A User Portrait of Express Software Based on Full Life Cycle Data

DOI : 10.36909/jer.ICCSCT.19473

Xuejian Zhao[1,2]*, Ke Zhao[2], Yimin Qiang[2]

1.Technology and Application Engineering Center of Postal Big Data, Nanjing University of Posts and Telecommunications, Nanjing 210003, China;
2.Modern postal College, Nanjing University of Posts and Telecommunications, Nanjing, 210003, China.

* Corresponding Author: zhaoxj@njupt.edu.cn

ABSTRACT

With the rapid development of traditional express industry, it is of great significance to study the portrait of express users. The express industry can realize the industrial transformation and upgrading by means of the express customer portrait. However, the research on the user portrait of express delivery is still scarce, at present. In this paper, a user portrait model based on life cycle data is proposed, which comprehensively describes the behavior preferences of users through multi-dimensional feature vectors. The model takes into account the basic attributes, preference attributes and feedback attributes of users, and uses the idea of classification before clustering to realize the segmentation of express users. In the classification stage, this paper fuses the K-means and the Support vector machine algorithm, adds the preference coefficient, and designs a new objective function to complete the user classification. In the process of clustering, we follow the idea of density-based peak clustering, combine the characteristic attributes of the multidimensional data of express users, add the characteristic coefficient, modify the index calculation formula in the model, and complete the clustering of express users. The simulation data show that the user portrait model proposed in this paper can achieve better segmentation of courier users, with better accuracy and timeliness.
Keywords: Logistics terminal; User portrait; Data mining; Integrated algorithm.

INTRODUCTION

The development of e-commerce makes its related industries have undergone rapid changes, express logistics is one of which cannot be ignored. The Intelligent Express service combined with computer technology is developing rapidly, which brings more convenience to human beings. At the same time users also express services to put forward more requirements. In order to meet many new challenges, express industry began to develop new products that can provide personalized services for users, in order to stand out in the fierce market competition. For finding a service scheme that is close to the users, it is necessary to study the users' information deeply, obtain the results of the users' key needs and user groups, and recommend the express service which is more suitable for the users(Wang et al., 2020).

In-depth study of the express user information including the processing of user data, the construction of user portraits and other methods.(Liu X, 2019)used radar entropy method to build user's portrait which integrates behavior, service and psychology, and then used k-means clustering to get four user groups, which provides decision support for express delivery model.(Tang X, 2020)carried on the data processing to the user's trial feedback information on the Intelligent Logistics Park platform, refined the user's behavior data on the platform, and analyzed the user's satisfaction to the express service.(Dang X, 2020) took the online order users of supermarket chains as the research object, constructed the portrait to realize the user clustering in the community, thus matches the personalized express delivery strategy for the users. (Vasićetal., 2021)designed an eight-dimensional measurement model based on confirmatory factor analysis and partial least squares analysis to determine how the dimensions of express services affect user satisfaction, accurate access to express user satisfaction. When building the cold chain logistics distribution model, (Zhang et al., 2021) collected the user's location and information to build a picture, adding user demand constraints for the express distribution model, and improving user satisfaction on the distribution network.

Most of the existing research on express delivery users focus on a specific problem. However, for express delivery enterprises, from the registration information to the completion of the order evaluation, the data generated during the whole life cycle can be used to build the user portrait. Therefore, this paper proposes an end-user portrait model for express delivery, which divides the whole life-cycle data into attribute categories and describes the user behavior with multi-attribute vector model. Then we use the method of one-time classification and one-time clustering to improve the calculation process according to the multi-dimensional vector model, complete the user data mining and information extraction, and realize the user group partition.

EXPRESSEND-USERPORTRAITBUILDING

This paper takes the common users who use the express terminal program as the research object, and analyzes the behavior data produced by the whole life cycle. In the process of analysis, we first classify these data into three categories: basic attribute, preference attribute and feedback attribute, and then construct a data vector with practical significance for each attribute, finally, three vectors are combined to form a multi- attribute vector user portrait model with integrated multi-attribute information, as shown in Figure 1.

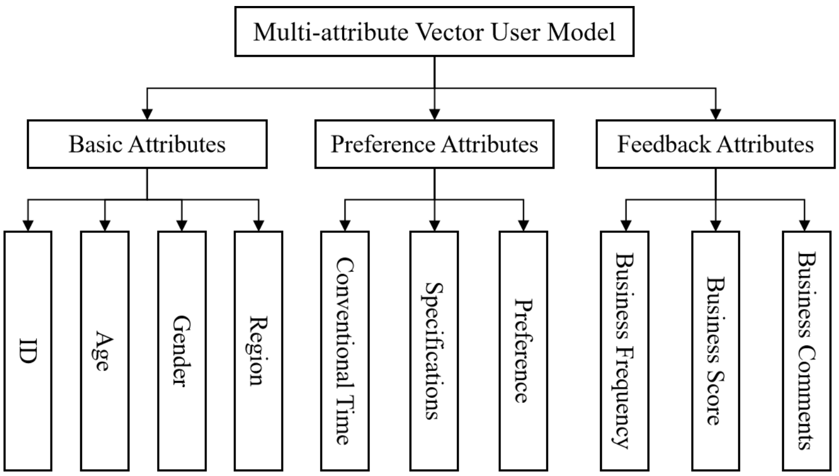

Figure 1. Multi-attribute vector user portrait.

2.1 Basic attribute vector

User's basic attributes refer to the user's basic information, mainly including ID, age, gender and region. For the express related data, most of the basic information value is not high, the difference between the data on the impact of user behavior is small. But the basic information can be added to the user portrait model to help depict the user image(Wu et al., 2021).

According to the actual situation, the age of users can be divided into the following stages: 0 ~ 20-year-old users to the majority of students, often in the middle of the day or night, and winter and summer vacation time is not fixed; Most office workers are aged 21 to 50, and the collection time is concentrated in the noon and evening. The mobile phone is most popular in this age group, and the user group is the largest. Most of the people over 50 are retired or unemployed, although the age span is large, but because of the more decentralized collection time, and the number of people using express procedures are small, it falls into a broad category.

The efficiency, convenience and transportation cost of receiving and sending express mail are largely determined by the area where the users live(Liu et al., 2020).Therefore, it is appropriate to promote different services for users in different regions, such as East China, South China and other trade-intensive areas suitable for the promotion of quantitative preferential activities, to increase the number of users using express delivery; And the northeast, northwest and other relatively small trade volume and farther away from the place, the promotion of price concessions business will be easier to attract users to order.

B is used to represent the basic attribute vector of the user. Combined with the above-mentioned index analysis, the vector is expressed as follows:

$$B = \{ID, age, gender, region\} \tag{1}$$

2.2 Preference attribute vector

The user preference attribute is the usual receiving and sending time, express specifications and the preference of the user by the terminal program through the user behavior analysis and record, which can reflect the habit and preference of the user for receiving and sending express, thus, it can be used to analyze the stability of the enterprise by users.

The user's usual receiving and sending time may depend on the user's occupation and other factors, which can reflect the user's free time (Vu et al.,2020).Recording the index makes it easier for express terminals to improve their user satisfaction by making it easier for users to send pick-up codes, business offers or communicate home pickups near their normal times.

Conventional Express specifications can be directly divided into large-package express and small-package express. Statistical users in the enterprise used to send express specifications, can be analyzed in the enterprise users prefer to send large or small express, so as to continue to develop user preference business, look for defects in another specification business and improve. We can also on this basis to launch related business concessions to users, so as to stabilize users.

User Preference Enterprises can directly reflect the degree of users to express companies, indicators can be divided into only the enterprise, including the enterprise and no enterprise. User preferences include the enterprise, usually users can be divided into stable user groups, can recommend the cycle type of preferential business or quantitative preferential business, such as the more the more the discount sent more stable users. When the user preference does not have the enterprise, the preference company is the competitor, this kind of user belongs to the loss group, needs to consider may establish the business advantage, creates the convenience for the user to retain the loss user.

P is used to represent the user's preference attribute vector, and combined with the above analysis, the vector is expressed as:

$$P=\{conventional\ time, specifications, preference\} \tag{2}$$

2.3 Feedback attribute vector

Feedback information is the most direct reflection of user's psychology in user portrait, and it is very important in user portrait construction and user location segmentation (Wanget al.,2019).Different user portrait has different settings in the feedback information processing (Gu et al., 2018). This paper gives a numerical evaluation of the comments, and gives a formula for user evaluation index.

There will be a series of feedback after the user completes the delivery service, in which the ratings and comments on the service are direct feedback results, and there are indirect feedback user satisfaction indicators such as the number of times the user uses the delivery service. Direct feedback and indirect feedback are combined to form a feedback vector to measure users' satisfaction with the company's express delivery.

Suppose F represents the user feedback attribute vector; R_i represents the feedback index value after the user uses express for the ith time and n represents the number of times the user has used express delivery. The feedback attribute vector is defined as follows:

$$F=\{R_1,R_2,\cdots R_n\} \tag{3}$$

In the above vector, need to define the ith transaction of the feedback index R_i calculation. This variable is determined by the user's ratings and comments for each order. The score value is directly crawled from the user's score data, however, the evaluation of comments needs word extraction, emotion evaluation and rating assignment, and the calculation methods are as follows.

After getting the information of user comments on the program, we first use the JIEBA participle database in python for word segmentation to get the collection of keywords expressing emotional information in the content of comments, and then call sentiments method to loop the keywords, calculate the user satisfaction expressed by each comment and assign a value to it. The assignment method is as follows:

Table 1. Feedback comments assignment table.

Satisfaction	Very dissatisfied	Not satisfied	General	More satisfied	Very satisfied
Score	1	2	3	4	5

Set user satisfaction ratings of 1 to 5, corresponding to 1 to 5 points, respectively, the lower the score means that the lower the satisfaction, so as to get a user satisfaction rating of a courier business review e .

Assuming that s is the value of the user's rating of the order, the formula for calculating the feedback rating indicator is as follows:

$$R_i=\alpha\times s+\beta\times e \tag{4}$$

α and β in the formula represent the weight of user ratings and comments, respectively. When this order user has only ratings and no comments, scoring weights $\alpha = 1$,indicating that the percentage of the score in the calculation is 100%;when users both rate and comment, both weights are the same, $\alpha = \beta = 0.5$, indicating that user ratings and reviews are 50/50;when the user has neither a rating nor a comment, $R_i = 6$,that means the default is that the user's satisfaction with this order is above the medium level.

2.4 Multi-attribute vector user portrait

After three attribute vectors are constructed, we synthesize them into a multi-dimensional vector user portrait model. Suppose UP is multi-attribute vector model, which can be expressed as follows:

$$UP = \{B, P, F\}$$
$$\begin{cases} B = \{ID, age, gender, region\} \\ p = \{conventional\ \ time, specifications, preference\} \\ F = \{R_1, R_2, \cdots R_n\} \end{cases} \tag{5}$$

The above-mentioned multi-attribute vector user portrait model based on end-user life cycle data covers all the information that can express the implicit data such as user preference and satisfaction. In addition, we carried out corresponding analysis of different indicators in the process of building models, so that express enterprises can have a preliminary understanding of users in the construction of the model.

USER GROUPSEGMENTATIONBASEDONUSERPROFILR

After building the end-user portrait model of express delivery, we can segment the user group by classification and clustering based on the portrait, which is convenient to recommend different delivery services to users. Based on the previous section of the Courier user portrait, this paper proposes a classification and a clustering process. In the classification, the integrated algorithm of K-means and SVM is used to classify the users into stable users and lost users. In clustering, peak density-based clustering algorithm is used to divide two categories into different grades, indicating different stability and loss of users. Then, we complete the user segmentation of the express terminal program, the specific process as shown in Figure 2.

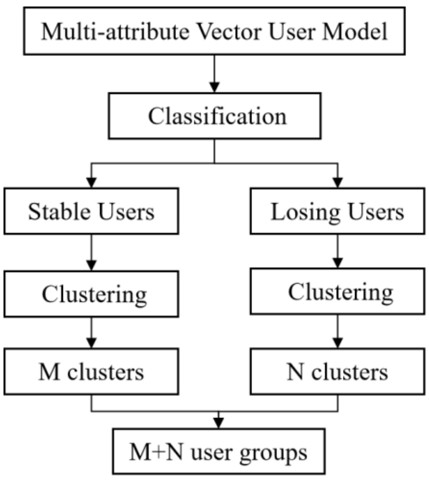

Figure 2. Flow chart for user segmentation.

3.1 The Classification

In classification process, this paper adopts the integrated classification algorithm based on K-means and SVM. SVM is a common machine learning classification algorithm with good performance, but it is a supervised learning algorithm, which needs to train the data learning classification process before the formal test. In order to improve the efficiency and performance of classification, we use the unsupervised clustering results provided by K-means algorithm as the training data of SVM classification, and input them into SVM model. Then SVM adjusts the segmentation hyperplane according to the K-means training data to get the optimized classification result.

During the classification process, we categorize users into two distinct categories, so we set the initial K value of K-means to 2.The detailed process is as follows:

$X=\{x_1,x_2,\cdots x_n\}$ is a multi-dimensional user data vector based on the multi-dimensional vector user portrait, which contains the user's basic attributes, preference attributes and feedback attribute data.

$A=\{a_1,a_2\}$ is assumed that it is the proposed initial class cluster, respectively on behalf of the Express Enterprise's stable users and users on the verge of loss of two categories.

We introduce a binary variable $\left[z_{ij}\right]$ to test which cluster the data points should be grouped into. The value of the variable is defined as:

$$z_{ij}=\begin{cases}1 \quad if \left\|x_i-a_j\right\|^2=\min\limits_{j=1or2}\left\|x_i-a_j\right\|^2 \\ 0 \quad otherwise\end{cases} \tag{6}$$

In the formula, $\left\|x_i-a_j\right\|^2$ calculate the Euclidean distance between the Data Point and the cluster center. The feedback attribute vector dimension may be different due to different users using express delivery and evaluating orders. Therefore, when calculating the Euclidean distance, we stipulate that if the dimension of the sample vector is different, the missing bit value is replaced by 0.

The initial cluster center is defined with binary variables as follows:

$$a_j=\frac{\sum_{i=1}^{n} z_{ij}x_{ij}}{\sum_{i=1}^{n} z_{ij}} \tag{7}$$

Considering the influence of different feature indexes on user location in sample vector is different, we introduce the index weight into the objective function to consider the distribution characteristics of data synthetically.

Suppose the weight vector is $W=\{\omega_1,\omega_2\cdots\omega_n\}$.

Among the three attributes, user preference and user feedback attribute value have a great influence on the classification results, making the weights of these two attributes $\omega_i = 3$.Other characteristic indicators reflect the stability of the ability of the user is weak, so make its weight $\omega_i = 1$.

Combine the binary variable $\left[z_{ij}\right]$ and the weight vector W to get the improved K-means' objective function:

$$F(z, A) = \sum_{i=1}^{n} (z_{i1}\omega_i \|x_i - a_1\|^2 + z_{i2}\omega_i \|x_i - a_2\|^2) \tag{8}$$

The objective of the algorithm is to minimize the objective function. The two clustering centers of K-means are updated continuously until the results no longer change, which makes the sample learning process before SVM classification completed. Then we use the labeled data as the input of SVM training classification algorithm, find the optimal hyperplane in the data feature space and solve it by the traditional quadratic programming method.-The quadratic programming model is as follows:

$$\begin{aligned} &\min \phi(w) = \frac{1}{2} w^T \cdot w \\ &s.t.\ \ z_{ij}\left[w^T \cdot x_i + b\right] \geq 1 \end{aligned} \tag{9}$$

In the process of K-means computation, we have introduced the binary variable $\left[z_{ij}\right]$ to partition the data, so we directly use it to replace the variables used in the traditional algorithm to distinguish between positive and negative classes in the quadratic programming constraint of SVM.

We obtain the optimal classification hyperplane by solving quadratic programming, and adjust the results of two clusters of labeled data obtained by previous K-means clustering based on it. Then we train the new classification hyperplane with the adjusted results. Repeat these two steps and update the optimal hyperplane until the classification results remain unchanged. This result is the optimal result of classification, which divides the end-user into two categories: stable and loss.

3.2 The Clustering

In order to locate and subdivide users in multiple levels, a clustering process is designed after classification. In the clustering process, the feedback vector of users is used as the data set, and the idea of DPC is used to cluster and subdivide the stable users and lost users respectively.

DPC clustering needs to define two important parameters: relative distance and local density. Because the sample vector dimensions of the above analysis may not be uniform, here we use min-type distance idea to define the relative distance parameters.

d is the relative distance between data points. α is the custom weight coefficient. n is the vector dimension and F_i is the input user feedback vector. We define the formula of the relative distance is as follows:

$$d = \alpha \cdot \sqrt[n]{\sum_{i=1}^{n} |F_i|^{n}} \tag{10}$$

The weight coefficient α in the formula is defined according to the Express Enterprise Index of the user's preference. If the user has a preference for only the business, $\alpha = 3$. If the user has a preference for more than one business and includes the business, $\alpha = 2$ .If the user has a preference for no business, $\alpha = 1$.

We also add user preference weights to the local density formula calculated using Gauss's kernel:

$$\rho_i = \alpha \cdot \sum_{i \neq j} \exp\left(-\frac{d_{ij}^{\ 2}}{d_c^{\ 2}}\right) \tag{11}$$

In the formula, ρ_i is the local density of each vector, d_{ij} is the distance between two points and d_c is the truncated distance specified in this paper.

According to the idea of DPC, we calculate the relative distance and local density of each sample vector, and choose two points with the largest index as cluster center. Then we calculate the Euclidean distance of the remaining data points to the cluster center, as in the previous SVM calculation process, if the vector dimensions are different, we fill the gaps with 0. According to the numerical value, we divide the data points into the nearest cluster, updating the cluster center repeatedly until the result no longer changes.
After clustering, stable users and lost users may be subdivided into M and N classes respectively. M and N represent different stability of M user groups and different loss of N user groups, M + N user groups in total. To these user groups, express delivery enterprises can make multi-level business recommendation according to the difference of stability and loss. The more stable the user can recommend the cumulative business benefits and quantitative benefits, and the degree of loss of users to establish a significant convenience or preferential terms. Through multi-level positioning, enterprises achieve personalized recommendation, provide personalized user services and improve user satisfaction.

EXPERIMENTALSIMULATION

In order to display the user information contained in the end-user portrait of express delivery and the result of user location subdivision after one classification and one clustering, we obtain the relevant data of express delivery users from a specific end-user program and import it through Python programming, displaying user profile information, and simulating the user segmentation through a classification and a clustering of the dataset.

4.1 User portrait emulation

According to the process of building the model, we classify the collected information of express users into three attributes, and display all the feature data of each user's portrait model, makes it easy to view user details. The result is shown in Figure 3 (The NaN in the figure represents a null value).

	ID	age	gender	region	conventional time	Specifications	preference	R1	R2	R3	R4	R5	R6	times
0	1	0-20	female	Huadong	noon and evening	S	Include this enterprise	6	5.0	6.0	NaN	NaN	NaN	3
1	2	40-50	male	Huanan	evening	S	Only this enterprise	7	8.0	8.0	7.0	8.0	7.0	6
2	3	0-20	female	Huazhong	evening	L	Include this enterprise	7	6.0	7.0	7.0	6.0	NaN	5
3	4	30-40	female	Huabei	noon and evening	S	Include this enterprise	6	8.0	7.0	NaN	NaN	NaN	3
4	5	50+	male	Northwest	noon and evening	S	No such enterprise	4	3.0	NaN	NaN	NaN	NaN	2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
195	196	50+	female	Huadong	all day	L	Only this enterprise	7	5.0	6.0	4.0	10.0	10.0	6
196	197	50+	female	Huadong	noon and evening	L	Only this enterprise	10	10.0	5.0	8.0	8.0	9.0	6
197	198	50+	female	Huadong	all day	L	No such enterprise	2	NaN	NaN	NaN	NaN	NaN	1
198	199	50+	female	Huadong	all day	L	No such enterprise	2	2.0	NaN	NaN	NaN	NaN	2
199	200	50+	female	Huadong	evening	L	No such enterprise	1	2.0	NaN	NaN	NaN	NaN	2

Figure 3. Part of the user information detail diagram.

In order to analyze the basic attributes of users, preference preferences, satisfaction with the enterprise and other information, we carried out data processing and display for different indicators of users:

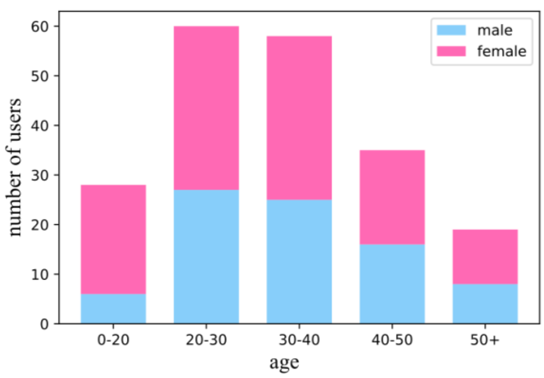

Figure 4. Sex-age chart.

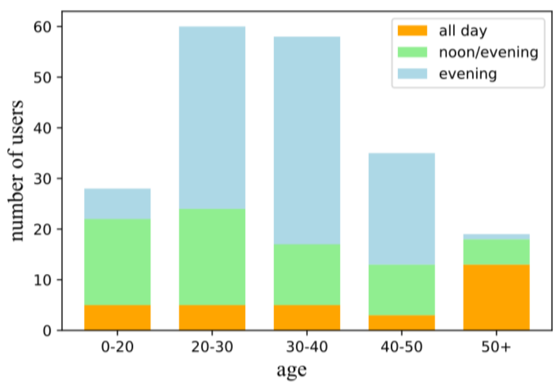

Figure 5. Time of receipt-age chart.

We quantified the users in the data set by sex and common time of receipt and delivery for different age groups. Based on the results in Figure 4, we can see that the users of the express terminal are concentrated in the age group of 20 to 50 years old, and the youth aged 20 to 40 years use the terminal the most. And there are more women than men in most age groups. According to Figure 5, there is a relationship between the age distribution and the time of receiving and sending for different age groups. The 0-20 age group has more students, so they often receive and mail express packages at noon and at night. The 20-50 age group has more users who work, so they receive and mail express packages at night. and the 50 + age group has more retirees, whom can get express delivery most of the day.

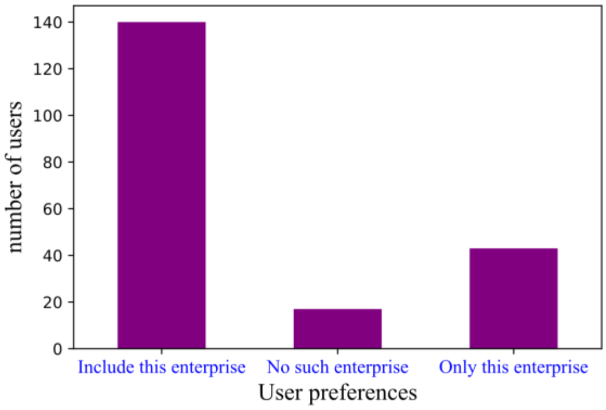

Figure 6. User preference enterprise distribution.

We make a statistical presentation of the enterprise with the index of user preference which has a greater impact on user segmentation. As can be seen from the graph above, in the enterprise end-users, most of them preferences are included in the enterprise or only the enterprise preference. People who have a preference for only this enterprise can often be directly identified as stable users, while people who have a preference for including this enterprise need to be specified based on their other feedback. In addition, a small number of users do not like the business of the enterprise, we should carefully study this part of the user feedback, to make appropriate measures to retain lost users.

Average the user's score and display the box graph according to different age groups:

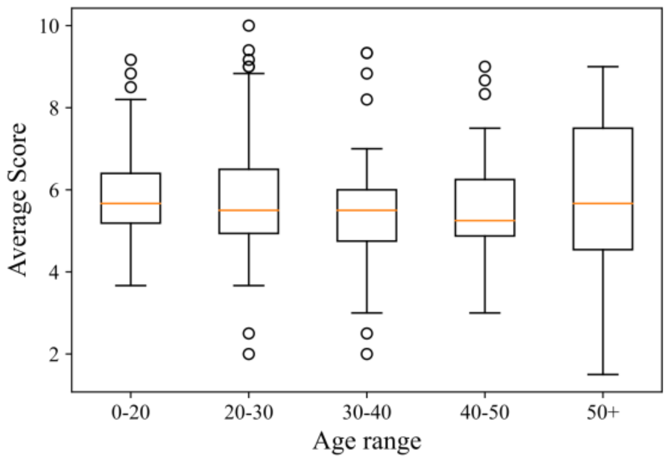

Figure 7. User ratings for different age groups.

According to Figure 7, we can see that different age groups’ average score for the Courier Enterprise has no much difference, which are between 5-7 points, belonging to the upper middle position. It is recommended that enterprises continue to optimize their business processes and enhance their Customer satisfaction.
For the selected end-users, we count the number of times users used the enterprise in 10 days, and according to the number of times they use to calculate the average of their business rating:

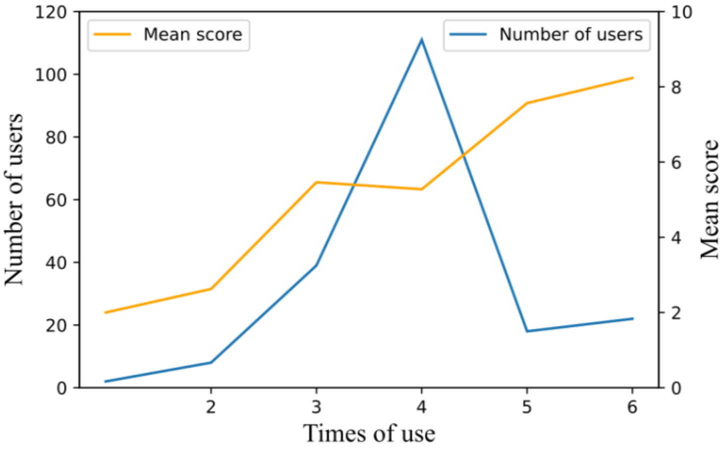

Figure 8. Graph of the average score and the number of users with the number of users.

As can be seen from Figure 8, this express has been used four times by the largest number of people. With the increase of the number of users using the express, the average value of users' evaluation of the business gradually increases, that means users with higher evaluation of this express are more willing to use this express.

4.2 User segmentation simulation

The above user profile data chart can only understand the basic situation of the enterprise user groups, but cannot accurately know whether users are loyal to the enterprise's express service. Therefore, we should carry on the depth mining and the analysis to the user information, through a classification and a clustering, displays the user subdivision localization result. We modify the traditional K-means and SVM integration algorithm program to generate the first classification results as shown in Figure 9:

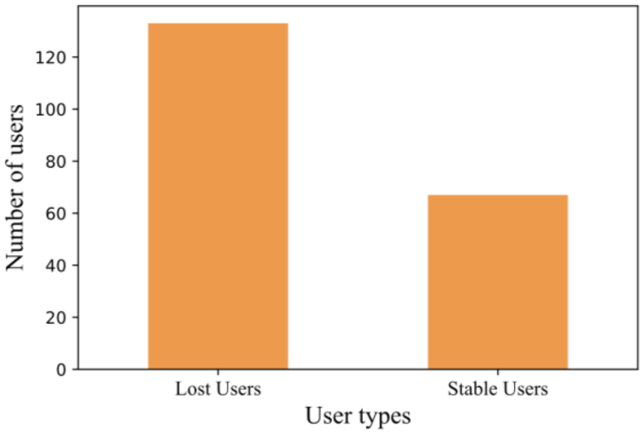

Figure 9. Results of the classification.

From figure 9, we can see that after the first classification, about two-thirds of the end-users belong to the lost users. The preference this enterprise user many but loses the user to be equally many. The reason for this phenomenon may be that many users use many express delivery companies at the same time, or often passively accept delivery companies, so even if the use of the express service, but not keen with the enterprise's express service.

In order to understand the stability and loss of these two types of users in detail, we then carried out a clustering process to subdivide the user group location and run the compiler file to get the results as shown in Figure 10:

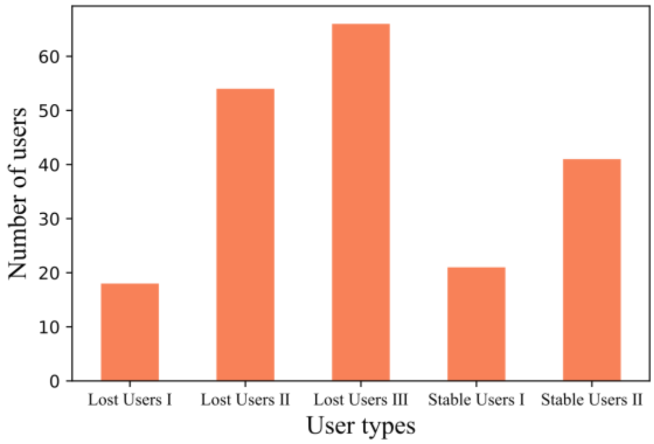

Figure 10. Results of the clustering.

After clustering without setting the number of categories, all users were divided into two categories of stable users and three categories of lost users, a total of five user groups.Grades I to III in the figure represent the degree of stability or loss from high to low. Enterprises should make different business recommendations to different levels of users to try to stabilize users or recover lost users. For the loss of high-level users need to be through a significant convenience or preferential terms to recover.

CONCLUSION

This paper proposes a user profile model based on the whole life cycle data generated by the user on the express terminal program, which divides the user features into three categories and forms a multi-dimensional vector model to describe the user's behavior information on the terminal. The model takes account of the basic information of users, so it can also build the initial portrait for new users without using records, effectively alleviating the problem of data sparsity and cold-start.

Aiming at the proposed multi-dimensional vector user portrait model, this paper designs a data mining method of one-time classification and one-time clustering. In the classification of users are divided into stability and loss of two major categories. In the clustering of the two categories of users in accordance with different degrees of stability and loss subdivision. The simulation results show that the improved algorithm can accurately achieve the user group positioning subdivision, providing a basis for the business promotion of express delivery enterprises.

However, the selected data set used in the experimental simulation stage is small, and the conclusion is not objective enough because of the lack of user portrait construction and data mining analysis under the mass data. At the same time, the design of the model and algorithm is simple, and a large number of data processing efficiency may be low.

REFERENCES

Wang, Q., Huo, B. &Zhao, X. 2020. What makes logistics integration more effective? Governance from contractual and relational perspectives. Journal of Business Logistics. 41(3) 259-281.

Liu, X. 2019. Research on optimization of community joint distribution based on user portrait. Beijing Jiaotong University.

Tang, X. 2020. Research on smart logistics model based on Internet of Things technology[J]. IEEE Access, 8 151150-151159.

Dang, X. 2020. Optimization of O2O Instant Delivery Strategy in Yonghui Supermarket Based on User Portrait. Logistics Engineering and Management. 42(12) 32-35.

Vasić, N., Kilibarda, M., Andrejić, M.&Jović, S. 2021. Satisfaction is a function of users of logistics services in e-commerce. Technology Analysis & Strategic Management. 33(7) 813-828.

Zhang, S., Chen, N., She, N. & Li, k. 2021. Location optimization of a competitive distribution center for urban cold chain logistics in terms of low-carbon emissions. Computers & Industrial Engineering. 154 107120.

Gu, H., Wang, J., Wang, Z., Zhuang, B. & Su, F. 2018. Modeling of user portrait through social media. 2018 IEEE international conference on multimedia and expo (ICME). IEEE, 1-6.

Chen, Y., He, J., Wei, W., Zhu, N & Yu, C. 2021. A multi-model approach for user portrait. Future Internet. 13(6) 147.

Yarushkina, N., Filippov, A., Moshkin, V., Namestnikov, A. & Guskov, G. 2019. The social portrait building of a social network user based on semi-structured data analysis. CEUR Workshop Proceedings/14th International Conference on Interactive Systems: Problems of Human-Computer Interaction, IS. 2475 119-129.

Tkachev, N. S., Mishchenko, P. V. &Zanekina, D.D. 2018. The System for Determining the Portrait of a User of Telecom Services[C]//2018 XIV International Scientific-Technical Conference on Actual Problems of Electronics Instrument Engineering (APEIE). IEEE, 552-554.

Alvarez, J., Léger, P. M., Fredette, M., Chen, S. L., Maunier,B. & Senecal,S. 2020. An enriched customer journey map: how to construct and visualize a global portrait of both lived and perceived users' experiences? Designs. 4(3) 29.

Wu, F., Ren, J., Lyu, F., Yang, P., Zhang, Y., Zhang, D. & Zhang, Y. 2022. Boosting Internet Card Cellular Business via User Portraits: A Case of Churn Prediction.IEEE INFOCOM 2022-IEEE Conference on Computer Communications. 640-649.

Liu, C., Park, E. M. & Jiang, F. 2020. Examining effects of context-awareness on ambient intelligence of logistics service quality: user awareness compatibility as a moderator. Journal of Ambient Intelligence and Humanized Computing. 11(4) 1413-1420.

Vu, T. P., Grant, D. B&Menachof, D. A. 2020. Exploring logistics service quality in Hai Phong, Vietnam. The Asian Journal of Shipping and Logistics. 36(2) 54-64.

Wang, C., Daneva, M., Sinderen, V. M.& Liang, P. 2019. A systematic mapping study on crowdsourced requirements engineering using user feedback. Journal of software: Evolution and Process. 31(10) e2199.

Santos, R., Groen, E. C. &Villela, K. 2019. An Overview of User Feedback Classification Approaches. REFSQ Workshops.

Oriol, M., Stade, M., Fotrousi, F., Nadal, S., Varga, J., Seyff, N., Abello, A., Franch, X., Marco, J. &Schmidt, O. 2018. FAME: supporting continuous requirements elicitation by combining user feedback and monitoring. 2018 IEEE 26th international requirements engineering conference (re). 217-227.

Younes, W., Adreit, F., Trouilhet, S. & Arcangeli, J.P. 2020. Agent-mediated application emergence through reinforcement learning from user feedback. 2020 IEEE 29th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE). 3-8.

Yigitbas, E., Hottung, A., Rojas, S.M., Anjorin, A.,Sauer, S. & Engels, G. 2019. Context- and data-driven satisfaction analysis of user interface adaptations based on instant user feedback. Proceedings of the ACM on Human-Computer Interaction.3(EICS) 1-20.

Liu, C., Feng, Y., Lin, D., Wu, L. & Guo, M. 2020. IoT based laundry services: an application of big data analytics, intelligent logistics management, and machine learning techniques. International Journal of Production Research. 58(17) 5113-5131.