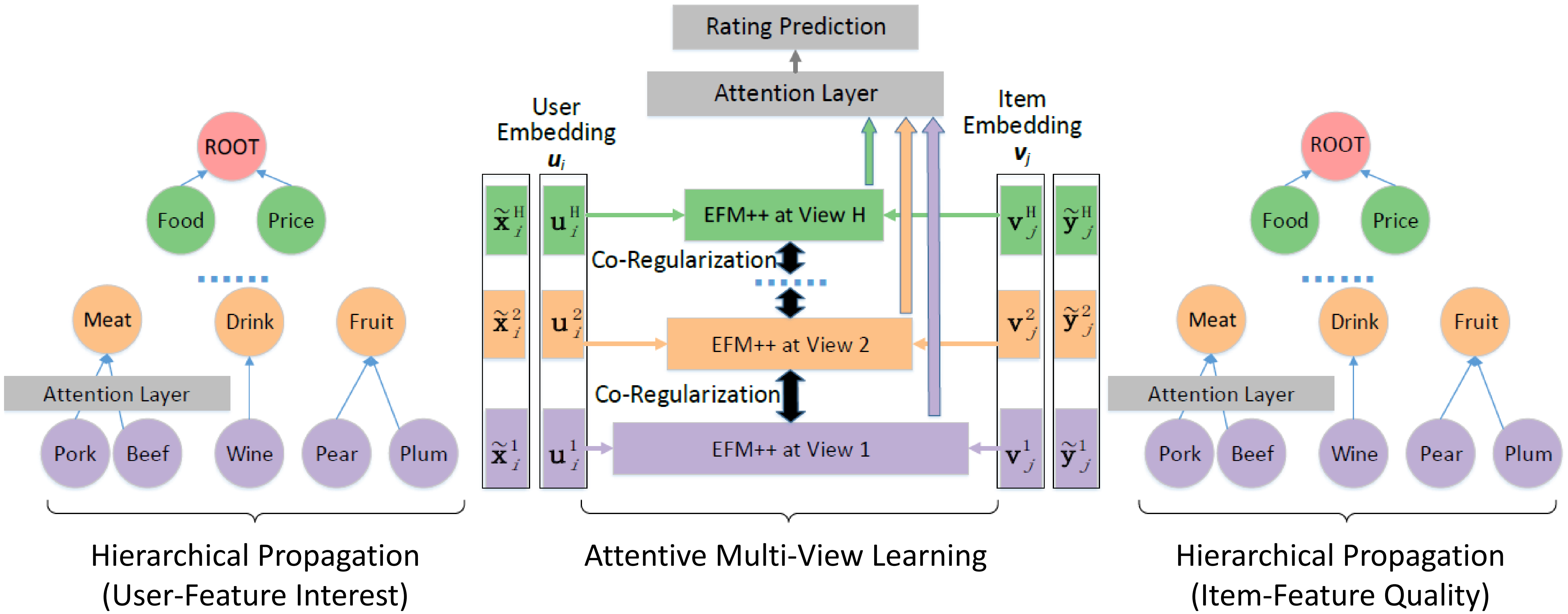


30-year-old male user



Model

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



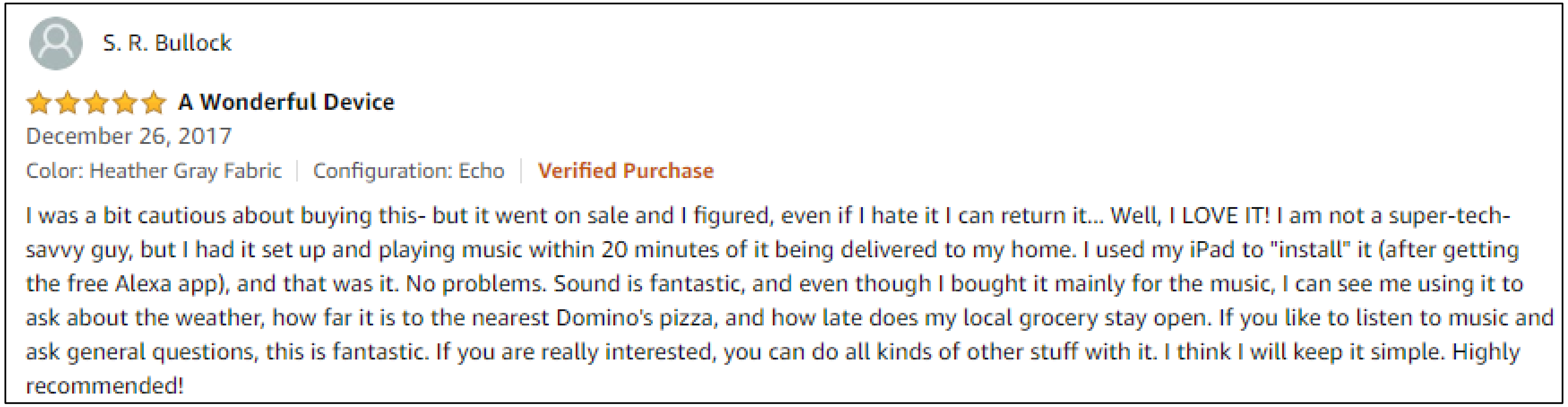
Data

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

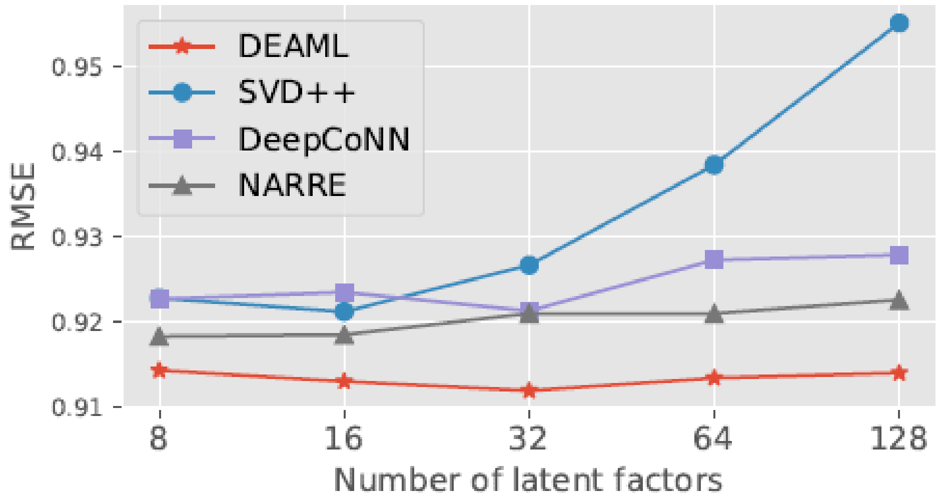


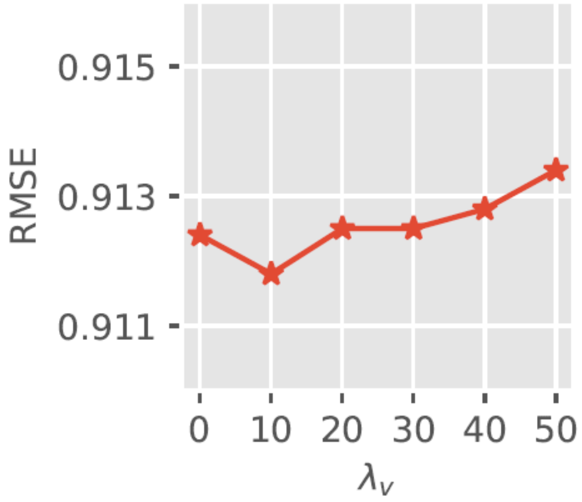
Yelp

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

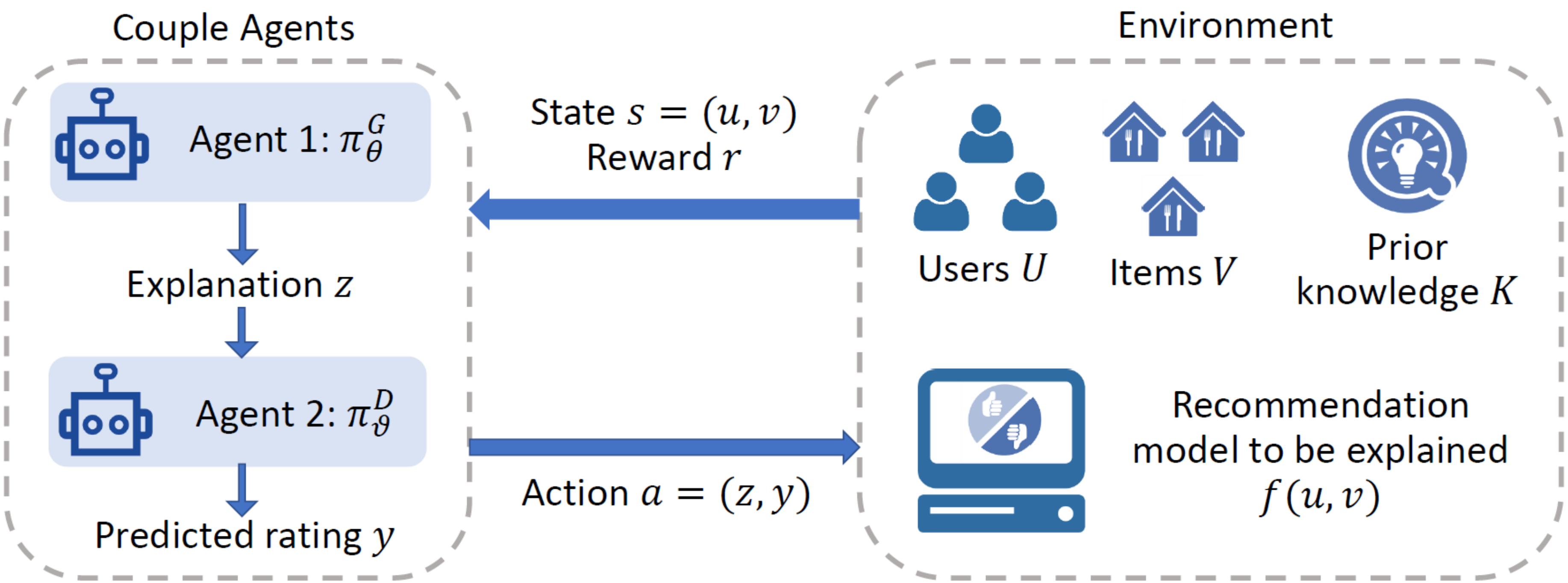
Explainability

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

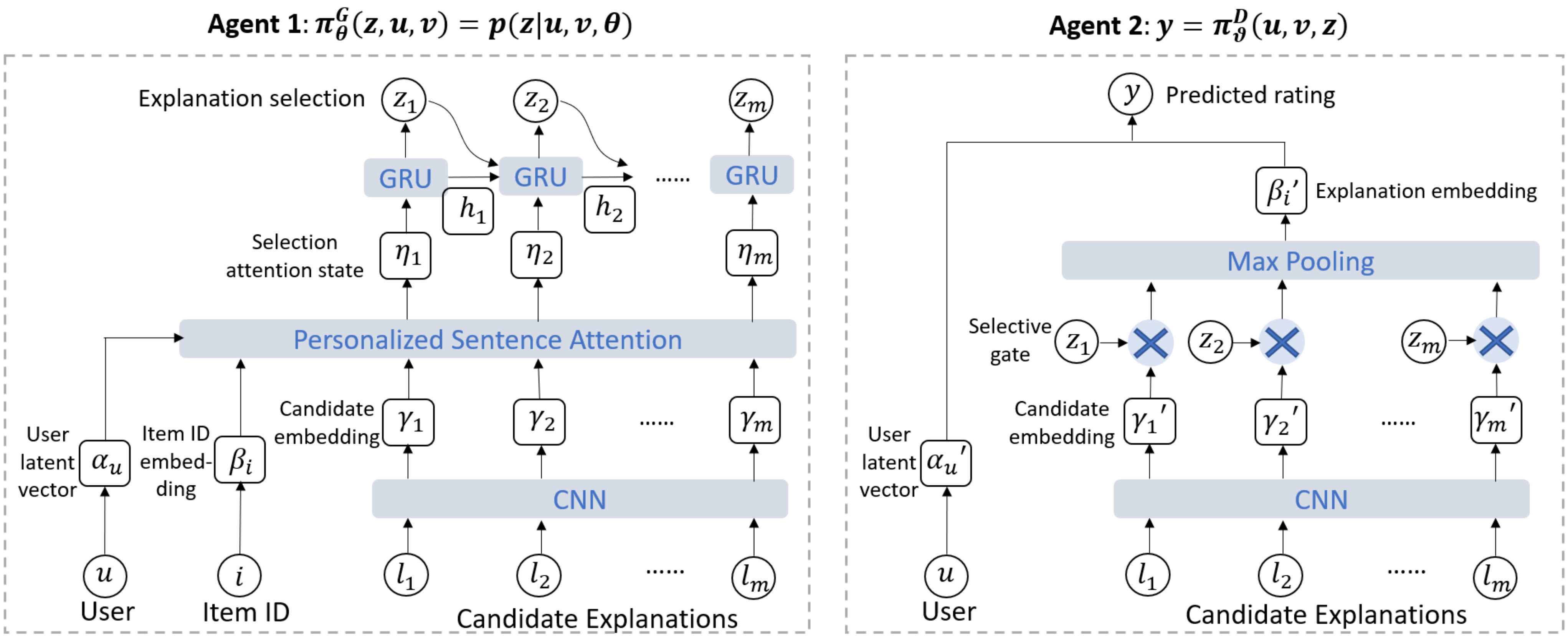
Average score on explanation usefulness. <30 and ≥ 30 refer to two age groups.

	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**

Reinforcement Learning Framework for Explainable Recommendation



Couple Agents



Optimization Goal

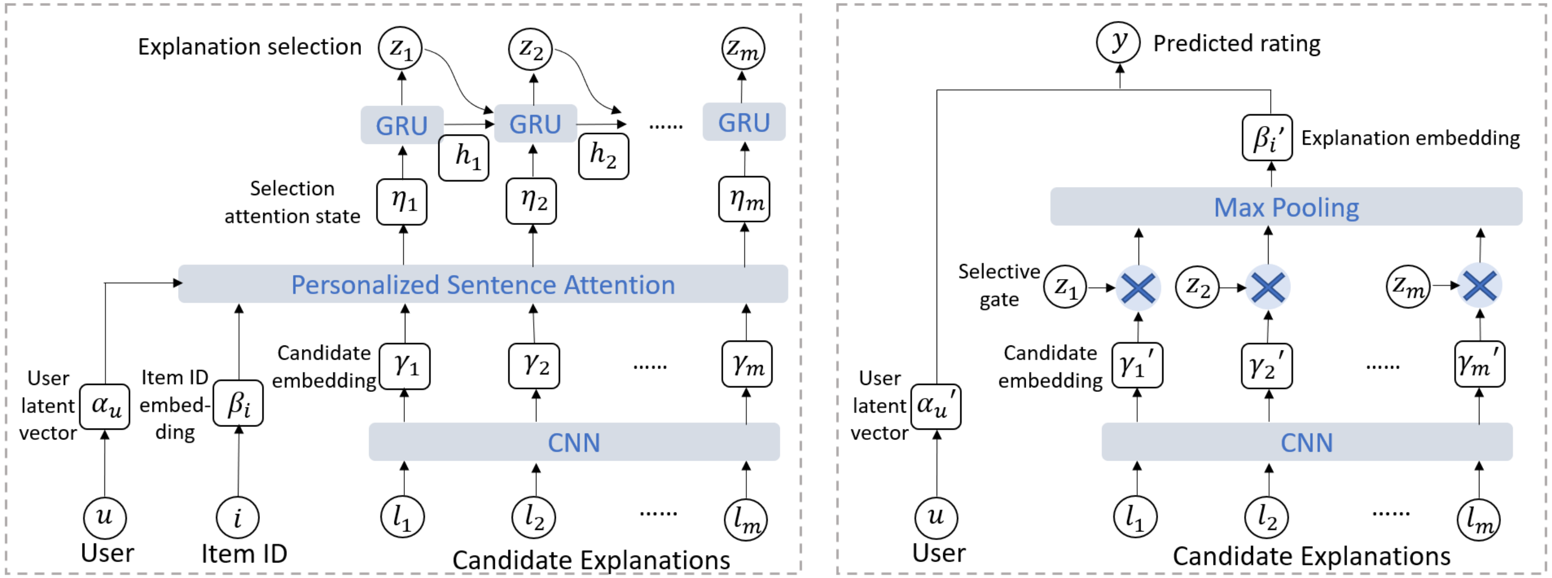
$$\arg\max_{\boldsymbol{\theta},\boldsymbol{\vartheta}} \sum_{\boldsymbol{u},\boldsymbol{v}} E_{\boldsymbol{z}\sim p(\cdot|\boldsymbol{u},\boldsymbol{v},\boldsymbol{\theta})} \overbrace{\left[\mathcal{L}(f(\boldsymbol{u},\boldsymbol{v}), \pi^{D}_{\boldsymbol{\vartheta}}(\boldsymbol{u},\boldsymbol{v},\boldsymbol{z})) + \Omega(\boldsymbol{z})\right]}^{\text{Reward } r}.$$

Model explainability

Presentation quality

Agent 1: $\boldsymbol{\pi^{G}_{\theta}(z,u,v) = p(z|u,v,\theta)}$

Agent 2: $\boldsymbol{y = \pi^{D}_{\vartheta}(u,v,z)}$



Evaluation

	Amazon_Toys_and_Games	Yelp_2018_LasVegas
#users	19,412	23,196
#items	11,924	13,433
#reviews and ratings	167,597	568,454

Explaining different recommendation models trained on the **Amazon_Toys_and_Games** dataset. Here NMF, PMF, SVD++, and CDL are recommendation models to be explained. M_c: presentation quality M_e: explainability

	M_c					M_e				
	NMF	PMF	SVD++	CDL	GT	NMF	PMF	SVD++	CDL	GT
Random	0.006	0.007	0.035	0.010	0.030	-1.329	-1.046	-0.150	-1.080	-0.981
NARRE	0.012	0.022	0.038	0.043	0.048	-1.271	-1.032	-0.142	-0.967	-0.927
Ours	**0.025**	**0.028**	**0.048**	**0.079**	**0.155**	**-1.234**	**-0.956**	**-0.130**	**-0.956**	**-0.903**

Explaining different recommendation models trained on the **Yelp_2018_LasVegas** dataset. Here NMF, PMF, SVD++, CDL, and GT are recommendation models to be explained.

	M_c					M_e				
	NMF	PMF	SVD++	CDL	GT	NMF	PMF	SVD++	CDL	GT
Random	-0.030	-0.030	-0.031	0.012	0.007	-0.478	-0.287	-0.266	-0.517	-1.488
NARRE	-0.015	-0.000	0.018	0.031	0.038	-0.448	-0.266	-0.239	-0.482	-1.424
Ours	**0.018**	**0.037**	**0.041**	**0.227**	**0.168**	**-0.421**	**-0.258**	**-0.232**	**-0.460**	**-1.380**

Case Study

Frequent words in reviews:

User A **chicken**, **buffet**, portions, **sushi**, **beef**

User B **service**, **pizza**, **server**, **table**, **clean**

	NARRE	User A	User B
Item 1	By the way, try to park at the side of gold coast farthest from the rio if you want to have a shorter walk, which is healthier than it sounds due to less secondhand smoke exposure.	The **chicken**'s feet was tasty, so were the **har gow**.	In the past we had **trouble communicating with the staff** because they usually speak in their own language , this last time though it seems they have hired more **English speaking staff** and it was **considerably easier to order**.
Item 2	If you needa **fajita**, your search should end here.	They came with red & green **peppers** and **onions**. First, I thought the **salsa** was delicious, and i appreciated it was actually spicy versus the mild you typically receive.	Overall, the **service** throughout our meal was swift & friendly.
Item 3	Unfortunately, after living in the city for a few years and trying a lot of wonderful **food** that this city has to offer, we returned for a visit and I was less than impressed.	It was the perfect **burger**, **cheesy** with just the right amount of dressing and **chips**!	At least **put the stuff in a fancy container**?

Words related to food Words related to services

Conclusions and Future Work

- Personalized recommendation systems will continue to develop in various directions, including effectiveness, diversity, computational efficiency, and explainability

- Develop an easy-to-use tool for implementing deep learning based user representation and recommendation models
- Collaborate with researchers in psychology, sociology and other disciplines

Thanks!