Modeling Dual Period-Varying Preferences for Takeaway Recommendation

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Code&data： https://github.com/17231087/DPVP.git.

Reported by ChangJiang Hu

Introduction

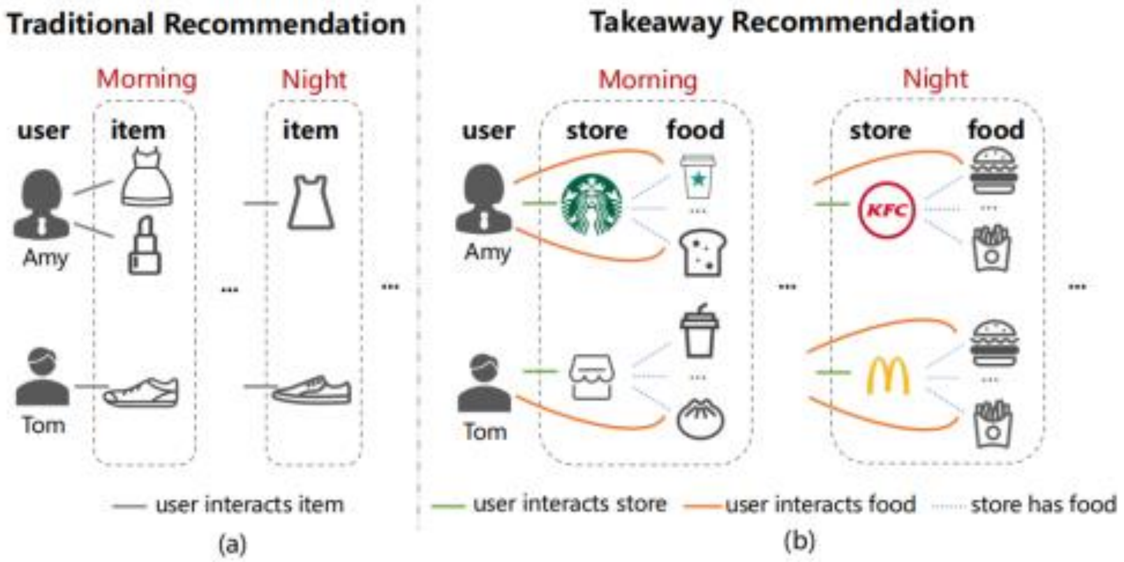


Figure 1: Illustration of differences between traditional recommendation and takeaway recommendation.

(1) Traditional recommendation commonly focuses on users' single preferences for items while takeaway recommendation needs to comprehensively consider users' dual preferences for stores and foods.

(2) Conventional recommendation generally models continuous changes in users' preferences from a session-level or day-level perspective. However, in practical takeaway systems, users' preferences vary significantly during the morning, noon, night, and late night periods of the day

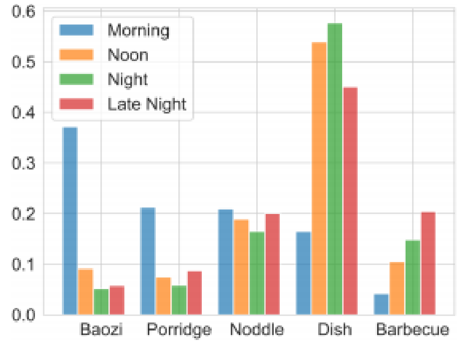


Figure 2: Proportion distribution of clicks between users and five major food categories in four different time periods. Note that the sum of the proportions of the five food categories in each time period is equal to 1.

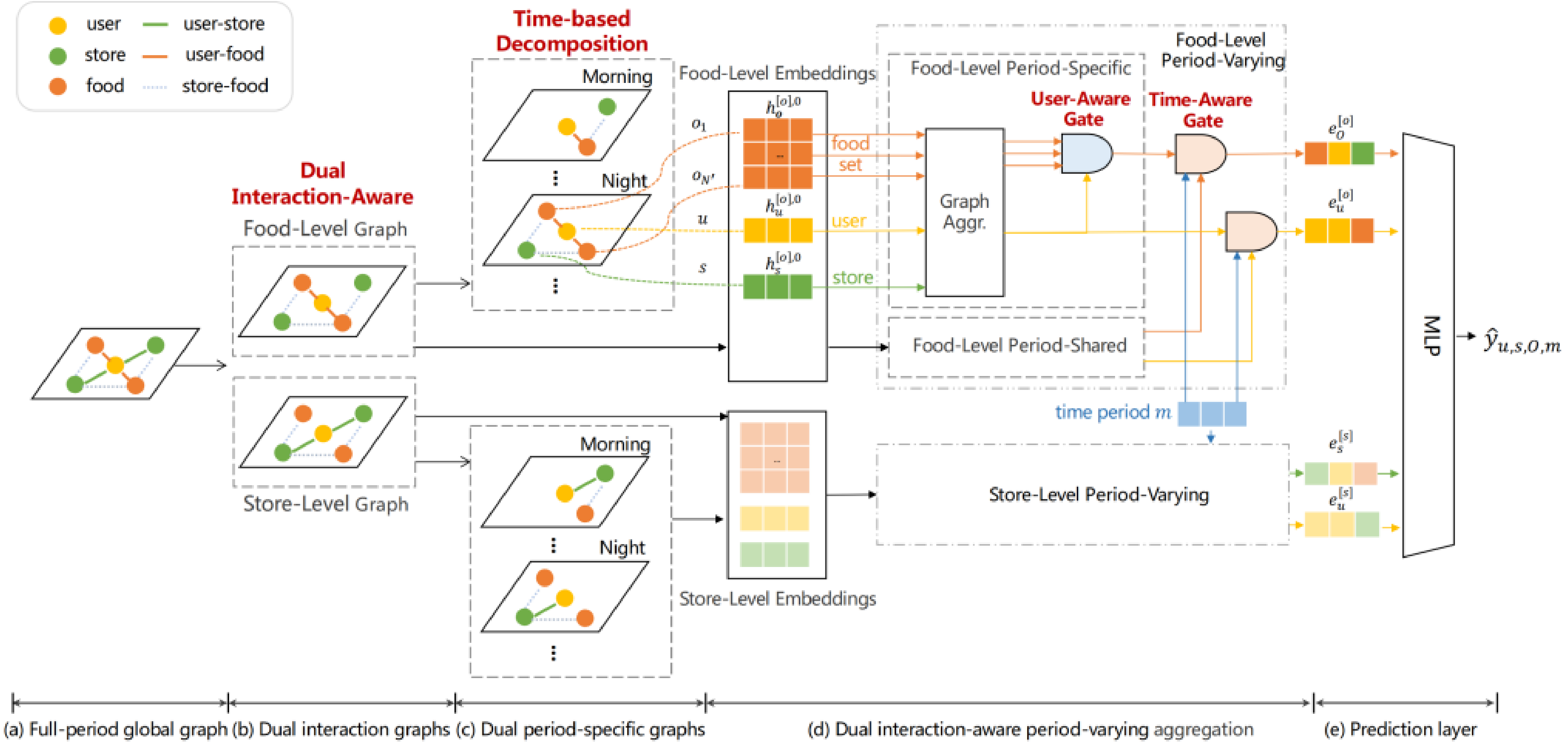


Figure 3: Overview of our proposed DPVP model.

PRELIMINARIES

Definition 1： Period-Varying Ternary Interaction Data

$x = (u, s, O, m)$ $u \in \mathcal{U}$ interacts N foods $O = \{o_1, o_2, \cdots, o_N\}$ (where $o_j \in \mathcal{O}, \forall j = 1, 2, ..., N$) in store $s \in \mathcal{S}$ at time period $m \in \mathcal{M}$.

Definition 2： Full-Period Global Graph

$\mathcal{G} = \{\mathcal{U} \cup \mathcal{S} \cup \mathcal{O}, \mathcal{E}_{\mathcal{US}} \cup \mathcal{E}_{\mathcal{UO}} \cup \mathcal{E}_{\mathcal{SO}}\}$

For each record $x = (u, s, O, m)$ $\{u, s, o_j\}$

$(u, s) \in \mathcal{E}_{\mathcal{US}}$, $(u, o_j) \in \mathcal{E}_{\mathcal{UO}}$ $(s, o_j) \in \mathcal{E}_{\mathcal{SO}}$.

Definition 3. ***Takeaway Recommendation***. Given the *period-varying ternary interaction data* $\mathcal{X}$ and *full-period global graph* $\mathcal{G}$, DPVP aims to recommend the stores $s \in \mathcal{S}$ with the food set $\Gamma(s)$ that user u would be interested in at time period m.

Dual Period-Varying Multigraphs Construction

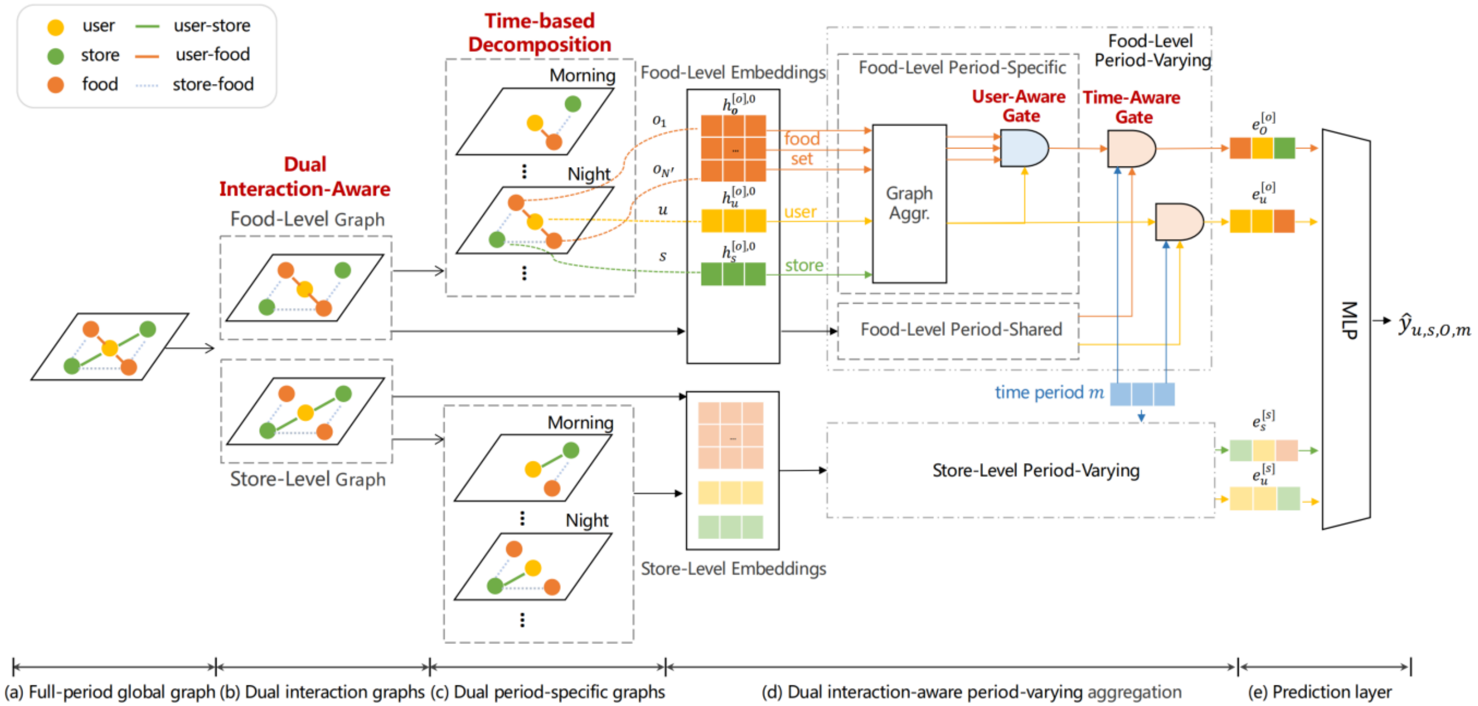
1: Dual Interaction-Aware Module

$$\mathcal{G}^{[o]} = \{\mathcal{U} \cup \mathcal{S} \cup \mathcal{O}, \mathcal{E}_{\mathcal{UO}} \cup \mathcal{E}_{\mathcal{SO}}\},$$
$$\mathcal{G}^{[s]} = \{\mathcal{U} \cup \mathcal{S} \cup \mathcal{O}, \mathcal{E}_{\mathcal{US}} \cup \mathcal{E}_{\mathcal{SO}}\}. \quad (1)$$

2: Time-Based Decomposition Module

$$w_c^m = \mathbb{I}(c_t = m),$$
$$\mathcal{E}^m = \{w_c^m * c\}, \forall c \in \mathcal{E}, \quad (2)$$

$$\mathcal{G}_m^{[o]} = \{\mathcal{U} \cup \mathcal{S} \cup \mathcal{O}, \mathcal{E}_{\mathcal{UO}}^m \cup \mathcal{E}_{\mathcal{SO}}^m\},$$
$$\mathcal{G}_m^{[s]} = \{\mathcal{U} \cup \mathcal{S} \cup \mathcal{O}, \mathcal{E}_{\mathcal{US}}^m \cup \mathcal{E}_{\mathcal{SO}}^m\}. \quad (3)$$



Dual Interaction-Aware Preference

1: Dual Embedding Layers

$$H_u^{[o]} \in \mathbb{R}^{|\mathcal{U}|\times d} \qquad H_u^{[s]} \in \mathbb{R}^{|\mathcal{U}|\times d}$$

$$h_u^{[o],0} \qquad h_u^{[s],0}$$

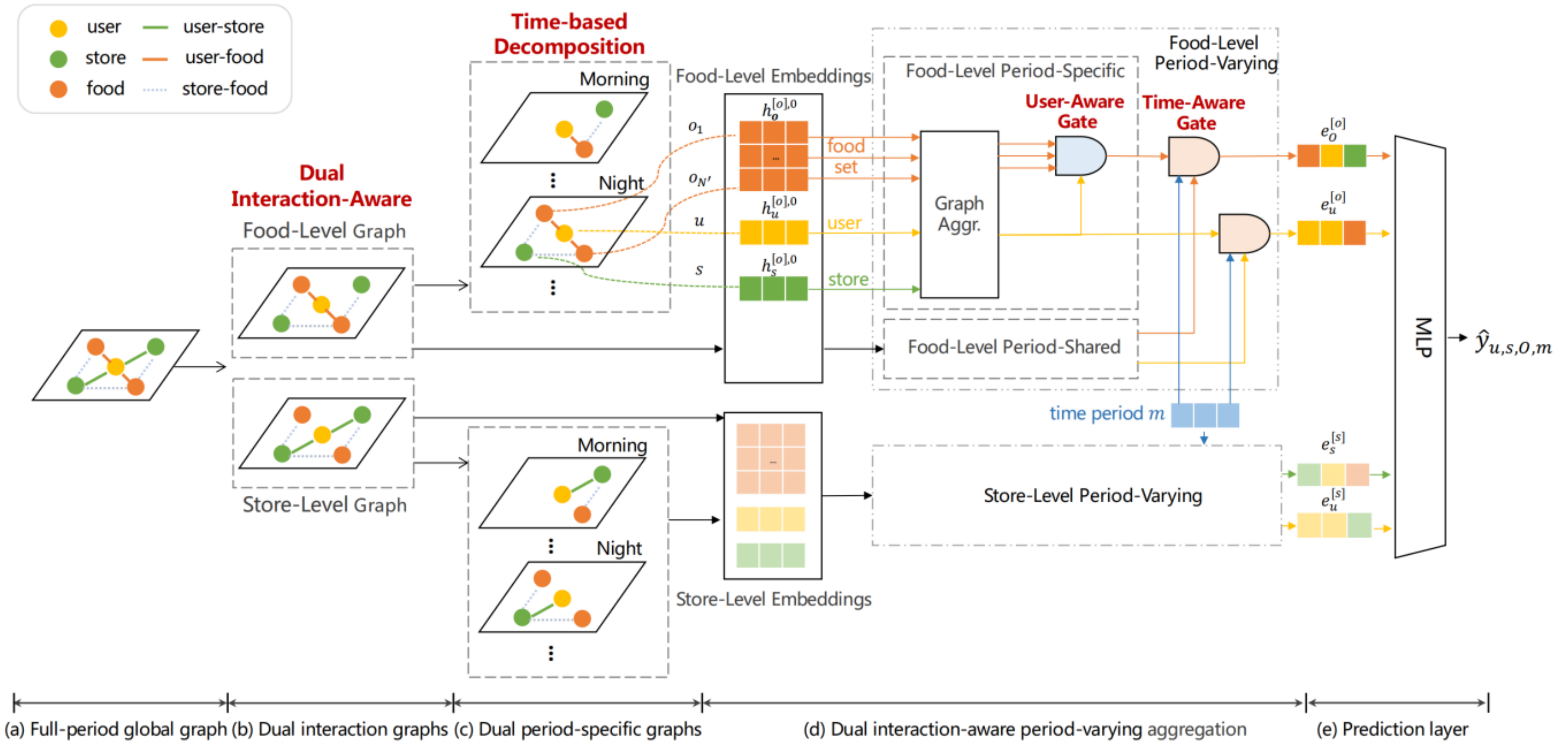
$$h_{u,m}^{[o],0} = h_u^{[o],0} \qquad h_{u,m}^{[s],0} = h_u^{[s],0}$$

2: Single-Level Preference

$$\mathbf{h}_{o,m}^{[o],l+1} = \frac{1}{c_{o,m}^{(u,o)}} \sum_{(u,o)\in\mathcal{E}_{UO}^m} \mathbf{h}_{u,m}^{[o],l} + \frac{1}{c_{o,m}^{(s,o)}} \sum_{(s,o)\in\mathcal{E}_{SO}^m} \mathbf{h}_{s,m}^{[o],l}, \tag{4}$$

$$\mathbf{h}_{u,m}^{[o],l+1} = \frac{1}{c_{u,m}^{(u,o)}} \sum_{(u,o)\in\mathcal{E}_{UO}^m} \mathbf{h}_{o,m}^{[o],l},$$
$$\mathbf{h}_{s,m}^{[o],l+1} = \frac{1}{c_{s,m}^{(s,o)}} \sum_{(s,o)\in\mathcal{E}_{SO}^m} \mathbf{h}_{o,m}^{[o],l}. \tag{5}$$

$$\mathbf{h}_{o,m}^{[o],*} = \sum_{l=0}^{L} \alpha_l \mathbf{h}_{o,m}^{[o],l}, \quad \mathbf{h}_{u,m}^{[o],*} = \sum_{l=0}^{L} \alpha_l \mathbf{h}_{u,m}^{[o],l}, \tag{6}$$



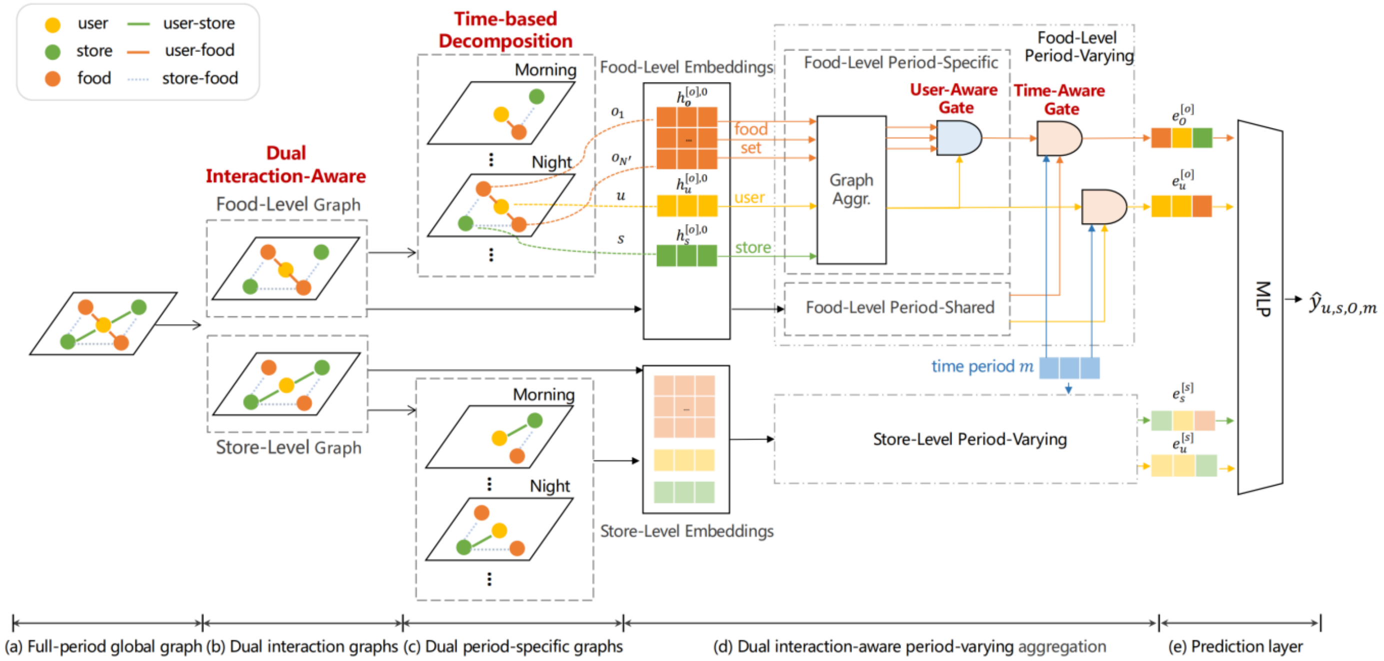
3: Personalized Food Representation

$$g_u(o_i) = \frac{exp(\mathbf{h}_{o_i,m}^{[o],*} \times \mathbf{h}_{u,m}^{[o],*\top})}{\sum_{j=1}^{N'} exp(\mathbf{h}_{o_j,m}^{[o],*} \times \mathbf{h}_{u,m}^{[o],*\top})},$$
$$\mathbf{h}_{O,m}^{[o],*} = \sum_{i=1}^{N'} g_u(o_i)\mathbf{h}_{o_i,m}^{[o],*}. \tag{7}$$

Period-Varying Preference

$$g_m(u,m) = \frac{exp(\mathbf{h}_{u,m}^{[o],*} \times [\mathbf{h}_u^{[o],*}, \mathbf{e}_m]^\top)}{\sum_{k=1}^{M} exp(\mathbf{h}_{u,k}^{[o],*} \times [\mathbf{h}_u^{[o],*}, \mathbf{e}_k]^\top)}, \tag{8}$$

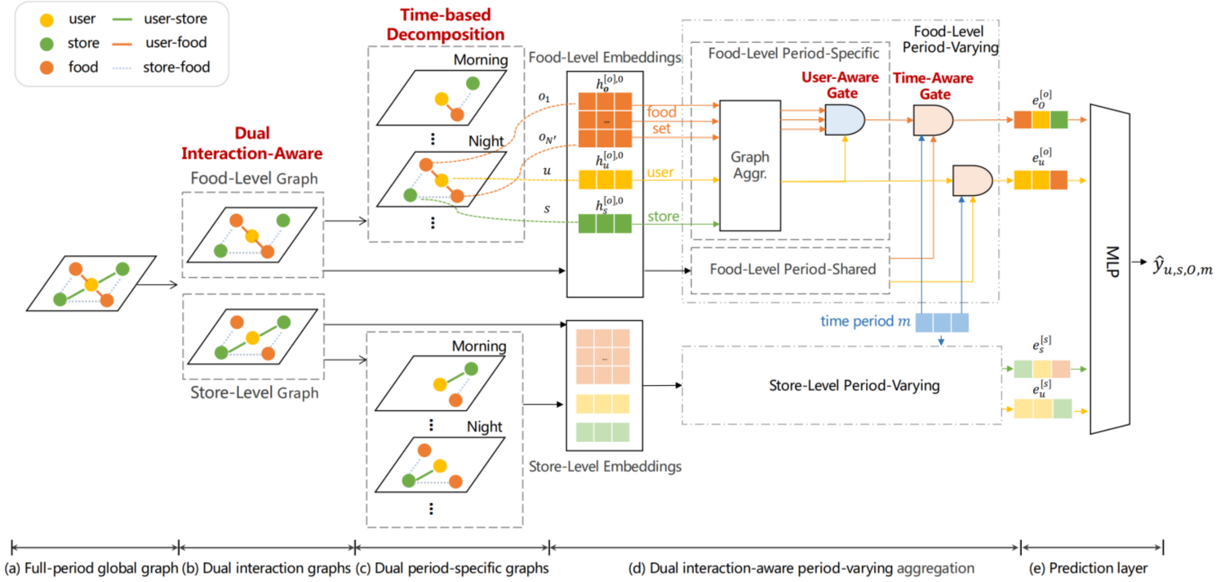
$$\mathbf{e}_{u,m}^{[o]} = \sum_{m=1}^{M} g_m(u,m)\mathbf{h}_{u,m}^{[o],*},$$



Prediction and Optimization

$$\hat{y}_{u,s,O,m} = MLP([\mathbf{e}^{[o]}_{u,m}, \mathbf{e}^{[o]}_{O,m}, \mathbf{e}^{[s]}_{u,m}, \mathbf{e}^{[s]}_{s,m}]). \tag{9}$$

$$\mathcal{L} = \sum_{(u,s,s') \in Y, O=\Gamma(s), O'=\Gamma(s')} -\ln \sigma(\hat{y}_{u,s,O,m} - \hat{y}_{u,s',O',m}), \tag{10}$$



Experiments

Table 3: The statistics of the two datasets from Meituan.

Dataset	#User	#Store	#Food	#User-Store Interaction
MT-small	56,887	4,059	5,952	180,283
MT-large	385,381	18,770	17,111	1,492,164

Experiments

Model	MT-small				MT-large			
	Hit@10	NDCG@10	AUC	MRR	Hit@10	NDCG@10	AUC	MRR
NeuMF	0.3957	0.2104	0.7814	0.1788	0.4554	0.2488	0.8198	0.2101
DNN	0.4190	0.2503	0.7549	0.2188	0.6073	0.3898	0.7903	0.3174
ENMF	0.5513	0.3845	0.7356	0.3450	0.5911	0.4285	0.7496	0.3887
SimpleX	0.4851	0.2710	0.8171	0.2276	0.5634	0.3289	0.8457	0.2763
GCN	0.4446	0.2478	0.7968	0.2110	0.6288	0.4199	0.8535	0.3698
GAT	0.4384	0.2488	0.7529	0.2105	0.6202	0.3871	0.8361	0.3290
NGCF	0.5009	0.2839	0.8163	0.2411	0.6358	0.4222	0.8593	0.3725
HGT	0.4467	0.2474	0.8032	0.2097	0.6217	0.3905	0.8352	0.3329
LightGCN	0.4942	0.2784	0.7979	0.2330	0.6309	0.4250	0.8562	0.3756
Ultra-GCN	0.3666	0.2057	0.7624	0.1777	0.4959	0.3164	0.7751	0.2840
SVD-GCN	0.5745	0.3973	0.8205	0.3402	0.6370	0.4248	0.8609	0.3736
DPVP(full-period global graph)	0.5094	0.3022	0.7875	0.2562	0.6324	0.4117	0.8621	0.3592
DPVP	**0.6167***	**0.4180***	**0.8392***	**0.3715***	**0.6599***	**0.4563***	**0.8741***	**0.4075***
Imp%	+7.3455	+5.2102	+2.2791	+7.6812	+3.5950	+6.4877	+1.3919	+4.8366

Table 1: Overall performance on MT-small and MT-large datasets. The last row Imp% indicates the relative improvements of the best performing method (bolded) over the strongest baselines (underlined) and marker * indicates that the improvement is statistically significant compared with the best baseline (paired t-test with p-value < 0.005).

Experiments

Model	MT-small				MT-large			
	Hit@10	NDCG@10	AUC	MRR	Hit@10	NDCG@10	AUC	MRR
DPVP(user-food)	0.3990	0.2531	0.7487	0.2298	0.4054	0.2299	0.7651	0.1986
DPVP(food-level)	0.4438	0.2750	0.7804	0.2444	0.4547	0.2842	0.7845	0.2602
DPVP(user-store)	0.5355	0.3432	0.7888	0.3017	0.6110	0.3879	0.8558	0.3359
DPVP(store-level)	0.5461	0.3588	0.7902	0.3161	0.6271	0.4158	0.8639	0.3664
DPVP(global level)	0.5865	0.3909	0.8296	0.3467	0.6494	0.4476	0.8714	0.3998
DPVP	**0.6167***	**0.4180***	**0.8392***	**0.3715***	**0.6599***	**0.4563***	**0.8741***	**0.4075***

Table 2: Impact of dual interaction-aware preference modeling and * indicates p-value < 0.005.

Experiments

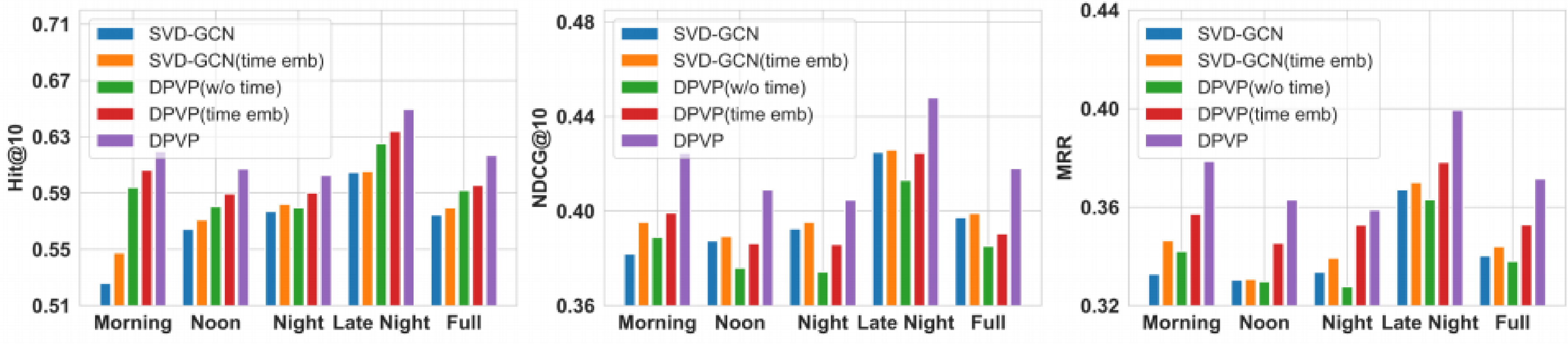


Figure 4: Impact of period-varying modeling on results for different time periods in MT-small dataset.

Experiments

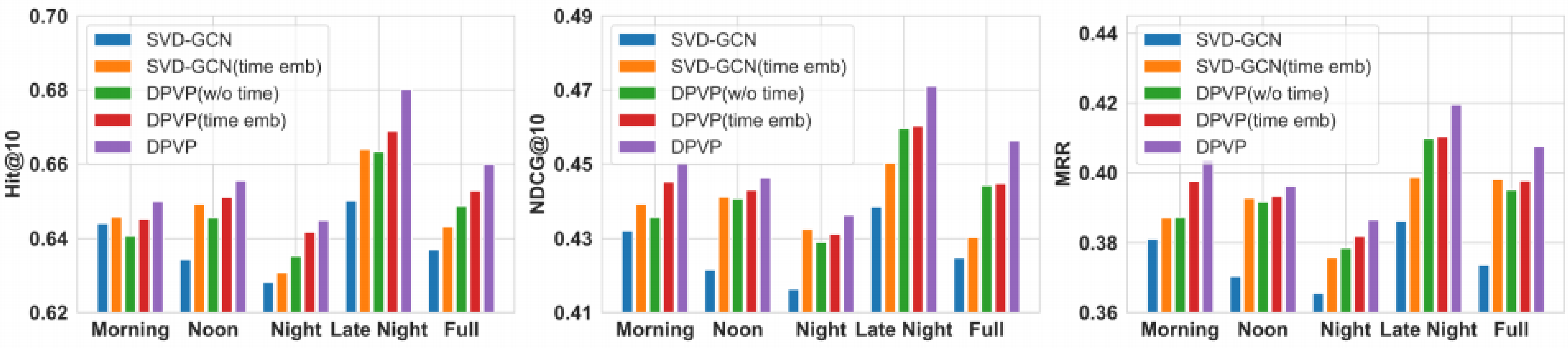


Figure 5: Impact of period-varying modeling on results for different time periods in MT-large dataset.

Experiments

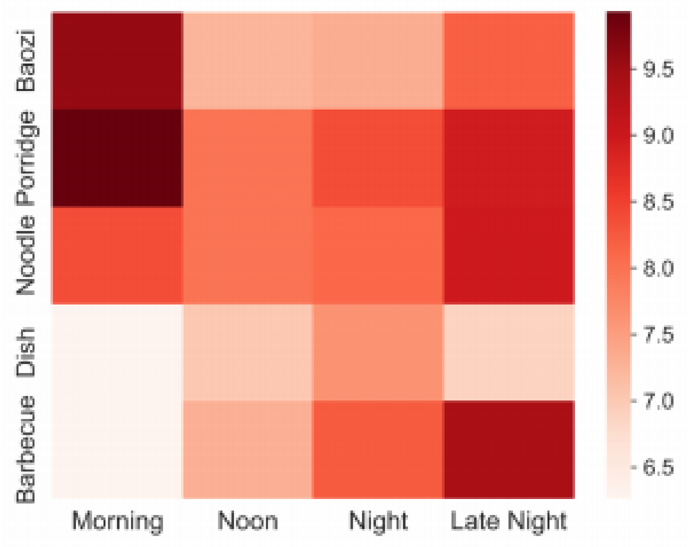


Figure 6: Visualization of the average predicted scores of five major food categories over different time periods.

Experiments

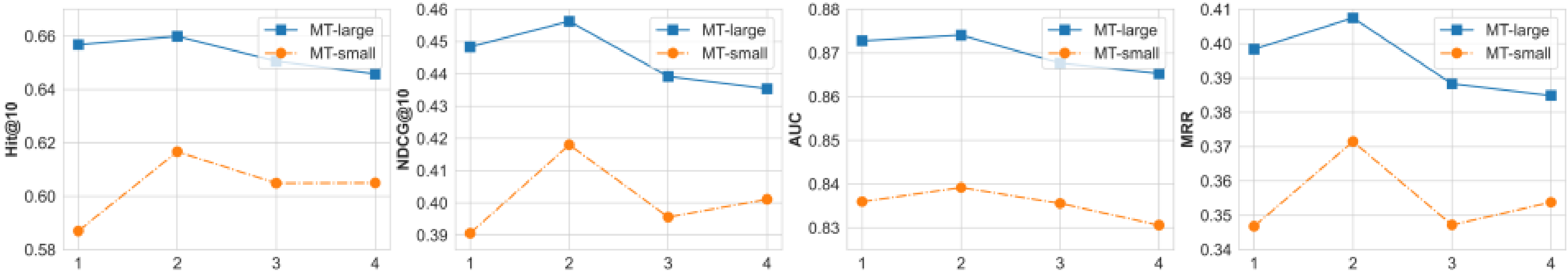


Figure 7: Performance w.r.t the number of layers L on the two datasets.

Experiments

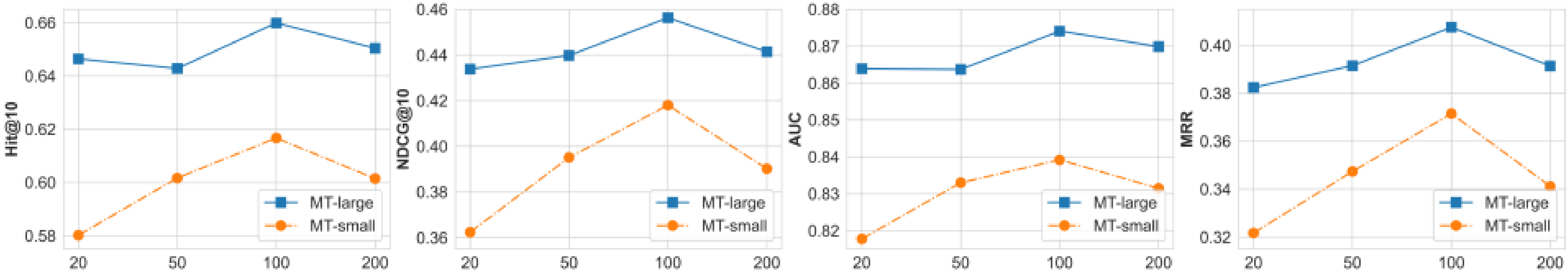


Figure 8: Performance w.r.t the dimension of embedding vectors d on the two datasets.

Experiments

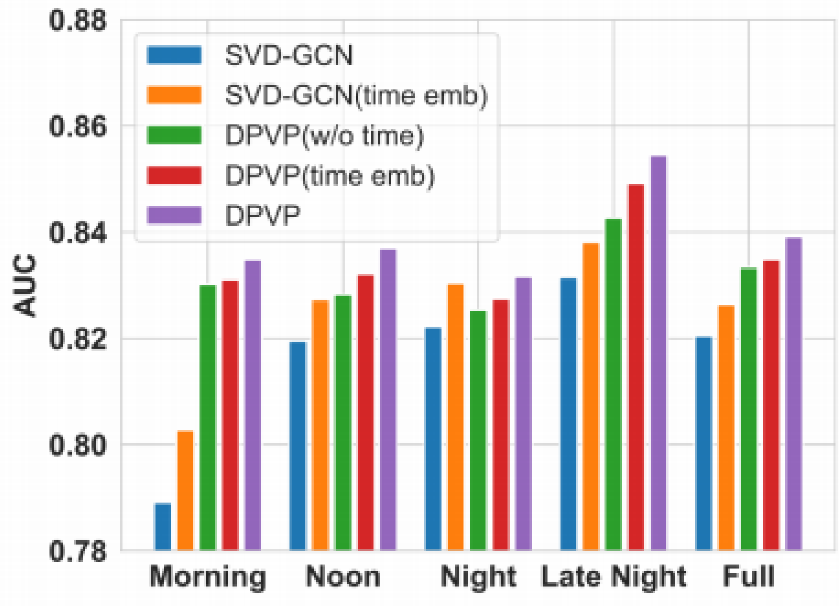


Figure 9: Impact of period-varying modeling on results for different time periods on AUC metric in MT-small dataset.

Experiments

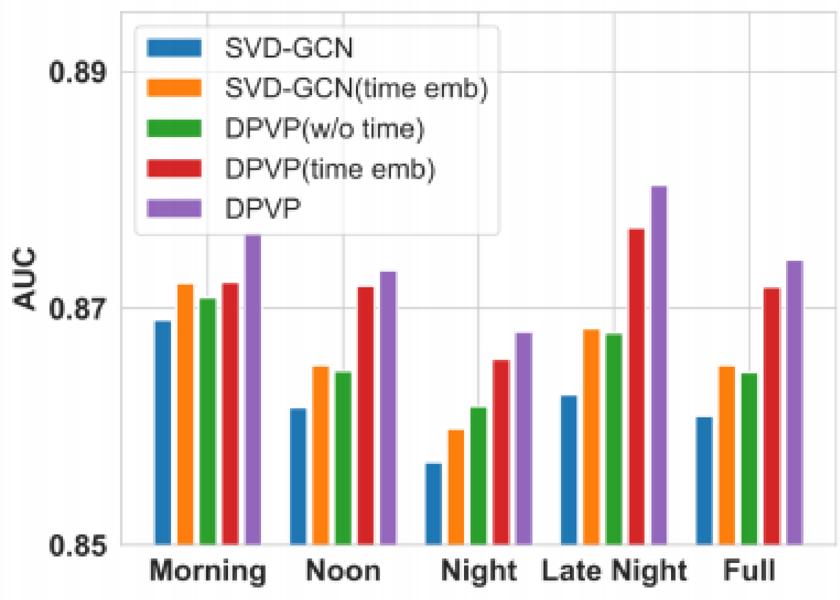


Figure 10: Impact of period-varying modeling on results for different time periods on AUC metric in MT-large dataset.