TEM: Tree-enhanced Embedding Model for Explainable Recommendation

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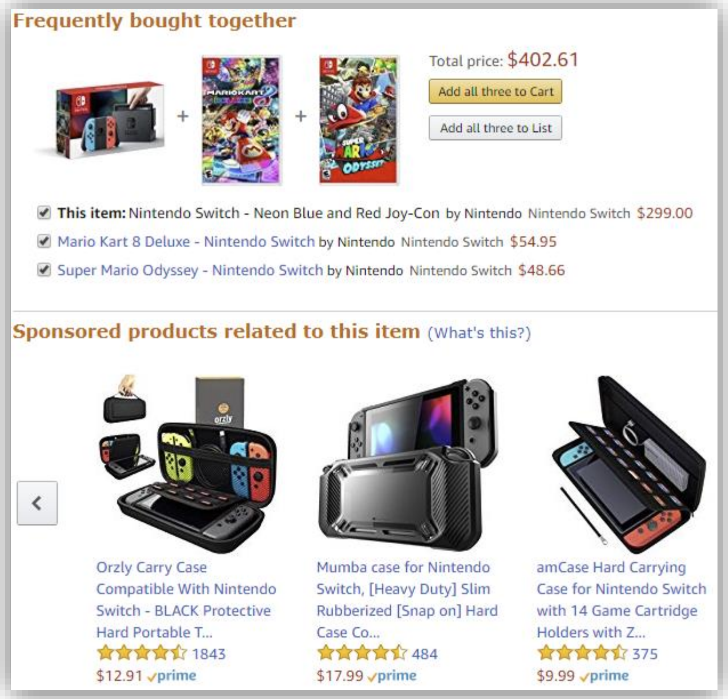
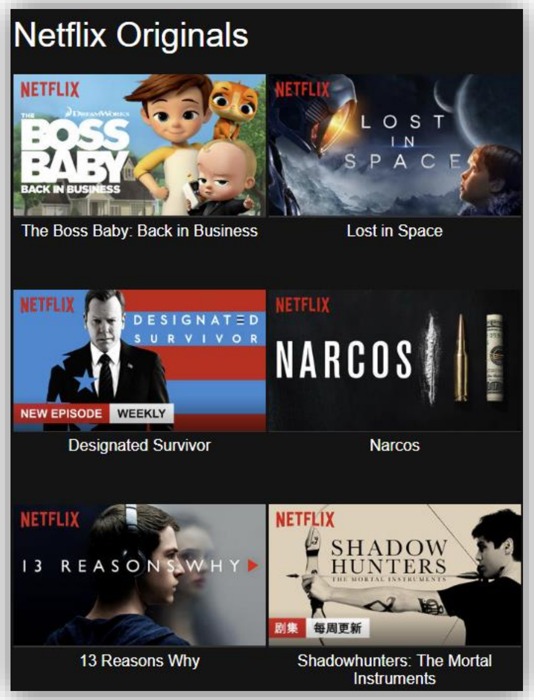
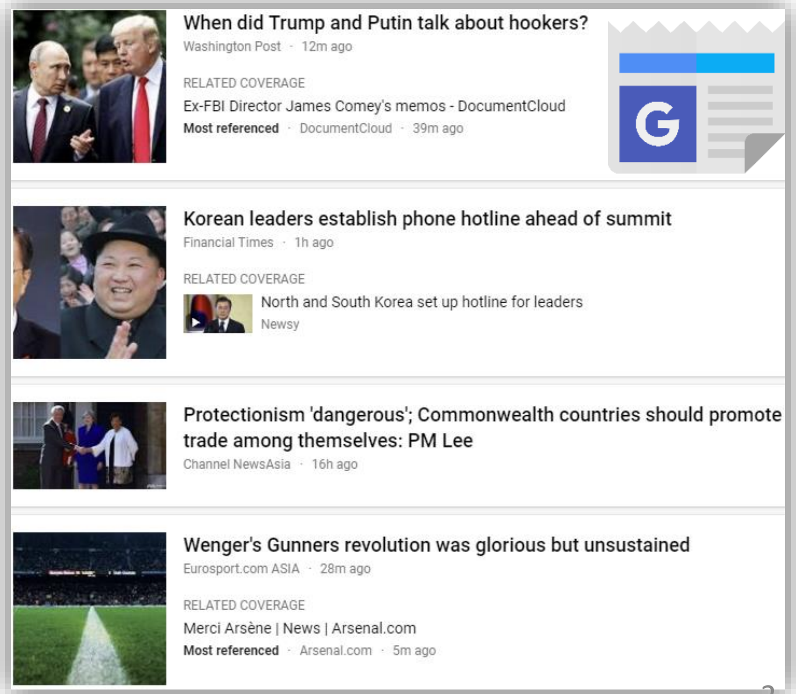
Value of Recommender Systems (RS)

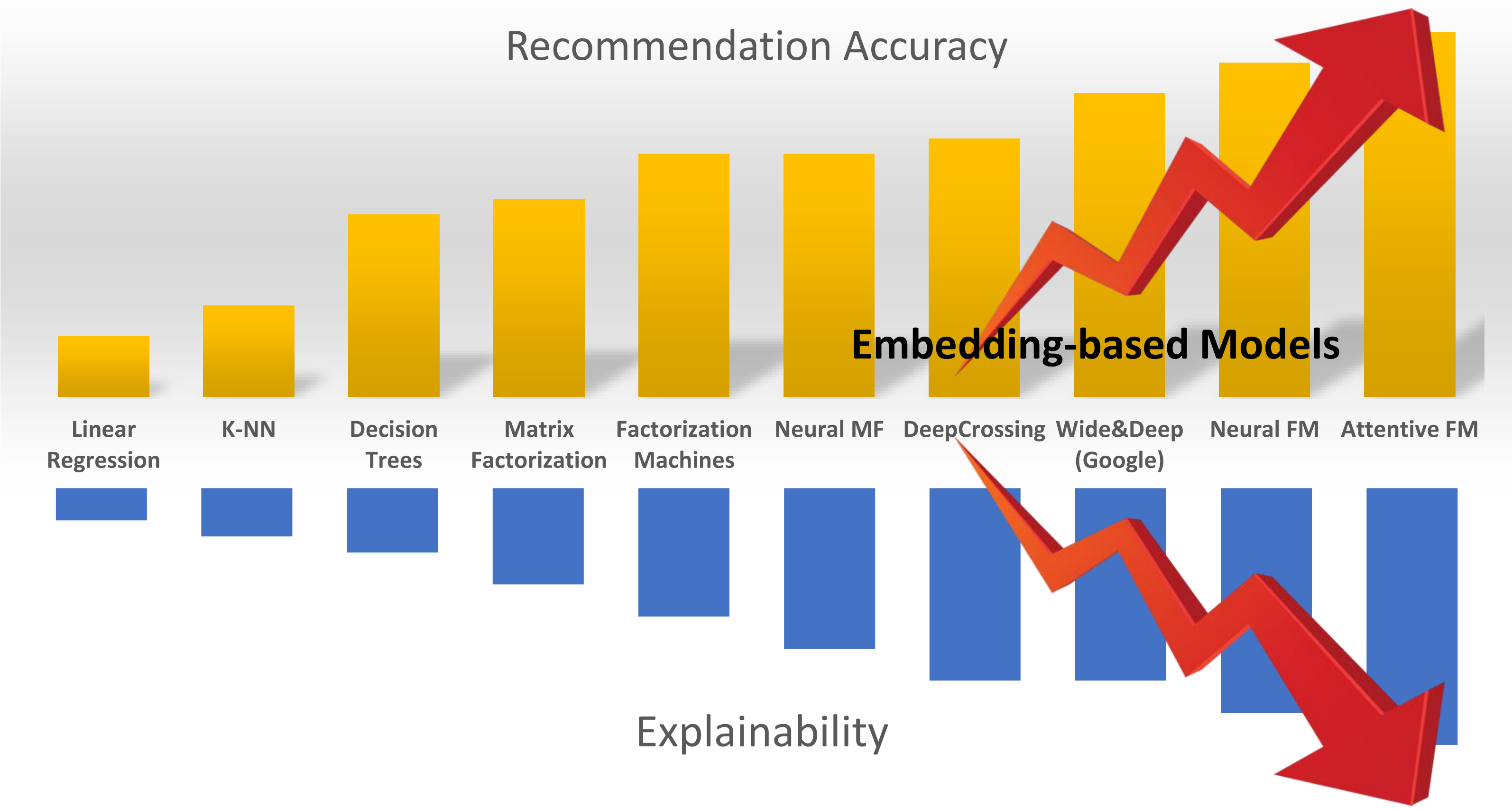
- **Amazon**: 35% sales from recommendations
- **Netflix**: 80% TV shows discovered are recommended
- **Google News**: RS generates 38% more click-through







Trade-off of Accuracy & Explainability

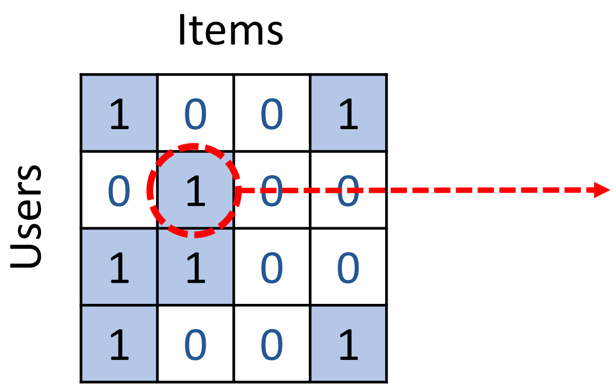


Our Goal:

- **Explainable**: be transparent in generating a recommendation & can identify the key rules for a prediction
- **Accurate**: achieve the same level or comparable performance as embedding-based methods

Embedding-based Models

❖ **Embedding-based Models:** Learn latent factors for each feature (IDs & side Info)



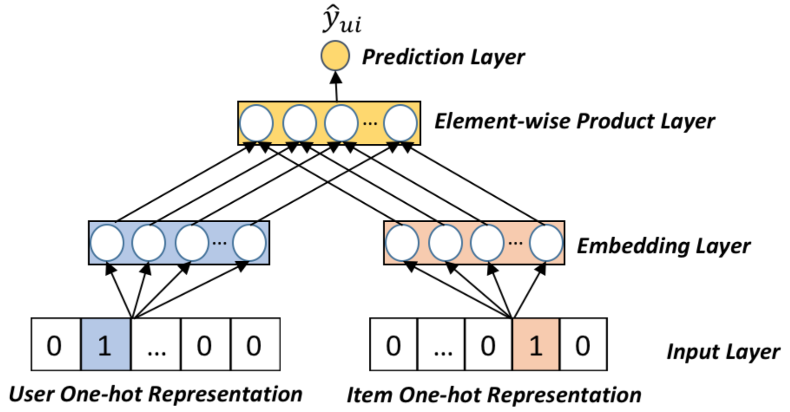
User-Item Interactions

Matrix Factorization (MF)

Input: user ID, item ID

Interaction: Inner Product

$$\hat{y}_{MF}(u,i) = b_0 + b_u + b_i + \mathbf{p}_u^\top \mathbf{q}_i$$

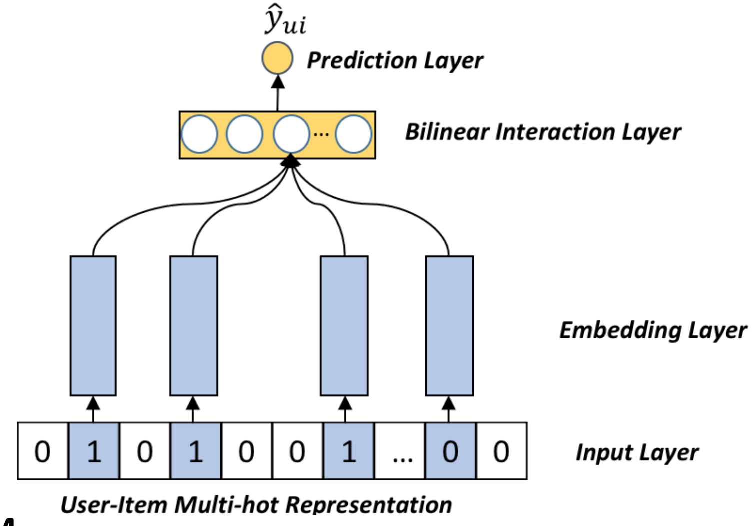


Factorization Machine (FM)

Input: user ID, item ID, side features ID

Interaction: Element-wise Product

$$\hat{y}_{FM}(\mathbf{x}) = w_0 + \sum_{t=1}^{n} w_t x_t + \sum_{t=1}^{n} \sum_{j=t+1}^{n} \mathbf{v}_t^\top \mathbf{v}_j \cdot x_t x_j,$$



Neural Network Methods

NCF, Deep Crossing, Wide&Deep, DIN, NFM

Explainable Recommendation

Recommended List:

- $\hat{y}_{u3} = 0.9$
- $\hat{y}_{u1} = 0.7$
- $\hat{y}_{u5} = 0.3$
- $\hat{y}_{u2} = 0.2$

Black-box Model

- Why did RS recommend it?
- Why not something else?
- How do I correct an error?

End User/ Data Scientist

Items

Users

1	0	0	1
0	1	0	0
1	1	0	0
1	0	0	1

User-Item Interactions

Recommended Reason

Users of <City: SG, Age: 18-25, Style: Sci-Fi> like items of <Price: $$, Attribute: Science>

…

Explainable Model

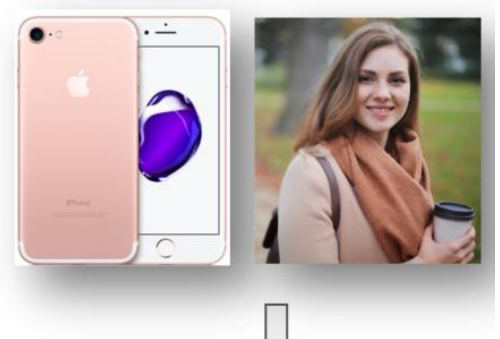
- I understand why
- I understand why not
- I know how to correct RS

End User/ Data Scientist

Transparency, Trust, Explainability, Scrutability

Cross Features

- **Cross Feature:** combinatorial feature that crosses (or multiplies) multiple individual input features.
- **Why?**
  - Higher-order feature interactions: e.g., [Age * Occupation *Gender]
  - Explicit decision rules

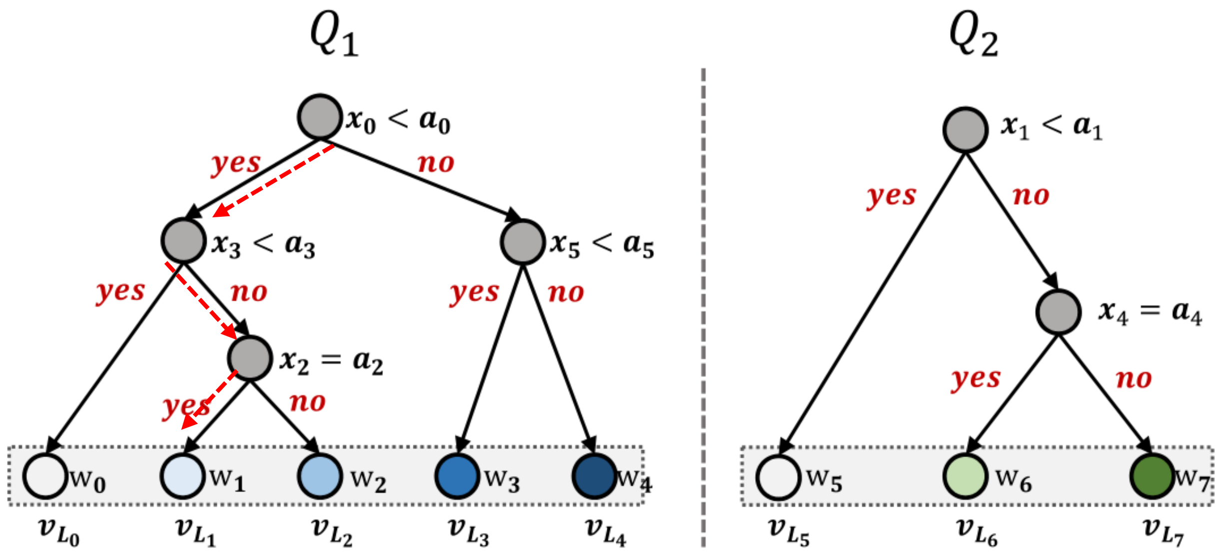


Users of <Gender=female & Age=20-25 & Income Level=$8,000> tend to adopt items of <Color=Pink & Product=Apple>.

Tree-based Methods

Decision Tree (DT):

- Each node splits a feature variable into two decision edges based on a value.
- A **path** from the root to a leaf -> a decision rule (like a **cross feature**).
- The leaf node -> the **prediction value**.



leaf node v_{L_2} represents $[x_0 < a_0]\&[x_3 \geq a_3]\&[x_2 \neq a_2]$

Forest (ensemble of trees)

- Since a single tree may not be expressive enough, a typical way is to build a **forest**, i.e., an ensemble of additive trees

$$\hat{y}_{GBDT}(\mathbf{x}) = \sum_{s=1}^{S} \hat{y}_{DT_s}(\mathbf{x}),$$

# of trees

Prediction of the *s*-th tree

Tree-based vs. Embedding-based Model

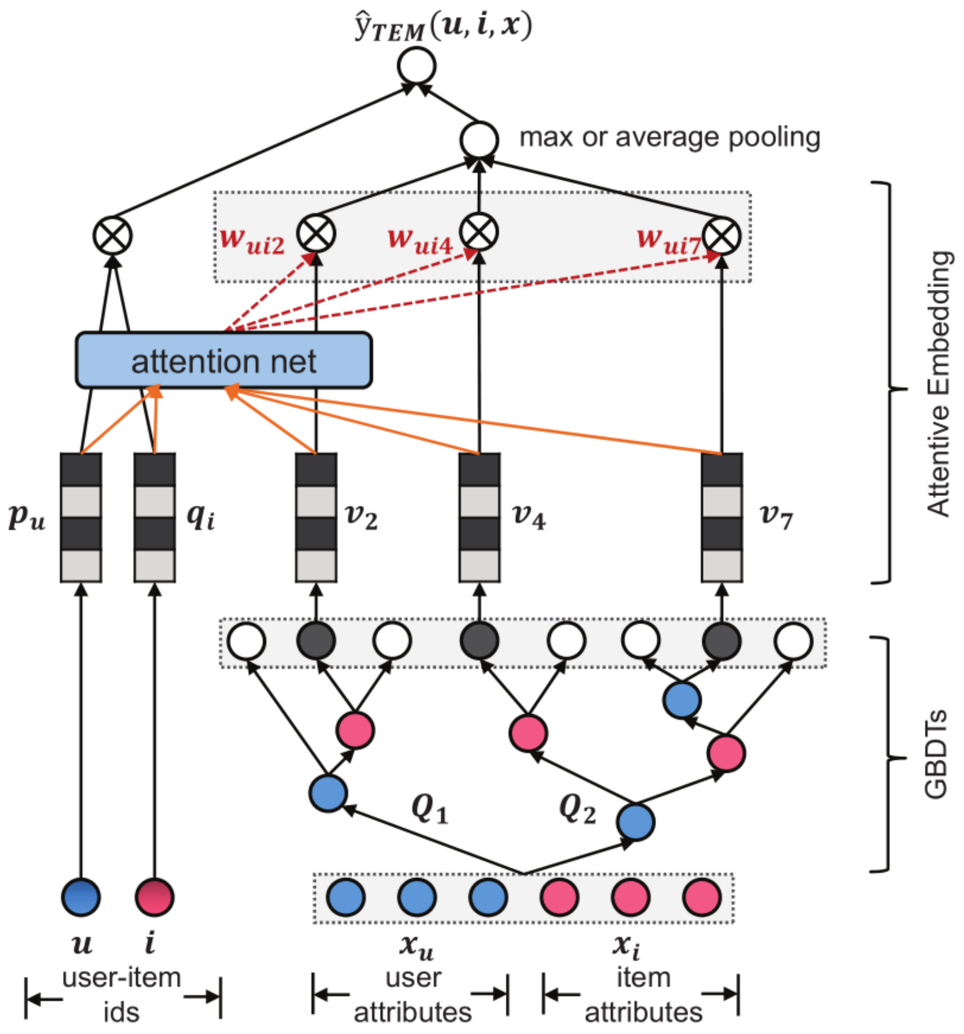
Tree-based Model (e.g., GBDT)	**Embedding-based Model (e.g., DNN, FM)**
+ Strong at continuous features	+ Strong at categorical features
+ Explainable	- Blackbox
+ Low serving cost	- High serving cost
- Weak generalization ability to unseen feature combinations.	+ Strong generalization ability to unseen feature combinations.

Why not combining the strengths of the two types of models?

Tree-enhanced Embedding Model

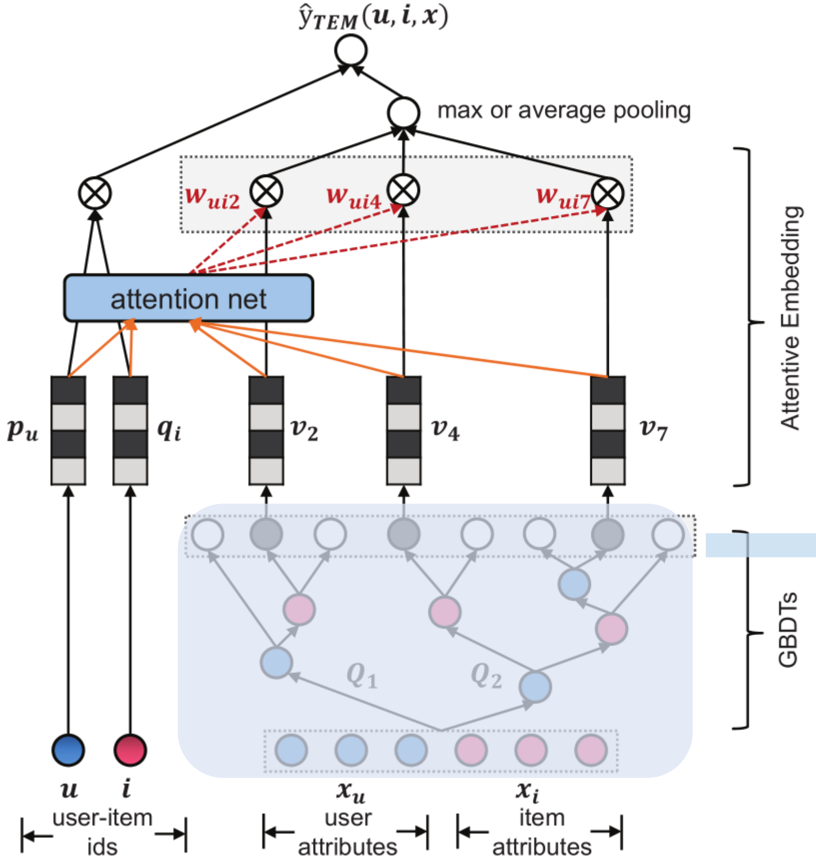
- **Concrete Reasons**: Explicitly discover effective cross features from rich side information of users & items

- **Explicit Decision Process**: Estimate user-item matching score in an explainable way

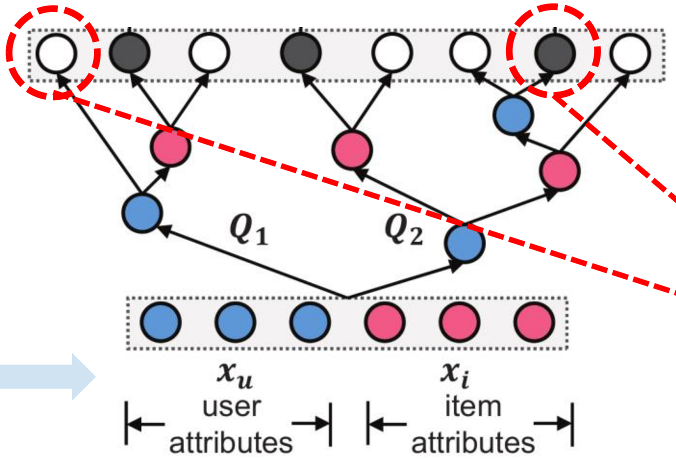


Constructing Cross Features

- **Traditional Solution:** manually cross all values of feature variables
- **Our Solution:** GBDT -> automatically identify useful cross features
- **We bulid GBDT on user attributes and item attributes.**



$$\mathbf{q} = GBDT(\mathbf{x}|Q) = [Q_1(\mathbf{x}), \cdots, Q_S(\mathbf{x})]$$



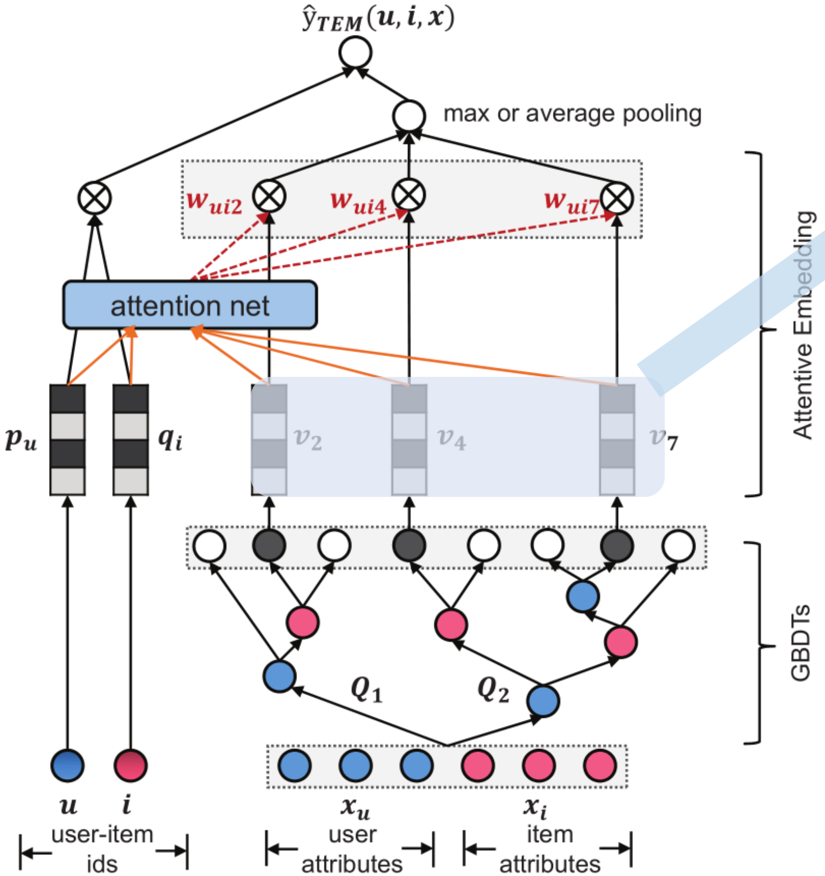
$x_0 \leftarrow Age$	$x_1 \leftarrow Expert\ Level$	$x_2 \leftarrow Restaurant\ Tag$
$a_0 \leftarrow 18$	$a_1 \leftarrow 4$	$a_2 \leftarrow French$
$x_3 \leftarrow Country$	$x_4 \leftarrow Traveler\ Style$	$x_5 \leftarrow Price$
$a_3 \leftarrow France$	$a_4 \leftarrow Luxury\ Traveler$	$a_5 \leftarrow \$\$\$\$$

(1) v_{L_1}: [Age< 18] & [Country≠France] & [Restaurant Tag= French].
(2) v_{L_7}: [Expert Level≥ 4] & [Traveler Style≠Luxury Traveler].

Explicit Cross Features with easy-to-comprehend semantics!

Cross Features Embedding

- **Primary Consideration:** seamlessly integrate cross features with embedding-based CF
- **Our Solution:** embed them into user-item latent space



$$\mathbf{q} = GBDT(\mathbf{x}|Q) = [Q_1(\mathbf{x}), \cdots, Q_S(\mathbf{x})].$$

Multi-hot encoding of cross-feature ID

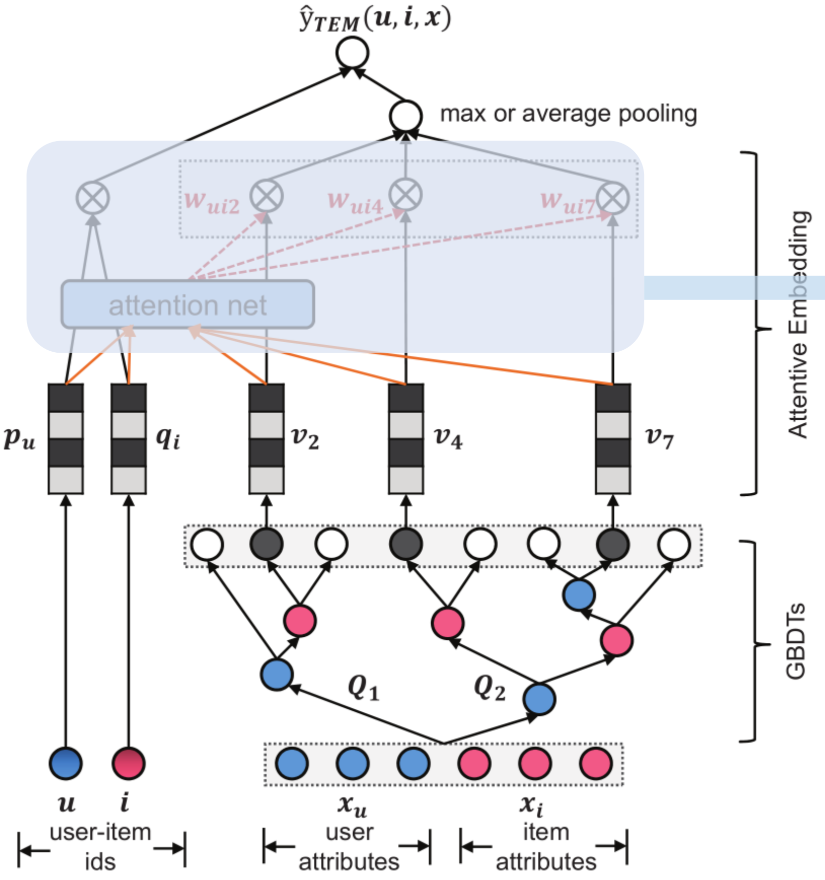
$$\mathcal{V} = \{q_1\mathbf{v}_1, \cdots, q_L\mathbf{v}_L\}$$

Embedding for each cross-feature ID

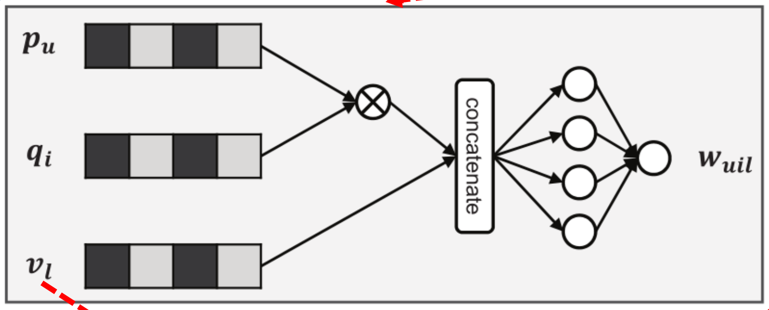
The correlations among cross features may be captured in the embedding space.

Attention Network

- **Primary Consideration:** different cross features contribute differently for a prediction
- **Solution**: Attention Network



$$\begin{cases} \mathbf{e}_{avg}(u,i,\mathcal{V}) = \frac{1}{|\mathcal{V}|}\sum_{\mathbf{v}_l\in\mathcal{V}} w_{uil}\mathbf{v}_l, \\ \mathbf{e}_{max}(u,i,\mathcal{V}) = max\_pool_{\mathbf{v}_l\in\mathcal{V}}(w_{uil}\mathbf{v}_l), \end{cases}$$



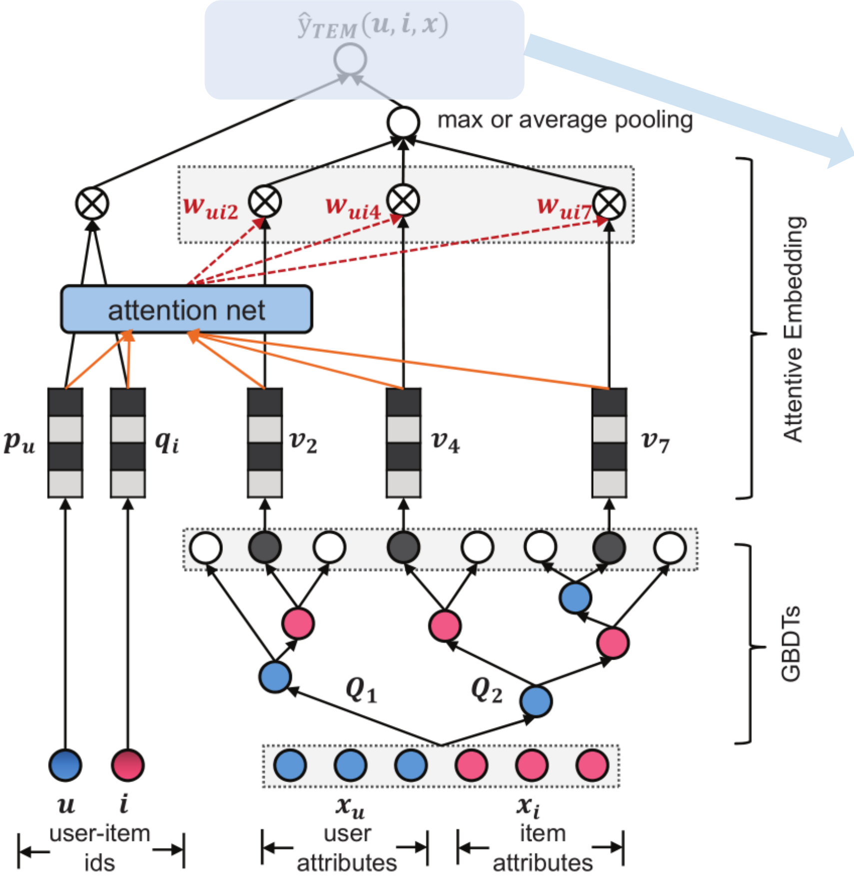
attention net

$$\begin{cases} w'_{uil} = \mathbf{h}^\top ReLU(\mathbf{W}([\mathbf{p}_u \odot \mathbf{q}_i, \mathbf{v}_l]) + \mathbf{b}) \\ w_{uil} = \frac{exp(w'_{uil})}{\sum_{(u,i,\mathbf{x})\in\mathcal{O}} exp(w'_{uil})} \end{cases}$$

- **Easy-to-comprehend cross features**
- **Explicit contribution of each cross feature to the final prediction**

Final Prediction

- **Primary Consideration:** explicit decision process & similarity-based + cross feature-based explanation mechanism
- **Solution:** Simple linear regression



$$\hat{y}_{TEM}(u, i, \mathbf{x}) = b_0 + \sum_{t=1}^{m} b_t x_t + \mathbf{r}_1^{\top}(\mathbf{p}_u \odot \mathbf{q}_i) + \mathbf{r}_2^{\top}\mathbf{e}(u, i, \mathcal{V})$$

Similarity

Cross Feature

$$\mathcal{L} = \sum_{(u,i,\mathbf{x})\in\mathcal{O}} -y_{ui}\log\sigma(\hat{y}_{ui}) - (1-y_{ui})\log(1-\sigma(\hat{y}_{ui})),$$

- Pointwise logloss
- Pointwise regression loss
- Pairwise Ranking loss

OUTLINE

- Introduction
- Motivation
- Tree-enhanced Embedding Model
- Experimental Results
- Conclusion

Experimental Settings

- **Research Questions:**
  - **RQ1**: Compared with the state-of-the-art recsys methods, can TEM achieve comparable accuracy?
  - **RQ2**: Can TEM make the recsys results easy-to-interpret by using cross features and the attention network?
- **Tasks:** Attraction Recommendation & Restaurant Recommendation
- **Dataset**: TripAdvisor

tripadvisor

Table 2: Statistics of the datasets.

Dataset	User#	User Feature#	Item#	Item Feature#	Interaction#
LON-A	16, 315	3, 230	953	4, 731	136, 978
NYC-R	15, 232	3, 230	6, 258	10, 411	129, 964

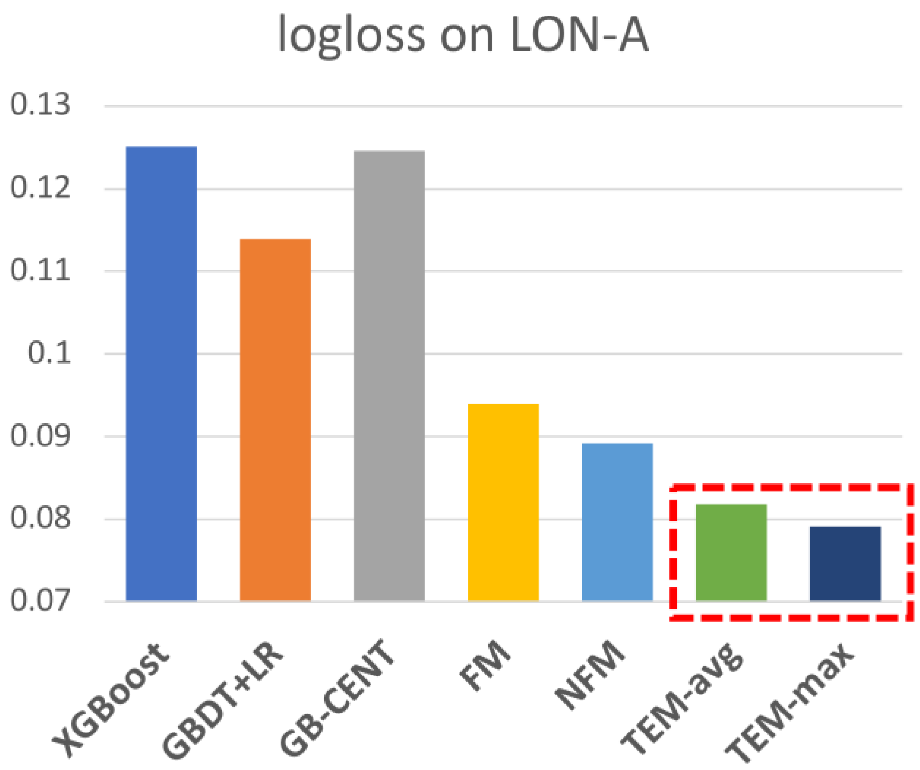
Table 3: Statistics of the side information, where the dimension of each feature is shown in parentheses.

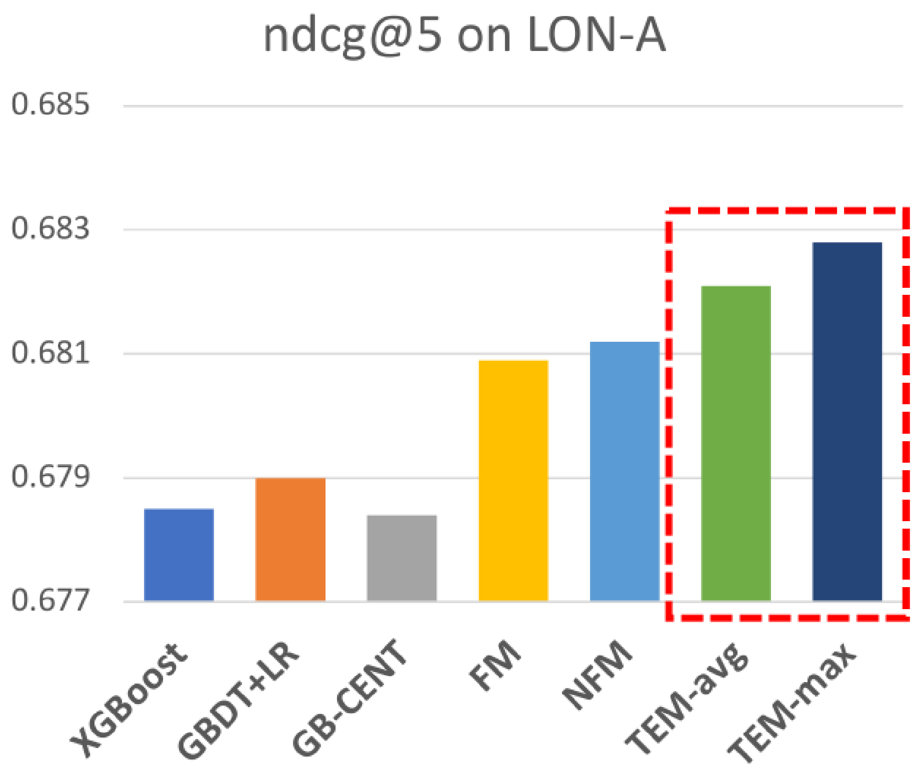
Side Information	Features (Category#)
LON-A/NYC-R User Feature	Age (6), Gender (2), Expert Level (6), Traveler Styles (18), Country (126), City (3, 072)
LON-A Attraction Feature	Attributes (89), Tags (4, 635), Rating (7)
NYC-R Restaurant Feature	Attributes (100), Tags (10, 301), Price (3), Rating (7)

Baselines

- **XGBoost:** the state-of-the-art tree-based model
- **GBDT+LR [ADKDD'14]:** feeding the cross features extracted from GBDT into the logistic regression
- **GB-CENT [WWW'17]:** modeling categorical features with embedding-based model, numerical features with decision trees.
- **FM:** a generic embedding model that implicitly models all the second-order cross features
- **NFM [SIGIR'17]**: the state-of-the-art factorization model under the neural network framework
- **Evaluation Protocols**:
  - logloss: indicate the generalization ability of each model
  - ndcg@k: reflect the top-k recommendation performance

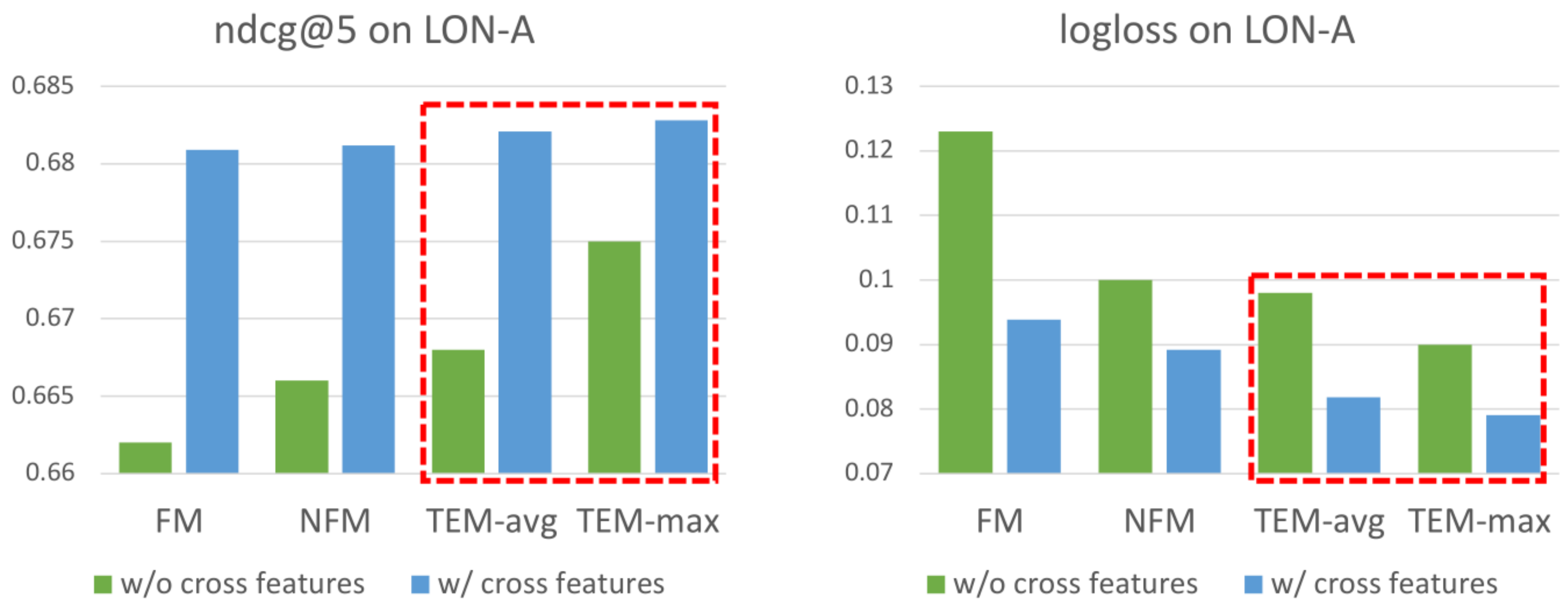
RQ1: Overall Performance Comparison





- **Observations:** **Comparable Expressiveness & Accuracy**
  - TEM achieves the best performance w.r.t. logloss.
  - TEM achieves comparable ndcg@5 to NFM.

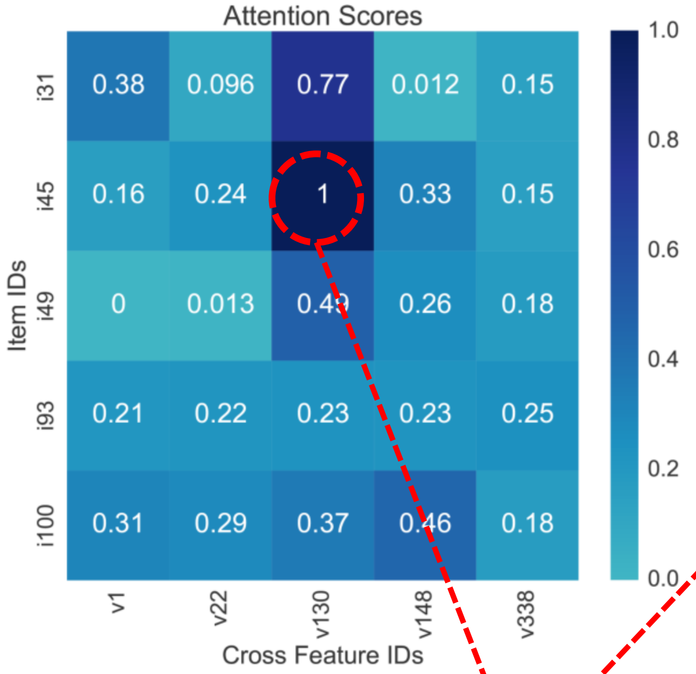
RQ1: Effect of Cross Feature Modeling



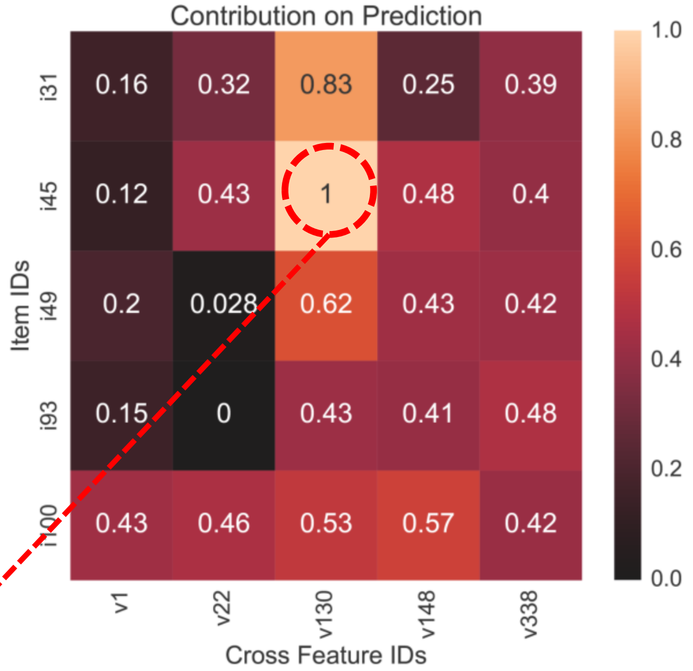
- **Without cross feature modeling:**
  - All methods have worse performance
  - TEM is still better than others, due to the utility of attention network (can learn which features are more important for a user-item prediction).

RQ2: Case Study of Explainability

Sampled a user and check her predictions.



Attention Score



Contribution of each cross feature

- **V130**: User Gender=*Female*] & [User Style=*Peace and Quiet Seeker*] ⇒ [Item Attribute=*Sights & Landmarks*] & [Item Tag=*Walk Around*]
- **V148**: [User Age=30-40] & [User Country=*USA*] ⇒ [Item Tag=*Top Deck & Canary Wharf*]

We attribute the user's preferences on **The View from the Shard** to her special interests in the item aspects of **Walk Around**, **Top Deck** & **Canary Wharf**.

TEM can provide more informative explanations based on a user's preferred cross features.

Conclusions

- We proposed a tree-enhanced embedding method (TEM), which seamlessly combines the generalization ability of embedding-based models with the explainability of tree-based models.
- Owing to the explicit cross features from tree-based part & the easy-to-interpret attention network, the whole prediction process of our solution is transparent & self-explainable.

Future Work:

1. Jointly learn the tree-based and embedding-based
2. Relational reasoning over KG (symbolic logics) + Deep Learning
3. How to evaluate the quality of explanations?

THANK YOU

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