Why Not Together? A Multiple-Round Recommender System for Queries and Items

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Content

- Problem Background
  - Item Recommendations and Query Recommendations
  - Current Challenges
- Architecture
  - Relational Graph as Bridge
  - Recommender System as Initializer
  - Label Propagation as Updater
- Experiment
- Conclusion

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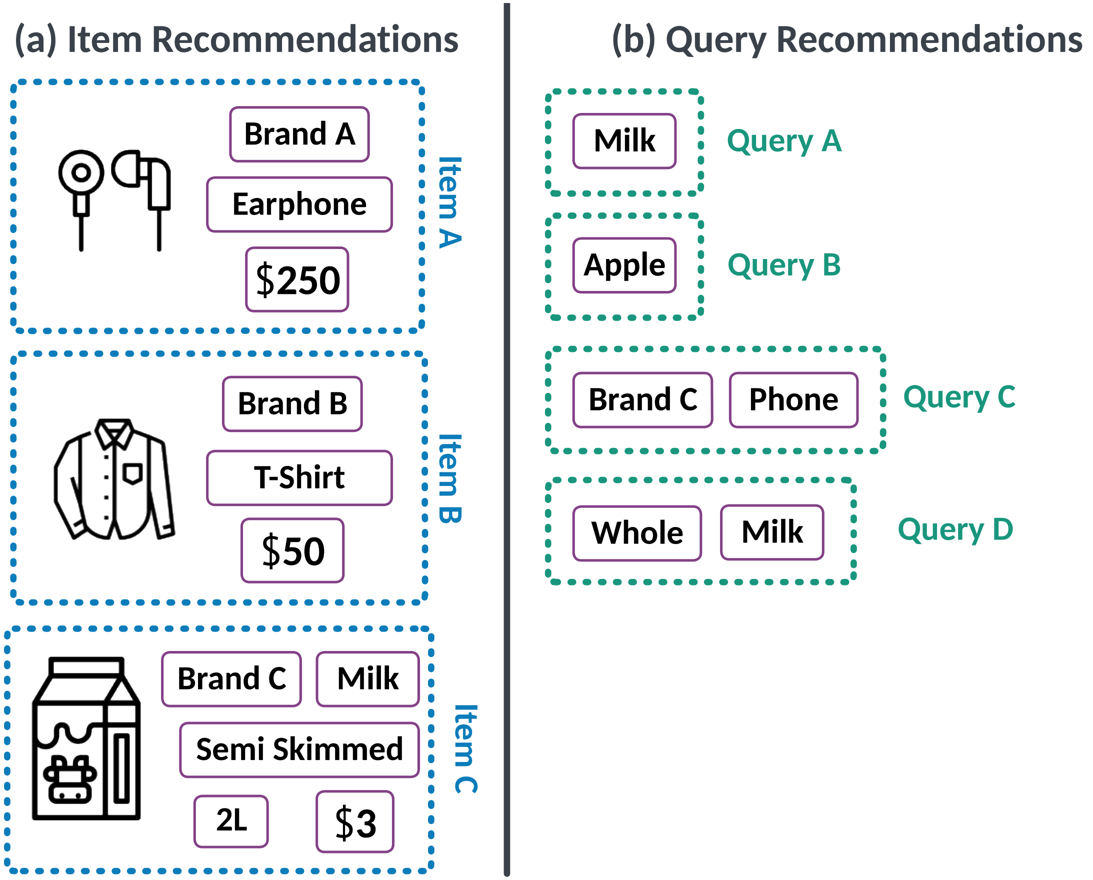
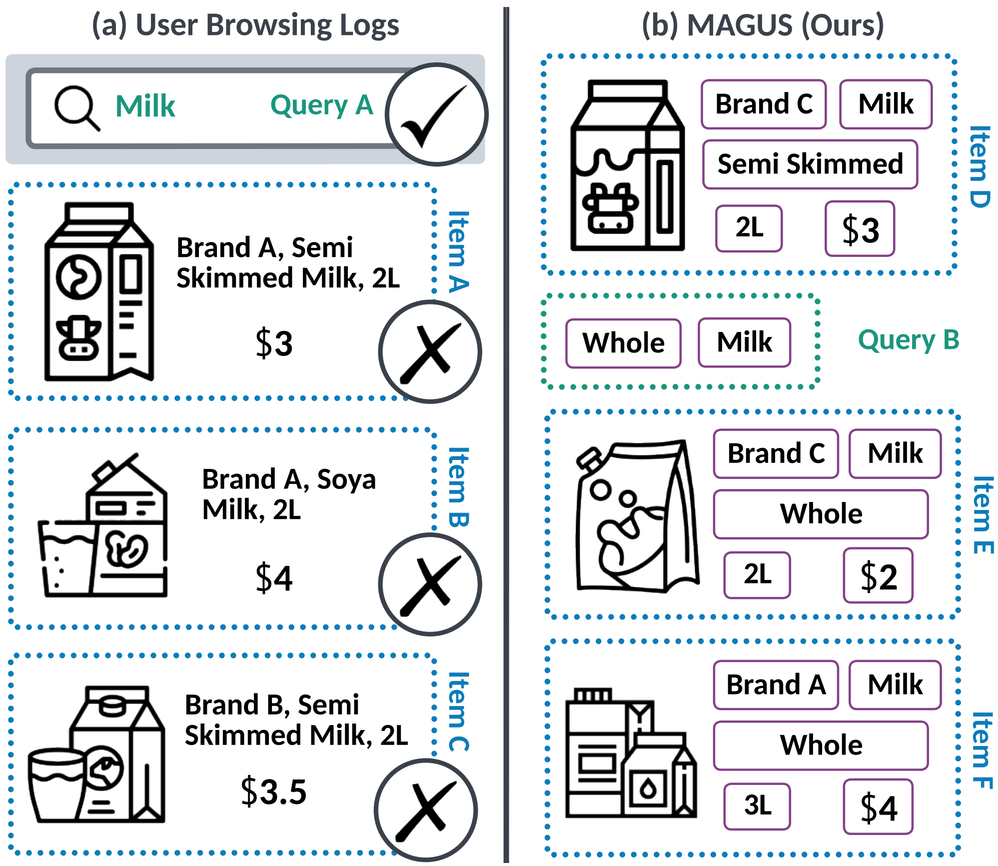
Joint Recommendations of Items and Queries



Previous literature separately investigate item and query recommendations, neglecting the correlations among them.

Figure: Comparisons between item recommendations and query recommendations.

Joint Recommendations of Items and Queries



User may search for a milk, but leave negative feedback on the returned milk items.

Query information provide positive signal, whereas item information provide negative ones.

Queries delineate user needs at an abstract level, providing a high-level description, whereas items operate on a more specific and concrete level, representing the granular facets of user preference.

Figure: Correlations between item recommendations and query recommendations.

Current Challenges

- **[How to draw connections between items and queries?]** To jointly consider the items and queries, a core challenge lies in creating a unified metric for evaluating queries and items.
- **[How to model interdependence among queries?]** Unlike items, queries exhibit a significant degree of dependence. Here are three possible scenarios for each query-query pair: (i) Mutual improvement: selecting one query increases the likelihood of selecting the other query in the following round (e.g., selecting Milk would raise the probability of selecting Whole Milk in the next round). (ii) Mutual inhibition: selecting one query decreases the probability of selecting the other query in the following round (e.g., if a user selects Milk, it is unlikely that she would select Beef because milk and beef belong to distinct categories. (iii) Mutual Independence: the selection of one query has minimal or negligible effects on the user's decision regarding the other query (e.g., selecting Milk does not significantly influence the user's preference for On Sale).

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Relational Graph as Bridge

Our main idea is to establish a relational graph to bridge queries and items via their sharing words (and combinations of words).

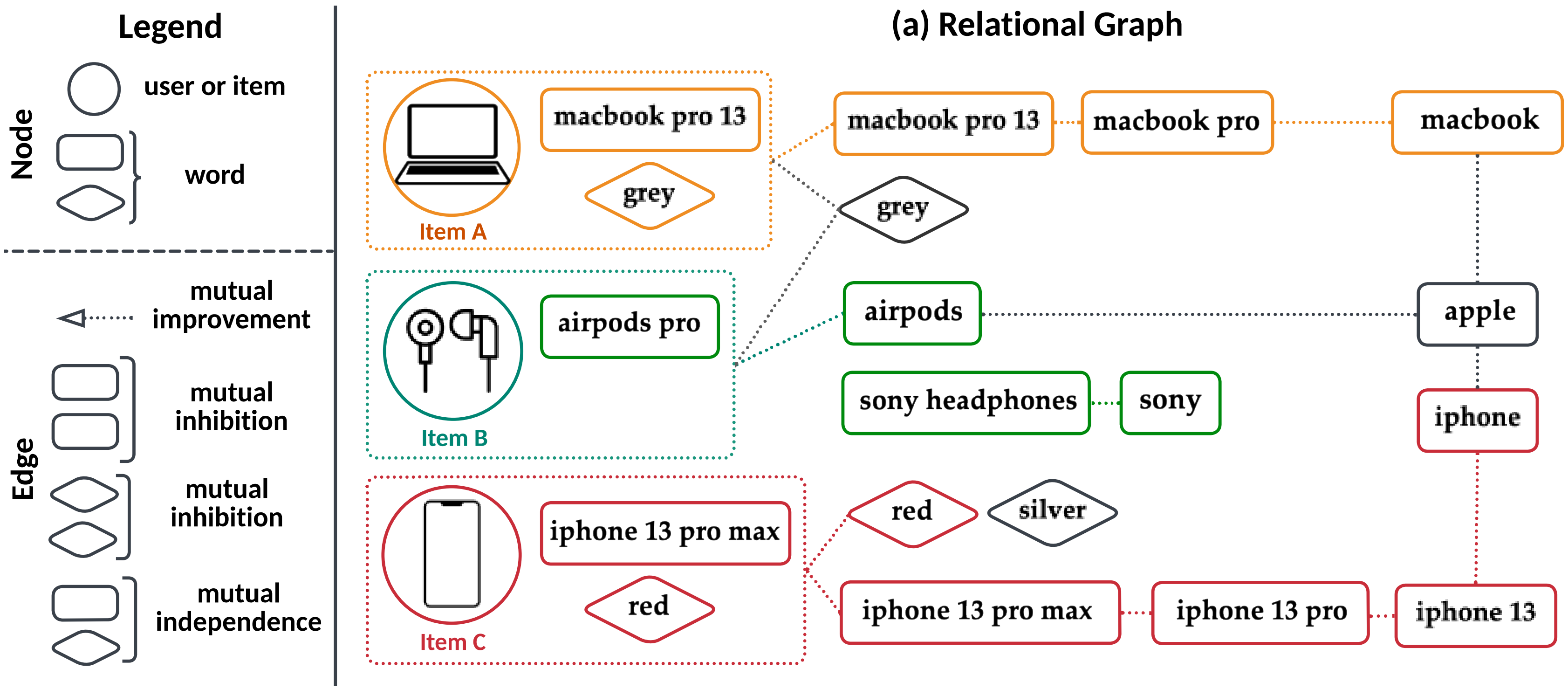
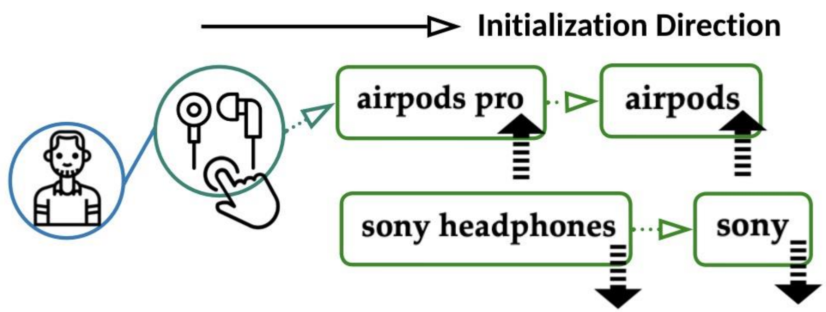


Figure: Overview of our relational graph which encodes the connections between queries and items and interdependence among queries.

Recommender System as Initializer

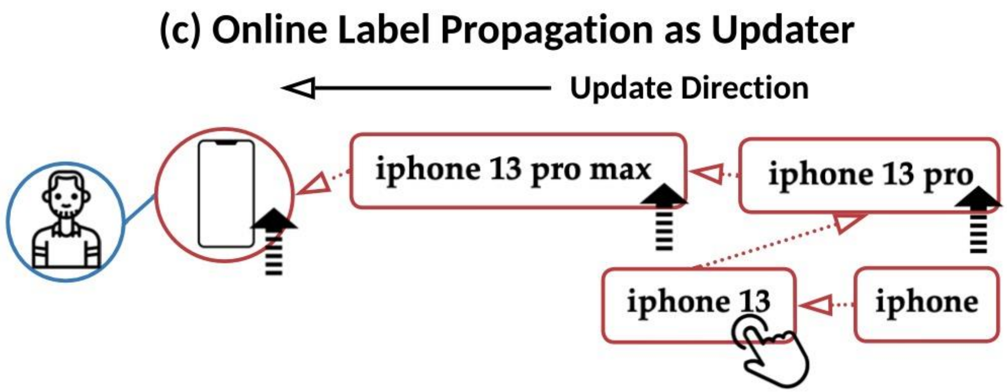
(b) Offline Recommender System as Initializer



Offline trained recommendation models are used as initializer to assign scores to those nodes representing items and then propagate to other nodes on the graph.

$$\widehat{y}_v = \begin{cases} \psi_{\mathrm{RE}}(v), & v \in \mathcal{E}_{\mathrm{ITE}} \\ 0, & v \in \mathcal{E}/\mathcal{E}_{\mathrm{IT}} \end{cases} \qquad \widehat{y}_{v'} \leftarrow \begin{cases} \widehat{y}_{v'} + w_{v'v''} \cdot \widehat{y}_{v''}, & \langle v', v'' \rangle \in \overrightarrow{\mathcal{R}}^{+}, \\ \widehat{y}_{v'} - w_{v'v''} \cdot \widehat{y}_{v''}, & \langle v', v'' \rangle \in \overrightarrow{\mathcal{R}}^{-}, \\ \widehat{y}_{v'}, & \langle v', v'' \rangle \in \mathcal{R}^{\perp} \cup \overleftarrow{\mathcal{R}}^{+} \cup \overleftarrow{\mathcal{R}}^{-}, \end{cases}$$

Label Propagation as Updater



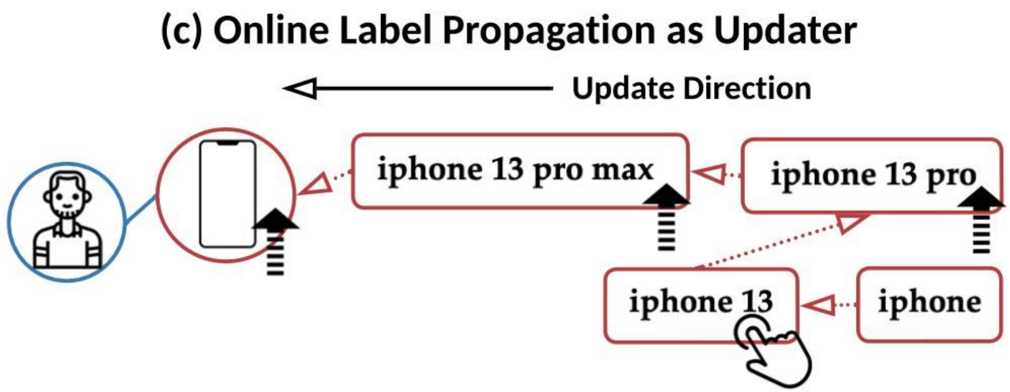
In a multiple-round recommender system, at each round, the system needs to normalize all the scores of nodes in range of 0 to 1:

$$\widehat{y}_v \leftarrow \frac{\widehat{y}_v - \min(\{\widehat{y}_{v'} | v' \in \mathcal{E}\})}{\max(\{\widehat{y}_{v'} | v' \in \mathcal{E}\}) - \min(\{\widehat{y}_{v'} | v' \in \mathcal{E}\})}, v \in \mathcal{E}.$$

Then, we select a node with the highest score to recommend:

$$a_{\mathsf{MAGUS}} = \arg\max_{a \in \mathcal{A}} \psi_{\mathsf{MAGUS}} = \arg\max_{v \in \mathcal{A}} \widehat{y}_v,$$

Label Propagation as Updater



The corresponding user feedback is encoded by reassigning scores to corresponding nodes:

$$\widehat{y}_v \leftarrow \begin{cases} 1, & v \in \mathcal{E}^+, \\ 0, & v \in \mathcal{E}^-, \end{cases}$$

Then, we update the scores of other nodes by the propagation:

$$\widehat{y}_{v'} \leftarrow \begin{cases} \min(1, \widehat{y}_{v'} + w_{v'v''} \cdot \widehat{y}_{v''}), & \langle v', v'' \rangle \in \overleftarrow{\mathcal{R}}^+, \\ \max(0, \widehat{y}_{v'} - w_{v'v''} \cdot \widehat{y}_{v''}), & \langle v', v'' \rangle \in \overleftarrow{\mathcal{R}}^-, \\ \widehat{y}_{v'}, & \langle v', v'' \rangle \in \mathcal{R}\perp \cup \overrightarrow{\mathcal{R}}^+ \cup \overrightarrow{\mathcal{R}}^-. \end{cases}$$

Algorithm

Algorithm 1 The MAGUS System

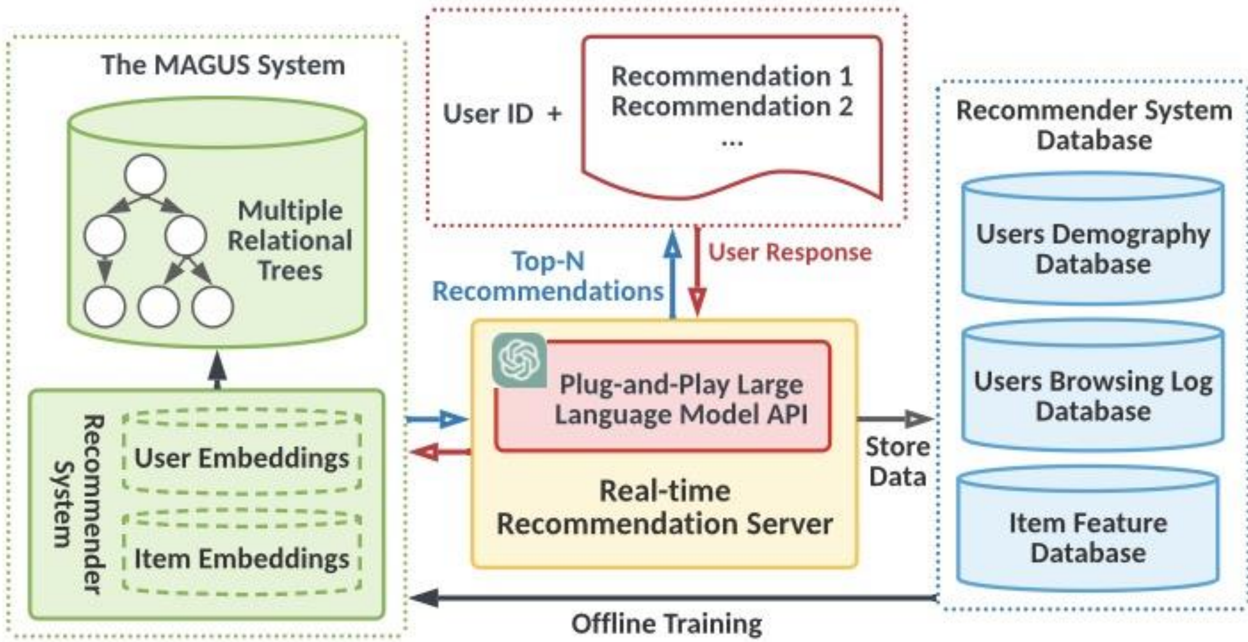
INPUT: positive and negative browsed items for all users $\{\mathcal{H}_u^+ | u \in \mathcal{U}\}$ and $\{\mathcal{H}_u^- | u \in \mathcal{U}\}$; optional: searched queries for all users $\{\mathcal{H}_u^q | u \in \mathcal{U}\}$.

OUTPUT: recommended query or item a_{MAGUS} at each round.

```
Offline train a recommendation model ψ_RE(·) upon H_u^+s and H_u^-s for u ∈ U.
Offline build a relational graph G = (E, R) by Definition 3.1.
Offline compute the weights of the edges in R using Eq. (3) or Eq. (14).
for each online session for user u do
    Initialize k = 0.
    Initialize the scores of all nodes using Eqs. (2), (4), and (5).
    repeat
        Normalize the scores of all nodes using Eq. (6).
        Compute a_MAGUS using Eq. (7).
        Recommend a_MAGUS and receive corresponding response.
        Update the scores of the nodes using Eqs. (8) and (9).
        Go to next round: k ← k + 1.
    until a_MAGUS ∈ V_TARGET or k > K_MAX.
    Collect session data into H_u^+ and H_u^-.
end for
Update ψ_RE(·) using data in new H_u^+s and new H_u^-s.
```

Our approach can be regarded as a combination of non-parametric recommendation methods relying on connections between queries and items, and parametric recommendation methods based on user browsing logs.

Integrate LLMs into MAGUS



Prompt Design for MAGUS

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Experiment

Table 1: Results comparison of items recommendations in terms of SAC, and joint recommendations of both queries and items in terms of RA@3, SA@3, and SA@5. Since SAC metric measures the performance on the single-round item recommendation task, we do not report SAC for MAGUS and MAGUS$^+$. * indicates $p < 0.001$ in significance tests compared to the best baseline.

Methods	Amazon				Alipay				Tmall			
	SAC	RA@3	SA@3	SA@5	SAC	RA@3	SA@3	SA@5	SAC	RA@3	SA@3	SA@5
MPS	0.332	0.612	0.174	0.255	0.298	0.541	0.125	0.181	0.312	0.575	0.164	0.208
Hybrid	0.394	0.665	0.312	0.406	0.365	0.592	0.286	0.345	0.344	0.592	0.295	0.337
FM	0.634	0.773	0.672	0.757	0.716	0.815	0.767	0.846	0.718	0.832	0.745	0.824
FM+CRM	/	0.787	0.675	0.760	/	0.826	0.798	0.867	/	0.880	0.771	0.852
FM+ME	/	0.794	0.688	0.771	/	0.817	0.789	0.860	/	0.847	0.754	0.831
FM+EAR	/	0.795	0.695	0.769	/	0.825	0.796	0.866	/	0.878	0.765	0.850
FM+MAGUS	/	**0.816***	**0.742***	**0.798***	/	**0.843***	**0.825***	**0.888***	/	**0.894***	**0.791***	**0.877***
DeepFM	0.676	0.784	0.693	0.798	0.730	0.825	0.787	0.875	0.729	0.843	0.766	0.841
DeepFM+CRM	/	0.796	0.705	0.805	/	0.840	0.817	0.882	/	0.879	0.802	0.881
DeepFM+ME	/	0.795	0.698	0.794	/	0.835	0.811	0.879	/	0.856	0.775	0.864
DeepFM+EAR	/	0.810	0.743	0.807	/	0.839	0.818	0.884	/	0.885	0.800	0.885
DeepFM+MAGUS	/	**0.833***	**0.767***	**0.811***	/	**0.851***	**0.832***	**0.895***	/	**0.903***	**0.814***	**0.892***
PNN	0.688	0.788	0.690	0.792	0.741	0.833	0.775	0.870	0.722	0.823	0.753	0.831
PNN+CRM	/	0.807	0.714	0.798	/	0.851	0.844	0.899	/	0.870	0.798	0.827
PNN+ME	/	0.813	0.749	0.805	/	0.845	0.820	0.884	/	0.855	0.776	0.845
PNN+EAR	/	0.814	0.747	0.802	/	0.853	0.845	0.898	/	0.872	0.801	0.863
PNN+MAGUS	/	**0.839***	**0.772***	**0.817***	/	**0.865***	**0.852***	**0.911***	/	**0.884***	**0.812***	**0.876***
MMoE	0.631	0.770	0.663	0.744	0.703	0.802	0.745	0.811	0.723	0.842	0.752	0.830
MMoE+MAGUS	/	**0.801***	**0.725***	**0.776***	/	**0.833***	**0.820***	**0.876***	/	**0.898***	**0.802***	**0.881***
DIN	0.697	0.798	0.696	0.813	0.757	0.845	0.793	0.886	0.736	0.855	0.774	0.848
DIN+MAGUS	/	**0.845***	**0.775***	**0.828***	/	**0.878***	**0.865***	**0.922***	/	**0.904***	**0.818***	**0.902***
LSTM	0.692	0.789	0.690	0.808	0.752	0.840	0.782	0.876	0.728	0.846	0.759	0.837
LSTM+MAGUS	/	**0.840***	**0.773***	**0.821***	/	**0.870***	**0.861***	**0.918***	/	**0.901***	**0.808***	**0.892***
GRU	0.707	0.803	0.699	0.818	0.762	0.848	0.799	0.889	0.732	0.852	0.771	0.845
GRU+MAGUS	/	**0.848***	**0.788***	**0.831***	/	**0.882***	**0.871***	**0.926***	/	**0.909***	**0.821***	**0.901***
RGCN	0.668	0.781	0.687	0.784	0.736	0.828	0.785	0.877	0.722	0.828	0.747	0.825
RGCN+MAGUS	/	**0.841***	**0.775***	**0.824***	/	**0.873***	**0.860***	**0.912***	/	**0.897***	**0.810***	**0.893***
RGCN+MAGUS$^+$	/	**0.852***	**0.787***	**0.831***	/	**0.882***	**0.870***	**0.925***	/	**0.903***	**0.820***	**0.902***
RGAT	0.675	0.785	0.695	0.794	0.748	0.838	0.782	0.878	0.730	0.843	0.762	0.839
RGAT+MAGUS	/	**0.850***	**0.785***	**0.828***	/	**0.878***	**0.868***	**0.921***	/	**0.905***	**0.817***	**0.897***
RGAT+MAGUS$^+$	/	**0.867***	**0.798***	**0.840***	/	**0.891***	**0.879***	**0.933***	/	**0.911***	**0.826***	**0.914***
GIPA	0.688	0.798	0.707	0.799	0.756	0.847	0.796	0.885	0.751	0.849	0.778	0.843
GIPA+MAGUS	/	**0.856***	**0.798***	**0.834***	/	**0.877***	**0.867***	**0.918***	/	**0.912***	**0.824***	**0.902***
GIPA+MAGUS$^+$	/	**0.881***	**0.785***	**0.849***	/	**0.892***	**0.881***	**0.934***	/	**0.919***	**0.832***	**0.918***

Experiment

Conclusion

- MAGUS

Thanks for Your Listening