O^2-SiteRec: Store Site Recommendation under the O2O Model via Multi-graph Attention Networks

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***Abstract*—The emergence of Online-to-Offline (O2O) stores based on delivery platforms (e.g., Uber Eats, DoorDash, and Eleme) provides great convenience to people's lives. In the O2O model, one of the essential problems for merchants is to select a suitable store site, i.e., store site recommendation problem. We argue that the existing works for the traditional brick-and-mortar stores cannot address this problem due to two unique factors in the O2O model including (i) dynamic supply caused by courier capacity and dispatching strategies and (ii) various customer demands caused by delivery distance and customer preferences. To incorporate these new factors, we design O^2-SiteRec, a store site recommendation method under the O2O model via multi-graph attention networks, which consists of (i) a courier capacity model based on a multi-semantic relation graph attention network to capture courier capacity; (ii) a heterogeneous multi-graph based recommendation model, where the courier capacity, customer preferences, and context features are fused. We evaluate our method based on one-month real-world data consisting of 39,465 stores and 23.6 million orders from one of the largest O2O platforms in China. Experimental results demonstrate that our method outperforms state-of-the-art baselines in various metrics.**

I. Introduction

Online-to-Offline (O2O) model is an increasingly important business model in recent several years. In general, existing brick-and-mortar stores or new stores first join an O2O platform with large-scale customers, and then the platform directs customers to these stores for online purchases. After the purchases, the platform completes the rest of the procedure such as payment, logistics, and delivery [1], [2]. A typical example of such a model is on-demand delivery that a customer places an order online through an O2O platform such as Instacart [3], Uber Eats [4], Deliveroo [5], MeiTuan [6] and Eleme [7]; then a courier picks up the order from a brick-and-mortar store and delivers the order to the customer in a short time (e.g., from 30 minutes to 1 hour) [8], [9]. Compared to the traditional stores that only accept orders by in-person visits of customers, the stores under the O2O model working with a delivery platform provide a great convenience for purchases without physical traveling of customers, which attract more and more customers especially during the pandemic.

In this work, we target on the problem of store site recommendation under the O2O model. Existing work of store site recommendation can be divided into two categories: (i) small-scale survey-based methods and (ii) large-scale data driven methods. In the survey-based methods [10], [11], people carefully design questionnaires and interviews to obtain feedback from small-scale volunteers, which may result in some biased feedback. More recently, with the ubiquitously available infrastructures such as smartphones, we have a new opportunity to collect large-scale multi-source data such as check-in data, rating data, and search engine queries. Researchers analyze these data and build feature-based machine learning models to identify the site with potentially high profits for stores [12]–[17]. Our work also falls into this category.

However, existing data-driven studies are mainly designed for offline brick-and-mortar stores, which are not suitable to solve the store site recommendation problem under the O2O model due to significant differences in both supply and demand aspects. (i) In the supply aspect, offline brick-and-mortar stores only depend on factors such as good storage. However, in addition to those factors, O2O stores are also limited by the courier capacity in O2O platforms. For example, if the capacity of couriers could not meet the real-time customer demand, the platforms would shrink the delivery scope of stores to reduce the demand, which directly reduces the total number of orders of the stores [18]. (ii) In the demand aspect, previous studies have validated the usefulness of store-level customer preferences based on customer consumption behavior [19]. However, as the service changes from offline to online, the customer consumption behavior also evolves. For example, to ensure short time delivery, people cannot place the order in the far-away stores, which is not limited in the traditional offline services as people can move in person.

To bridge the gap, we aim to design a store site recommendation framework for O2O stores considering the new aspects of both the supply and demand. The opportunity for our work is that O2O platforms naturally record the information of couriers and customers for accounting purposes, which provide rich information of supply and demand for store site recommendation under the O2O model. (i) In the supply aspect, the platform collects couriers' trajectory data from APIs of online map service [20] deployed in couriers' smartphones, which provides us the opportunity to explore the impact of the courier capacity on store site recommendation; (ii) In the demand aspect, customer order records provide us the opportunity to exploit fine-grained customer preferences.

Leveraging these opportunities for store site recommendation has the following challenges. (i) For the supply aspect, it is not straightforward to quantify the courier capacity and

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the relationship between the capacity and the O2O store site recommendation. We found that a naive solution of counting the number of couriers cannot reflect the actual capacity (details in Section II-B1). Further, courier capacity dynamically impacts both the store delivery scope and the customer choice, which makes it a complex relationship. (ii) For the demand aspect, the impact of surrounding customers on O2O store site recommendation is affected by multiple dynamic heterogeneous factors including the courier capacity, delivery distance, customer preferences and historical interaction. It is challenging to fuse the impact of these heterogeneous factors for O2O store site recommendation.

To address these challenges, we design O^2-SiteRec, a store site recommendation framework based on multi-graph attention networks. For the supply aspect, to capture the courier capacity, we construct a courier mobility multi-graph and utilize the delivery time to quantify the courier capacity. Based on this graph, we design a courier capacity model based on multi-semantic relation graph attention network to obtain fine-grained courier capacity features. For the demand aspect, we construct a region-type heterogeneous multi-graph, which models the complex semantic relations among multiple views of regions and store types in different periods. We design a heterogeneous multi-graph based recommendation model to capture customer preferences affected by multiple heterogeneous factors and other interaction information for site recommendation. In particular, our main contributions are as follows.

- To our best knowledge, we are the first to study the store site recommendation under the Online-to-Offline (O2O) model. We analyze the unique characteristics of O2O stores from both the supply (e.g., the additional delivery courier capacity) and demand (e.g., the evolving customer consumption patterns) aspects. These characteristics are essential for store site recommendation under the O2O model, which enable our work to address the limitations of traditional store site recommendation methods.
- We design a novel store site recommendation framework under the O2O model via multi-graph attention networks, named O^2SiteRec. It consists of (i) a courier capacity model based on a multi-semantic relation graph attention network to capture courier capacity features; (ii) a heterogeneous multi-graph based recommendation model with node-level and time semantics-level aggregation, where the courier capacity, customer preferences, and context features are fused.
- We evaluate our framework based on one-month real-world data consisting of 39,465 stores and 23.6 million orders from one of the largest O2O platforms, i.e., Eleme. We compare our model with three categories of baselines including store site recommendation methods, graph-based general recommendation methods and heterogeneous graph methods. The experimental results demonstrate that the proposed approach outperforms other state-of-the-art methods, which show 12.18% of improvement in the NDCG@3 metric and 9.01% of improvement in the Precision@3 metric. In addition, we rigorously evaluate the effectiveness of critical components of our model (e.g., the courier capacity model, the region-type heterogeneous graph based recommendation model and attention mechanisms) and the impacts of various factors (e.g., different store types and different distributions of candidate region sets) on the performance of our model. The result shows that these critical components boost the store site recommendation effect and our model performs well for these various factors.

II. Motivation

In this section, we first introduce the details of our dataset and then describe observations of the supply aspect (i.e., courier capacity) and the demand aspect (i.e., customer behavior) that motivate our design.

A. Data

Our work is based on one of the largest O2O platforms called Eleme, where we utilize three types of data including (i) order data; (ii) couriers' trajectory data; (iii) context data.

Order Data: A record in order data logs the information including (i) spatial information such as the source location (i.e., the store location) and the destination location (i.e., the customer's location) for order delivery; (ii) temporal information such as order creating time, order pickup time, and delivery time reported by couriers. Besides, we also have other context data such as the distance between customers and stores as well as store types. We list the fields utilized in this work in Table I. In total, the order data includes 23.6 million orders involving 39,465 stores with 122 types (e.g., light meal, coffee and snack) in Chinese city Shanghai from October, 2020 to November, 2020. To protect privacy, all the customer ids are anonymized by the platform. Further, customers' exact locations are replaced by coarse-grained regions with the size of 500 meters by 500 meters. In addition, we utilize region-level aggregated customer statistics, which do not reveal individual customers' information. Similarly, the store information is also pre-processed to protect privacy.

Couriers' Trajectory Data: Couriers' trajectory data contain continuous location information obtained from smartphones when couriers are working. The location information is uploaded to the platform every 20 seconds under courier consents including courier ID, GPS locations, and timestamps.

Context Data: We further introduce the public data including Point of Interests (POIs) and road networks to represent the context information. We obtain POI data based on the open API from an online map service provider [20] and extract the road networks from OpenStreetMap [21]. These data are utilized to describe the features of different regions in the city, which are important for store site recommendation.

B. Supply Aspect: analysis of courier capacity

We discuss how to quantify the courier capacity and how the courier capacity impacts stores and customers.

TABLE I: An example of order data

Spatial	Store Longitude	Store Latitude	Customer Longitude	Customer Latitude
	121.4910	31.2495	121.4736	31.2357
Temporal	Order Creation	Order Acceptance	Pickup Reporting	Delivery Reporting
	10/19/2020 11:39	10/19/2020 11:40	10/19/2020 11:50	10/19/2020 12:23
Context	Store ID/Customer ID	Order ID/Courier ID	Customer-Store Distance (m)	Store Type
	S001/U001	O001/C001	3780	Cafe

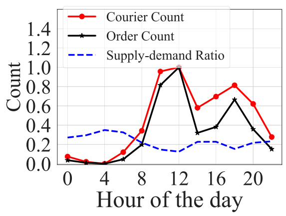


Fig. 1: Order and courier count

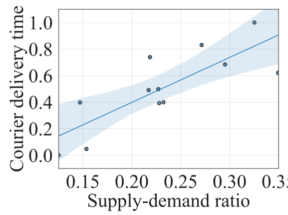


Fig. 2: Correlation of delivery time and supply-demand ratio

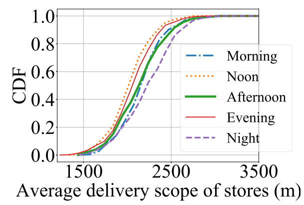


Fig. 3: Average delivery scope of stores

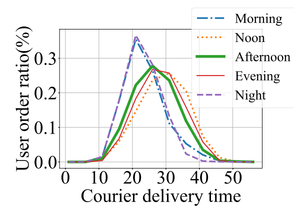


Fig. 4: Distribution of courier capacity in different periods

1) How to quantify courier capacity: A straightforward way to quantify the courier capacity is to count the number of couriers. Fig. 1 shows the number of couriers (i.e., supply), the number of orders (i.e., demand), and the supply-demand ratio (i.e., the number of couriers divided by the number of orders) every two hours in Shanghai. The number of couriers and orders is normalized. We find there is the highest number of couriers and orders during the noon rush hour of order placement (i.e., from 10 am to 2 pm) and evening rush hour (i.e., from 4 pm to 8 pm). If we utilize the number of couriers to quantify the courier capacity, the courier capacity is considered sufficient during these two periods. But in fact, each courier is assigned with multiple orders due to surging order quantity in these two periods, and the courier capacity through counting the number of couriers is underestimated. However, the supply-demand ratio can be utilized to represent courier capacity. As shown in the Fig. 1, the supply-demand ratio is lower in the noon rush hour and evening rush hour, which indicates the lower courier capacity.

The supply-demand ratio mentioned above is at city-level but it does not reflect the region-level supply-demand ratio, which has a finer-grained spatial granularity for site recommendation. Directly applying the same calculation form for the region-level supply-demand ratio is inaccurate due to the mobility of couriers between different regions and concurrent order dispatch. To solve the problem, intuitively, we use delivery time as a measure of courier capacity. For example, when the courier capacity is restrained, the delivery time is increased due to assigning multiple orders to each courier and dispatching long-distance couriers. We further study the correlation between courier capacity (i.e., supply-demand ratio) and delivery time. We calculate the supply-demand ratio and delivery time every two hours for the whole city in one month. Shown as in Fig. 2, the courier's delivery time is related to the courier capacity, which shows the consistency with the city-level supply-demand ratio. In the following analysis and design, we utilize the delivery time to quantify the courier capacity.

2) The impact of courier capacity on stores: In Fig. 3, we analyze the average delivery scope (measured by the farthest delivery distance) of stores in 5 different periods (i.e., morning, noon rush hour, afternoon, evening rush hour, and night). The delivery scope of a store in different periods is inconsistent. For example, compared with the afternoon and night, the courier capacity is restrained at noon rush hour, and the delivery scope is reduced. Due to the influence of the courier capacity, the stores in different periods have different delivery scopes. In order to ensure a good customer experience, the platform conducts a pressure control process. The platform controls delivery pressure by scaling up or down the delivery scope. Each store has a multi-level delivery scope. At the rush hour, the platform scales down the delivery scope because the capacity is restrained. During the afternoon, it is considered to scale up the delivery scope to attract customers. Therefore, the courier capacity determines the delivery scope of the store, which directly affects the number of orders.

3) The impact of courier capacity on customers: We study the distribution of the courier capacity under the same delivery distance, i.e., 2.5km-3km, in 5 periods as shown in Fig. 4. Delivery time is different even under the same delivery distance due to the various courier capacity of each region. The courier capacity in different periods is not consistent, indicating that it changes over time. For the delivery distance of 2.5km-3km, customers are inclined to choose a store with a 20-30 min delivery time in the noon and evening rush hour. As the delivery time increases, the number of corresponding orders gradually decreases because the customer cannot tolerate the long waiting time. In other words, the courier capacity affects the customer's time experience and choice. When conditions permit, customers expect orders delivered as soon as possible. If the delivery time is too long, the less chance that customers choose this store.

4) Summary: The couriers act as a link between the stores and the customers, where courier capacity has great impacts on both the stores and the customers. On the one hand, courier capacity determines the delivery scope of the store, which directly affects the number of store orders. On the other hand, courier capacity affects the customer's time experience and choice, which indirectly affects store orders.

C. Demand Aspect: analysis of customer behavior

1) The correlation of customer preferences and orders: For orders in each region, we count the the number of orders of each type. For customer preferences, we count the number of orders of each type from customers of nearby regions in a given range (e.g., $3km$). Then we calculate the Pearson correlation between the orders and customer preferences.

TABLE II: Correlation between customer preferences and orders in different radius

Radius (km)	1	2	3	4	5
Correlation coefficient	0.725	0.726	0.736	0.720	0.710

We show the results in Table II. We can see that the correlation coefficient between customer preferences and orders is greater than 0.7 for different given ranges. When the correlation coefficient is greater than 0.6, it is typically considered to be strongly correlated. In addition, there are tiny differences in various ranges. The customer preferences around 2-3km are most relevant because these customers are the primary consumers of these stores. For stores over $3km$, they may be out of the delivery scope. For stores within $2km$, customers may choose to pick up in person instead of using O2O services.

2) Customer preferences in different periods: We count the total number of orders for each store type in five periods in the whole city and then rank them. We select the top 3 store types for each period to study the customer preferences at different periods. As shown in Fig. 5, we can see that the

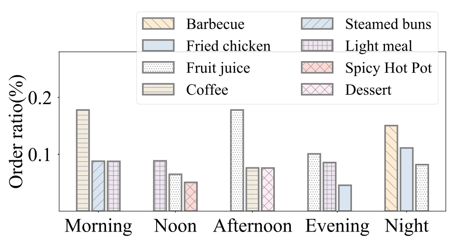


Fig. 5: Top popular store types in the whole city in different periods

preferences of customers in diverse periods are different. There are two main reasons for this phenomenon: (i) The preferences of customers in diverse periods are inherently different. (ii) There are different population in the same area at different periods. For example, some people go to work in one region in the morning and return to another region after getting off work in the evening.

3) Summary: The data analysis shows that the correlation coefficient between customer preferences and orders is high, where customer preferences play an important role in store site recommendation under the O2O model. Further, the customer preferences change over time as the preferred stores are changing along the day, which motivates us to consider diverse time periods in the modeling part.

III. Design of O^2-SiteRec

A. Preliminary

Definition 1: Region. The city is partitioned as a set of two-dimensional grids with a size of $\xi \times \xi$ (e.g., ξ = $500m$). Each grid represents a region.

Definition 2: Region Geographical Graph. We utilize a graph $G_{ge} = \{V, E_{ge}\}$ to model geographical proximity between regions, where V denotes the node set with node $r \in R$ representing regions and the edge $E_{ge}(r_i, r_j)$ represents the connection between r_i and r_j with a distance less than a threshold (i.e., $800m$). The attribute of the edge $E_{ge}(r_i, r_j)$ is the distance between two regions.

Definition 3: Courier Mobility Graph. We utilize a graph $G_c^t = \{V, E_c^t\}$ to model the actual delivery time of the courier between regions during period t, where the edge $E_c^t(r_i, r_j)$ represents that couriers have mobility behavior between region r_i and region r_j. The attribute of the edge $E_c^t(r_i, r_j)$ is the delivery time from region r_i to region r_j.

In addition, the mobility status of the courier changes over time. We utilize a multi-graph structure [22] to represent this heterogeneous interaction. **Courier mobility multi-graph** is defined as a multi-graph $G_c = \cup\{G_c^t\} = (V, E_c)$, where $E_c = \{E_c^{t_1}, E_c^{t_2}, ...\}$ represents the edge set in different periods.

Definition 4: Region-Type Heterogeneous Graph. Each region has two views: store view and customer view. In the store view, we define **store-region** as the region under the store view that represents which types of stores are available in this region. In the customer view, we define **customer-region** as the region under the customer view that represents which types of stores are preferred by customers in this region. Note that both the store-region and customer-region are the subset of all the regions. We utilize a heterogeneous graph $G_h^t = \{V_h, E_h^t, X_h\}$ to model the relations among regions in different views and store-type in period t, which is shown in Fig. 6. V_h are nodes consisting of store-region nodes $s \in S$, customer-region nodes $u \in U$ and store-type nodes $a \in A$. X_h^t is node attributes, which is detail in Section III-C. E_h^t are edges consisting of S-U edges E_{S-U}^t, S-A edges E_{S-A} and U-A edges E_{U-A}^t.

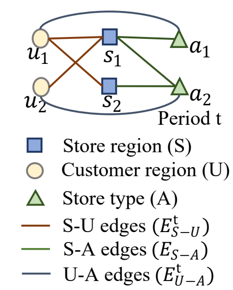


Fig. 6: Region-Type Heterogeneous Graph

- $E_{S-U}^t(s, u)$ means that the customer-region u is in the delivery scope of the store-region s in period t. Based on historical delivery scopes and distances, we calculate probabilities and determine which nodes have edges between them, to consider the impact of courier capacity on the delivery scope of the store. Specifically, for a target region, we first shrink down the candidate regions within its farthest delivery distance. We build an edge between the target region and a candidate region if the distance is less than the average delivery distance. Otherwise, we calculate an order ratio (i.e., the number of historical orders of these candidate regions with the target region divided by the total number of historical orders of the target region) to determine whether there is an edge . We filter out regions with low order ratios because there may be some exception orders. The edge attribute $\phi_{su,t}$ is a multi-dimensional vector composed of various factors that affect the interaction between the customer and the store in period t (details in Section III-C).

- $E_{S-A}(s,a)$ means that there are stores with the store-type a in the store-region s. The edge attribute ϕ_{sa} is a multi-dimensional vector, which contains commercial features and the history order number (details in Section III-C).
- $E^t_{U-A}(u,a)$ means that customers in the customer-region u prefer the store with store-type a in period t. The edge attribute $\phi_{ua,t}$ is the number of historical transactions.

In addition, customer preferences and the interaction between the customer-region and the store-region change over time, which means that edges are different in different periods. To incorporate the changes, we define **Region-Type heterogeneous multi-graph** as a multi-graph $G_h = \cup\{G^t_h\} = (V_h, E_h, X_h)$, where $E_h = \{E^{t_1}_h, E^{t_2}_h, ...\}$ denotes edge sets in different periods.

Problem Formulation. We formulate the problem of store site recommendation under the O2O model as follows:

$$\hat{p}_{sa} = F_\theta(G_h, G_c, G_{ge}) \tag{1}$$

we input the region-type heterogeneous multi-graph G_h, courier mobility multi-graph G_c and region geographical graph G_{ge} to learn a model F_θ that can predict the number of orders p_{sa} of the target type a (e.g., light meal and snack) in the region s.

After obtaining the model, for a given target store type a, we utilize the model to predict the number of orders for all candidate store-regions $S = (s_1, s_2, ..., s_j)$ and select the top-ranked regions as recommendation results.

B. Overview

The framework of O^2-SiteRec is given in Fig. 7, which consists of the following three modules:

Module 1: Data processing. We first extract features from the context data and order data. These features are utilized as attributes of nodes and edges in the region-type heterogeneous multi-graph (details in Section III-C).

Module 2: Courier capacity modeling. Based on the courier mobility multi-graph, we design a courier capacity model to capture fine-grained courier capacity embedding, which is utilized as the input for the region-type heterogeneous multi-graph (details in Section III-D).

Module 3: Heterogeneous multi-graph based recommendation. Based on the region-type heterogeneous multi-graph and edge embedding from the courier capacity model, we design a heterogeneous multi-graph based recommendation model with node-level and semantics-level aggregations to capture customer preferences affected by multiple factors and interaction information between store-region and store-type (details in Section III-E).

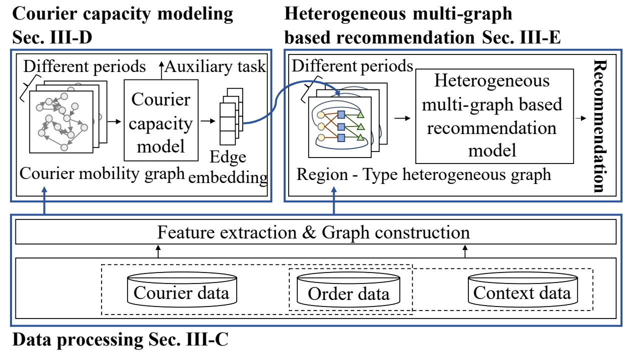


Fig. 7: Framework of O^2-SiteRec

C. Data Processing

We first extract geographic features including POI set, POI diversity, traffic convenience, and store diversity for each region. These geographic features are considered as attributes of both the store-region node and the customer-region node.

- POI set: it is a vector, where each dimension represents the number of POIs in a specific type in each region.
- POI diversity: it is defined as the information entropy of the proportion of all types of POI appearing in a region.
- Traffic convenience: it is a vector composed of the number of intersections and roads in a region.
- Store diversity: it is defined as the information entropy of the proportion of all types of stores in a region.

In addition, for a specific type a in a store-region s, we extract commercial features [17] including competitiveness and complementarities. These features are attributes of E_{S-A}.

- Competitiveness: it reflects competition from nearby stores of the same type, which is defined as the number of stores of the same type in the region divided by the total number of nearby stores.
- Complementaritiess [12], [15], [17]: it represents that stores of different types can potentially benefit each other because of their complementary characteristics e.g., coffee shop and bread shop. It is defined as $f^{cp}_{sa} = \sum_{a^*} log(\rho_{a^*-a})(N_{sa^*} - N_{a^*})$, where $\rho_{a^*-a} = \frac{2N_{set}(a^*,a)}{N_A(N_A-1)}$; N_{sa^*} is the number of stores with type a^* in region s; N_{a^*} is the average number of stores of type a^* that appear in all regions; $N_{set}(a^*, a)$ is the appearance number of the pair-wise type a^* and a; N_A is the number of all the store types.

We also extract features that affect the interaction between the customer-region and the store-region including distance and historical transaction records, which are used as the attributes of E^t_{S-U}.

- Distance: it is defined as the distance between the store-region and the customer-region.
- Historical transaction records: it is defined as the number of historical transactions between the store-region and the customer-region.

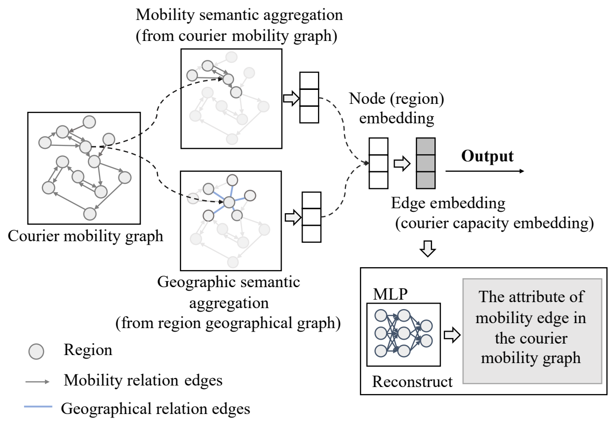


Fig. 8: Design of courier capacity model. (i) For each region node, we get the node embedding by geographic semantic aggregation and mobility semantic aggregation. (ii) We concatenate two node embeddings as the edge embedding to reconstruct the attribute of the mobility edge in the courier mobility graph. (iii) We output the obtained edge embedding of courier capacity.

D. Courier Capacity Modeling

It is not straightforward to capture the fine-grained courier capacity due to courier mobility. Intuitively, geographically adjacent regions have similar courier capacity, and regions with mobility relations have some correlation. We design a courier capacity model based on a multi-semantic relation graph attention network to capture courier capacity.

For each subgraph G_c^t of period t, we conduct the following steps as shown in Fig. 8. We first find two kinds of neighbors for each node, i.e., geographic semantic neighbors and mobility semantic neighbors from region geographical graph and courier mobility graph, respectively. We get the node embedding by geographic semantic aggregation and mobility semantic aggregation, which are concatenated as the edge embedding to reconstruct the attribute of the mobility edge in the courier mobility graph. The edge embedding is then utilized as an input for the region-type heterogeneous multi-graph (details in Section III-E). Further, the training of this module is utilized as an auxiliary task to optimize the training of the main task.

1) Geographic semantic aggregation: we represent each region i with an initial embedding $b_i^0 \in \mathbb{R}^{d_1}$, where d_1 is the embedding size. For the geographic neighborhood N_i^{geo} of the region i, we utilize the distance between regions to calculate the weights, which is defined as

$$\alpha^{geo}(i,j) = \frac{exp(dis(i,j))}{\sum_{k \in N_j^{geo}} exp(dis(k,j))} \tag{2}$$

where $dis(i,j)$ represents the distance between region i and region j. We get the embedding $b_{g,i}^l$ of the region i after the l-th geographic semantic aggregation, which is defined as

$$b_{g,i}^l = \sigma(\sum_{j \in N_i^{Geo}} \alpha^{geo}(i,j) b_{g,j}^{l-1}) + b_{g,i}^{l-1} \tag{3}$$

where $b_{g,j}^{l-1}$ represents the embedding of region j after the (l-1)-th geographic semantic aggregation and $\sigma(\cdot)$ is an activation function.

2) Mobility semantic aggregation: For the semantic neighborhood N_i^{mob} of the region i, we calculate the weights $\alpha^{mob}(i,j)$ between different neighbors according to GAT [23], which is defines as $\alpha^{mob}(i,j) = softmax(\sigma(\psi^T [b_i^0, b_j^0]))$. Then we get the embedding $b_{s,i}$ of the region i after the mobility semantic aggregation, which is defined as

$$b_{s,i} = \sigma(\sum_{j \in N_i^{mob}} \alpha^{mob}(i,j) b_j^0) + b_i^0 \tag{4}$$

where ψ is the parameterized attention vector. b_i^0 and b_j^0 are initial embeddings of region i and region j respectively.

3) Obtain edge embeddings by reconstructing the attribute of mobility edge in courier mobility graph: The final embedding b_i of the region i is calculated by combining the embedding of the two aspects (i.e., geographic and mobility), which is defined as

$$b_i = \sigma(W_b [b_{g,i}^l, b_{s,i}]) \tag{5}$$

where W_b is a trainable weight. We combine two region embeddings as the edge embedding $em_{i,j}^c$ and then feed it into the MLP for delivery time prediction, which is defined as $\hat{DT}_{i,j} = \sigma(W_1[b_j, b_i])$. W_1 is a trainable weight. The loss functions of the task is defined as

$$O_1 = \frac{1}{|E|} \sum_{i,j \in E} ||DT_{i,j} - \hat{DT}_{i,j}|| \tag{6}$$

where $|E|$ is the number of observed edges in the courier mobility graph. $DT_{i,j}$ is the ground truth delivery time in the courier mobility graph. The edge embedding containing courier capacity is utilized as an input for the region-type heterogeneous multi-graph.

E. Heterogeneous Multi-graph based Recommendation

Intuitively, whether a region is suitable for a specific store type is affected by customer preferences around it. We construct a region-type heterogeneous multi-graph to model complicated relations among store-region, customer-region, and store-type. Specifically, we design a heterogeneous multi-graph based recommendation model to capture customer preferences and the interaction information between store-region and store-type for site recommendation. The model contains a node-level aggregation to consider the effect of edge attributes (e.g., multiple factors) and a time semantics-level aggregation to consider multi-graph structure.

Fig. 9 depicts the design of the heterogeneous multi-graph based recommendation model consisting of five major steps including (1) node attributes fusion; (2) edge attributes fusion for the E_{S-U}^t; (3) node-level aggregation to obtain store-region embeddings and store-type embeddings in different periods; (4) result fusion from different subgraphs by the time semantics-level aggregation; (5) order number prediction.

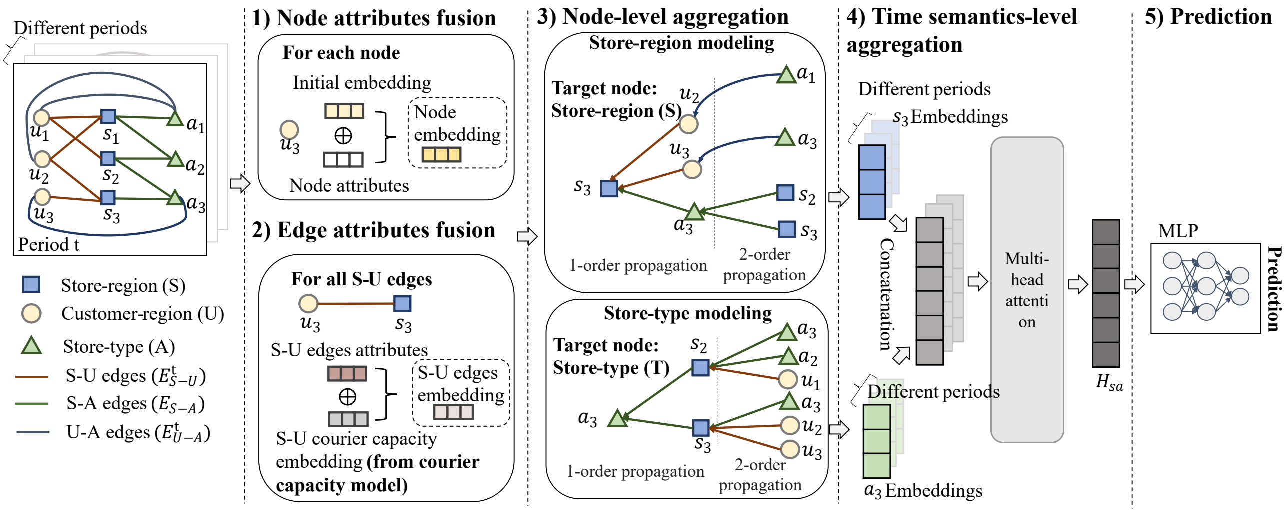


Fig. 9: Design of heterogeneous multi-graph based recommendation model

1) Node attributes fusion: we represent each node ID with an embedding to represent the latent features. Formally, we represent store-region s, customer-region u and store-type a with initial embeddings $h_s^{'} \in \mathbb{R}^{d_2}$, $z_u^{'} \in \mathbb{R}^{d_2}$ and $q_a^{'} \in \mathbb{R}^{d_2}$, respectively, where d_2 is the embedding size. Then we fuse the initial embedding and node attributes to get the node fusion embedding. Fusion embeddings of store-region, customer-region and store-type are defined as $h_s^0 = \sigma(W_S[h_s^{'}, f_s])$, $z_u^0 = \sigma(W_U[z_u^{'}, f_u])$ and $q_a^0 = q_a^{'}$.

2) Edge attributes fusion: For $E^t_{S-U}(s,u)$, we fuse the edge attributes $\phi_{us,t}$ with the edge embedding $em^c_{us,t}$ from the courier capacity model to obtain the new combined edge attributes, which contains multiple factors including the courier capacity, delivery distance, and historical interaction. The new edge attributes $\phi^{'}_{us,t}$ is defined as $\phi^{'}_{us,t} = [\phi_{us,t}, em^c_{us,t}]$.

3) Node-level aggregation: For the subgraph G_h^t in period t, each node aggregates information from its neighbors to update its node embedding when performing the node-level aggregation. Specifically, we get the store-region node embedding and the store-type node embedding by the store-region modeling and the store-type modeling, respectively.

(i) Store-Region Modeling. On the one hand, for the target node store-region, we learn preferences of customer-regions within its delivery scope through E^t_{S-U}. On the other hand, we capture the high-order interaction information between store-regions and store-types through E_{S-A}. The embedding $h^l_{s,t}$ of the store-region node s after l-th aggregation is defined as

$$h^l_{s,t} = \sigma(W^l_S(Aggre(z^{l-1}_{u,t}|u \in N^t_{S-U}(s)) + Aggre(q^{l-1}_{a,t}|a \in N_{S-A}(s)) + h^{l-1}_{s,t})) \tag{7}$$

where W^l_S is trainable weight. $N^t_{S-U}(s)$ and $N_{S-A}(s)$ represent neighbors of store-region s based on E^t_{S-U} and E_{S-A}, respectively. $Aggre$ is a aggregation function, which is defined in detail later. $z^{l-1}_{u,t}$, $q^{l-1}_{a,t}$ and $h^{l-1}_{s,t}$ are embeddings of customer-region node u, store-type node a and store-region node s after (l-1)-th aggregation. For customer-region node u, the embedding $z^l_{u,t}$ capture the store-type it prefers through E^t_{U-A} after l-th aggregation, which is defined as

$$z^l_{u,t} = \sigma(W^l_U(Aggre(q^{l-1}_{a,t}|a \in N^t_{U-A}(u)) + z^{l-1}_{u,t})) \tag{8}$$

where W^l_U is trainable weight and $N^t_{U-A}(u)$ represent neighbors of customer-region u based on E^t_{U-A}.

(ii) Store-Type Modeling. For the target node store-type, we capture the store-region it interacts with and high-order information through E_{S-A}. The embedding $q^l_{a,t}$ of store-type node a after l-th aggregation is defined as

$$q^l_{a,t} = \sigma(W^l_A(Aggre(h^{l-1}_{s,t}|s \in N_{A-S}(a)) + q^{l-1}_{a,t})) \tag{9}$$

where W^l_A is trainable weight and $N_{A-S}(a)$ represent neighbors of store-type a based on E_{S-A}.

Aggregation function (Aggre). In order to consider the different edge types and attributes of edges in the heterogeneous graph, we design an aggregation function, which estimates the importance of each source node by the node attributes, the edge attributes, and the edge type.

We utilize the multi-head attention mechanism [24] to calculate the importance score. In the following, we utilize the store-region node (i.e.,target node) and the customer-region node (i.e., source node) as an example. Firstly, in order to take into account the effect of different edge types, we set a trainable parameter W_e, which is shared by the same edge type. Secondly, in order to utilize the edge attributes, we combine the embedding $z^{l-1}_{u,t}$ of the source node (e.g., customer-region u) and the edge attributes $\phi_{us,t}$ as a fused vector. For the i-th attention head, we project the fuse vector above into the i-th key vector with a linear projection $W^i_{k,U}$. The i-th key vector $K^i(u)$ is defined as

$$K^i(u) = W^i_{k,U}\sigma(W[z^{l-1}_{u,t}, \phi_{us,t}]) \tag{10}$$

Similarly, we project the target node (e.g., store-region node s) into the i-th query vector with a linear projection $W^i_{q,S}$. The i-th query vector $Q^i(s)$ is defined as $Q^i(s) = W^i_{q,S}h^{l-1}_{s,t}$.

Finally, we combine the query vector, the key vector and the edge type to calculate the importance of the i-th attention head and normalize it with the softmax function [25] to get the weight of the i-th attention head, which is defined as

$$\alpha^i(u,s) = softmax(\sigma(K^i(u)W_e Q^i(s)^T)) \tag{11}$$

Then we aggregate the information of neighboring nodes and concatenate the output of the multi-head attention to get the final representation of $Aggre$, which is defined as

$$Aggre(z_{u,t}^{l-1} | u \in N_{S-U}^t(s)) = \overset{I}{\underset{i=1}{||}} \sigma(\sum_{u \in N_{S-U}^t(s)} K^i(u)\alpha^i(u,s)) \tag{12}$$

where $||$ denotes the vector concatenation operator.

4) Time semantics-level aggregation: With the embedding of the store-region and the store-type (i.e., $h_{s,t}^l$ and $q_{a,t}^l$) in each subgraphs during period t, we first concatenate them to get an embedding $H_{sq,t}$ defined as $H_{sq,t} = [h_{s,t}^l, q_{a,t}^l]$. Considering different regions and store types generally have unequal importance in different periods (e.g., breakfast stores are busier in the morning period), we utilize a multi-head attention mechanism to calculate the importance of each period. For the i-th attention head, we project the concatenated embeddings from all the periods into the i-th key vector $K_{t_j}^i(H_{sa})$ with a linear projection W_k^i, which is defined as

$$K_{t_j}^i(H_{sa}) = W_k^i[H_{sa,t_1}, H_{sa,t_2}, ..., H_{sa,t_J}] \tag{13}$$

Then we project the embedding H_{sa,t_j} for period t_j into the i-th query vector $Q_{t_j}^i(H_{sa})$ with a linear projection W_q^i.

$$Q_{t_j}^i(H_{sa}) = W_q^i H_{sa,t_j} \tag{14}$$

The attention weight $\alpha_{t_j}^i$ is computed as the inner product of the query vector and key vector and normalized with the softmax function. Finally, we calculate the weight sum of the key vector $K_{t_j}^i(H_{sa})$ and concatenate the output of the multi-head attention as the final embedding H_{sa}, which is defined as

$$H_{sa} = \overset{I}{\underset{i=1}{||}} \sigma(\sum_{j=1}^{J} \alpha_{t_j}^i K_{t_j}^i(H_{sa})) \tag{15}$$

5) Prediction: we feed the embedding H_{sa} into a multilayer perceptron (MLP) for order number $\hat{p}_{sa}$ prediction, which is defined as $\hat{p}_{sa} = \sigma(W_2 H_{sa})$. The loss function O_2 of this task is defined as

$$O_2 = \frac{1}{|N|} \sum_{s,a \in N} (\hat{p}_{sa} - p_{sa})^2 \tag{16}$$

where $|N|$ is the number of observed data and p_{sa} is the ground truth order number about store-region s on the store-type a.

F. Model Training Process

The objective function that combines the two tasks is formulated as

$$Loss = O_2 + \beta O_1 \tag{17}$$

where β is a trade-off parameter. There are four initial embeddings in our model, and they are randomly initialized and jointly learned during the training stage. To alleviate the overfitting, the dropout strategy is applied to our model.

IV. Evaluation

In this section, we conduct extensive experiments to answer the following research questions.

- RQ1: How does our model O^2-SiteRec perform compared with baselines?
- RQ2: How effective are the courier capacity and customer preferences for store site recommendation under the O2O model?
- RQ3: How effective are our technical components (i.e., node-level aggregation and time semantics-level aggregation)?
- RQ4: How do factors impact the performance?
- RQ5: How do hyper-parameters affect the performance?

A. Evaluation Methodology

1) Datasets: We conduct experiments on a real-world dataset and a simulation dataset, respectively. Details of the real-world dataset are in Section II-A. In addition, we build a simulation dataset to verify the generalizability of our model. Specifically, we utilize an open dataset [26], [27], which lacks our necessary attributes (i.e., customer location and store type). We match it with data in the database to get the store type. Then we use distance to randomly generate the customer's location based on historical transaction patterns.

2) Ground truths and experiment settings: We utilize the number of orders of each type in a region as the ground truth. In each experiment, we randomly select 80% of historical interactions (i.e., the number of orders) between store-region and store-type as training data and the rest as test data. Specifically, we train our model based on 80% of the data then apply it in the rest 20% of the data to predict the number of orders in candidate regions for each target type. Multiple rounds of experiments are conducted to show the result variance and statistical test. Each region has the size of 500m $\times$ 500m in the experiments. By comparing our prediction results with the ground truth, we evaluate our performance. We utilize the average value from all types in test data as the final result.

3) Implementation: We implement our method and baselines with Pytorch 1.7.0 in Python 3.8 environment and train it with 16GB memory and Tesla V100-SXM2 GPU. The embedding size of the courier mobility multi-graph is set to 20, and the embedding size in the region-type heterogeneous multi-graph is set to 90. We apply Adam optimizer, and the learning rate is set to 1e-4. The activation function of network layers is ReLU, and the batch size is set to 128. For multi-head attention-based methods, We set head number as 5 in node-level aggregation and head number as 2 in time semantic-level aggregation. The parameter β in the loss function is set to 0.2. We set the layer l as 2.

4) Metrics: We evaluate the model with both the prediction accuracy and the ranking metrics.

Prediction accuracy: We utilize Root Mean Squared Error (RMSE) to evaluate our model.

Ranking:

- Normalized Discounted Cumulative Gain (NDCG): We choose the NDCG defined in [12] which considers the hit positions of the regions and has a higher score if the hit regions in the top positions.
- Precision
$$\text{Precision@K} = \frac{L_K \cap L_N}{k} \quad (18)$$
where L_K is the list of the top k predicted regions and L_N is the list of the top N regions with the greatest order number. In the experiments, we set N to 30.

5) Baselines: We compare our model with four categories of baselines including store site recommendation methods based on collaborative filtering, graph-based general recommendation methods, heterogeneous graph methods, and variants of our model.

Store site recommendation baselines:

- **CityTransfer** [17]: CityTransfer is a store site recommendation method based on matrix factorization. Considering our work is in a different setting, we discard the inter-city knowledge association module.
- **BL-G-CoSVD** [15] : BL-G-CoSVD is a method based on matrix factorization, which recommends store types.

Graph-based general recommendation baselines:

- **GraphRec** [28]: GraphRec is a graph-based general recommendation method. In our work, we utilize the sub-graph (i.e., the store-region and customer-region bipartite graph) in the region-type heterogeneous graph to replace the social graph.
- **GC-MC** [29]: GC-MC is a general recommendation system with a graph neural network architecture.

Heterogeneous graph baselines:

- **RGCN** [30]: RGCN is the first paper in the graph neural network field that considers different types of edge. In our work, we utilize RGCN to deal with region-type heterogeneous multi-graph.
- **HGT** [31]: HGT is a heterogeneous graph method. we utilize HGT to deal with region-type heterogeneous multi-graph.

Each baseline is presented with two settings considering the different settings in the O2O model.

- **Original**: baselines are trained with features defined in the original papers.
- **Adaption**: considering the uniqueness of the O2O model and the task of store site recommendation, we add additional features (e.g., courier capacity features, customer preference features, and location-based features) to the baselines. For the customer preferences in a region, we use the number of orders of each type from customers of all the nearby regions in a predefined range (i.e., 2km); for the delivery time in a region, we use the average delivery time of all history orders in this region. If there are missing values in one region, we utilize the average value of the nearby regions to complete it.

Variants of our model:

- O^2**-SiteRec without Courier Capacity (w/o Co)**: In order to verify the impact of courier capacity, the courier capacity model is removed. In addition, the S-U edges in the region-type heterogeneous multi-graph is constructed without considering courier capacity. The results are in Sec IV-C1.
- O^2**-SiteRec without Courier Capacity & Customer Preference (w/o CoCu)**: we remove the courier capacity model as well as two edges (i.e., S-U edges and U-A edges) in the region-type heterogeneous multi-graph to verify the role of both courier capacity and customer preferences. The results are in Sec IV-C1.
- O^2**-SiteRec without Node-Level Attention (w/o NA)**: To verify the effect of multiple heterogeneous factors and the aggregation function we design in node-level aggregation, we utilize mean aggregation to replace the aggregation function we designed in node-level aggregation. The results are in Sec IV-C2.
- O^2**-SiteRec without Time Semantics Level Attention (w/o SA)**: In order to verify the role of the multi-head attention mechanism in time semantics-level aggregation, we utilize mean aggregation to replace the attention mechanism. The results are in Sec IV-C3.

B. Overall Performance (RQ1)

We compare our approach with the baselines on two datasets and report the comparison results in Table III and Table IV, respectively. The results are the average performances of all the store types in test data. In the experiments of the simulation data, each baseline is only presented with Adaption settings and some metrics in Sec IV-A4 due to space limitation.

Overall, our method O^2-SiteRec consistently outperforms all the baseline methods on two datasets. The performance on the simulation dataset is worse than the real-world dataset due to the noise generated by the simulation and data sparsity. We also conduct a t-test for the significance test that our results are statistically significant with p-value$<$0.05 compared to the best baseline HGT.

Comparison to store site recommendation baselines (i.e., CityTransfer and BL-G-CoSVD). Our model is better than the site recommendation baselines for brick-and-mortar stores on two datasets. The possible reason is that just using location-related features for site recommendation cannot be adapted to the O2O scenario due to the courier capacity and the evolving customer consumption patterns. When we add the courier and customer features, the performance of these models improves, which indicates that the information of couriers and customers contribute to store site recommendation under the O2O model.

TABLE III: Performance comparison of different approaches on the real-world data

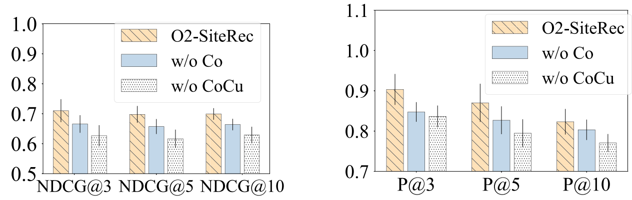
		NDCG@3	NDCG@5	NDCG@10	Precision@3	Precision@5	Precision@10	RMSE
CityTransfer	Original	0.6013	0.6234	0.6298	0.8056	0.8001	0.7902	0.0698
	Adaption	0.6192	0.6316	0.6445	0.8199	0.8137	0.7925	0.0687
BL-G-CoSVD	Original	0.5740	0.5865	0.5904	0.7608	0.7685	0.7522	0.1180
	Adaption	0.5776	0.5933	0.6088	0.7465	0.7706	0.7603	0.1101
GC-MC	Original	0.5445	0.5585	0.5837	0.7365	0.7350	0.7451	0.0705
	Adaption	0.5715	0.5825	0.6036	0.7598	0.7623	0.7501	0.0692
GraphRec	Original	0.5762	0.5825	0.6003	0.7821	0.7513	0.7266	0.0687
	Adaption	0.6274	0.6251	0.6398	0.8287	0.8124	0.7967	0.0680
RGCN	Original	0.5457	0.5537	0.5789	0.7593	0.7575	0.7279	0.0697
	Adaption	0.5524	0.5711	0.5993	0.7892	0.7641	0.7378	0.0684
HGT	Original	0.6149	0.6127	0.6258	0.8145	0.7984	0.7667	0.0681
	Adaption	0.6331	0.6298	0.6409	0.8276	0.8195	0.7762	0.0678
O^2-SiteRec	-	**0.7102****	**0.6978****	**0.7003***	**0.9034***	**0.8701***	**0.8232***	**0.0637***

** (*) means the result is significant according to T-test at level 0.01 (0.05) compared to HGT.

TABLE IV: Performance comparison of different approaches on the simulation data

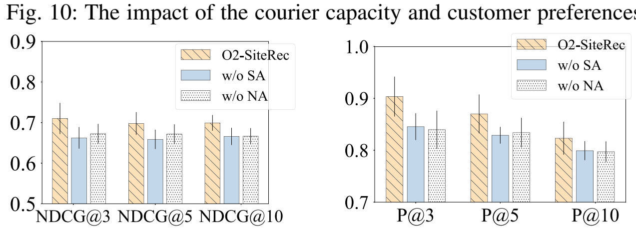
	NDCG@3	NDCG@5	Precision@3	Precision@5
Citytransfer	0.5677	0.6017	0.7777	0.7333
BL-G-CoSVD	0.5669	0.5993	0.7555	0.7066
GC-MC	0.5618	0.5935	0.7800	0.74333
GraphRec	0.5489	0.5801	0.7619	0.7238
RGCN	0.5499	0.5751	0.8040	0.7600
HGT	0.5657	0.6028	0.7963	0.7666
O^2-SiteRec	**0.6201***	**0.6509***	**0.8667***	**0.8200***

* means the result is significant according to T-test at level 0.05 compared to HGT.



(a) NDCG@K (b) Precision@K

Fig. 10: The impact of the courier capacity and customer preferences



(a) NDCG@K (b) Precision@K

Fig. 11: The effect of attention mechanisms

Comparison to graph-based general recommendation baselines (i.e., GraphRec and GC-MC). Graph-based recommendation methods are not as effective as our method due to the inability to capture complex relationships in the heterogeneous graph. These methods do not perform well in the Original setting while the performance improved in the Adaption setting, which means that it is difficult to utilize general recommendation methods directly for store site recommendations without considering the unique context.

Comparison to heterogeneous graph baselines (i.e., RGCN and HGT). Heterogeneous graph methods can capture practical information such as user preferences from the heterogeneous graph. However, they are still not as effective as our method. The possible reason is that they cannot consider the effect of edge attributes (e.g., multiple factors between store-region and customer-region) and multi-graph structure. In addition, we notice that HGT outperforms RGCN. The possible reason is that RGCN only utilizes simple message-passing that cannot fully capture the relationship.

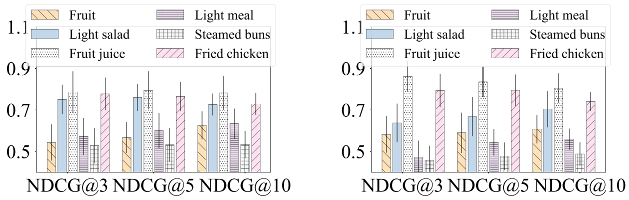
C. Ablation Study (RQ2 & RQ3)

1) The impact of the courier capacity and customer preferences: To understand the roles of courier capacity and customer preferences, we compare O^2-SiteRec with its two variants (i.e., w/o Co and w/o CoCu).

The performance of O^2-SiteRec and its variants is shown in Fig. 10. Firstly, we analyze the effectiveness of the courier capacity. When we do not consider any influence of the courier capacity, O^2-SiteRec w/o Co performs worse than O^2-SiteRec. It means that courier capacity is essential for boosting the recommendation performance. Secondly, we further investigate the impact of customer preferences. We find that without considering courier capacity and customer preference, the performance of recommendation deteriorates significantly. It justifies our assumption that courier capacity and customer preferences play an important role in store site recommendation under the O2O model, which improves the performance of store site recommendation.

2) The effect of node-level attention: To get a better understanding of the technical design, we further evaluate the effect of attention mechanisms. There are two different attention mechanisms in node-level aggregation and time semantics-level aggregation. We compare O^2-SiteRec with its two variants (i.e., w/o NA and w/o SA).

The results of the node-level attention on O^2-SiteRec are shown in Fig. 11. We observe that O^2-SiteRec w/o NA has worse performance than O^2-SiteRec. In the node-level attention, we consider the node attributes, the edge attributes (e.g., multiple heterogeneous factors), and the edge types when calculating the importance. O^2-SiteRec w/o NA replaces the aggregation function we designed by mean aggregation. These



(a) HGT (b) GraphRec

Fig. 12: Performance of different store types on the baselines

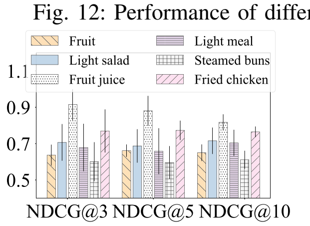


Fig. 13: Performance of different store types on O^2-SiteRec

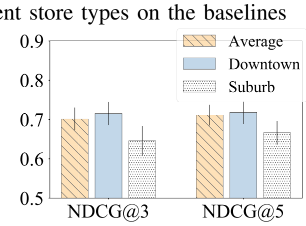


Fig. 14: The impact of the geographic distribution of regions

results demonstrate (i) multiple heterogeneous factors affect the interaction between store-region and customer-region; (ii) aggregation function in the node-level aggregation can effectively consider the influence of the edge attributes and the edge types.

3) The effect of time semantics-level attention: The results of time semantics-level attention on O^2-SiteRec are shown in Fig. 11. We observe that O^2-SiteRec w/o SA obtain worse performance than O^2-SiteRec. In O^2-SiteRec w/o SA, we utilize mean aggregation to replace the attention mechanism. These results demonstrate that (i) various types of stores have different concerns for different periods; (ii) the time semantics-level attention effectively distinguishes the importance of different periods.

D. Impacts of Factors (RQ4)

1) Results for different store types: Different store types generally have different region preferences. In order to have a clear understanding of the recommendation results for different types of stores, we select six types (light meal, light salad, fruit, steamed buns, juice, and fried chicken) to show the results, respectively. These six types are selected based on two principles: (i) the selected types have particular popularity; (ii) the selected types are common in daily life. We show the results of O^2-SiteRec and other baselines in Fig. 12 and Fig. 13, respectively. We only present the result of HGT and GraphRec due to the space limitation.

The result shows that O^2-SiteRec has good performances in most of the store types. In addition, we noticed some variability in the results for different types of stores, which may be determined by the inherent properties of the store type and how much data is available. For example, the stores with the type of steamed bun perform slightly worse than other types. The reason could be that people are more likely to finish their breakfast on the way to work rather than ordering food through O2O platforms due to time constraints. Besides, the variation in the performance of our model across store types is relatively small compared to other baselines.

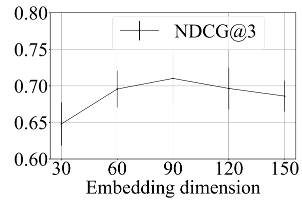


Fig. 15: Effect of different embedding sizes

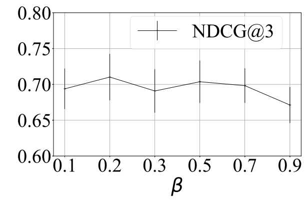


Fig. 16: Performance with different β

2) The impact of the geographic distribution of regions: In this part, we verify the performance of our method in different types of regions (i.e., geographic distribution). Specifically, we consider three types: downtown, suburb, and average (i.e., all the regions). As shown in Fig. 14, we can see that our model generally performs well for the various distribution of regions. The downtown regions perform slightly better than the average regions. The suburban regions performs worse than the other two settings. The main reason is that there are sparse data and insignificant features in the suburbs and it is challenging to discover the pattern of store sites.

E. Parameter Sensitivity (RQ5)

1) Effect of Different Embedding Sizes: Fig. 15 shows the performance comparison $w.r.t.$ the size of embedding in the region-type heterogeneous multi-graph. Overall, the performance is relative stable under different sizes. The best embedding size is 90. It indicates that a smaller embedding size has insufficient representation while a larger embedding size may increase complexity and cause overfitting. Given the space limitation, we only present the result of NDCG@3 while other matrices have the similar observations.

2) Performance with different β: We further study the sensitivity of our model to the parameter β. We present the result based on NDCG@3 in Fig. 16. The overall performance is stable. In our work, we select 0.2, which produces the best result for our model.

V. Discussion

Lessons learned: Based on the results from our paper, we summarize the following lessons learned:

- *Store site recommendation under the O2O model should take the courier capacity and customer preferences into consideration*, which makes it significantly different from the traditional brick-and-mortar store site recommendation. As shown in Fig. 10, the performance deteriorates significantly when ignoring the courier capacity and customer preferences. Similar results are obtained in the comparison of our model with baselines of Original setting in Table III.
- *Multiple heterogeneous factors influence the interaction between store-region and customer-region.* The performance of the model deteriorates when multiple heterogeneous factors are removed (as shown in Fig. 11). It also validates that the critical component of our model, i.e., node-level aggregation, effectively exploits the effect of multiple heterogeneous factors.

- *Various types of stores in different regions are sensitive to different periods*. As shown in Fig. 5, the popularity of store types changes a lot in different periods. We model this with time semantics-level aggregation, which improves the performance as shown in Fig. 11.

Limitation: (i) We evaluate our model O^2-SiteRec on a real-world dataset from one of the largest O2O platforms in China. However, due to the privacy and sensitivity of data, the period of evaluation datasets is one month and only in Shanghai. We further expect to analyze our model with the dataset from multiple cities and with long periods. (ii) In fact, many stores are registered on more than one platform. The model could be more accurate if we can obtain the data from multiple platforms. (iii) We only consider simple geographic proximity competition and complementarity while store competition under the O2O model becomes complicated due to delivery services from multiple platforms, which will be considered in our future work.

Ethics and privacy: The order data and couriers' trajectory data utilized in this paper are collected due to the operational characteristics of O2O platforms. For the customer information, all the customer IDs have been anonymized by the platform and customers' exact locations are replaced by coarse-grained regions with the size of 500 meters by 500 meters. We utilize the aggregated statistics of customers in each region, not involving the privacy information of individual customers. Similarly, store information is pre-processed in the same way. Couriers' trajectory data is under the consent agreement of the couriers, and we do not utilize this information to track the detailed trace of the couriers but only infer delivery time.

VI. Related Work

A. Store Site Recommendation

Existing works of store site recommendation can be divided into two categories: (i) small-scale survey-based methods and (ii) large-scale data driven methods. In the survey-based methods [10], [11], people carefully design questionnaires and interviews to obtain feedback from small-scale volunteers.

More recently, with the ubiquitously available infrastructures such as smartphones, we have a new opportunity to collect large-scale multi-source data such as check-in data, rating data, and search engine queries. Based on these data, a lot of works [12]–[17], [19], [32], [33] tend to build feature-based learning models that explore the features of stores from multi-source data. Geo-spotting [12] extracts a series of geographic and mobility features from city data to predict the popularity of candidate locations. The satellite image is ulitized in [13], [32] for business location selection. Some works [16], [19] consider the feedback of customers to recommend store sites.

There are also some works that are different from the general store site recommendation [15], [17], [34]–[36]. CityTransfer [17] focus on cross-city chain store location recommendation. Yu *et al.* [15] aims at recommending the shop types for a given location. Lian *et al.* [36] focus on store survival analysis. The most similar scenario is Deepstore [14] focusing on predicting the consumption level of different users. The purpose and considering supply (courier capacity) in our work make it significantly different.

These studies are mainly designed for offline brick-and-mortar stores, which are not suitable to solve the problem under the O2O model due to the significant differences in both the supply and demand aspects.

B. Graph Neural Networks and Applications in Recommendation Systems

Graph neural network work is generally divided into two categories, namely spectral-based GNNs [37], [38] and Spatial-based GNNs [23], [39]. However, the real-world graph usually comes with multi-types of nodes and edges and traditional graph neural network cannot be directly applied to heterogeneous graphs. Many existing works [40], [41] use meta-path to deal with heterogeneous graphs, which convert the heterogeneous graphs into homogeneous graphs. Other works directly deal with heterogeneous graphs without meta-path [30], [31], [42].

One of the most important applications of graph neural networks is recommendation systems [43]. The interaction between users and items is the core information, and they naturally form a user-item bipartite graph [29], [44]. In addition, the recommendation system adds other auxiliary information (e.g., social network and knowledge graph) to solve data sparsity and cold start problem [45]. Some studies [28], [46]–[48] have added a social network to the user side, which believes that their friends will influence personal interests. Other studies [49]–[51] add a knowledge graph to the item side to reveal the deep relationship between the user and the item, and also make the recommendation interpretable.

However, graph-based recommendation methods cannot be directly applied to our scene due to different data characteristics. Inspired by these methods, we utilize a heterogeneous multi-graph to model relations among store-region, customer-region, and store-type. We need to consider the multi-graph structure and the effect of edge attributes in our work.

VII. Conclusion

In this work, we focus on the problem of store site recommendation under the O2O model. We design a store site recommendation framework via multi-graph attention networks named O^2-SiteRec, which considers the courier capacity, customer preferences, and context features. The evaluation results show that O^2-SiteRec achieves 12.18% of improvement in the NDCG@3 metric and 9.01% of improvement in the precision@3 metric compared to other state-of-the-art methods.

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