Periodic Prompt on Dynamic Heterogeneous Graph for Next Basket Recommendation

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***Abstract*—In next basket recommendation, baskets are usually formed through a large number of user interactions with items in the early stage. In general, the existing methods for next basket recommendation primarily focus on historical purchase behavior of users, assuming that user purchase interests are static, and overlook the dynamic and diverse changes in user purchase interests. In order to fully capture dynamic user interests and provide users with more diverse recommendations, we propose our method, Dynamic Heterogeneous Graph Prompt (DHGP), for next basket recommendation. By constructing a dynamic heterogeneous graph, we can adequately consider the influence of various interactive behaviors on the user's baskets at different times. Furthermore, we introduce a periodic dynamic heterogeneous prompt strategy to capture the interest directions between baskets from different users and provide users with more diverse interest directions. Extensive experimental validation on six real world datasets demonstrates that our method shows strong applicability across datasets under various conditions and outperforms several state-of-the-art recommendation methods. To the best of our knowledge, DHGP is the first next basket recommendation method that effectively combines dynamic and heterogeneous information. The implementation code is accessible at https://github.com/AllminerLab.**

***Index Terms*—next basket recommendation, graph neural network, graph prompt, dynamic and heterogeneous information**

I. Introduction

The next basket recommendation task is a common real-world scenario that aims to predict the items a user will interact with in the next basket based on historical user-item interaction data. Unlike traditional recommendation tasks, the next basket recommendation does not consider the temporal order of items within a basket, and the items within a basket are typically interrelated to some extent. Overall, a common challenge in recommendation systems is how to well capture the direction of user interests over time.

Existing collaborative filtering recommendation methods generate recommendations based on users' historical behavior data by leveraging similarities between users or items. For instance, the studies in [1]–[3] attempt to predict changes in user interests by incorporating temporal factors and personalized frequencies. However, collaborative filtering approaches often assume that user interests are static, which results in poor performance in capturing changes in user interests. In graph-based recommendation system methods, the existing approaches [4], [5] introduce either heterogeneous data or dynamic information separately within a graph structure to capture the complex relationships between users and items. However, the graph-based recommendation methods can not jointly consider the dynamic and heterogeneous information, failing to capture more diverse semantic information about user interests. Furthermore, according to [6], [7], an interesting conclusion is drawn that users' interaction interests are often influenced by other users and society, and this influence exhibits a certain lag effect, requiring a specific time period to alter user interaction behaviors. Therefore, how to well consider the development of user interests during the recommendation process is a crucial and worth exploring problem.

To tackle the issues mentioned, we propose a Dynamic Heterogeneous Graph Prompt (DHGP) model. Our approach consists of two main modules: dynamic heterogeneous graph learning and periodic prompt design. In the dynamic heterogeneous graph learning module, we derive an optimal graph structure from the dynamic heterogeneous data. For the periodic prompt design, we create a candidate set of prompts featuring the most influential items related to different users from the previous time period. For the current "target" user, we randomly select an item that is not connected to this user from the candidate set as a prompt and perform feature aggregation based on this prompt information. This design allows us to capture the diverse interaction interests of various users. Finally, we predict the items for each user's next basket using the generated prediction vector.

The main contributions of this paper are as follows:

- To the best of our knowledge, this is the first attempt to unify dynamic and heterogeneous information in a recommendation method, demonstrating excellent performance

and generalizability across a wide range of real-world datasets.
- The periodic prompt design considering the lag effect is able to learn the right diverse users' interaction interests, thereby better capturing changes in user interests for the next basket.
- Extensive experiments show that our proposed DHGP method outperforms existing state-of-the-art methods.

II. Related Work

A. Graph Based Recommendation

Graph-based data representations are increasingly important in recommendation systems due to their effectiveness in capturing relationships between nodes. Graph Neural Networks (GNNs) allow better aggregation of neighborhood information and access to higher-order neighbors [8], [9]. Considering that user behaviors and item attributes in the real world often exhibit diversity and dynamics, graph-based recommendation methods [5], [10], [11] have gradually expanded to deal with the integration of heterogeneous and dynamic information and there are a few methods can combines heterogeneous and dynamic information effectively [12]–[14] . Recently, inspired by large language models,some studies have introduced prompt tuning methods into GNNs and recommendation field [15]–[20], whose goals are to bridge the gap between pre-trained models and various downstream tasks, and capture more information.

B. Next Basket Recommendation

In the field of next basket recommendation (NBR), researchers aim to predict items that users are likely to choose in their next baskets. Current approaches can be mainly categorized into two classes: collaborative filtering based methods and deep learning based methods. Collaborative filtering methods recommend items by leveraging similarities between users and items [2], [3], while deep learning techniques learn implicit relationships between users and items to improve the performance [8], [21], [22]. Relevant works have been done to have a better understanding of the diverse user interests [1], [23], [24].

III. Propose Method

A. Framework Overview

In this paper, to formulate the user's possible purchasing interests with multiple types of interaction behaviors, our goal is to develop a recommendation model capable of adapting to complex dynamic heterogeneous graphs across various real-world scenarios, while balancing the trade-off between repeated recommendations (i.e., items previously interacted by the user are recommended) and exploratory recommendations (items not yet interacted by the user are recommended). To achieve our objectives, we propose the Dynamic Heterogeneous Graph Prompt (DHGP) method.

In this model, we first employ graph attention search to integrate dynamic and heterogeneous information and obtain attention parameters for each item at different timestamps relative to the user. And then, to preserve the optimal structure of the dynamic and heterogeneous graph, the link prediction training strategy is adopted. With the periodic prompt design, we finally enable the model to maintain the user's original preferences while acquiring additional interaction interests, thereby achieving the superior recommendation performance. The framework of our work is illustrated in Fig. 1.

B. Dynamic Heterogeneous Graph Learning

Graph Attention Search. A search strategy is provided for the optimal graph structure that can adapt to a variety of different realistic dynamic heterogeneous scenarios. This strategy captures heterogeneous messages on different timestamps through the calculation of the attention mechanism for updating the node representation. In the definition of neighbor set, we use the subscript to represent the heterogeneous information, the superscript to represent the timestamp of the node:

$$\mathcal{N}_r^t(u) = \{v : (u,v) \in \mathcal{E}^t, \phi_e(u,v) = r\}, \tag{1}$$

where $\mathcal{E}_t$ is the set of all edges with timestamp t, ϕ_e is the mapping function of edge types, and r is the edge type. The dynamic neighborhood $\mathcal{N}(u)$ is the set of all neighbors of node u across different timestamps and edge types:

$$\mathcal{N}(u) = \bigcup_{r,t} \mathcal{N}_r^t(u). \tag{2}$$

For each node u at the timestamp t, and its neighbor node v at the timestamp t', we use $\mathbf{h}_u^t$ and $\mathbf{h}_v^{t'}$ to represent their feature vectors. Then we use a set of mapping functions to calculate the query vector $\mathbf{q}_u^t$, key vector $\mathbf{k}_v^{t'}$, and value vector $\mathbf{v}_v^{t'}$:

$$\mathbf{q}_u^t = \mathcal{F}_q^{\phi_n(u),t}(\mathbf{h}_u^t), \tag{3}$$

$$\mathbf{k}_v^{t'} = \mathcal{F}_k^{\phi_n(v),t'}(\mathbf{h}_v^{t'}), \tag{4}$$

$$\mathbf{v}_v^{t'} = \mathcal{F}_v^{\phi_n(v),t'}(\mathbf{h}_v^{t'}), \tag{5}$$

where $F_q^{\phi_n(u),t}$, $F_k^{\phi_n(v),t'}$, and $F_v^{\phi_n(v),t'}$ are the mapping functions according to the different types of nodes and timestamps.

And then the attention parameters $\alpha_{uv}^{tt'}$ between each node u at the timestamp t and its neighbor nodes v at the timestamp t' can be calculated:

$$\alpha_{uv}^{tt'} = F_r^{\phi_e(u,v),\Delta t}(\mathbf{q}_u^t, \mathbf{k}_v^{t'}), \tag{6}$$

where $F_r^{\phi_e(u,v),\Delta t}$ is a mapping function based on the edge type and the time difference $\Delta t = t - t'$ between the original node and its neighbors. Moreover, $\alpha_{uv}^{tt'}$ here implicitly indicates the accumulated influence of node v on node u after a time period Δt.

After calculating the attention parameters, we normalize the attention parameters of all neighbor nodes to ensure that the sum of their attention parameters is one:

$$\hat{\alpha}_{uv}^{tt'} = \frac{\exp(\alpha_{uv}^{tt'})}{\sum_{v' \in N(u)} \exp(\alpha_{uv'}^{tt'})}. \tag{7}$$

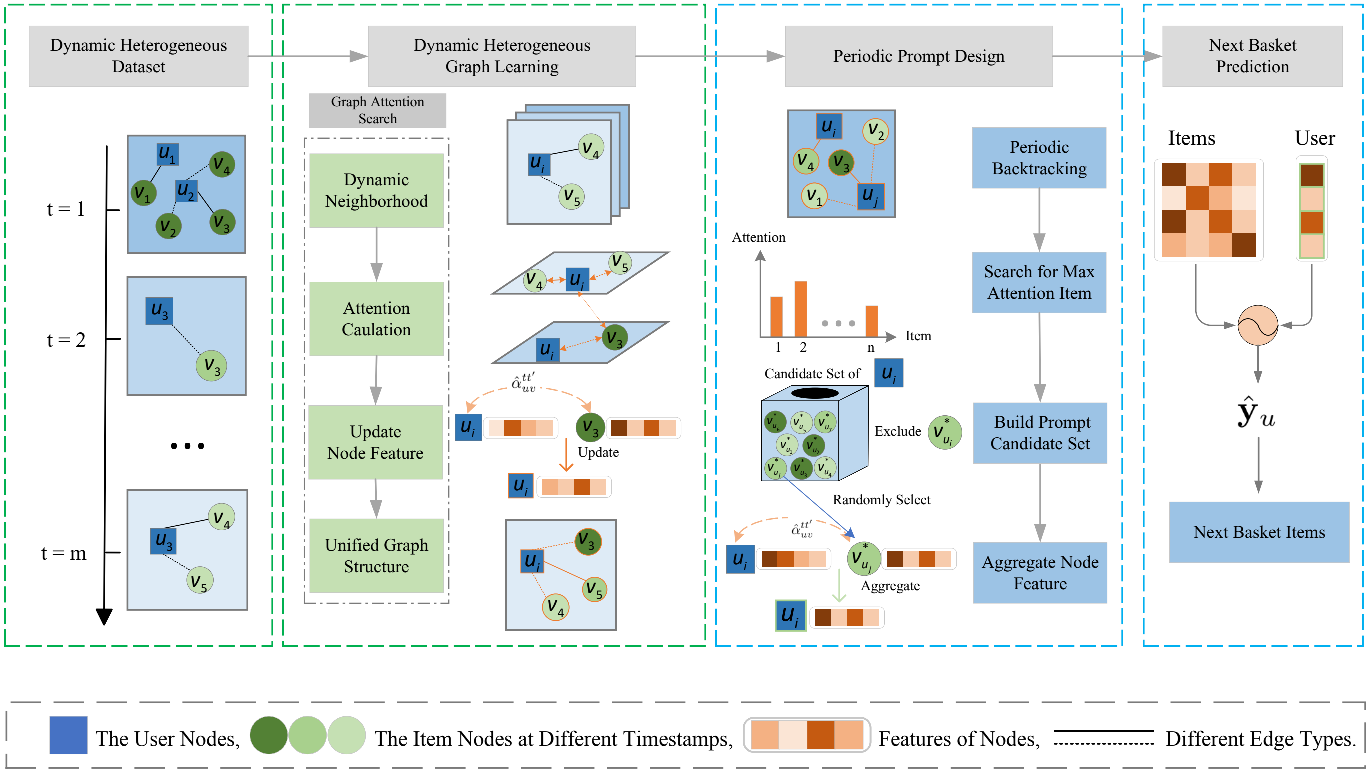

Fig. 1: The framework of our proposed method Dynamic Heterogeneous Graph Prompt. Given a dynamic and heterogeneous dataset, the dynamic heterogeneous graph learning module can calculate the attention parameters between users and items under different timestamps, and tailor a unified graph structure. Then, in the periodic prompt design module, we fetch the unified graph structure from a previous time period, search for the most influential item in each user's basket and construct a periodic prompt candidate set. For a certain user, an unconnected item is randomly selected from the set as a periodic prompt. By this way, we can make sure that each user is aggregated with a different item. After that, we calculate the prediction vector to recommend next basket items for each user.

The information about the node and its neighbors can be finally aggregated:

$$\mathbf{h}_u^t = \text{Update}\left(\mathbf{h}_u^t, \sum_{v \in \mathcal{N}(u)} \hat{\alpha}_{uv}^{tt'} \mathbf{v}_v^{t'}\right). \tag{8}$$

Through the calculation of the attention parameters, we can obtain the optimal structure of the dynamic heterogeneous graph, which allows us to fully consider the dynamic and heterogeneous information, and unify the heterogeneous relationship under different timestamps.

Link Prediction Training. To effectively preserve the optimal structure of the dynamic heterogeneous graph, we utilize the dot product of the two learned node representations for link prediction. Specifically, the cross-entropy is employed as the loss function, which is defined as follows:

$$L = -\sum_{(u,v)\in\mathcal{E}^+} \log \sigma(\mathbf{h}_u^\top \mathbf{h}_v) - \sum_{(u',v')\in\mathcal{E}^-} \log \sigma(-\mathbf{h}_{u'}^\top \mathbf{h}_{v'}), \tag{9}$$

where $\mathcal{E}^+$ denotes the set of positive edges and and $\mathcal{E}^-$ denotes negative edges, respectively. σ denotes the sigmoid function, and $\mathbf{h}_u$ and $\mathbf{h}_v$ are the final output node feature representations of node u and node v.

C. Periodic Prompt Design

Based on the dynamic heterogeneous graph learning, the heterogeneous and dynamic relationships between users and items in real-world scenarios can be better captured. To further characterize the probable purchasing interests of multiple users in the recommendation task, the periodic prompts are well-designed.

As studied in [6], [7], individual purchasing interests as well as interaction behaviors are significantly influenced by the others and society, and it is worth noting that such an influence often exhibits a lag effect, which can be observed from different users. The lag effect occurs, since there is a time gap between when users are influenced and when they engage in new purchasing behavior. Only when the accumulated influence reaches a certain threshold does it trigger new interactions from the user. Therefore, by using attention parameters as the signal of accumulated influence, we design a periodic prompt, and provide additional interest directions to the user without altering their original interaction interests, which enables the model to better capture these delayed changes in interaction behaviors to some extend.

After graph attention search, we apply feature embeddings and linear transformations to each node in the test set.

$$\mathbf{X}_i = \mathbf{W} \cdot \text{featemb}(\mathbf{X}_i^{\text{dict}}) + \mathbf{b}, \tag{10}$$

where $\mathbf{X}_i^{\text{dict}}$ represents the original features of the corresponding node. $\mathbf{W}$ and $\mathbf{b}$ are the weight matrix and bias term of the linear transformation, respectively. Then, for each user node, we go back to the previous timestamp, i.e., $t-T$, and find the neighbor node with the highest attention parameters

$$v_{u_i}^* = \underset{v \in \mathcal{N}(u_i)}{\text{argmax}}\, \hat{\alpha}_{u_i v}^{t(t-T)}, \tag{11}$$

where T denotes the length of the time period, and $v_{u_i}^*$ (i.e., the most influential node on u_i) is used for periodic prompt design. Note that there would be a periodic prompt candidate set containing multiple $v_{u_i}^*$ about different users:

$$\mathcal{V}^* = \{v_{u_1}^*, v_{u_2}^*, ..., v_{u_n}^*\}. \tag{12}$$

For fairness, we randomly select a prompt node $v_{u_i}^* \in \mathcal{V}^*$ for each user node u_j, and make sure that i $\neq$ j. Then we use our aggregate function to transfer the information representation from node $v_{u_i}^*$ to node u_j:

$$\mathbf{h}_{u_j}^t = \text{Aggregate}(\{\mathbf{h}_{u_j}^t, \mathbf{h}_{v_{u_i}^*}^{t-T}, \alpha_{u_i v^*}^{t(t-T)} \mid i \neq j, v_{u_i}^* \in \mathcal{V}^*\}). \tag{13}$$

Once $v_{u_i}^*$ is selected as a periodic prompt to u_j, it would be deleted from the periodic prompt set $\mathcal{V}$, in order that distinct item information can be aggregated to different users. By aggregating the periodic prompt, feature vector of users can retain the characteristics of their original interaction interests while incorporating the probable interaction interests induced by other users.

D. Next Basket Prediction

After obtaining the user feature vectors enhanced with periodic prompts, we can use them for the next basket prediction. For each user u, we compute a prediction vector by multiplying their feature vectors with the features of all items:

$$\hat{\mathbf{y}}_u = \mathbf{h}_u^\top \mathbf{X}, \tag{14}$$

where $\hat{\mathbf{y}}_\mathbf{u}$ is the prediction vector for user u, $\mathbf{h}_u^\top$ is the transposed feature vector of user u, and $\mathbf{X}$ is the feature matrix of all items. Based on this prediction vector, we can obtain the similarity between the user and each item, which is used to predict the next basket.

IV. Evaluation

In this part, we evaluate our model with six real-world datasets from three different domains, where two datasets (i.e., Alibaba and Ecomm) are related to the online e-commerce, and the others (i.e., four sub-datasets of DrugStore) are about offline pharmacy.

A. Experimental Settings

To measure the effectiveness of our method, we select several datasets with dynamic heterogeneity in the real world, including Alibaba[1], Ecomm[2], and DrugStore. The specific statistics of these datasets and the statistics of the basket sequences can be found in TABLE I. We select a duration of one week, representing 7, as the time period for the Alibaba and Ecomm datasets. Since the DrugStore dataset uses one week as a timestamp, we choose 2 as its time period, representing 2 weeks.

To evaluate the effectiveness of DHGP, we compare it with ten state-of-the-art baseline models in the recommendation domain, including XSimGCL [23], SelfCF [2], NCL [25], SSL4Rec [22], DirectAU [3], GAT [26], HTGNN [13], GCN [27], LightGCN [8] and RGCN [28].

In the experiment, we try to make predictions for the last N sequence baskets, and adopt three widely used Hit Ratio@K (HR@K), F1@K and Mean Average Precision@K (MAP@K) as the metrics, where K is set to 10 and 20.

B. Overall Performance Comparison

In our experiment, we perform a comparative analysis of our proposed DHGP model against several state-of-the-art baseline models for the top-K recommendation task. To ensure a fair comparison, we reevaluate the baseline models using our dataset. The results of this comparison are summarized in the TABLE II. Based on these results, we have observed the following points:

- It is evident that our proposed DHGP method demonstrates competitive performance across six real-world datasets. Among these, HTGNN performs well on the Alibaba dataset but shows relatively ordinary performance on the Ecomm dataset. This indicates that the manually constructed dynamic heterogeneous graph structures may not adapt well to different datasets, leading to varied performance across different scenarios. In contrast, our DHGP method consistently shows good performance across multiple datasets with diverse scales and structures, proving its adaptability and effectiveness in various scenarios.
- Our method, DHGP, shows greater improvement on the Alibaba and Ecomm datasets compared to the DrugStore dataset. As shown in Table I, the Alibaba and Ecomm datasets have a higher number of edges, indicating richer heterogeneous information. Additionally, there are more diverse shopping scenarios in these two datasets and there

[1]https://tianchi.aliyun.com/dataset/46
[2]https://tianchi.aliyun.com/competition/entrance/231719

TABLE I: The statistics information of different datasets

Dataset	Timestamps	Nodes		Baskets		Edges			
		User	Item	Average length	Average size	Buy	Click	Cart	Favorite
Alibaba	31	317	3,078	4.22	47.92	4,048	57,597	11,143	7,359
Ecomm	10	1,476	34,505	9.23	13.95	5,529	57,917	15,066	6,701
DrugStore-luohu	60	7,136	1,990	3.27	21.45	153,128	-	-	-
DrugStore-qianjiang	60	4,513	3,613	3.20	26.24	118,412	-	-	-
DrugStore-tangkenglu	60	9,285	4,417	2.74	19.96	185,304	-	-	-
DrugStore-yingchuan	60	4,510	3,623	2.56	20.80	79,777	-	-	-

TABLE II: Comparison of Different Algorithms on Various Datasets. The best performance is highlighted in bold, while the second-best performance is in underline. The performance improvement is defined as Improv. $= \frac{\text{Our result}-\text{The best baseline result}}{\text{The best baseline result}}$.

Dataset	Metrics	XSimGCL	SelfCF	NCL	SSL4Rec	DirectAU	GAT	HTGNN	GCN	LightGCN	RGCN	DHGP	Improve
Alibaba	MAP@10	0.0202	0.0191	0.0223	0.0053	0.0025	0.0049	0.1610	0.0001	0.1564	0.0559	**0.1629**	1.22%
	HR@10	0.0743	0.0793	0.0811	0.0220	0.0101	0.1321	0.5245	0.0038	0.0777	0.4415	**0.5736**	9.35%
	F1@10	0.0272	0.0296	0.0297	0.0077	0.0037	0.0058	0.0459	0.0011	0.0280	0.0282	**0.0473**	3.00%
	MAP@20	0.0157	0.0157	0.0117	0.0117	0.0047	0.0156	0.1516	0.0150	0.0143	0.0738	**0.1517**	0.11%
	HR@20	0.1182	0.1335	0.1335	0.0524	0.0304	0.3394	0.6380	0.0226	0.1318	0.6742	**0.6923**	2.68%
	F1@20	0.0242	0.0271	0.0270	0.0102	0.0071	0.0154	0.0555	0.0006	0.0264	0.0485	**0.0588**	5.94%
Ecomm	MAP@10	0.0083	0.0323	0.0103	0.0085	0.0084	0.0084	0.0012	0.0012	0.0016	0.0092	**0.0396**	22.65%
	HR@10	0.0135	0.0185	0.0168	0.0111	0.0092	0.0068	0.0137	0.0076	0.0232	0.1598	**0.2187**	36.79%
	F1@10	0.0095	0.0130	0.0125	0.0078	0.0068	0.0029	0.0099	0.0060	0.0084	0.0028	**0.0174**	33.55%
	MAP@20	0.0063	0.0376	0.0077	0.0060	0.0047	0.0047	0.0012	0.0012	0.0069	0.0104	**0.0539**	43.60%
	HR@20	0.0214	0.0255	0.0261	0.0203	0.0160	0.0223	0.0242	0.0243	0.0232	0.3037	**0.4451**	46.54%
	F1@20	0.0095	0.0311	0.0115	0.0090	0.0071	0.0060	0.0099	0.0006	0.0094	0.0042	**0.0345**	10.78%
DrugStore luohu	MAP@10	0.0142	0.0317	0.0310	0.0042	0.0078	0.0098	0.0267	0.1003	0.0312	0.0712	**0.1091**	8.83%
	HR@10	0.0243	0.0542	0.0531	0.0071	0.0134	0.0483	0.2409	0.4766	0.0534	0.3768	**0.6383**	33.92%
	F1@10	0.0190	0.0430	0.0423	0.0056	0.0108	0.0007	0.0174	0.0422	0.0422	0.0064	**0.0539**	25.52%
	MAP@20	0.0112	0.0233	0.0230	0.0040	0.0067	0.0144	0.0410	0.1036	0.0228	0.0387	**0.1334**	28.85%
	HR@20	0.0383	0.0796	0.0786	0.0135	0.0229	0.1083	0.4759	0.7154	0.0781	0.3961	**0.8771**	22.61%
	F1@20	0.0180	0.0374	0.0369	0.0063	0.0108	0.0064	0.0294	0.0594	0.0367	0.0120	**0.0671**	13.10%
DrugStore qianjiang	MAP@10	0.0163	0.0658	0.0452	0.0079	0.0086	0.0612	0.2273	0.1758	0.0446	0.0031	**0.2284**	0.51%
	HR@10	0.0228	0.1070	0.0632	0.0110	0.0120	0.7529	0.7808	0.8103	0.0624	0.0244	**0.8154**	0.62%
	F1@10	0.0216	0.0805	0.0579	0.0095	0.0110	0.0448	0.0680	0.1204	0.0574	0.0011	**0.1503**	24.94%
	MAP@20	0.0126	0.0867	0.0304	0.0065	0.0068	0.0316	0.0354	0.3353	0.3101	0.0044	**0.3704**	10.48%
	HR@20	0.0352	0.0867	0.0850	0.0183	0.0189	0.8641	0.9027	0.8825	0.8680	0.0742	**0.9221**	2.14%
	F1@20	0.0199	**0.0940**	0.0472	0.0097	0.0105	0.0735	0.0734	0.0802	0.0483	0.0023	0.0854	-9.14%
DrugStore tangkenglu	MAP@10	0.0199	0.0261	0.0264	0.0057	0.0082	0.0038	0.3042	0.0540	0.0268	0.0511	**0.3049**	0.23%
	HR@10	0.0349	0.0458	0.0464	0.0100	0.0120	0.0987	0.8515	0.1493	0.0470	0.4827	**0.8915**	4.70%
	F1@10	0.0261	0.0342	0.0341	0.0071	0.0120	0.0005	0.0507	0.0173	0.0345	0.0310	**0.0697**	37.47%
	MAP@20	0.0155	0.0207	0.0205	0.0046	0.0055	0.0105	0.1797	0.0714	0.0202	0.0387	**0.1935**	7.69%
	HR@20	0.0543	0.0691	0.0701	0.0178	0.0262	0.8641	0.8670	0.2336	0.0696	0.2336	**0.8877**	2.39%
	F1@20	0.0228	0.0331	0.0328	0.0074	0.0087	0.0119	0.0355	0.0314	0.0313	0.0150	**0.0410**	15.58%
DrugStore yingchuan	MAP@10	0.0102	0.0271	0.0271	0.0048	0.0060	0.0116	0.2881	0.2861	0.0260	0.0712	**0.3010**	4.47%
	HR@10	0.0229	0.0507	0.0508	0.0089	0.0112	0.1014	0.9661	0.9469	0.0487	0.3768	**0.9957**	3.06%
	F1@10	0.0148	0.0368	0.0367	0.0064	0.0079	0.0064	0.0745	**0.0818**	0.0352	0.0233	0.0718	-12.31%
	MAP@20	0.0155	0.0207	0.0205	0.0046	0.0055	0.0105	0.1967	**0.2155**	0.0202	0.0387	0.2059	-4.48%
	HR@20	0.0543	0.0774	0.0766	0.0173	0.0207	0.2980	0.9838	0.9774	0.0755	0.3961	**0.9977**	1.41%
	F1@20	0.0228	0.0331	0.0328	0.0074	0.0087	0.0119	0.0553	**0.0601**	0.0393	0.0150	0.0535	-11.06%

are a wider variety of items. Therefore, compared to other baselines, our DHGP method can leverage the periodic prompt to learn diverse user interaction interests and provide a broader range of item recommendations. In contrast, the DrugStore dataset is focused on the pharmaceutical field with the user interests being more concentrated, and hence smaller improvements are achieved for our method in this dataset.

- Both collaborative filtering-based recommendation methods and graph-based recommendation methods are included. It can be observed that the graph-based recommendation methods generally outperform the collaborative filtering-based methods, and this may be due to the ability of graph-based models to effectively leverage heterogeneous and dynamic information within the data structure. Despite this, the proposed DHGP method further integrates the dynamic and heterogeneous information, resulting in even better performance.
- Across multiple datasets, although the basket sizes in the Alibaba and DrugStore datasets are smaller than those in the Ecomm dataset, the sequence lengths in Alibaba and DrugStore are longer. Our results show that the proposed method performs better on Alibaba and DrugStore, indicating that longer basket sequences provide the model with richer semantic information about purchase interests. More precisely, longer basket sequences enable our model to better learn the transitions of user interests between baskets, and thus more accurately predict the next basket of users.

V. CONCLUSION

The fundamental challenge of next basket recommendation lies in capturing user purchase interests from basket sequences. Existing methods often assume static shopping preferences, overlooking the dynamic and diverse nature of user interactions. In this paper, we propose the **D**ynamic **H**eterogeneous **G**raph **P**rompt **(DHGP)** method, which integrates dynamic and heterogeneous information to capture shifts in user interaction interests. Our dynamic heterogeneous graph learning adaptively determines the optimal graph structure, while the periodic prompt module selects influential items from users' previous baskets to update feature representations. Extensive experiments on six benchmark datasets show that DHGP is highly adaptable and significantly outperforms state-of-the-art recommendation models across different scenarios.

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