Research and Application of Business Ability Evaluation Based On DBSCAN Algorithm and Entropy Method

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Abstract. Based on the data of 95598 work sheets and quality inspection, this paper constructs customer commissioners business capability evaluation models of different business types. Firstly, through DBSCAN algorithm we mine the potential category characteristics of customer commissioners. Then, entropy method is used to score the customer commissioners under the target category comprehensively. Finally combining the clustering results and entropy score, the customer commissioners with relatively strong and weak business capabilities are identified accurately. By marking the business capacity labels for the corresponding customer commissioners, it has guiding significance for the post adjustment and business training, which can improve the quality of power supply service and customer satisfaction for customer service center.

Keywords: Customer Commissioners, Business Capacity Labels, DBSCAN Algorithm, Entropy Method

Preface
With the development and extension of the 95598 business, the traffic intensity continues to increase. In many cases, customers cannot solve problems through self-service methods, and they will turn to manual services. The increasing intensity and difficulty of manual services pose new challenges to the various business and service capabilities of customer service specialists. How to manage customer service personnel is an extremely important task facing the State Grid Customer Service Center, and scientifically and reasonably evaluating the business capabilities of customer service agents is the key to achieving accurate management of customer service personnel.

Currently, the State Grid Customer Service Center monitors and evaluates the service level of customer service specialists by sampling [1]. The quality inspection and evaluation adopts a scoring system. The final quality inspection results are obtained by summarizing the scores of each detail. Through the scores, the service ability of the customer service specialists is judged, and targeted management measures are taken. If, on the basis of quality inspection and evaluation, enrich the ability evaluation system, scientifically quantify the business ability level of customer service specialists under different business types and realize specific group identification. For example, by accurately locating a target group of customer service specialists with relatively outstanding and relatively weak
business capabilities, you can discover the business advantages and shortcomings of employees in time, adopt flexible job adjustments and necessary business training, thereby improving the quality of power supply services and customer satisfaction.

1. Customer Service Specialist's Business Ability Evaluation Model
Based on the quality inspection data under a certain business of the customer service commissioner, this paper sorts out the evaluation data of the customer service commissioner's ability index and establishes the customer service commissioner’s business ability evaluation model. Using the combination model of "density clustering + entropy method", mining the potential information of customer service agents, calculating the service ability scores of customer service agents, selecting customer service agents with relatively strong or weak business ability and labeling them accordingly.

1.1 Evaluation Indicators for the Ability of Customer Service Specialists
There are many factors to evaluate customer service specialists. In order to accurately describe the ability of customer service specialists. In this study, based on the quality inspection data of a certain business of the customer service commissioner, combing the evaluation indicators of the customer service commissioner's ability, initially divided into 6 primary indicators and 13 secondary indicators, as shown in Table 1. Among them, the 6 first-level indicators are: experience indicators, work order filling, work order dispatch, business capabilities, service capabilities, and service attitudes.

| Customer Service Specialist Ability Evaluation Index | First level indicator | Secondary indicators |
|-----------------------------------------------------|-----------------------|---------------------|
| Experience index                                   | Total call time        | Total number of work orders processed |
|                                                     | Total number of solutions |
| Work order filling                                 | Number of complete errors in work order content |
|                                                     | Number of timeout errors when filling in a work order |
| Work order dispatch                                | Distribute timely and accurate number of errors |
|                                                     | Classification and classification accuracy errors |
|                                                     | Number of chargebacks |
| Operational capacity                               | Answer the number of accurate errors |
|                                                     | Handling proficiency errors |
| Service capabilities                                | Number of service process specification errors |
|                                                     | Number of errors with good service awareness |
| Service attitude                                   | Number of errors with good service attitude |

Experience indicators refer to indicators that can quantify the experience of customer service specialists. This article selects the total call time of customer service specialists (seconds), the total number of work orders (times), and the total number of one-time solutions (times) to evaluate this indicator.

Work order filling includes the completeness and accuracy of work order filling. The accuracy of work order filling is very important for follow-up staff to deal with customer demands. This paper selects the number of complete errors in the work order content (number) and the number of timeout errors in the work order filling (number) to evaluate the indicator.

Work order dispatch means that customer service personnel dispatch work orders to relevant processing departments. The timely and accurate dispatch of dispatches affect the efficiency of handling customer requests. This paper selects three factors, namely, the number of timely and accurate errors in distribution (number), the number of accurate errors in classification and classification (number), and the number of return orders (number) to evaluate the indicator.

Business ability refers to the description of the professional level of customer service specialists in terms of the quality and efficiency of answering customer questions. This article selects the number of
accurate answers (number of errors) and the number of skilled handling errors (number) to describe this indicator.

Service ability refers to the description of the professional level of customer service specialists from the customer service process. This article selects the number of service process specification errors (number) and the number of good service awareness errors (number) to describe the indicator.

Service attitude is to evaluate the attitude of customer service specialists to customer service. This article selects the factor (number) of good service attitudes to evaluate this indicator.

1.2 Customer Service Specialist Business Capability Model

1.2.1 Data preprocessing. There are abnormal data such as null values in the service evaluation index data of customer service specialists. Aiming at the empty value, this article adopts the filling method, and filling the empty value with zero. For abnormal data such as negative numbers and special characters, the elimination method is used to delete the record and not include it in the valid data. Fields with zero source variance (for example: "Distribution Time Accurate Error Number") are eliminated. The dimensions of each field in the data width table are different. In order to eliminate the difference in dimensions, 13 index data need to be standardized [16]. And because there may be a strong correlation between various indicators, it is necessary to use the principal component method to reduce the dimensionality of the data before establishing the model. The principal component method [17~18] is a method of transforming multiple variables into a small number of principal components. The principle is to linearly transform n variables to obtain m (m <n) uncorrelated principal components. The eigenvalue ratios of the principal components of the 13 indicators are shown in Table 2. The cumulative contribution rate of the first eight principal components has reached more than 90%, and most of the information has been extracted to meet the need for dimensionality reduction.

Table 2. Results of principal component analysis

| principal component | Contribution rate | Cumulative contribution rate |
|---------------------|-------------------|-----------------------------|
| Factor1             | 0.466339303       | 0.466339303                 |
| Factor2             | 0.108527815       | 0.574867119                 |
| Factor3             | 0.096425332       | 0.671292451                 |
| Factor4             | 0.074847869       | 0.74614032                  |
| Factor5             | 0.056718451       | 0.802858771                 |
| Factor6             | 0.052506444       | 0.855365215                 |
| Factor7             | 0.043430586       | 0.898795801                 |
| Factor8             | 0.026337739       | 0.925133541                 |
| Factor9             | 0.024547586       | 0.949681126                 |
| Factor10            | 0.022839515       | 0.972520641                 |
| Factor11            | 0.013067485       | 0.985588126                 |
| Factor12            | 0.011477524       | 0.997065649                 |
| Factor13            | 0.002934351       | 1                           |

1.2.2 DBSCAN clustering. Commonly used clustering methods include K-means algorithm [2~5], hierarchical clustering algorithm [6~7], DBSCAN algorithm [8~11] and so on. This paper selects DBSCAN algorithm to cluster the preprocessed data, which is an unsupervised clustering algorithm based on sample density. Compared with other clustering algorithms, the DBSCAN algorithm does not need to determine the number of categories in advance, and can divide clusters according to different data sets, and is not sensitive to noise data.
Generally, two parameters need to be provided when using DBSCAN algorithm for clustering, one is the clustering radius \(\varepsilon\), and the other is the minimum number of samples into the cluster \(MinPts\). The selection of these two parameters directly affects the algorithm effect and clustering quality.

This article uses the method of cyclic tuning to determine the optimal value of cyclic tuning with the goal of minimizing the sum of various variances. When the optimal value is in the first 0.25 quantile (later 0.25 quantile) of the range of the undetermined parameter, adjust the range of the undetermined parameter forward (adjust backward) to ensure that the optimal parameter is in the middle range of the undetermined parameter range. This can effectively avoid local minimums within a certain range, and at the same time speed up parameter tuning and reduce the difficulty of calculation. The tuning ideas are as follows:

a) Initialization parameter \(\varepsilon\) and the value range of \(MinPts\);
b) Cycle values within the value range of the parameter \(MinPts\);
c) Circulate values within the range of parameter \(\varepsilon\);
d) Bring parameter \(\varepsilon\) and \(MinPts\) into the DBSCAN clustering model;
e) Calculate the sum of variance between classes;
f) Take the parameter with the smallest variance as the best parameter for this cycle;
g) If the best parameter is not within the \([0.25, 0.75]\) quantile range of the parameter range, adjust the parameter range and reinitialize the parameter range;
h) Until the best parameter is distributed in the \([0.25, 0.75]\) quantile interval of the parameter range, the cycle ends.

After tuning the above parameters, it is finally determined that the clustering radius is 0.12 and the minimum number of samples for the class is 8. At this time, the variance of the clustering results is the smallest, which is 3.185. In this clustering result, 17 classes and 1 abnormal data class are obtained. By digging into the characteristics of different types and further analysis, the "suspected business capabilities are outstanding" and "suspected business capabilities are weak" can be located. For specific analysis, please refer to the description in section 2.1.

1.2.3 Entropy method scoring. On the basis of locating the suspected business ability outstanding category and the suspected business ability weak category, it is necessary to further locate a customer service specialist with relatively outstanding and relatively weak business ability. This paper uses the entropy method [12–15] to comprehensively score the various indicators of the customer service commissioners in various types, in order to combine the clustering results and the entropy method score to comprehensively screen out the customer service commissioners with relatively outstanding and relatively weak business capabilities [16].

The entropy method is an objective weighting method that determines the weight of the index according to the degree of variation of the index value, and is widely used in the construction of evaluation models. The following describes the specific steps of the entropy method:

a) Data standardization

In order to eliminate the dimensional difference between the indicators, the data of each indicator needs to be standardized. The formula is as follows:

\[
x'_{ij} = \frac{x_{ij} - \bar{x}_j}{S_j} \quad (i = 1, 2, \ldots, n; \ j = 1, 2, \ldots, m)
\]

(1)

Among them,

\[
\bar{x}_j = \frac{1}{n} \sum_{i=1}^{n} x_{ij} \quad S_j = \frac{1}{n} \sum_{i=1}^{n} (x_{ij} - \bar{x}_j)^2
\]

\(\bar{x}_j\) is the sample mean of the \(j\) indicator, and \(S_j\) is the sample standard deviation of the \(j\) indicator.

b) Calculate the proportion of the index value of the \(i\) decision under the \(j\) index \(p_{ij}\),
\[ p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \]  
\[ (2) \]

c) Calculate the entropy value of the \( j \) indicator,
\[ e_j = -k \sum_{i=1}^{n} p_{ij} \ln(p_{ij}) \]  
\[ (3) \]

Among them, \( k = \frac{1}{\ln(n)} \), and meet \( e_j \geq 0 \).

d) Calculate information entropy redundancy,
\[ d_j = 1 - e_j \]  
\[ (4) \]

e) Calculate the weight of each indicator,
\[ w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \]  
\[ (5) \]

f) Calculate the comprehensive score of each decision,
\[ s_i = \sum_{j=1}^{m} w_j p_{ij} \]  
\[ (6) \]

Among them, \( w_j \) is the \( j \) index value of the \( i \) decision.

### Table 3. Weights of secondary indicators

| Index | First level indicator | Secondary indicators | Secondary index weight |
|-------|-----------------------|----------------------|-----------------------|
| Customer Service Specialist Ability Evaluation Index | Experience index | Total call time | 0.587 |
| | | Total number of work orders processed | 0.386 |
| | | Total number of solutions | 0.0268 |
| | Work order filling | Number of complete errors in work order content | 0.216 |
| | | Number of timeout errors when filling in a work order | 0.784 |
| | Work order dispatch | Classification and classification accuracy errors | 0.737 |
| | | Number of chargebacks | 0.263 |
| | Operational capacity | Answer the number of accurate errors | 0.693 |
| | | Number of skilled errors handled | 0.307 |
| | Service capabilities | Number of service process specification errors | 0.485 |
| | | Number of errors with good service awareness | 0.515 |
| | Service attitude | Number of errors in good service attitude | 1 |
In this paper, the entropy method is used to divide the weights of various business indicators of the customer service commissioner, and the difference in the amount of information covered between the indicators is used to determine the index weight, and the final entropy score is calculated to quantify the business ability of the customer service commissioner.

First, divide the weight of each secondary indicator corresponding to the six primary indicators in Table 1. Since there is only one secondary indicator under the primary indicator "service attitude", the weight of the secondary indicator is 1 by default. The weight division results of the secondary indicators are shown in Table 3.

Then, multiply the weights of each secondary index by their normalized index values and add them to obtain a comprehensive entropy score. The comprehensive score is the value of the first-level index. Next, the same method is used to divide the weight of the first-level index. The results are shown in Table 4.

**Table 4.** Weights of first level indicators

| index | First level indicator | First-level indicator weight | Secondary indicators weight |
|-------|-----------------------|-----------------------------|----------------------------|
|       | Experience index      | 0.00101                     | Total call time 0.587      |
|       |                       |                             | Total number of work orders processed 0.386 |
|       |                       |                             | Total number of solutions 0.0268 |
|       | Work order dispatch   | 0.105                       | Number of complete errors in work order content 0.216 |
|       |                       |                             | Number of timeout errors when filling in a work order 0.784 |
|       | Operational capacity  | 0.163                       | Classification and classification accuracy errors 0.737 |
|       |                       |                             | Number of chargebacks 0.263 |
|       | Service capabilities  | 0.277                       | Number of accurate errors answered 0.693 |
|       |                       |                             | Number of skilled errors 0.307 |
|       | Service attitude      | 0.315                       | Number of service process specification errors 0.485 |
|       |                       |                             | Number of errors with good service awareness 0.515 |
|       |                       |                             | Number of errors in good service attitude 1 |

It can be seen from the index weights finally divided by the entropy method in Table 4 that the
service capability and service attitude have the largest weight. At the same time, among the various secondary indicators under the primary indicator, the total call time, the timeout of the work order filling, the classification of the work order, the accuracy of the answer, the service awareness, and the service attitude all have a weight of more than 0.5. It shows that it is more important than other indicators under the various first-level indicators. The above weighting results are reasonable from a business perspective, and are basically in line with the status quo of customer service specialists.

2. Analysis of Results of Customer Service Specialist's Business Capability Model

2.1 Analysis of Clustering Results

As mentioned in section 1.2.2 above, 17 classes and 1 abnormal data can be obtained by density clustering. By analyzing the characteristics within the class, interpreting the hidden data information in each class, and mining the potential categories of customer service specialists, is the key problem to be solved by clustering.

Table 5 lists the specific clustering results. Analysis of Table 5 shows that more than 50% of the categories involving "complete work order content" errors account for 453 people. Among them, there are only three categories (class4-class6) with errors due to "complete work order content", with a total of 342 people. Separately use "work order handling proficiency", "service process", "work order classification", and "refund order" categories (class3, class7, class8/class15, class12) with the wrong reasons, and the number of people has reached more than 50. Among them, there were 119 "proficient work order handling" errors. In the combined error category, there are only five reasons for errors such as "complete work order content", "work order classification", "work order handling proficiency", "service process", and "refund order". Other reasons did not appear. It can be seen that in the daily work of customer service specialists, these five kinds of errors are very easy to appear. However, "work order filling", "accurate answer", "service awareness", "service attitude" and other reasons are wrong, and there are no characteristics that can be classified, indicating that these errors are rarely made in daily work.

Table 5. Results of density clustering

| class   | Business involved                                      |
|---------|-------------------------------------------------------|
| Abnormal data class | /                                                      |
| class1  | no                                                     |
| class2  | Complete work order content, accurate classification and grading |
| class3  | Proficient                                             |
| class4  | Complete ticket content                                |
| class5  | Complete ticket content                                |
| class6  | Complete ticket content                                |
| class7  | Service process specification                         |
| class8  | Accurate classification                               |
| class9  | Complete work order content and skilled handling       |
| class10 | Complete work order content and standard service process |
| class11 | Skilled handling, standardized service process         |
| class12 | Ticket chargeback                                      |
| class13 | Complete work order content, work order refund         |
| class14 | Accurate classification and classification, skilled handling |
| class15 | Accurate classification                               |
| class16 | Complete work order content and standard service process |
| class17 | Complete work order content, work order refund         |
There is also a special category that cannot be generalized. It gathers all the points that cannot be classified. This category is called abnormal data category. The abnormal data category is unavoidable in density clustering, and there are 384 people in this category. Further analysis of the data in the category shows that this category includes both the population with a high total number of errors and the population with fewer errors in the indicator. Although it is included in the abnormal data category, it requires special attention.

This article classifies the above categories with error characteristics together as "suspected business ability weak" category. In addition, there is a class1, the number of people in the class has reached more than 50% of the total number of people, a total of 1931 people, this class has the characteristics of "zero error". That is to say, all secondary indicators involving the number of errors have a value of zero and perform well in empirical indicators. This article classifies this category as "suspected business ability outstanding".

2.2 Analysis of the Results of Entropy Method

After DBSCAN clustering and analysis of class characteristics, the categories of "suspected business capabilities are outstanding" and "suspected business capabilities are weak" are summarized. On the basis of these two categories, in order to accurately locate a customer service agent with relatively outstanding and relatively weak business capabilities, this paper uses the entropy method to comprehensively score various indicators of the customer service agents in various categories. Finally, the clustering results and entropy method scores are combined to comprehensively screen out the customer service agents with relatively outstanding and relatively weak business capabilities, and correspondingly mark the business ability labels.

According to the index weight division results of customer service specialists in section 1.2.3, the entropy score of each customer service specialist can be obtained. The distribution of various ratings is shown in Table 6.

| class               | Max       | Min       | average value |
|---------------------|-----------|-----------|---------------|
| Abnormal data class | 0.616298  | 0.000426  | 0.037687      |
| class1              | 0.001008  | 0.000378  | 0.000958      |
| class2              | 0.004221  | 0.003839  | 0.004046      |
| class3              | 0.011722  | 0.011296  | 0.011614      |
| class4              | 0.010618  | 0.010404  | 0.010492      |
| class5              | 0.004233  | 0.003658  | 0.004081      |
| class6              | 0.007456  | 0.007006  | 0.007289      |
| class7              | 0.001003  | 0.00064   | 0.000878      |
| class8              | 0.001005  | 0.000582  | 0.000891      |
| class9              | 0.014948  | 0.014584  | 0.014815      |
| class10             | 0.004214  | 0.003878  | 0.004075      |
| class11             | 0.011713  | 0.011451  | 0.011591      |
| class12             | 0.009547  | 0.009156  | 0.009434      |
| class13             | 0.012643  | 0.012353  | 0.012494      |
| class14             | 0.011706  | 0.011512  | 0.011612      |
| class15             | 0.000544  | 0.000452  | 0.000486      |
| class16             | 0.007305  | 0.007164  | 0.007253      |
| class17             | 0.012736  | 0.012657  | 0.012693      |

It can be seen from Table 6 that, except for the abnormal data category and class1, the entropy scores of the other categories fluctuate in a small range around their average value, which has obvious hierarchy. According to the calculation rules of entropy score, the lower the value of various business
indicators related to the number of errors, the higher the index value related to the number of work orders, the number of one-time solutions, etc., the lower the entropy score. Combining the characteristics of the class, class1 is the "zero error" class, and the point with the smallest entropy score is in this class. The score interval is [0.000378, 0.001008]. There are also classes in this score interval: class7 is distributed in [0.00064, 0.001003], class8 is distributed in [0.000582, 0.001005], and class15 is distributed in [0.000452, 0.000544]. It can be seen that the score intervals of these four categories have intersections. The scores of the abnormal data category have a large span, distributed in [0.000426, 0.616298], and the point with the highest entropy score is in this category.

This paper proposes to use the "suspected business ability is weak" and "suspected business ability is outstanding" in the results of density clustering. Combining the entropy score to construct the business ability label of customer service specialists, the entropy score of the customer service specialists is sorted from small to large, and the first 0.05 quintile is used as the outstanding threshold of business ability, and the last 0.05 quintile is used as the threshold of weak business ability. For customer service specialists who meet the clustering results of "Suspected business ability outstanding" and less than the threshold of strong business ability, mark it as "A certain business ability outstanding" label; For customer service specialists who meet both the “suspected business ability weak” category and the threshold value of the weak business ability threshold of the density clustering result at the same time, mark it as “a certain business ability weak” label. According to the above rules, there were 134 customer service specialists who were finally labeled as "a certain business ability outstanding" label. 70 customer service specialists from the "zero error" category, labelled as "weak business capabilities", from the "abnormal data" category and category 9. The statistical results of the final ability evaluation model are shown in Table 7.

| label                          | Density clustering                     | Entropy method | Number of people | Class characteristics       |
|-------------------------------|----------------------------------------|----------------|------------------|----------------------------|
| Outstanding business ability  | Suspected business ability is outstanding | Top 0.05 quantile | 137              | Zero error                 |
| Weak business ability          | Suspected business ability is weak      | Last 0.05 quantile | 70               | Fill in work order content, processing skills, etc. |

Applying the same method to other business types, you can get the service capability labels of customer service specialists of different business types.

3. Conclusion

Based on 95598 work order data and quality inspection data, taking a certain business type as an example, this paper uses the algorithm of "density clustering + entropy method" to construct an evaluation model for the ability of customer service professionals. Excavate the potential category characteristics of customer service agents, locate 137 customer service agents with relatively outstanding business capabilities and 70 customer service agents with relatively weak business capabilities, and mark corresponding capability labels for the corresponding customer service agents. Applying the same method to other business types, you can get the service capability labels of customer service specialists of different business types. Different management strategies can be adopted for groups of customer service specialists with different ability labels. For customer service specialists with the label of "relatively weak business capabilities", they can develop suitable training plans to improve their short-board business capabilities; for the customer service specialists with the label of "relatively outstanding business ability", reasonable job adjustments and appropriate incentives can be arranged to give full play to the advantages of customer service specialists. Through precise positioning, timely detection of personnel and job matching problems, reasonable guidance, and implementation of policies in accordance with their aptitude, it can effectively improve the quality
of power supply services, reduce the probability of customer complaints, and increase customer satisfaction.

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