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Article

The sales behavior analysis and precise marketing recommendations of FMCG retails based on geography methods

Wang Luyao [1], Fan Hong [1,*] and Gong Tianren [1]

[1] State Key Lab for Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, 129 Luoyu Road, Wuhan 430079, China; 2481221266@qq. com

* Correspondence: 2481221266@qq. com; Tel. : +86-159-7221-1475

Abstract: With the rapidly increasing of people's purchasing power, the fast moving consumer goods (FMCG) industry is supposed to grow dramatically. In order to gain more market access and profile, it is important for the FMCG manufacturers and retailers to find the preferences and provincial characteristics of consumers, to develop more suitable goods distribution strategy. Based on retails marketing data with geographic characteristics, this paper proposes a new combination of geography methods to solve the problems in distribution of FMCG. Via multiple K-means clustering and cross validation of KNN half off, the mesoscopic sales features are extracted through the classification of retails, which can indirectly grasp the consumer behavior characteristics. Based on space division and Moran' I spatial autocorrelation arithmetic, two strategies are developed to satisfy consumer's needs and promote sales, including conservative and positive strategies. According to our analysis, the total sales volume of the regions will increase by 5.1% and 10.3%. This study can be applied to the provide purchase strategies for FMCG retails according to their locations. The research can explore the consumption potential of different areas, thus improving the profile of retails and the development of economy in more mesoscopic scale.

Keywords: FMCG; retail sales; geography methods; mesoscopic sales features; goods distribution strategy; development of economy.

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1. Introduction

Given the continuous development of the economy, and the popularization of the internet, people's consumption behavior has undergone tremendous changes[1]. The regional characteristics of consumers are becoming increasingly complex. The situation is typically prominent in the sales of fast moving consumer goods (FMCG) industry, which is becoming an important part of purchase choices of consumers [2]. To retailers and malls, the increasing demand of FMCG may means a higher profile. However, the unreasonable distribution of FMCG often cause waste and loss in some places, and shortage in another places, thereby indicating that retailers encounter difficulties in managing their purchase and sales strategies[3-5]. In European supermarkets, the attrition rate of FMCG can reach 15%–20%, which may block the development of a sustainable economy and lead to losses amounting to billions of dollars[6,7]. To reduce the profit loss, some retailers will set a higher price of FMCG, thereby leading to the decrease of consumers' purchase frequency[8]. The problem can also result in significant problems for the manufacturer, which accept the order from retailers[9]. The manufacturer cannot truly obtain the right consumer information to guide their production. The relevant knowledge of consumers' preferences and demand will be helpful for the conduct of future economic strategies of both the manufacturer and retailer [10].

For businesses, the adaptation to the changing consumer and grasp their preferences, based on which they adjust their marketing strategies in a timely manner, will definitely improve their sales. At present, traditional economic thought is unable to solve the increasingly complex marketing problems. Retailers possess considerable sales data, but the traditional thought usually incur weaknesses in the analysis of complex sales data, and encounter challenges in obtaining the

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information of consumer patterns and consumer behaviors. Ignoring such data may lead to the loss of market share for competitors and wrong marketing strategy for retailers[11].

To provide more reasonable businesses strategies, combining the marketing theory with new technology (data mining, big data, and machine learning) is essential. The related research about retail sales data combined with the characteristics of spatial areas is an important cross field of geography and economy. By studying the spatial distribution and sales of retailers, the different preferences of consumers in different areas can be efficiently revealed, thereby helping in the development of suitable marketing strategies and more profit.

The present research on retailers mainly focus on their spatial distribution such as spatial aggregation phenomenon. Many studies use different theories, such as central place theory[12], kernel density estimation[13], and distance attenuation theory[14]. These theories are used to estimate the commercial centers of retailers or malls, combined with external data such as media data or POI data[15]. Given limited data sources, current studies mainly analyze of the quantity and distribution of retailers[16,17], and attempt to observe their spatial characteristics. However, these studies did not consider the sales of retailers, which are the most important attributes of retail. Thus, the studies lack persuasion as guides for retailers. The study results can only describe the spatial aggregation of shops, but cannot reveal the quantifiable relationship between locations and sales of retailers, and cannot reveal the precise consumption level of areas. Research on the effectively extraction of consumer characteristics of each area or block, and providing microscopic guidance for retailers is relatively lacking.

A new combination of geography methods is proposed to solve the problem of the distribution and sales strategies of FMCG in retailers, thereby providing mesoscopic guidance for the development of a sustainable economy. In the process, the classification for retailers is conducted based on their FMCG sales data, via the K-Means algorithm and silhouette coefficient, thereby determining the sales characteristics of each class of retailer. The clustering results can reflect the consumption characteristics of the consumer groups in each retailer class. Then, the KNN algorithm is used to evaluate clustering accuracy. The positive correlation between sales and clustering characteristics is verified via linearly dependent analysis. As the store's distribution ratio became closer to the clustering center, the sales increased. Then, to improve the regional sales and to satisfy consumer demand, the optimization distribution strategies are proposed by using Moran's spatial correlation algorithm and space division method. In this experiment, we use FMCG sales data of 5614 retailers in Guiyang, the capital city of Guizhou Province in China, from 2015 to 2016. Then, we classify the retailers into three classes via the K-means algorithm and silhouette coefficient. After the verification of KNN and correction with sales, the clustering result is used for the optimizing strategy of retailers. Two strategies are proposed, as follows: the conservative, which can improve sales by 5.1%; and the positive, which can improve sales by 8.4–10.3%.

In this paper, we propose a combination of geography method to solve the problems of sustainability economy in micro-scale. The research results can provide effective guidance for the sales of FMCG like food and wine. Furthermore, the results can better satisfy consumer demand in different areas and reduce the loss of FMCGs, thereby promoting sustainable economic development.

2. Materials and Methods

2. 1. Clustering Algorithms

Clustering algorithms are methods that can efficiently separate a data set, and aggregate data into several classes based on their characteristics[18]. In data mining, some representative clustering algorithms are found, such as density-based spatial clustering of applications with noise (DBSCAN), Expectation-Maximization (EM), and K-means clustering algorithms[19]. Different clustering algorithms have different advantages and weakness. DBSCAN is a method that considers the objects' density in certain areas, which can indicate a good performance to data with significant noise. However, if the clustered objects of data are unsure, such as the high-dimensional data, the quality of clustering algorithms may be deeply influenced. K-means clustering algorithms, as a typical

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distance clustering algorithm that takes the distance of objects as a basic clustering reference, has better performance with high-dimensional data[20]. In K-means algorithm, the number of clusters k should be set before the algorithm. The silhouette coefficient can be used for the evaluation of different k numbers[21]. In our research, we evaluate silhouette coefficient with k value ranges of 2–8, and the best k was chosen as our cluster number.

2. 2. *KNN for the clustering evaluation*

To evaluate the accuracy of clustering, we introduced KNN (k-Nearest Neighbor) classification algorithm to evaluate the accuracy of clustering results as classified by the clustering centers calculated by the K-Means algorithm[22]. As a representative algorithm of the data mining classification algorithm, KNN can determine the categories of sample data only on the basis of the nearest one or the classification of a few samples. We can extract 3/4 of stores as training data and 1/4 of stores as test data. In the training process, we use the half off cross validation method to construct the classifier of the training process.. Given that the distribution of shops are nearly centralized, and to the data set with cross or overlap domain, KNN usually presents better performance than do other methods[23]. We use KNN algorithm for reclassification based on the cluster centers provided by K-means and for comparing the classification results with the results of K-Means.

2. 3. *Spatial Autocorrection*

Spatial autocorrelation, as an important research method in spatial statistics analysis, is a phenomenon that is used to explore the impact degree between nearby locations. It can be used to estimate the similarity of attributes of different areas. Spatial autocorrelation is often described by global and indicators, such as *Moran's I*, *Geary's C*, and *Getis's G*[24-26]. To measure how sales are spatially autocorrelated among retailers in Guiyang, this paper uses *Moran's I* values to assess the similarity of sales characteristics between nearby retailers. Improvement strategy is carried out based on the autocorrection results. The value of *Moran's I* is between -1 and 1. If the value is close to -1, then the shops with high sales are surrounded by low ones. By contrast, when the value is close to 1, that means shops with high sales are surrounded by high ones. If the values are close to 0, then the sales of shops are random with no obvious characteristics. In spatial autocorrection, the spatial weight matrix "W_{ij}"can be used to describe the spatial relationship between different areas[27], thereby representing the spatial weights that are assigned to pairs of units *i* and *j*. A row-standardized spatial weight matrix "W" is used to describe the neighbor relationships in spatial autocorrelation analysis [54]. W_{ij} represents the spatial weights that are assigned to pairs of units *i* and *j*. The formulas of global *Moran's* I and local *Moran's I* are as follows[28]:

$$I_{global} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} w_{ij}(x_i - \bar{x})^2} \tag{1}$$

$$I_{local} = \frac{n(x_i - \bar{x})\sum_{j}(x_j - \bar{x})}{\sum_{j}(x_i - \bar{x})^2} \tag{2}$$

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In the formulas, n represents the total number of spatial units, and the values of each unit are represented by X_i or X_j,and $\overline{X}$ is the average value of all units. W_{ij} is the spatial weight that represents the spatial relationship between units. To test the statistical significance of the observed Moran's I, the Z value is calculated:

$$Z\left(\frac{I_i - E(I_i)}{\sqrt{VAR(I_i)}}\right) \quad (3)$$

$E(I_i)$ and $VAR(I_i)$ are their theoretical expectation and theoretical variance. If the local Moran's I calculated above is greater than expected, then it can indicate that some places exist with positive local spatial autocorrelation. If the local Moran's I value is less than the expectation, then places exist with negative spatial autocorrelation. In the analysis of spatial autocorrelation, the "hot region" usually occupies places with relatively high values and are close to each other.

3. Cluster Analysis of Retails

3.1. Data Source

The main data set used in this paper is the monthly sales data of FMCG between 2015 and 2016 of the 5614 FMCG retail shops in Guiyang City, China. These shops comprise markets and small shops. The FMCG in these shops include fresh foods like meat and vegetable, and frozen foods, wine, hygiene products and so on. We choose three types of FMCG as our research object. Other data include road net and map data of Guiyang City to provide spatial references and base map.

3.2 Market Segmentation by Cluster Analysis

In the study of market segmentation, cluster analysis is usually a basal way to obtain the sales characteristics of different shops. The aim of data clustering is to form spatial data or multidimensional attribution data into several collections of clusters, and make the gap between different clusters as large as possible. By contrast, the differences in inner clusters are as small as possible[29]. The commonly used clustering algorithms include DBSCAN clustering algorithm and K-means clustering algorithm. Given that the categories of retail shops are usually more, and for high dimensional data clustering, the K-Means algorithm will have better accuracy compared to DBSCAN algorithm. Therefore, in this paper, we use K-means clustering algorithm as the clustering method.

As a clustering algorithm based on distance, the K-means algorithm is one of the most classic clustering algorithms; the algorithm uses the space between the object distance to evaluate the aggregation degree between objects. This distance can also be other features that can characterize the differences between object values[30]. The algorithm requires an appropriate clustering number, and will start with an initial cluster centers. Thus, the distance of all sample to the inner centers are obtained and merged into the nearest cluster center. Then, the initial clusters are formed. The new cluster centers are calculated from initial clusters *V(v1, v2, v3..)*, which are the core of initial clusters and are usually different from initial cluster centers. Through the new cluster centers, the sample data can form new clusters and cluster centers again. Given the constantly updating iterative clustering, until no new changes occur or are less than the threshold, we obtain the final clustering centers and the classification results[31].

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In this paper, we select three products that are represented by α, β and δ as the clustering objects that contain three dimensions. The sales of 5614 retail shops are apparently different. Only by classifying the shops by their sales of FMCG into several classes can we develop a pointed marketing program for every type of retail shops. To confirm the optimal number of clusters, the silhouette coefficient is introduced. It is a type of evaluation method that is used to estimate the consequences of clustering by a quantitative value that ranges between -1 and 1. The method was proposed by Peter J. Rousseeuw in 1986[32]. It can be used to the represent the similarity between the internal clusters and separation degree between different clusters. For an N-point data set, the calculation method of contour coefficient is as follows:

$$P = \frac{\sum_{i=1}^{N} \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}}{N} \tag{4}$$

where, *a(i)* represents the average distance of vector *i* to other points in its cluster, whereas *b(i)* represents the average distance of vector *i* to points of other clusters. By setting the cluster number as 2–8, the K-means cluster arithmetic was conducted with each number. The results from Fig. 1 indicate that the silhouette coefficient showed a decreasing trend. Thus, an effective choice of clustering number is 2 or 3. Considering that the discrepancy between 2 or 3 is wispy, we choose 3 as the clustering number to better distinguish retail shops.

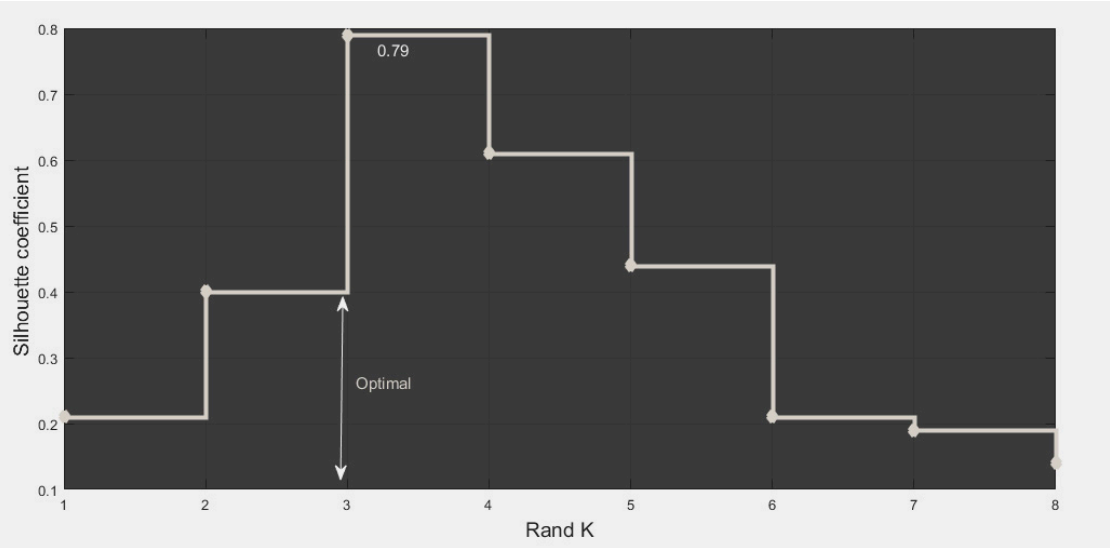

Figure1. The silhouette coefficient of each K value.

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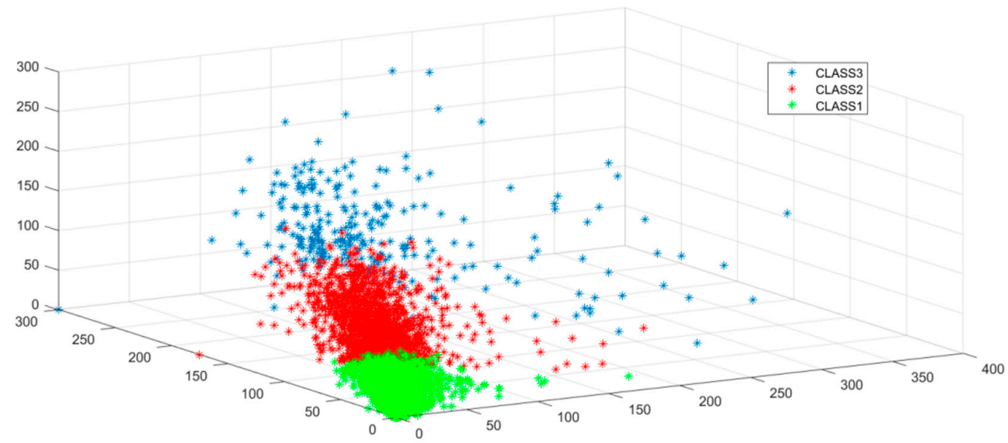

Figure2. K-Means Clustering results

After selecting the appropriate number of categories, the K-means clustering was conducted, and results are shown in Figure 2. The horizontal intersections of any two products represent the dimensional clustering results of the two.

Green dots in the figure represent shops of that sell the three types of goods, sales of which are high. The red dots represent the shops whose sales are general, and the black points represent shops with fewer sales. We calculate the clustering center of each type of shop and calculate the logarithm of clustering centers to weaken the gap between different magnitudes and make the diverge points more compact. To avoid the influence of some shops' sales abnormities and to obtain the general characteristics of shops, we use random sampling method for multiple clustering. We randomly selected 80% of stores for clustering. Thus, we obtain a group of different cluster centers. By discussing the distributions of these cluster centers, we obtain the statistical characteristics of the following Table 1 :

Table 1 cluster centers of 3 shops

Class	Sales(α)	Sales(β)	Sales(δ)	Color
Class 1	148.65	114.36	148.83	Green
Class 2	62.79	34.71	78.86	Red
Class 3	17.61	12.58	20.60	Black

The indicates that the shops were divided into three classes and that each class contains a clustering center of the goods of α, β, and δ. Class 1 represents the shops with high sales, in which the ratio of three products is (148.65, 114,36, 148,83). This kind of shops may be a supermarket or a big mall. The ratio may reflect the typical characteristics of this kind of shops. The table shows that the sales of α is nearly the same as δ. The sales of β is 66% of α and δ. Class 2 represents the shops with middle sales. The ratio of three products is (62.79, 34.71, 78.76). In this kind of shops, product δ is obviously more than α. The sales of β is about a half of α. Class 3 comprises small shops, and their sales are typically less than the other classes of shops.

3.3 Relationship between sales and cluster centers

The cluster centers calculated above indicate characteristics of different types of shops, which can indirectly reflect the demand of people. The cluster centers can truly reflect people's different needs of fresh food. Thus, how can we use this principle to satisfy people's needs and promote the profile of shops at the same time? To find the relationship between shop sales and the ratio of fresh food, we introduce the MLE (maximum likelihood estimation) method to estimate the optimal fitting function between shop sales and a variable called *M*. The variable is the variance of quarterly cluster centers and the standard deviation we have calculated above. The computational formula of *M* is as follows:

$$M(i) = \frac{\sum_{n=1}^{n=3} \sqrt{(xn(i) - Xn)^2 + (\mathrm{y1}(\mathrm{i}) - \mathrm{Yn})^2 + (\mathrm{z1}(\mathrm{i}) - \mathrm{Zn})^2}}{3} \qquad (5)$$

We calculate the cluster centers of every quarter and calculate *M(i)* of each month. We use maximum likelihood estimation method to find the relationship between *M(i)* and sales. The results are shown in Figure 3, as follows:

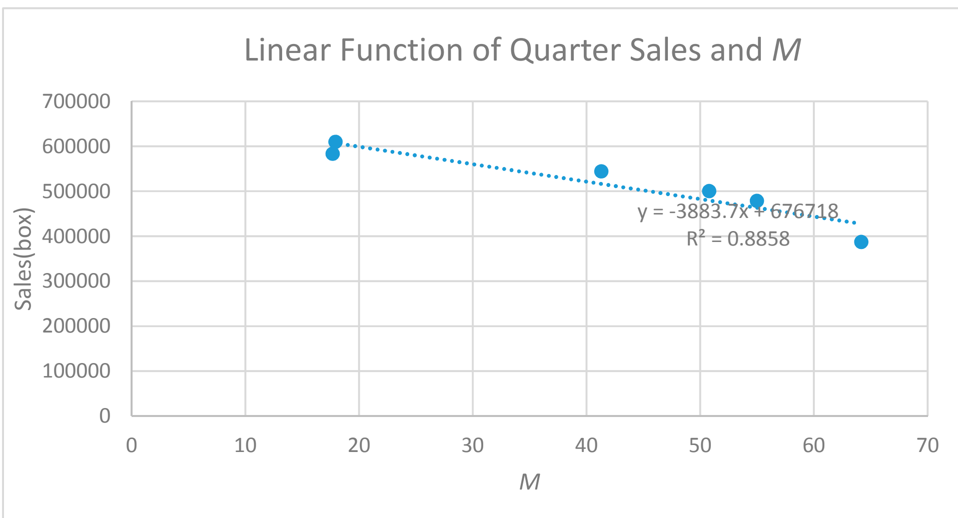

Figure3 Relationship between quarter sales and *M*

To evaluate the fitting degree of the equation, we introduce the goodness of fit concept, which is based on the similarity between predicted values and the actual value. The fitting statistics used in this paper is R^2. The greater the R^2, the closer their relationship is. The formula is as follows:

$$R^2 = \frac{\sum (y^* - \overline{y})^2}{\sum (y - \overline{y})^2} \qquad (6)$$

where y^* represents the real value, and $\overline{y}$ represents the average value. When R^2 ranges between 0–1, the closer to 1, the higher the degree it fitted. The closer to 0, the lower the degree it fitted. Table 2 shows the fitting results.

Table2. The fitting results of different Time Scale

Time Scale	Fitting function	Goodness of Fit (R^2)
Monthly	y=-918.32x+629416	0.5072
Quarterly	y = -3883.7x + 676718	0.8858

Results clearly indicate that high correlation occurs between shop sales and their monthly M value. Thus, if the shops want to improve their theoretical sales, they must adjust their current ratio to move closer to the standard products ratio.

The clustering center essentially reveals the population and acceptance for the retail brand. For each class of shop, if we take measures to move close to the cluster centers ratio, this approach will satisfy people's needs and fit the market demand. Such a situation can provide a guide for the improvement of sales and avoid busts the same time.

4. Spatial Optimization Strategies and Discussion

The realistic ratio should be maintained near the cluster centers. Thus, implementation of the principle is the main problem for retail shops.

The next part will focus on the implementation of different areas and different types of shops. In our K-Means clustering algorithm, the Guiyang City stores are divided into three categories. They have different clustering centers. Thus, the best choice is to formulate a strategy that aims at every class of shop.

For each store, their current distribution and ratio of products are different from the standard clustering center *X (X1, X2, and X3)*. The difference may be small for some shops but may be large for other shops. We blindly adjust the distribution strategy of every shop and dramatically shrink the gap between current ratio and standard clustering center. This approach will definitely cause the bust of products, thereby causing the risk of profit loss of shops. Thus, the precise marketing strategy will be based on spatial autocorrelation algorithm.

We take first class shops as experiment objects. The analysis of other two classed of shops is similar. A total of 453 shops are grouped in the first class. They are distributed around several areas of Guiyang. For every shop, a variance M exists. The variance can describe the gap between its current ratio and standard ratio. We chose shops whose M values are both small and indicate space aggregation. Then, we can decrease the gap between these shops to a larger degree and decrease the gaps of shops whose M values are high in small degrees.

Spatial correlation is an important research method in spatial statistical analysis; it is used to explore the degree of influence between regions. In spatial autocorrelation analysis, the "hot region" usually occupies places with relatively high values and are close to each other. However, in our dataset, the M value of shops with high sales is relatively small. Thus, to satisfy the discipline of autocorrection, we use a variance reciprocal to represent the gap between current products ratio and standard ratio. Furthermore, given that the order of magnitudes is nearly

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low, the variance reciprocal was multiplied by 100. We use M^* to represent the variance reciprocal, the formula is as follows:

$$M^* = \frac{1}{M} \times 100 \tag{7}$$

We use spatial autocorrelation analysis based on the M^* of first-class shops. The result is then used to determine the adjustment strategy of retail shops. We use two methods for analysis. First, we directly conduct spatial autocorrelation analysis for shop points. Second, we conduct spatial autocorrelation analysis based on the spatial segmentation method.

Given that the marketing characteristics of retail shops are often relatively regional, we can make adjustments following the regional characteristics of shops. Several space division means are available, including spatial weighted Voronoi diagrams, which can set sales as an attribute (weights) in spatial segmentation, and Delaunay triangulation. These two means can consider the differences between shops, but they also separate the contact among shops.

Compared to the previous two means, the grid diagrams have several advantages[33,34], as follows: they are simple and easy to overlay. However, the most important aspect is that the grid means can divide the shops into several layers based on their classes. Therefore, we selected grid means as the space division method.

For class 1 shops, sales are relatively high, and their trade areas are broader. Thus, we can give them a larger grid. For class 3 shops with a relatively low radiation area, we will set a smaller grid. By choosing different grid scales and calculating the R^2, we finally chose grid sizes of 300×300m, 150×150m, 70×70m meters as the respective scales of classes. The basic unit of the three shop classes is as follows:

The calculation method of each layer is similar. Thus, the first class of grid was chosen to calculate as an example. We set *i* to represent the grid number of level 1. Then, for grid *i*, we calculated the mean variance of M^* and mean sales *P* of shops located in grid *i*. The grid with shops is shown in Fig. 4.

(a) (b) (c)

Figure4 (a)300×300m grids;(b)150×150m grids;(c)70×70m grids.

We obtain a scatter diagram of M^* and mean sales, based on which we can establish the functional relationship between them by using maximum likelihood estimation. The results are shown in Fig. 5. Table 3 shows the effects of whether or not spatial division method is adopted.

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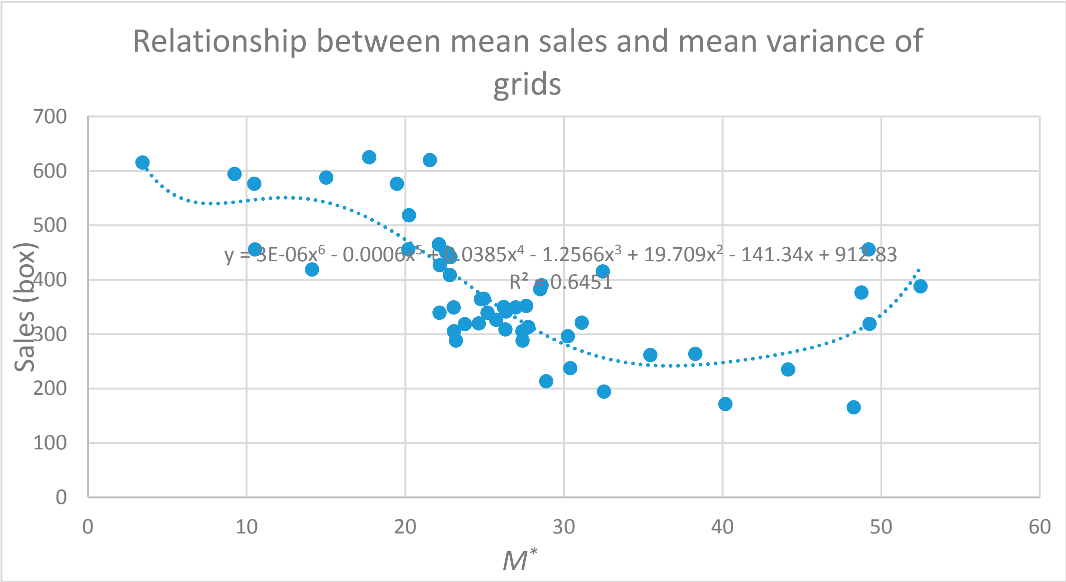

Figure5 Relationship between mean sales and mean variance of grids

Table 3 Goodness of fit of two methods

Elementary Unit	**Single retail**	**Grid**
correlation function	y = -6.7318x + 560.48	$y=3E\text{-}06x^6-0.0006x^5+0.0385x^4-1.2566x^3+19.709x^2-141.34x+912.83$
R^2	0.287	0.645

The table indicates that using the grid as a geographical unit is better than merely using single shop points. The sales model can provide support for planning the ratio of shops that belong to the same grid. The model can also predict the sales in each grid based on their variance.

Our goal is to improve the areas' total sales and adjust the sales strategy of shops whose current sales situation is not preferable, thereby improving their profile and satisfying consumers' demand at the same time. Our research provides an efficient method to do so. We take spatial autocorrection based on the M^* of first-class grid, Fig.6 shows the analysis results of shops that belong class 1. Table 4 shows the results of all classes.

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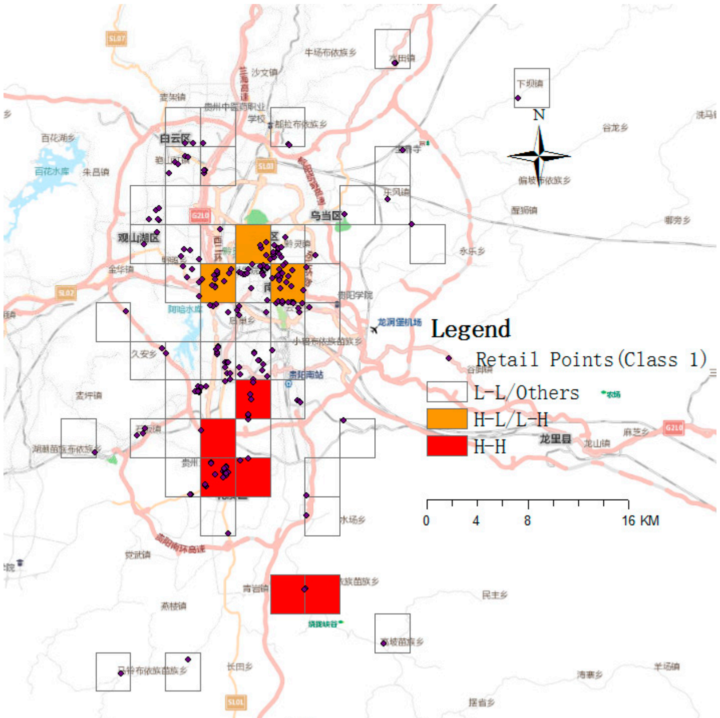

Figure 6. Spatial autocorrection results of first class

Table4 Results of 3 classes of retails

Autocorrection Results	Shop number	M*
Red	75	8.1
Orange	141	5.6
Lucency	237	2.9

The red regions are areas in which M^* values are obviously "high–high" aggregating. The ratio of shops in these regions is generally close to the clustering center, thereby indicating that the preference of consumers in these places is obvious. Thus, we can typically adjust the shops located in these areas but whose ratio is far away from the standard ratio, and drastically make their ratio closer to the clustering center. This approach will effectively improve their sales. When shops are in orange areas, the M^* values are "high–low" or "low–high" aggregation, and their ratio is secondary closer to clustering centers. These shops can be adjusted slightly, and the focus can be on improving the shops whose M^* values are below the average level in their grid. When shops are in the transparent grid, their M^* values are "low–low" aggregating or other situations. Thus, their statuses can be retained, or fine adjustments can be applied.

In this paper, we take out to specific adjustment strategies. The first is a conservative strategy. In this strategy, the shops in red areas with M^* values below 8.1 will be adjusted to 8.1. The theoretical sales, including sales with every product, will be calculated based on M^*. The shops in orange areas with M^* values below 5.6 will be adjusted between 5.0–5.6. Their theoretical sales are calculated. Furthermore, the statuses of shops in other areas are preserved. The second strategy is an aggressive one that will improve the M^* value by some percentage. The M^* values of shops in red areas will be improved by 15.3%, those of shops in orange areas will be improved by 5.1%, and those of the other shops will be improved 3.2%. Then, the ratio of products will be calculated. The best percentage can be confirmed by the marketing performance. Table 5 indicates the effect of different strategies to the marketing sales.

Table5 Influence of different strategies

Class	Actual sales	Sales under conservative strategy	Sales under positive strategy
Class 1	604	628	655
Class 2	415	438	457
Class 3	308	325	364
Increase Rate		5.1%	15.3%

Thus, even if the conservative strategy is adopted, the total sales volume of the region will increase by 5.1%. As long as the optimal matching rate is increased using the conservative strategy, M^* will increase, and the total sales volume of the region will further improve.

5. Conclusions

The traditional marketing strategy of the enterprise is often the controlling marketing strategy, which often functions from top to bottom and from inside to outside. This strategy is often characterized by difficulties in adapting to consumer needs; the strategy cannot address personalized consumer trends. Marketing strategies with traditional experience are often characterized by a certain lag, and difficulties arise in delineating the implementation strategy for each area. The research in this paper combines the popular marketing model with GIS spatial analysis theory and proposes solutions to the release of products. The research can also provide advice for some new shops, improve their profile, and avoid the risk of bust.

The characteristics of brand sales in the mesoscopic area are presented as the geographical unit, as are reasoning consumer group characteristics and the best products distribution ratio. The research also demonstrates the positive correlation between the ratio and the total sales volume, thereby providing the basis for the implementation of regional sales and precision distribution strategy. Following the combination of spatial correlation with marketing theory, this paper effectively implements the program, thereby providing conservative and aggressive strategies based on space optimization. Thus, we provide a high feasibility strategy of goods distribution and goods purchase for FMCG stores and enterprises.

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