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Identifying a good business location using prescriptive analytics: Restaurant location recommendation based on spatial data mining

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ABSTRACT

This study proposes a new prescriptive analytics method that aims to provide decision-makers with a systematic and objective approach to identify suitable locations, considering the spatial distribution of different types of restaurants. The method comprises of two main components: spatial co-location pattern mining and locationGCN, where locationGCN is based on graph convolutional network (GCN). The spatial co-location pattern mining is utilized to capture the spatial correlation of specific restaurant to determine the candidate location selection range. The locationGCN is designed to further screen out final suitable location ranges for the specific restaurant type. A case study using restaurant data from Xiamen Island collected from Dianping.com is conducted. The empirical results demonstrate that the algorithm achieves an accuracy of 74.88%, precision of 63.59%, and recall of 77.48%. Results indicate that the proposed approach can provide suitable location recommendations for specific types of restaurants based on existing restaurant distribution information.

1. Introduction

Selecting the right location is crucial for the business success (Chen & Tsai, 2016). Statistics reveal a harsh reality, with 17 % of restaurants failing within their first year, and a median lifespan of just 4.5 years for new restaurants (Luo & Stark, 2015). Chain restaurants, like The Cheesecake Factory in the United States, often employ a strategy of closing underperforming outlets while simultaneously opening new ones, leading to consumer churn (Soysal et al., 2019).

Many studies have concentrated on the descriptive analytics of location selection, exploring the correlation between restaurant location and regional characteristics at the regional unit level. However, a significant gap exists as these studies often lack concrete and practical methodologies to aid in making location decisions (Chen & Tsai, 2016).

Conversely, certain research efforts have focused on prescriptive analytics, utilizing methodologies like rough set methods (Chen & Tsai, 2016) and the analytic hierarchy process (Erdogan & Kaya, 2016). These studies transcend mere observation, offering practical solutions for restaurant companies to improve their decision-making processes. The core concept involves assigning weights to various indicators to obtain the evaluation scores. Nevertheless, a drawback of these methods is their uniform application of identical weights across diverse restaurant types. This limitation overlooks the intrinsic diversity and aggregation characteristics of various restaurant types, potentially leading to suboptimal location decisions.

The aggregation characteristics of restaurants often arise from the merging of diverse consumer groups, analogous to the impact of spatial dependence and spatial heterogeneity (Kim et al., 2020). Drawing parallels with the "coexistence" relationship among points of interest, the process of spatial co-location pattern mining enables the identification of restaurant types strongly correlated with specific categories in a given space (Yao et al., 2017). Stemming from economic geography, the geographical proximity theory posits that the spatial closeness of entities influences the performance of co-located actors, reflecting area characteristics (Nowinska, 2019). Consequently, the restaurant graph structure derived from co-location in different regions can provide valuable insights into understanding trade area characteristics and uncovering potential location opportunities. Nevertheless, it is noteworthy that there has been limited research specifically dedicated to exploring the structure of the restaurant graph.

Progress in computer science, data mining, and machine learning techniques has opened avenues for extracting spatial distribution

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information from existing restaurants (Kumar et al., 2018; Queenan et al., 2019). Nonetheless, effectively capturing the spatial distribution features of gatherings, particularly concerning restaurants, can still pose challenges.

This study introduces a prescriptive analytics framework that incorporates spatial co-location pattern mining and a graph convolutional network (termed as locationGCN). The aim is to effectively capture the spatial features of restaurants and provide support for location decisions. This framework contributes significantly to the field in several ways:

a) Theoretical Innovation: Theoretical innovation is a cornerstone of this study, emphasizing the consideration of the diversity of restaurant types in the location selection process. This recognizes the intricate superposition of restaurant characteristics, underscoring that, beyond distance relationships, other spatial relationships challenging to quantify through traditional methods should not be overlooked.
b) Methodology Innovation: The proposed method integrates advanced techniques from both spatial analysis (spatial co-location pattern mining) and machine learning (graph convolutional network). This comprehensive and data-driven approach captures and models the spatial features of restaurants. Spatial co-location pattern mining identifies the candidate location range, while the designed locationGCN delves into intricate spatial information beyond Euclidean data. This strategic use of locationGCN complements and addresses the limitations of spatial co-location.
c) Application Innovation: Focused on prescriptive analytics for location selection, our study introduces a novel data mining framework designed to provide decision support for restaurant location decisions. This framework extends the application of the combination of co-location and GCN to address challenges in the domain of location selection.

The paper is organized as follows: Section 2 reviews the relevant literature. Section 3 outlines the spatial data mining method proposed for location selection. In Section 4, empirical studies demonstrate the effectiveness of the proposed approach, with results compared to other methodologies. Finally, Section 5 concludes the paper and discusses future research directions.

2. Literature review

This work focuses on prescriptive analytics for location selection, offering a recommendation based on a spatial data mining method that incorporates co-location and GCN. In this section, we delve into each, emphasizing the aspects most pertinent to the problem under study.

2.1. Prescriptive analytics

Unlike descriptive and predictive analytics, prescriptive analytics is geared towards identifying the optimal course of action for the future. Its aim is to provide adaptive, automated, constrained, time-dependent, and optimal decisions (Charles Vincent et al., 2022). From a human intervention standpoint, prescriptive analytics can be divided into two types: decision-making and decision automation (Lepenioti et al., 2020). Decision-making involves offering recommendations, while decision automation entails the execution of the prescribed action.

Despite being considered relatively immature compared to descriptive and predictive analytics, prescriptive analytics has seen increased application in various fields in recent years. Examples include urban facility planning (Brandt et al., 2021), stochastic dynamic vehicle routing problems (Soeffker et al., 2022), and so on. These instances represent recent advancements in the field of business analytics.

Indeed, there is a growing trend towards employing machine learning and data mining for prescriptive analytics (Hauser et al., 2021; Notz & Pibernik, 2022). Lepenioti et al. (2020) have emphasized that prescriptive analytics models have the potential to provide more objective advice than traditional analysis. Therefore, in the context of location selection research, the integration of prescriptive analytics is seen to effectively mitigate the impact of subjectivity.

2.2. Location selection theory and approach

The location selection problem has been thoroughly examined in various literatures. Classic location theories, such as the central place theory (Bustin, 2020) and spatial interaction theory (Wieland, 1932), assert that the distance between the store and the customer is a crucial factor in location selection. Recent research reinforces the ongoing significance of geographic proximity in supply chain location selection (Bray et al., 2019). Additionally, Aksoy and Yetkin Ozbuk (2017) highlight accessibility and convenience as influential factors in hotel location selection.

As transportation advances, the significance of physical distance diminishes, but geographic convenience remains crucial. Studies have shifted focus to various trade area characteristics, including consumer factors (Dan & Marcotte, 2019), demographics (Cao et al., 2020), market conditions (Yang et al., 2017), and demand interactions (Huang et al., 2019). Yang and Mao (2020) argue that store distribution in a trade area results from both competition and agglomeration effects. Kim et al. (2021) used a spatial econometric model to identify spatial spillover effects of agglomeration economies. However, capturing the complex interaction solely through mathematical models remains challenging. This paper addresses this challenge by constructing a restaurant graph to capture spatial interaction information, focusing on mining spatial location relevance to discern regional characteristics.

Yang et al. (2017) showcased a strong correlation between the number of different restaurant types in each region and demographic characteristics. Their findings imply that the appropriateness of a location depends on the specific types of restaurants it hosts. Therefore, we emphasize the importance of considering the diversity of restaurant types in the process of location selection.

So far, a limited number of studies have delved into restaurant location issues (Chen & Tsai, 2016), while multi-criteria decision-making (MCDM) approaches are generally adopted in it (Liu et al., 2020). However, these methods often involve complex artificial evaluations and are inherently subjective. Therefore, this paper aims to introduce a novel prescriptive analytics method to enhance the efficiency and objectivity of restaurant location selection.

2.3. Spatial data mining

Recently, there has been a notable interest in spatial data mining methods, with the analysis of spatial associations being a crucial component (Bai et al., 2016). Particularly, spatial co-location has been successfully applied in studying location selection for hotels and other facilities (Yan et al., 2018). However, no scholars have applied co-location pattern mining to restaurant location research.

Spatial co-location models effectively capture the aggregation of spatial features, yet they often fall short in considering specific spatial relationships among points of interest and may not thoroughly explore these relationships (Wang et al., 2022; Yao et al., 2018). Some researchers have employed spatial co-location models for points of interest recommendations (Chen et al., 2022). However, they primarily mined relevant mobility patterns, and the effectiveness of these models is frequently hindered by data sparsity issues (R. J. Hu et al., 2022). There is also a significant portion of scholars who is dedicated to improving the efficiency of co-location algorithms (Z. Hu et al., 2022; Wang et al., 2024; Wu et al., 2022). However, no research exploring the integration of emerging graph deep learning techniques with co-location studies.

In recent years, various advanced models for location selection have been proposed (Jiao et al., 2020), incorporating metaheuristic algorithms (Dan & Marcotte, 2019), data mining (Chen & Tsai, 2016), and machine learning (Han et al., 2022). Among these, the graph convolutional network (GCN) stands out, which is a simplified graph convolutional neural network proposed by Kipf and Welling (2016).

The application of GCN has garnered increasing attention in recent research (Lee & Rhee, 2022). The widespread use of GCN is attributed to its ability to integrate node feature information and local structure information, facilitating the processing and learning of non-Euclidean data (Kipf & Welling, 2016). This capacity addresses the limitation of co-location methods, which often fall short in mining spatial interaction relationships between points. Non-Euclidean data, characterized by irregular spatial structures like social networks and points of interest networks, is well-suited for representation using a graph structure (Kipf & Welling, 2016). Consequently, our approach aims to combine spatial co-location pattern mining with GCN, creating an innovative spatial data mining framework tailored for restaurant location decisions.

3. Proposed method

In the following, we describe how we deal with the restaurant location selection problem as sequential decision processes. The processes are shown in Fig. 1.

Like other prescriptive analytics processes, the information model is constructed at first to predict which kind restaurant is encouraged to locate together with, where we introduce the co-location pattern mining to predict the candidate range of location selection. Then we propose the decision-making method based on locationGCN to further reduce the scope of location selection and determine the final location selection. To make the process clearer, we introduce the key parts of processes in this section.

3.1. Divide the dataset into training set and testing set

Referring to Bao and Wang (2018), to not disrupt the spatial continuity of the data, we divide the area into square grids of the same size and divide the dataset according to the number of grids. The partitioning process is shown in Appendix A algorithm 1.

3.2. Construct the restaurant graphs with labels

Using the obtained training set and testing set, separate restaurant graphs are constructed. Given that, in the real world, improper site selection often results in low restaurant revenue and eventual closure (Chen & Tsai, 2016), we can assume that the location selection of existing restaurants is generally appropriate to some extent. Therefore, a graph containing a specified type of restaurant is labeled 1, indicating the location is suitable for that type of restaurant. Conversely, if a specified type of restaurant is not present in the graph, it is labeled with 0, signifying that it is unsuitable for location selection.

Assuming that the specified type of restaurant is O, its corresponding restaurants in the space are set as O_λ ($\lambda \in [1, \Lambda]$), where Λ is the total number of the restaurant of type O. Then, with O_λ as the center of the circle, and the distance threshold $\widehat{d}$ as the radius, search the restaurant nodes that maintain the neighbor relationship with the restaurant O_λ to form a graph G_λ, which is labeled 1.

In addition, for the rest restaurants that do not keep the neighbor relationship with the specified type of restaurants, we use hierarchical clustering to merge them into cliques. To ensure that any two nodes in the same cliques keep neighbor relationship with each other, the hierarchical clustering based on longest distance method is adopted. It means that the distance between two cliques is measured by the distance between the farthest points within these two cliques. The clustering process as follows: merge the closest samples into one clique, and then merge the two closest cliques each time, where the merging operation is only taken when the distance between two cliques is shorter than distance threshold $\widehat{d}$. Consequently, when the distance between any two cliques beyond distance threshold $\widehat{d}$, the merging process stops, and final cliques are obtained, which are regarded as graphs labeled 0.

Fig. 2 shows the examples that contains five constructed graphs. Graph G_1, graph G_2, and graph G_5 are labeled 1, and graph G_3 and graph G_4 are labeled 0.

As shown in Fig. 2, the distance between graph G_3 and graph G_4 is determined by the distance between restaurant A3 and restaurant B4, because it is the farthest distance between nodes in graph G_3 and graph G_4. Besides Fig. 2 also shows the situation that there is more than one

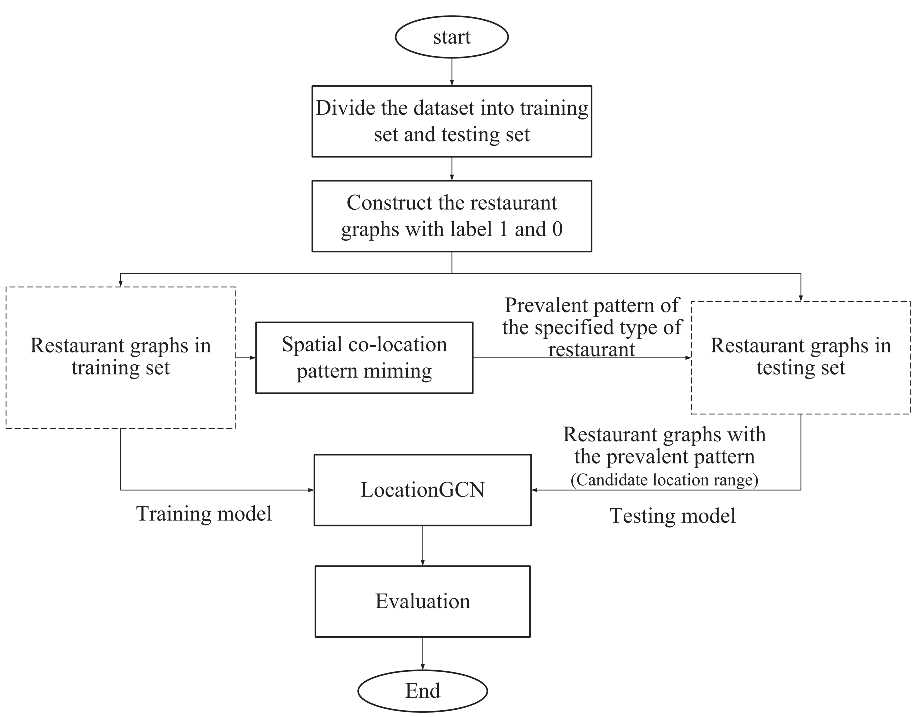


Fig. 1. The framework of proposed method.

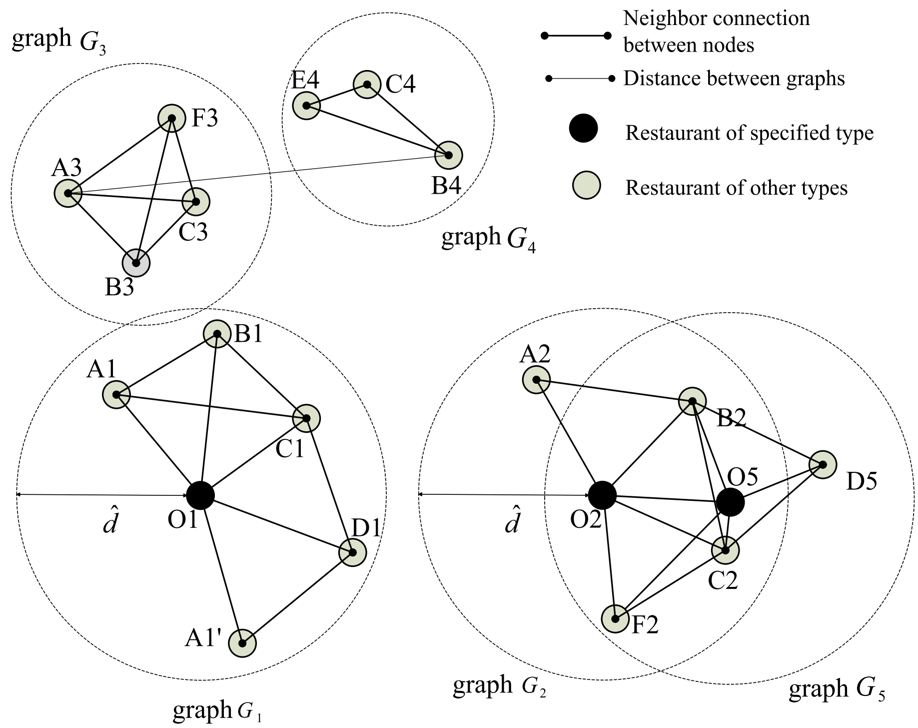


Fig. 2. Example for explanation of constructing graphs.

restaurant of the specified type in the constructed graph. Taking graph G_2 and graph G_5 as examples, both restaurant *O5* and restaurant *O2* are the specified type of restaurant. While in graph G_5, restaurant *O5* is taken as the central restaurant and restaurant *O2* is remained as the neighbor restaurant which has the same type as the central restaurant. But in graph G_2, it is reverse. It should be noted to distinguish the central restaurant and its neighbor restaurants though their types maybe the same.

3.3. Spatial co-location pattern mining

After obtaining the restaurant graphs, using the spatial co-location pattern mining based on maximal clique (Zhang et al., 2022) to find the prevalent co-location pattern of the restaurant with specified type. Because the focusing is to find out the types that the restaurants of specified type tend to locate around, the spatial co-location pattern mining process is only carried out based on the restaurant graph with label l in training set.

3.3.1. Basic concepts

Center restaurant: It identifies the restaurant object with specified type that we regard as the center of the restaurant graph.

Spatial feature of the restaurant in neighbor range: It is the type of neighbor restaurant, like the feature set of the graph G_1 in Fig. 2 is $\{A, B, C, D\}$.

Co-location pattern of specified type of restaurant: It is the set of a series of spatial features within the neighbor range of specified type of restaurant, besides, any two restaurants in co-location pattern keep neighbor relationships with each other. For example, one of co-location pattern of specified type restaurant in graph G_1 in Fig. 2 is $\{A, B, C\}$.

Spatial instance: It is the corresponding objects of spatial feature in locations, like the spatial instance of A in graph G_1 in Fig. 2 is $A1$ and $A1'$.

Spatial co-location instance: It is a set of objects where every object in the co-location pattern keeps the neighbor relationship with each other, like one of the instances of the co-location pattern $\{A, B, C\}$ in Fig. 2 graph G_1 is $\{A1, B1, C1\}$.

Prevalent co-location pattern of specified type of restaurant: When the occurrence frequency of spatial co-location pattern reaches a threshold, the spatial co-location pattern is considered prevalent.

It's essential to note that to distinguish whether there are another specified restaurant instances in neighbor range of the specified restaurant, the above sets do not contain the information of center restaurants instance. For example, if the instance of specified type O is a Chinese restaurant, and the prevalent co-location pattern is {Chinese restaurant, Japanese cuisine, snacks}, it means that Chinese restaurant tends to locate with other Chinese restaurant, Japanese cuisine restaurants, and snacks shop in the neighbor area. Therefore, a location that contains other Chinese restaurant, Japanese cuisine restaurants, and snacks is advise to as candidate addresses for Chinese restaurants.

In particular, the "Chinese restaurant" in prevalent co-location indicates that there is at least one another neighbor restaurant whose type is Chinese restaurant, and the neighbor Chinese restaurant tends to have a positive spillover effect on the central Chinese restaurant. Conversely, if the prevalent co-location pattern is {Japanese cuisine, snacks}, it represents that there is no other instance of specified type restaurant in the neighbor range, which may mean that if this type of restaurant gathers, it will mostly generate a fierce competitive effect. Thus, this type of restaurant tends to select location dispersedly.

3.3.2. Prevalent co-location pattern mining process

The process of prevalent spatial co-location pattern mining method with join-base is a time-consuming process (Yao et al., 2016). Therefore, the prevalent spatial co-location pattern mining method based on maximal clique (Zhang et al., 2022) is adopted in this paper. The process of the detail mining contains three main steps.

a) Finding the spatial co-location instances to obtain the corresponding spatial co-location pattern.

We only pay attention to the co-location pattern which contains the specified type of restaurant. Therefore, we focus on the restaurant distribution graph G_λ labeled 1, finding out the spatial co-location instances to determine the existing co-location patterns of specified type of restaurant. Based on the idea of Bron-Kerbosch algorithm (Zhang et al., 2022), the spatial co-location instances are found out by determining the maximal clique set of the specified type of restaurant. The process of mining the maximal clique set is shown in Appendix A algorithm 2, where the central restaurant instance is not shown in the maximal cliques.

Taking the Graph G_1 in Fig. 2 as an example, according to the Algorithm 1, the maximal cliques of specified type of restaurant in G_1 include $\{A_1, B_1, C_1\}$, $\{C_1, D_1\}$, and $\{D_1, A_1^{'}\}$. Therefore, the corresponding co-location patterns of specified type of restaurant is $\{A, B, C\}$, $\{C, D\}$, and $\{D, A\}$.

b) Calculating the participation rate and participation degree of each co-location pattern.

The spatial co-location pattern mining algorithm is used to capture the prevalent co-location pattern in training set, thus the counting of instances in this section is only in training set. We define the instance number that each feature participates to the co-location pattern instances as symbol a, and the total spatial instance number of each feature as symbol b, then the participation rate of each feature in co-location pattern is the ratio of a to b. It's important to note that b contains the spatial instance of feature point in the graph labeled 0. While the participation degree of spatial co-location pattern is the minimum value of the participation rate. Taking the co-location pattern $\{A, B, C\}$ in Fig. 2 as an example, its participation degree is $\frac{3}{4}$.

c) Determining the prevalent co-location pattern.

Initially, a hyper-parameter named participation threshold is determined. When participation degrees of spatial co-locations surpass the participation threshold, we categorize the spatial co-location pattern as a prevalent co-location pattern.

The process of determining the prevalent co-location patterns is shown in Appendix A algorithm 3. When the current spatial co-location pattern is not prevalent, it needs to continue to judge whether its subsets are prevalent. The judging process only stops when the subset only contains one feature, or it is a prevalent co-location pattern.

The obtained prevalent co-location pattern represents a stable market state, reflecting the experiential information of location selection (Bao & Wang, 2018). It unveils the distribution characteristics of restaurants, indicating which types of restaurants tend to cluster together. Unlike previous literature (Yan et al., 2018), we retain all prevalent co-location patterns rather than only focusing on those with a large number of feature types. However, relying solely on prevalent co-location patterns is inadequate for determining the appropriate location for a specified type of restaurant, as it overlooks other restaurant features. Therefore, prevalent co-location patterns are only used to establish the candidate location selection range, and locationGCN is introduced to further explore spatial information to determine the final locations.

3.4. LocationGCN model construction

The distribution of restaurants in space often seems irregular, and under the interaction of spillover effects and competitive relations, different types of restaurants may adopt different location strategies. locationGCN can analysis the spatial relationships of different types of restaurants to further reduce the scope of location selection. In this section, we firstly introduce the definition of graph information, which is as the input of locationGCN, then the specific mining process is described, and the final location selection is decided.

3.4.1. Definition of graph information

Define the graph as $G = (V, E, X)$, where V denotes the set of vertexes, and $V = \{v_i | i = 1, 2, ..., n\} \in R^n$, n is the total number of nodes in each graph, E represents the set of edges, and X is the normalized feature matrix of node, $X = [x_1, x_2, ..., x_n]^T \in R^{n \times c}$, where each feature is a c dimension feature vector, $x_i \in R^c$.

To mitigate the impact of information from the central restaurant in the graph labeled 1 on the classification results, the feature vector of the central restaurant node is intentionally left empty. Consequently, the central node lacks feature information but serves as a conduit for other nodes to exchange information.

Based on Tobler's first law of geography that the closer the distance is, the stronger the spatial objects are related (Joo et al., 2017), we use the distance relationship between restaurants to describe the relationship between restaurants. Therefore, the adjacent matrix is shown as formula (1):

$$A_{ij} = \begin{cases} \frac{1}{d_{ij}}, (v_i, v_j) \in E \\ 0, (v_i, v_j) \notin E \end{cases} \tag{1}$$

Where A_{ij} is the adjacency relationship between node v_i and v_j, which forms the adjacency matrix A, $A \in R^{n \times n}$. Symbol d_{ij} denotes the distance between restaurant nodes. Only when there is a connection between node v_i and v_j, there is an adjacency correlation between them.

Then the input graph information of locationGCN is obtained, including feature matrix and adjacent matrix.

3.4.2. locationGCN network structure

locationGCN takes restaurant graph set as the input, and outputs the corresponding labels. The network structure of locationGCN is shown as Fig. 3. There are three important modules: convolution layer, global pooling layer, and softmax function.

a) Convolutional layer.

This paper constructs the convolution model based on the model proposed by Kipf and Welling (2016), which is shown as formula (2):

$$H_V^{(l+1)} = \sigma\left(\widetilde{D}^{-\frac{1}{2}}\widetilde{A}\widetilde{D}^{-\frac{1}{2}}H_V^{(l)}W^{(l)}\right) \tag{2}$$

Formula (2) is the propagation rule for GCN, symbol $H_V^{(l)}$ is the output of all nodes in the layer l, $H_V^{(0)} = X$, $\widetilde{A} = A + I$, $\widetilde{D}_{ii} = \sum_j \widetilde{A}_{ij}$, and symbol $W^{(l)}$ is the parameter matrix to be trained for the layer l, and σ is the activation function.

The convolutional layer is employed to aggregate spatial information for each point. The output from the previous layer serves as the input for the current layer. After each convolutional layer, the information for the points is updated.

b) Global pooling layer.

As this paper involves multiple graph classification, the global pooling layer is utilized to consolidate the outcomes of all nodes on a single graph to derive the graph's classification information. Following the approach outlined in the literature (Li et al., 2015), the pooling mechanism is defined by formula (3).

$$\widetilde{Y}_\lambda = \tanh\left(\sum_{v \in V} \sigma\left(f_1\left(H_v^{(l+1)}, x_v\right)\right) \odot \tanh\left(f_2\left(H_v^{(l+1)}, x_v\right)\right)\right) \lambda = 1, 2, 3, ..., TG \tag{3}$$

where symbol $\widetilde{Y}_\lambda$ is the outputs of global pooling layer of graph G_λ, TG is the total number of graphs, $f_1(\cdot)$ and $f_2(\cdot)$ are the full connected functions, and its inputs are convoluted feature and the normalized feature of each node in G_λ. $\sigma(\cdot)$ is a soft attention mechanism, which can make the networks pay more attention to the more important points. $\tanh(\cdot)$ is an activation functions, and $\odot$ is an operational symbol, which can multiply elements of two matrices based on their corresponding position.

c) Softmax function

As it is a binary classification problem, the softmax function is applied to map the output results of the pooling layer into the range of 0–1, as depicted in formula (4).

$$\widehat{Y}_\lambda = \mathrm{softmax}(\widetilde{Y}_\lambda) = \frac{\exp\left(\widetilde{Y}_\lambda\right)}{\sum_\lambda \exp\left(\widetilde{Y}_\lambda\right)} \lambda = 1, 2, 3, ..., TG \tag{4}$$

where symbol $\widehat{Y}_\lambda$ is the predictive value, which refers to the probability that graph G_λ corresponds to label 1, then its probability of label 0 is

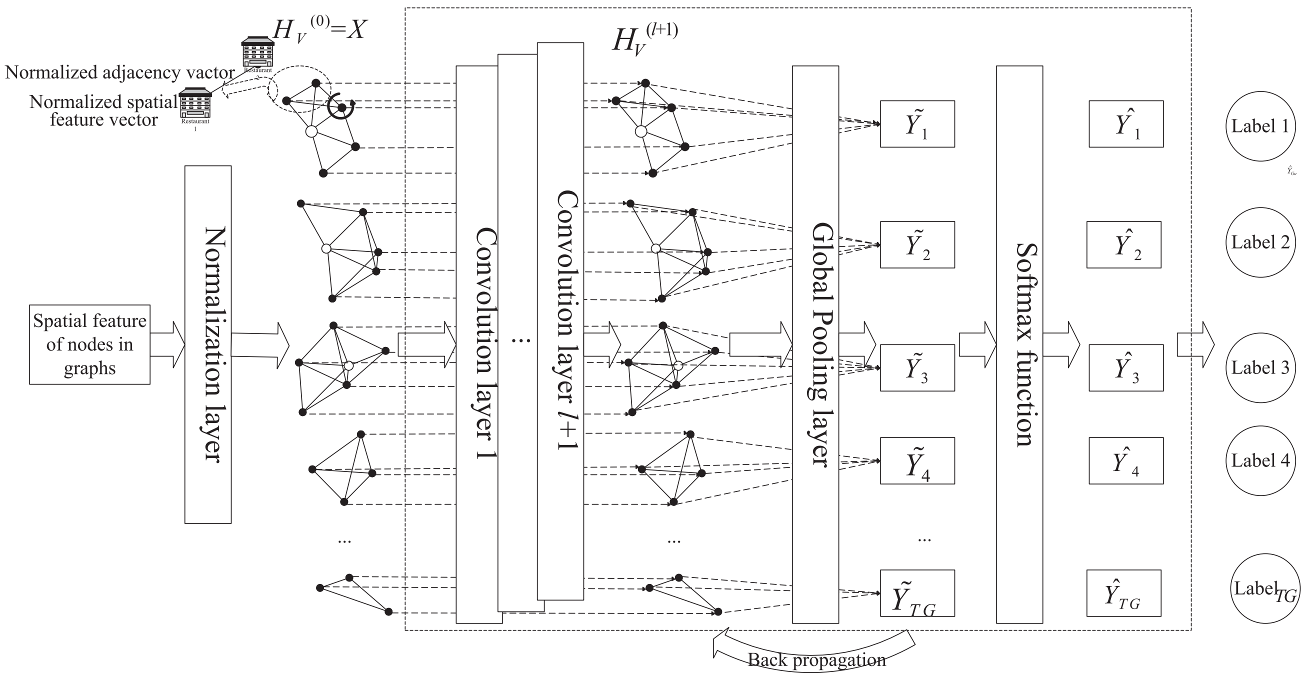


Fig. 3. The network structure of locationGCN.

$1 - \widehat{Y}_\lambda$.

The entire network utilizes a backpropagation algorithm for weight updates, and we employ the adaptive moment estimation (Kingma & Ba, 2014) as the optimizer. Given that this study is a classification problem, we compute the loss function using cross-entropy, as illustrated in formula (5).

$$L = -\sum_{\lambda} Y_\lambda \ln \widehat{Y}_\lambda \lambda = 1, 2, 3, ..., TG \tag{5}$$

where symbol Y_λ is the actual value of G_λ.

Finally, the predict label value u_λ is determined by the formula (6):

$$u_\lambda = \begin{cases} 0, \widehat{Y}_\lambda < 0.5 \\ 1, \widehat{Y}_\lambda \geqslant 0.5 \end{cases} \tag{6}$$

3.4.3. Determine final location selection scope

Using locationGCN, we conduct a secondary screening on instances in the testing set that meet the criteria of the prevalent co-location pattern. Subsequently, we identify the restaurant instances that are most suitable for the specified restaurant to gather. Managers can make informed decisions on the optimal location for the specified restaurant by referring to these identified restaurant instances. The final location selection scope, depicted in the shaded area, is illustrated in Fig. 4.

As depicted in Fig. 4, three restaurants (A, B and C) are notably associated with the specified type of restaurant. By taking the distance threshold $\widehat{d}$ as the radius, the optimal scope for the location selection of specified restaurant is determined by the overlap of the three regions, indicated by the shaded area.

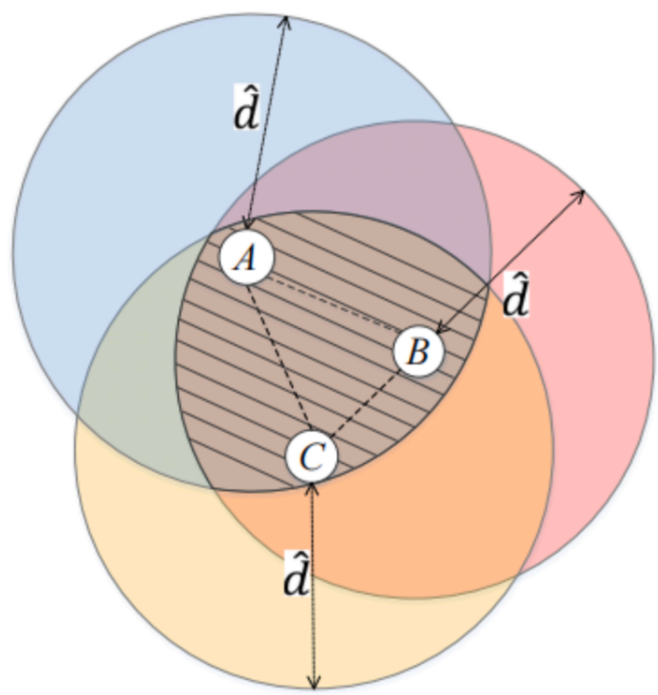


Fig. 4. The illustration of final scope of location selection.

3.5. Evaluation method

The predicted results can be classified into four categories:

True positive (TP): The actual value is positive ($Y = 1$), and the predicted value is positive ($\widehat{Y} = 1$).

False positive (FP): The actual value is negative ($Y = 0$), and the predicted value is positive ($\widehat{Y} = 1$).

True negative (Soysal et al.): The actual value is negative ($Y = 0$), and the predicted value is negative ($\widehat{Y} = 0$).

False negative (FN): The actual value is positive ($Y = 1$), and the predicted value is negative ($\widehat{Y} = 0$).

For classification problems, this paper employs four main evaluation indicators: accuracy, precision, recall, and AUC. Formulas (7), (8), and (9) depict the calculation of accuracy, precision, and recall. Meanwhile, AUC represents the area under the ROC curve, with the ROC curve's abscissa denoted as FPR (as shown in formula (10)), and the ordinate equivalent to recall. AUC values exceeding 75 % indicate a well-performing predictive model.

$$accuracy = \frac{TP + FN}{TP + FP + TN + FN} \tag{7}$$

$$precision = \frac{TP}{TP + FP} \tag{8}$$

$$recall = \frac{TP}{TP + FN} \tag{9}$$

$$FPR = \frac{FP}{FP + TN} \tag{10}$$

A total of 10 experiments are conducted, and the average of all evaluation values is calculated to represent the algorithm's performance under various parameter settings.

4. Case study

4.1. Data acquisition

We utilized restaurant data from the "Food" section of the website "https://www.dianping.com" in December 2019 as a sample for our study. Dianping.com is the leading platform for consumer reviews of daily consumption experiences in China, comparable to Google Review. The extracted fields include restaurant name, code, type, administrative district, specific address, average price, taste, environment, and service rating.

We created a feature vector for each restaurant node, incorporating the average price, taste rating, environment rating, service rating, and restaurant type. To validate the accuracy of the restaurant data, we cross-referenced it with information obtained from Baidu Map (https://map.baidu.com). After acquiring basic details, we utilized the Baidu Map open platform (https://lbsyun.baidu.com) to retrieve the longitude and latitude of each restaurant based on its address.

4.2. Data pre-processing

We classified the crawled restaurant data into two tiers, H1 and H2 (refer to Appendix B), based on the official restaurant industry classification standard from the State Food and Drug Administration (SFDA) and the National Bureau of Statistics (NBS) "Statistical Classification of Living Services (2019)." This classification was complemented by *Dianping.com's* own categorization method, aligning with the respective criteria.

The initial parameters for the algorithm are defined as follows: for co-location pattern mining, the distance threshold ($\hat{d}$) is set to 100 m, the participation threshold is 0.3, and the training set proportion is 2/3. In LocationGCN, the validation set proportion is 1/2, the number of iterations is 200, and the initial learning rate is 0.01.

4.3. Location selection experiment

4.3.1. Data description

We gathered a total of 13,539 pieces of restaurant data from *Dianping.com* for Xiamen Island, utilizing the latitude and longitude information of the crawled restaurants. Some nodes overlapped on the map due to proximity or being on different floors of the same location, rendering them not visible.

4.3.2. Example of calculation analysis

We use the grid method to process data, dividing the map of Xiamen Island into 71 grids. Each grid is approximately 1510 m wide. The grids can cover the entire range of the Xiamen Island map, and the redundant area is relatively small. Then, 47 grids are used as training areas and 24 grids as the test areas.

We chose "Dinner-Western food" and "Fast food-Western food" as examples, with second tier category "Western food". The results of the algorithm can be observed for restaurants with the same taste at different price levels.

The results indicators for the two experiments are presented in Table 1. The ultimate prevalent co-location patterns for restaurants of the type "Dinner-Western food" include: {Dinner-Japanese food, Casual dining-Cafes, Dinner-Seafood}, while for restaurants of the type "Fast food-Western food" include: {Fast food-Seafood, Casual dining-Drinks}, {Dinner-Seafood, Dinner-Hotpot, Casual dining-Cafes}, {Dinner-BBQ, Casual dining-Drinks, Fast food-Western food}. Fig. 5 illustrates the algorithm's results for these two types of restaurants.

Table 1 reveals that the algorithm yields different results for specified types of restaurants under different categories. Restaurants categorized as "Dinner-Western food" tend to be more upscale, offering higher-quality products and dining environments. Among the strongly associated restaurants in this category, aside from cafes, there are mainly higher-priced formal dining options, indicating a higher spending capacity among these consumers. In contrast, "Fast food – Western food" covers a larger area on the island and has more prevalent co-location patterns, suggesting a broader association with various restaurant types. In terms of accuracy, the algorithm for "Dinner-Western food" is less precise because there are more false positives (areas with yellow dots but not covered by blue dots in Fig. 5 (a)). However, this also implies the presence of potential consumers in these areas and the possibility of emerging new restaurants of this type.

Compared to the high-end "Dinner-Western food," "Fast food – Western food" is more accessible and has a wider distribution. It exhibits more prevalent co-location patterns, showing strong associations not only with other fast food and casual dining establishments but also with some restaurants in the formal dining category. The presence of multiple prevalent co-location patterns indicates that the distribution of "Fast food – Western food" restaurants is influenced by three main types of patterns, as reflected in the results. It is conceivable that these three distribution patterns represent three types of shopping areas suitable for locating "Fast food-Western food" restaurants, each with the potential to attract different preferences.

Taking one of the patterns of the "Fast food-Western food" type, {Dinner-Seafood, Dinner-Hotpot, Casual dining-Cafes}, as an example, it represents the characteristic of a large commercial plaza, while {Fast food-Seafood, Casual dining-Drinks} is more akin to the setup of an affordable food court. In terms of the numerical results, Fig. 5 (b) shows that some shop locations are still not identified, indicating more false-negative cases (areas with only blue dots but not covered by yellow dots in Fig. 5 (b)). This results in a low recall in the findings, suggesting that there might be a different clustering pattern with other types of restaurants in the test area compared to the training area for "Fast food – Western food".

4.3.3. Sensitivity analysis

To assess the impact of each parameter on the algorithm results and identify suitable parameters, experiments are conducted for all categories in sequence. The average values of the evaluation indicators obtained in each experiment are then used to gauge the algorithm's performance.

a) *Number of neural network layers.* The results (Table 2) indicate a noticeable drop in the accuracy of the algorithm when increasing the number of convolutional layers. This decline could be attributed to the expanded consideration of neighboring nodes by LocationGCN, extending from the first level to multiple levels when increasing the

Table 1
Calculation results of the algorithm in %.

Specify type	Accuracy	Precision	Recall	AUC
Dinner – Western food	75.66	30.61	83.33	78.98
Fast food – Western food	80.28	69.49	73.21	78.71

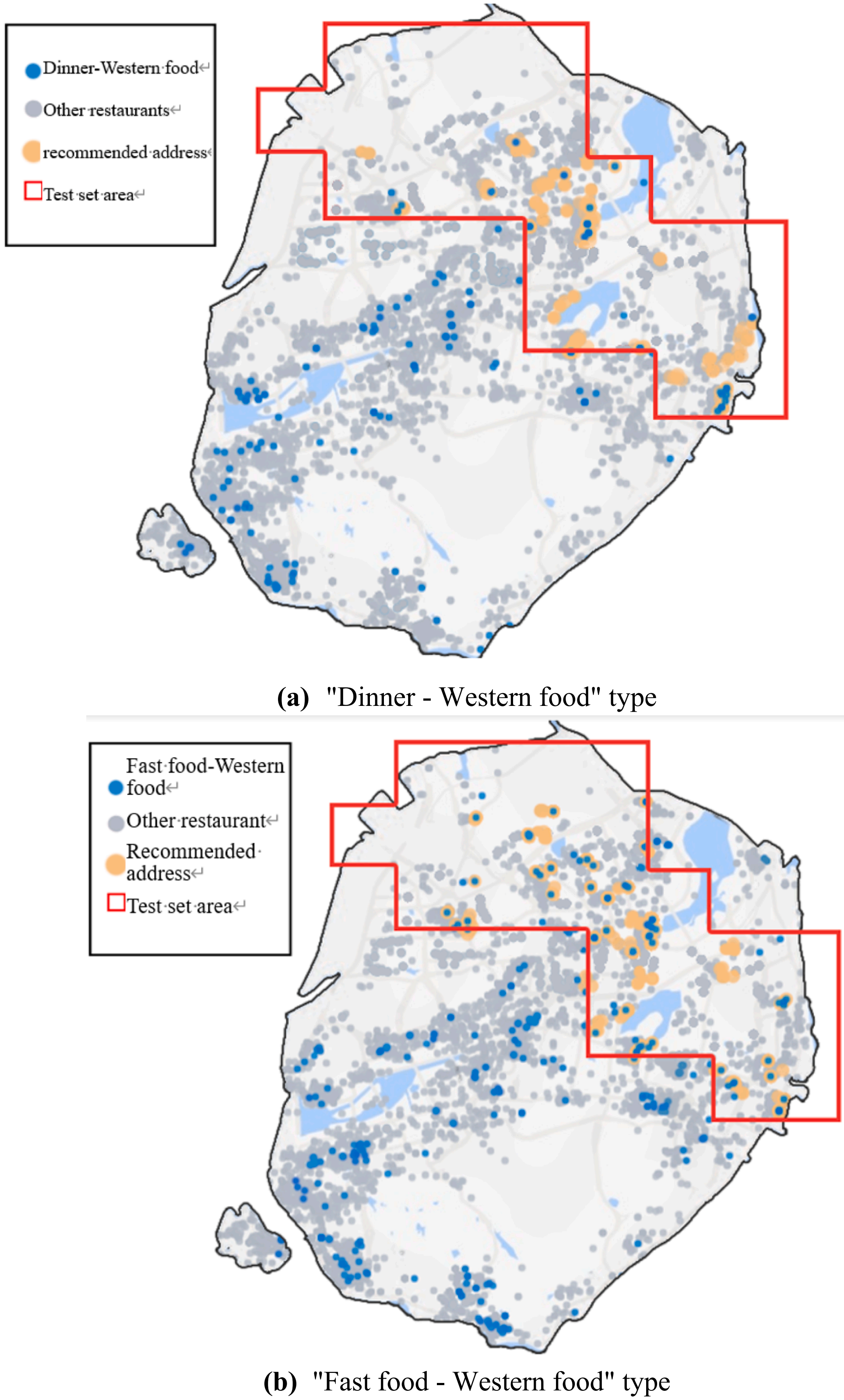


Fig. 5. Results of the algorithm. (a) "Dinner – Western food" type. (b)"Fast food – Western food" type.

number of convolutional layers. Excessive convolutional layers may lead to over-smoothing, causing the distinctions between nodes to blur and diminishing the algorithm's effectiveness. Consequently, the algorithm employs only one convolutional layer.

b) *b.Distance threshold.* As depicted in Fig. 6, in this experiment, the optimal distance threshold is found to be between 50 m and 100 m, indicating that restaurants within this proximity around the specified type of restaurant have the most significant impact. This contrasts notably with the findings of Bao and Wang (2018), who identified

Table 2
Performance of the algorithm with different number of convolution layers (Unit: %).

Number of convolution layers	Accuracy	Precision	Recall	AUC
1	74.88	63.59	77.48	75.40
2	61.70	50.00	27.78	55.27
3	59.96	42.99	26.14	52.93

the optimal distance threshold as 2 km. The difference arises due to the relatively close clustering of restaurants in this study compared to the location of POIs in the literature, necessitating a smaller optimal distance threshold for the algorithm.

c) *Participation threshold.* As shown in Fig. 7, when the participation threshold is too small, all indicator values are low. This is due to a large number of less-associated restaurant patterns being considered as prevalent co-location patterns in LocationGCN. On the other hand, when the participation threshold is too large, fewer patterns are retained, leading to the omission of many viable regions, causing a decrease in accuracy, recall, and AUC. Consequently, the participation threshold is set at 0.3.

4.3.4. *Algorithm comparison results*

To affirm the superiority of the co-location + LocationGCN algorithm in this study, comparative experiments were conducted. The results, based on the data introduced in section 4.3.1, are presented in Table 3.

The experimental data show that the co-location + LocationGCN algorithm employed in this study outperforms other machine learning algorithms. This superiority can be attributed to several factors. Firstly, the traditional co-location algorithm, which filters the number of categories included in the pattern to obtain the final prevalent co-location pattern, tends to discriminate some feasible regions as infeasible, resulting in its lowest recall. Additionally, the traditional co-location algorithm can only capture spatial information from Euclidean data, neglecting the complex superposition of restaurant characteristics, leading to high false positives (FP) and low precision. Secondly, using LocationGCN alone lacks a filtering indicator for restaurant types initially, resulting in bias generated by data imbalance. Lastly, the CNN algorithm cannot effectively consider the spatial distribution of restaurants; it only takes the type of restaurants and other information as input data, leading to lower performance across all indicators compared to the algorithm used in this study. Consequently, the co-location and LocationGCN-based algorithm proves more suitable for location selection decision-making.

4.4. *Prescriptive analytics of restaurant locations and consumer preferences*

To investigate how diverse flavors and price ranges influence the spatial arrangement of restaurants in distinct regions, we conducted an

Table 3
Comparison of the performance of the various algorithms (Unit: %).

Algorithms	Accuracy	Precision	Recall	AUC
co-location + LocationGCN (Algorithm for this study)	74.88	63.59	77.48	75.39
co-location	63.93	55.17	21.19	55.42
LocationGCN (Kipf & Welling, 2016)	69.40	64.89	40.40	63.62
co-location + CNN	32.34	24.69	39.07	40.06

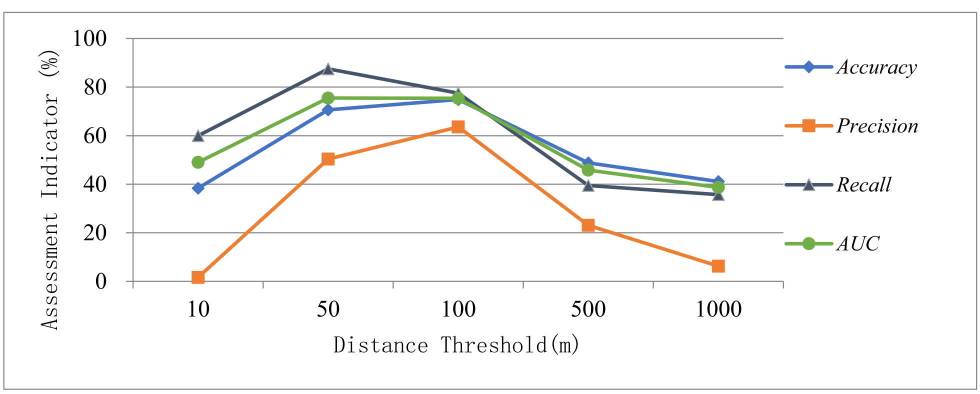


Fig. 6. Effect of distance thresholds on algorithm performance.

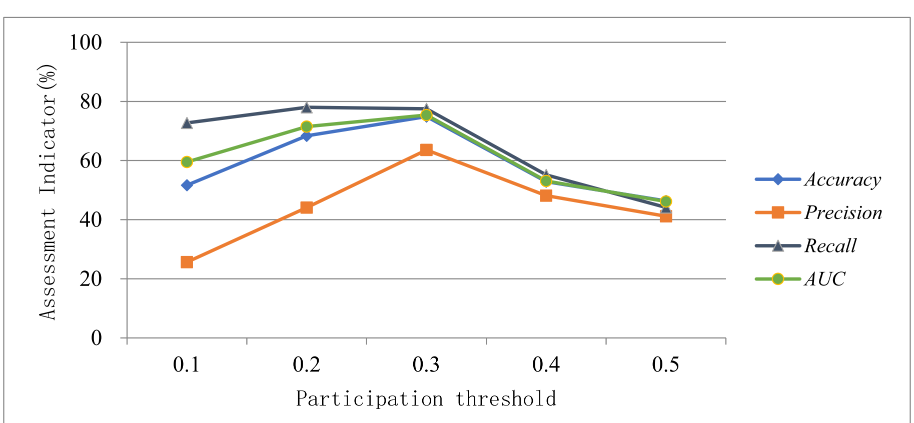


Fig. 7. Effect of participation threshold on algorithm performance.

additional experiment focusing on the administrative districts of Xiamen City. Subsequently, we performed a prescriptive analysis of restaurant location decisions, formulating corresponding marketing strategies based on the experimental findings. The specified restaurant types in this experiment are "Dinner – Western" and "Fast Food – Western", with the algorithm parameters configured as outlined in the previous section.

Table 4 displays the prevalent patterns for specified restaurants in different regions. The prevalent co-location patterns exhibit minimal overlap in each district, indicating that consumer preferences for specific types of restaurants differ across various areas.

By amalgamating the prevailing co-location patterns based on regions, it emerges that the high-end "Dinner-Western food" restaurants tend to cluster with other formal dining establishments. In contrast, the "Fast food – Western food" restaurants show a propensity to associate with other fast-food eateries. Notably, "Fast-food-Western food" exhibits a pronounced correlation with "Fast food-Noodle restaurant," possibly indicative of shared attributes such as quick meal turnover. Consequently, for those contemplating the opening of a "Fast-food-Western food" restaurant, it is advisable to consider locations near establishments with a high turnover rate.

Furthermore, the identified prevalent patterns offer insights into whether restaurants of the same type in a specific area tend to cluster together. For instance, in Siming District, the pattern {Dinner-BBQ, Casual dining-Drinks, Fast food-Western food} suggests that "Fast food – Western" establishments in this area exhibit a preference for co-locating with similar types, indicating potential benefits from spillover effects within the same category. Consequently, for a new "Fast food – Western" restaurant in Siming District, it is advisable to consider locating in proximity to other establishments of the same type.

To conduct a more in-depth market analysis and provide strategic marketing insights, a kernel density heat map is presented in Fig. 8. Notably, high-rated and high-consumption restaurants are primarily situated in Huli and Siming districts (Fig. 8 (d)), while low-rated and high-consumption restaurants are exclusively found in Huli district (Fig. 8 (b)). This suggests that high-consumption restaurants in Siming district tend to exhibit higher customer satisfaction. This correlation could be attributed to the abundance of tourist attractions in Siming District, coupled with generally higher spending levels among Siming district residents. Consequently, the likelihood of negative sentiments arising from high prices leading to low scores is diminished.

Furthermore, the analysis of Fig. 8 (b) and (d) reveals a scarcity of high-consumption restaurants in Tongan District. This observation aligns with the absence of prevalent co-location patterns for "Formal Dining – Western food" in Tongan District (Table 4). Consequently, if you are considering opening a high-consumption restaurant, Tongan may not be a favorable choice.

The aforementioned inference aligns with the classic 4P theory. The existing restaurant distribution graph structure serves as a valuable indicator of the demographic characteristics in the respective area. For instance, if the restaurant distribution graph indicates a clustering of establishments with high ratings and high consumption levels, it implies a preference among residents for high-consumption restaurants. This insight can offer valuable references for product positioning and consumer targeting in marketing strategies.

Table 4
The prevalent pattern for specified restaurants in different regions.

Type Region	Formal Dining – Western food	Fast food – Western food
Xiamen as a whole	{Dinner-Seafood, Casual dining-Drinks}	{Fast food-Noodle restaurant, Casual dining-Drinks}, {Fast food-Western food, Casual dining-Drinks}
Siming District	{Dinner-Seafood, Dinner-BBQ, Dinner-Japanese food, Dinner-Fujian food}, {Fast food-Western food, Casual dining-Drinks}	{Dinner-Seafood, Dinner-Hotpot, Casual dining-Cafes}, {Dinner-BBQ, Casual dining-Drinks, Fast food-Western food}, {Snacks-Fried food, Casual dining-Drinks, Fast food-BBQ }
Huli District	{Dinner-Japanese food, Casual dining-Cafes, Dinner-Seafood}	{Fast food-Noodle restaurant, Casual dining-Drinks}, {Dinner-BBQ, Casual dining-Drinks, Fast food-Western food}
Tongan District	{ }	{Snacks-Other}, {Fast food-Western food}
Haicang District	{Dinner- BBQ}	{Fast food-Fujian food}
Jimei District	{Casual dining-Drinks, Snacks-Other}, {Fast food-Other}	{Fast food-Noodle restaurant, Casual dining-Drinks, Dessert-Bread dessert, {Fast food-Fujian food, Fast food-Noodle restaurant, Snacks-Others, Snacks- Spicy Hot Pot}
Xiangan District	{ }	{Fast food-Western food, Casual dining-Drinks}

5. Conclusion and discussion

In this study, we introduced a novel prescriptive analytics method for location selection recommendations by integrating spatial co-location pattern mining and LocationGCN. We collected and analyzed a dataset comprising 13,549 pieces of data to validate the effectiveness of our proposed framework. The experimental results demonstrate that our approach surpasses existing methods in performance.

5.1. Implications for research

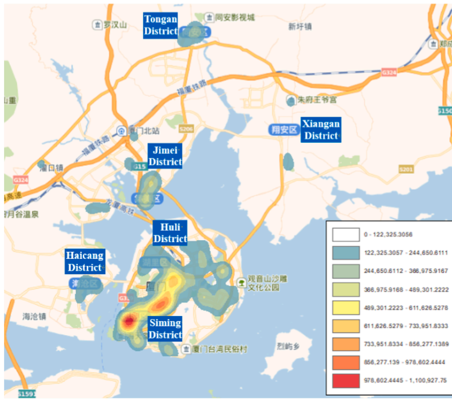
Firstly, the framework proposed in this study provides insights into the diversity of restaurant types, offering implications not only for the restaurant industry but also for other service sectors. In contrast to traditional studies that mainly examine the correlation between restaurant location and regional characteristics (Yang et al., 2017), this research delves deeper, investigating the non-linear and intricate connections among features and their superpositions within clustered restaurants.

Secondly, this study offers novel prescriptive analytics framework for restaurant location selection. It utilizes spatial co-location pattern mining to determine the candidate location selection range instead of MCDM, which eliminates the reliance on extensive operational data that may be difficult to obtain. Furthermore, the LocationGCN is used to determine the final location selection results by learning the spatial distribution characteristics between different restaurant nodes, which compensates for the deficiency of simple co-location not being able to capture spatial specific relationships (Yan et al., 2018).

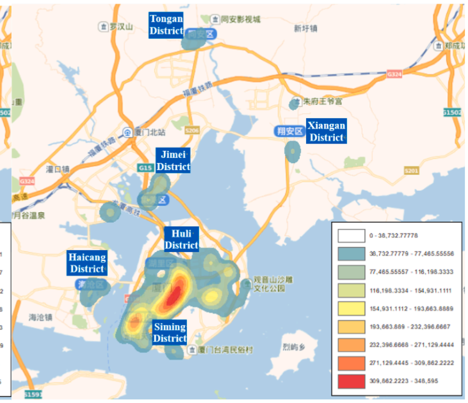
Lastly, this study introduces a fresh perspective on industrial clusters and supply balance when assessing consumer demand. In contrast to traditional methods like spatial econometrics modeling (Yu, 2019), which often depend on extensive economic indicators and data, our proposed framework leverages graph-structured data and freely available social media information for spatial analysis. Examining successful restaurants in a specific region sheds light on the genuine needs of that area from a supply perspective. This approach opens up new avenues for research into the location dynamics of other consumer-oriented service industries, such as hotels and tourism attractions.

5.2. Managerial implications

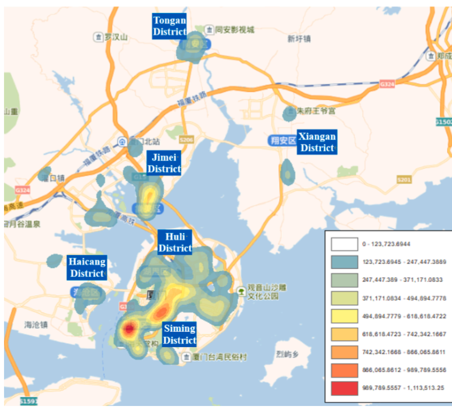
Firstly, in contrast to traditional location methods that demand extensive investigations across various trade areas (Cheng, 2018), this study employs an intelligent algorithm to discern the spatial distribution information of restaurants. By considering both the spillover effects and competition dynamics among restaurants, it provides a rational location range for the specified restaurant. This approach streamlines the cost of location selection in the early stages of decision-making, thereby



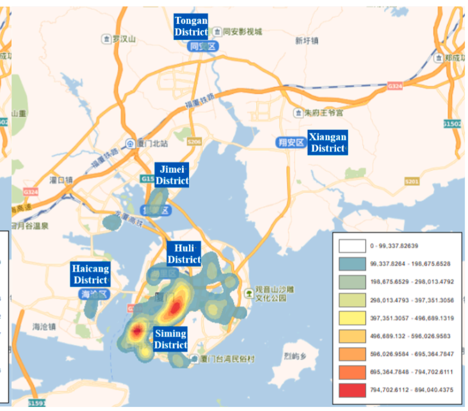
(a) Low rating and low consumption



(b) Low rating and high consumption



(c) High rating and low consumption



(d) High rating and high consumption

Fig. 8. Kernel density heat map of restaurants with different ratings and consumption levels. (a) Low rating and low consumption (b) Low rating and high consumption. (c) High rating and low consumption (d) High rating and high consumption.

mitigating the risk of opening a store in an inappropriate location.

Secondly, the outcomes of this study reveal that the prevalent patterns for the same type of restaurant differ across various districts, offering insights into how services can be more effectively designed and marketed. For instance, in the case of a formal dining western restaurant, the prevalent patterns in Huli District and Siming District are distinct. If a firm plans to establish a formal dining-Japanese restaurant in Huli District, it might explore joint marketing and promotion opportunities with coffee shops. However, if the firm is considering a similar restaurant in Siming District, it may incorporate BBQ services in its offerings and marketing strategies.

Finally, this study highlights the value of information derived from the restaurant graph structure for both operational and marketing purposes, emphasizing the complementary nature of these two disciplines. As a result, it suggests that marketing managers should collaborate with operations managers in the initial stages of location selection. This managerial insight extends beyond restaurant location selection and operations, providing relevant for addressing location issues in various industries such as hotels, retail outlets, and others.

5.3. Limitations and future works

This study comes with certain limitations, suggesting avenues for future research. Firstly, the analysis only accounts for the distance of restaurant nodes on a two-dimensional plane. Subsequent research could extend this to three dimensions to delve deeper into consumption behavior. Secondly, the study overlooks the impact of takeaway services, which could be an influential factor in store location decisions. Future studies might explore the implications of takeaway services on restaurant locations. Lastly, enhancing the classification granularity of restaurants could improve the interpretability of algorithm results. Future investigations could leverage text mining and image recognition to address this aspect.

CRediT authorship contribution statement

Shuihua Han: Resources, Funding acquisition, Conceptualization. **Linlin Chen:** Writing – original draft, Methodology, Formal analysis, Data curation. **Zhaopei Su:** Writing – original draft, Visualization, Software, Investigation, Formal analysis. **Shivam Gupta:** Writing – review & editing, Supervision, Project administration. **Uthayasankar Sivarajah:** Supervision, Resources, Project administration.

Appendix A

Algorithm 1. Dataset partitioning process

Input: Dataset $D = \{cube_1, cube_2, \ldots, cube_c\}$, the proportion of training set is p.

Initialization: Defining training set as D_1, testing set as D_2, and candidate neighbor set as $\overline{D_2}$
$cube_j \leftarrow random(D)$// Randomly selecting a cube as the beginning cube.
$D_2 \leftarrow D_2 + cube_j$ // Adding the cube into testing set.
While size(D_2) < ρ(1-p) //ρ is the total number of cubes.
$\overline{D_2} \leftarrow \overline{D_2} + neighbor(D_2)$//Adding all neighbor cubes of testing set into candidate neighbor set.
$cube_m \leftarrow random(\overline{D_2})$ // Randomly selecting a cube from candidate neighbor set.
$D_2 \leftarrow D_2 + cube_m$ // Adding the selected cube into testing set.
$D_1 \leftarrow D - D_2$//Obtaining the training set
output: Training set D_1 and testing set D_2

Algorithm 2. Obtain the maximal clique

Input: Graph G_λ and point set $E(G_\lambda) = \{O, m_2, m_2, \ldots, m_n\}$ //$O, m_2, m_2, \ldots, m_n$ are the points in Graph G_λ.

Initialization: Defining maximal clique set $Q(G_\lambda) = \{Q_k | k \in [1, n]\}$.
for k **in** [1, n] // n is the total number of points in graph G_λ.
Q_k.add (O, m_k) // Adding point O and point m_k into Q_k.
for j **in** (k, n]
$\gamma \leftarrow$Ture
for i **in** [1, k]
if $\{m_k, m_j\} \subseteq Q_i$ //Deleting m_j if connection between $m_k$andm_j has existing in Q_i.
$\gamma \leftarrow$False
break
if γ = False
continue
$\varphi \leftarrow$True
for q **in** $E(Q_k)$ //$E(Q_k)$ is point set of Q_k.
if $qm_j = 0$ // There is no connection between point q and point m_j.
$\varphi \leftarrow$False //m_j is not the point we are searching for.
break
if φ = True //Judging if point m_j has relationship with all points in $E(Q_k)$.
Q_k.add (m_j) // Adding point m_j into Q_k.
output: $Q(G_\lambda) = \{Q_k | k \in [1, n]\}$ // The maximal clique set of Graph G_λ.

Algorithm 3. Determining the prevalent co-location pattern, named ***colo_tree*()**

Input: Spatial co-colocation pattern P

Initialization: Prevalent co-location pattern set $\overline{\overline{P}}$ Participation threshold PI
While size(P) > 1 // The judging process only continue when there are at least two features.
if $pi(P) \geqslant PI$ // Calculating its participation degree and comparing it with participation threshold.
if P ***not*** **in** $\overline{\overline{P}}$
$\overline{\overline{P}} \leftarrow \overline{\overline{P}} + P$ // Updating the prevalent co-location pattern set
else
for f **in** P //Obtaining the subsets of P
sub_$P \leftarrow$P
sub_$P \leftarrow$sub_$P - f$ //Deleting a feature from P to obtain the subset
self. ***colo_tree***(sub_P) //Embedding the algorithm 3 *colo_tree* to further judge current subset, //In new cycle, the input is sub_P
output: $Q(G_\lambda) = \{Q_k | k \in [1, n]\}$ // The maximal clique set of Graph G_λ

Appendix B. . Restaurant type hierarchy

H1	H2
Dinner(23 items in total)	Eg. Fujian food, Northeast food, BBQ and others
Fast food(24 items in total)	Eg. Fujian food, Northeast food, BBQ and others
Snacks(4 items in total)	Eg. Pasta, Fried food, Spicy Hot Pot and others
Casual dining(3 items in total)	Cafes, drinks, bars
Dessert(1 item in total)	Bread dessert

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