KKMA - A Calculation Method for KANO Classification Based on User Reviews

A P Lu, Y F Sun, Z Lei, G Li, J Jing, W Liu and C J Hu
Advisory Engineer, PCSD Quality, Global Supply Chain, Lenovo Ltd. Company, 100193, P.R. China
E-mail: luap@lenovo.com

Abstract. KANO model classification is helpful for us to recognize customer needs and to improve their satisfaction. The traditional method uses standard questionnaires to conduct surveys, classifies product attributes according to the survey results. However, with the increase of product complexity and the speed of product iteration, the method of survey is more and more unable to meet our analysis needs; coupled with the increasing number of customers who do not want to give feedback for questionnaires, low responds ratio rate leads poor feedback quality which affects the reliability of the research results. Although many studies are about KANO model classification, few of them focus on how to improve responds ratio rate. This article creates a new method for KANO model classification. By collecting customer reviews and rating score, we build up regression model between the score and the degree to which product attributes meet user needs according to their text expression. Based on the curve shape of the model coefficients and the value of the coefficient we can identify which KANO classification will a product attribute belongs to. The experiment study for gaming notebook has proved that this method is efficient and can be widely used in other products. We call this method as KKMA (Kano, K-means, MDS, Ad boost).

1. Introduction
With the continuous deepening of big data in various fields, it has become a mainstream model to promote product quality improvement and product research by tapping the potential needs of customers. As a mainstream tool, the KANO model establishes a user demand model from the perspective of user satisfaction, can identify customer demand trends and identify different types of customer needs [1], and has been widely used. However, how to achieve the optimal extraction from customer needs to product feature parameters and reduce the adverse effects of fuzzy information has always been an important research content of domestic and foreign researchers. Yang [2] have proposed a product development task allocation method based on cluster analysis and bilateral matching based on the comprehensive satisfaction of customer personnel. By clustering the preferences of personnel, the evaluation decision of the optimal task set is realized. Duan et al. [3] introduced the theory of quality function allocation based on the KANO model, which improved the credibility of customer demand analysis. Li et al. [4] established an optimization model for the importance of customer needs based on the competitive evaluation data of customer needs. In view of the complex and changeable psychological conditions of customers,
Meng [5] constructed a customer demand classification method based on the fuzzy KANO model, which makes the method easier to apply.

Instead of conducting survey for KANO model classification, this article creates a method to realize KANO classification of product attribution based on customer reviews and customer satisfaction overall rating scores. We collect customer reviews and overall rating scores about gaming notebook from JD.com, use NLP (Natural Language Processing) technology to deal the data, K-means classing algorithm to grade customer perception level regarding each product attribute according to their text expression, then build up regression model between the overall rating score and the graded customer satisfaction of each product attribution. By analysis the regression model coefficient for each product attribution and match the coefficient curve shape with KANO needs definition we can determine which KANO model classification should a product attribution belongs to.

User reviews refer to text descriptions about product use experience, service experience or other aspects expressed by users after purchasing a certain product or using a certain service, and giving a comprehensive overall rating score. An example of customer reviews refer figure 1. Consider two basic elements of the Kano model questionnaire: 1. product attributes to be studied, 2. user satisfaction about each product attributes. Obviously these two elements can be obtained from user reviews.

Element 1: Product attributes to be classified. Given product A, in the description of reviews, users mention their perception of certain aspects of product A. Put all customer reviews together, we can get all attributes that cared about by customers.

Element 2: User satisfaction. The comprehensive rating score given by the user reflects the user's satisfaction, together the reviews describe how much they like or dislike about certain attributions.

Based on the above considerations,

- The process of collecting user reviews is equivalent to the process of issuing Kano questionnaire

We can build correlation study between the comprehensive overall rating score (y) and their perception level (x) in their reviews about certain product attribution.

Figure 1. An example of Customer Reviews and Overall Rating Scores

2. Kano classification calculation based on reviews
The Kano classification calculation based on reviews data includes six main steps: 1. Customer reviews data and overall rating score data collection, 2. product attribute extraction, 3. user experience sentiment grading, 4. regression model calculation between overall rating score and customer perception level regarding a certain product attribute, 5. model tuning, and 6. Kano classification to determine product attributes.

2.1. Collect data
This research object is gaming notebook, in order to carry out the analysis we collected every customer reviews and rating score from JD.com about gaming notebook. Delete non-value reviews, e.g. too short review, non-valid information review and the pseudo-accounts of the three-party stores reviews.
2.2. Extract product attribution

In order to implement the Kano classification calculation based on user reviews, we need to label product attributes for each review so as to identify the product attributes mentioned in it.

First, create product attribution list based on the objective situation of the product (including structure, function, design, etc.). Second, using NLP (Natural language process) to segment reviews and extract content characteristics. Third, map content characteristics with attribution list as to identify what attribution is mentioned in the review.

Below is an example of label review with product attribution:

"The appearance is very beautiful, and the performance is very good. I tried several games that I often play, and all of them can be easily handled, which meets my requirements. However, when playing games, the fan sound is a bit loud, and other times it is fine, almost silent. n highly recommended! ! !"

Label result is as below:

Mentions 1: “The appearance is very beautiful”, Attribution Aesthetics

Mentions 2: “I tried several games that I often play, and all of them can be easily handled, which meets my requirements”, Attribution Performance

Mentions 3: “when playing games, the fan sound is a bit loud”, Attribution Fan noise

The object of this study is gaming notebook. We total collected 120,000 reviews and segmented them into 246,000 mentions, total labelled 162 product attributes for them.

There are many algorithms for word segmentation, which are not described here in detail, please refer to related literature. The implementation of attribute labelling uses a combination of model training and rule-based mapping.

2.3. Grade user experience sentiment

Grading user experience sentiment, refers to the degree of preference expressed by the user's description. In order to achieve the classification of sentiment intensity, we take the method of word clustering. We took grading calculation base on the result in 2.2. In 2.2, a total of 162 types of product attributes were obtained. Considering the validity of the data volume sample, the attributes with data sample greater than 1000 (a total of 38 categories) were selected for word clustering calculations.

The word clustering calculation adopts the edit distance algorithm to calculate the distance matrix of the review segment of each attribute separately, and then uses the MDS algorithm to assign two-dimensional coordinates to each word according to the distance matrix, and performs segmentation based on the segment coordinates for each attribute. K-means clustering set the number of clusters to 7.

The calculation method of edit distance is as follows: dynamic rule

$$
Eidit(i,j) = \begin{cases} 
Eidit(i-1, j)+1 & \text{if } j = 0 \\
Eidit(i, j-1)+1 & \text{if } i = 0 \\
\min \left\{Eidit(i-1, j-1)+[A[i] \neq B[i]]\right\} & \text{otherwise}
\end{cases}
$$

(1)

The following Figure 2 is the result of clustering about the "price" attribute. It should be noted that the labels 1 to 7 of the cluster are disordered. 1 may not represent the strongest negative sentiment classification, and 7 may not be the strongest positive sentiment classification.
2.4. Regression model calculation between overall rating score and customer perception level regarding a certain product attribute

The regression model uses multiple linear regression, with the overall rating score as the dependent variable \( y \) (continuous), and the customer perception level for each segmented review as the independent variable \( x \) (classification) for regression.

Since the independent variables are categorical (7 grades), each independent variable should be converted into 7 dummy variables. Example: The attribution \( i \) corresponds to the reviews segment belonging to the third of the seven categories, then \( x_{i,j} = 1, x_{j} = 0 \) \((j \neq 3)\).

Examples, Suppose there are two product attributions: Running speed (speed) and Memory Capacity (capacity), the segmented reviews mentioning these two needs are divided into 7 categories by clustering methods, which reflect different levels of customer perception.

7 dummy variables for running speed are: \( x_{speed(1)}, x_{speed(2)}, x_{speed(3)}, x_{speed(4)}, x_{speed(5)}, x_{speed(6)}, x_{speed(7)} \). For a review, if it mentioned running speed and customer perception level is 3, then \( x_{speed(3)} = 1, x_{speed(j)} = 0 \) \((j \neq 3)\), for those reviews did not mention running speed, then their \( x_{speed(j)} = 0 \) \((j = 0, 1, 2, 3, 4, 5, 6, 7)\).

7 dummy variables for Memory Capacity is similar with running speed. So the regression equation is as blow:

\[
y = a + b_{speed(1)}x_{speed(1)} + b_{speed(2)}x_{speed(2)} + \ldots + b_{speed(7)}x_{speed(7)} + b_{capacity(1)}x_{capacity(1)} + \ldots + b_{capacity(7)}x_{capacity(7)}
\]

\( y \) is the rating score, for a review it mentioned running speed with customer perception level is 3, and mentioned memory capacity with customer perception level is 4, then \( y = a + b_{speed(3)} + b_{capacity(4)} \).

- Coefficient, \( b_{speed(3)} \), means how much will the running speed with customer perception level3 contribute to score \( y \).
- Since the scores are actually discrete \(\{1, 2, 3, 4, 5\}\), therefore when fitting the score, the fitting result is rounded (less than 1 counts as 1 point, and greater than 5 counts as 5 points) as the final fitting result, which is used to evaluate the accuracy of the fitted model.

For each review, establish a regression equation between the review score \( y \) and the customer perception level \( x \) to which the review segment belongs, from which seven coefficients of 38
product attributes are calculated. The coefficient of attribute $i$ is expressed as: $b_{ij}, j = 1,2,3,4,5,6,7$, where each coefficient is characterized by the j-th level of the attribute $i$ will increase the score $y$.

2.5. Model tuning
Because the reviews data is severely imbalanced (samples with a score of 5 account for more than 80% of the total sample), performing a single regression will make almost all samples fit 5 points. Therefore, the weighted Ad boost algorithm is used to solve the imbalance problem through iterative correction.

Algorithm steps:
- Set the weight coefficient of the score $i$ ($i = 1,2,3,4$) as $P_i: P_i = (\text{total sample size} / (\text{sample size with score } i \times 10)) ^ 0.05$
- Set the initial weight of each sample to $1 / \text{total sample size}$
- Replaceable sampling from the original sample according to the weight, the number of samples is 5 times the total sample size, this is to ensure that the corresponding sample of the comment segment of each emotion level can be drawn
- Multivariate linear regression is performed on the sampled sample with the score as the dependent variable, and the category of the required comment segment as the independent variable.
- Using the original sample as the test set, substitute the regression model for fitting, round the fitting result, compare with the original scoring sample, and record the sample with incorrect fitting.
- Increasing the sampling weight for a sample with a bad fit:
  - $\text{err} = \text{sum}(\text{ratio*ind})$
  - $c = (1/2)*\log((1-\text{err})/\text{err})$
  - $\text{ratio} = \text{ratio*exp}(c*\text{ind})$
- According to the previously calculated weight coefficient $P_i$, further increase the sampling weight for the samples with a fitting error and with score value as 1, 2, 3 or 4, these samples can have a greater influence on the model. Iterate multiple times (4 times are used in this model), and get 4 fitted models respectively. Using the coefficient $c$ of each fitted model as the proportion, the four models are combined into a final model.

2.6. Determine Kano classification for each product attributes
In 2.5, the regression equation coefficients $b_{ij}, i = 1, 2, 3... 38; j = 1, 2, 3 ... 7$, each coefficient represents the j-th level of the attribute $i$ will increase the score $y$.

The regression model finally obtained 7 coefficients corresponding to each attribution, plotted the 7 coefficients in an order from lower to highest, with the y axis as the coefficient value and x axis as the customer perception level. Determine each attribution KANO classification base on coefficient value and the curve shape. Figure 3. is the KANO model definition.

![Figure 3. KANO Model Definition](image)
Result summary: gaming notebook has total 38 main attributes, among them 14 are Must-be quality, 14 are One-dimensional Quality, 4 are Attractive Quality and 6 are Compound quality. Details in below Table 1.

**Table 1.** Gaming Notebook 38 product attribution KANO needs classification result

| 14 Must-be Quality          | 14 One-dimensional Quality          |
|-----------------------------|-------------------------------------|
| 1. Human services           | 1. Thermal                          |
| 2. Quality Impression | Overview                           | 2. Performance Overview            |
| 3. Running speed            | 3. Logistics                        |
| 4. Performance configuration| 4. Package                          |
| 5. Aesthetics               | 5. After-sale Service               |
| 6. Display overview         | 6. Special Applications             |
| 7. Quality Impression | Quality                            | 7. Audio sound quality              |
| 8. Quality Impression | Brand                              | 8. Graphics performance             |
| 9. System Reliability       | 9. Appearance workmanship           |
| 10. Marketing channels      | 10. Keyboard | Overview                        |
| 11. Order delivery          | 11. Battery life                    |
| 12. Machine noise           | 12. Software                        |
| 13. Display | light leakage                      | 13. Order experience                |
| 14. Price | Overview                          | 14. Size/Weight                     |

| 4 Attractive Quality          | 6 Compound Quality          |
|-------------------------------|-----------------------------|
| 1. Keyboard Feeling          | 1. Deliver Speed Mustbe+Attractive |
| 2. Memory Capacity           | 2. Power on/off speed Mustbe+Attractive |
| 3. Keyboard Backlight        | 3. Screen Definition Mustbe+Attractive |
| 4. Appearance Material       | 4. Fan Noise Mustbe+Attractive |
|                               | 5. Display Collar Mustbe+Attractive |
|                               | 6. Price Value Mustbe+One-demention |

3. Analysis and verification

**3.1. Analysis of the coefficient distribution of 38 attributes**

As mentioned above, each coefficient is characterized by the degree to which the j-th level of the attribute i will increase the score y.

The coefficient less than 0, means the user is not satisfied. The larger the absolute value, the more dissatisfied it is. An absolute value close to 0 indicates that customer is basically acceptable.

A coefficient greater than 0 means user satisfaction. The larger the absolute value, the more satisfied customer is.

The boundary of the coefficient value is an important condition for us to judge the classification of product attributes. By analysing the distribution of all coefficient values, we found that 0.2 is the boundary value. **Figure 4.** 38 Attribution $b_{ij}$ Distribution

- View the classification information of the perception level of these coefficients. For the j-th level of the product’s i attribute, when the coefficient is close to 0.2, the corresponding user's perception level is basically satisfied;
- When the coefficient is greater than 0.2, the j-th level of the product’s i attribute will be very satisfied
- When the coefficient is less than -0.2, the j-th level of the product’s i attribute will be very dissatisfied
3.2. Detailed classification

**Attractive Quality**: When the product does not have the attribute / function, the user's satisfaction will not be too low, and when the attribute has a certain level the user will be very satisfied. From the following curve shapes, we can see that the **keyboard feelings**, **memory capacity** and **keyboard backlight** are obviously close to the exponential trend and coefficient value higher than 0.2 means that the user is very satisfied. For the **cover material**, although the exponential characteristics of its curve shape are not obvious, the coefficient value range from -0.2 to 0.5 means some possible kind of material will make customer very happy, we judge it as attractive quality. **Figure 5. Coefficient curvy of Keyboard Feelings, Keyboard Backlight, Cover Material and Memory Capacity**.

**Must-be Quality**: When the product does not have the attribute / function, the user will be extremely dissatisfied. When the attribute is provided, the user will be satisfied, but with the increase of the attribute's degree, the user's satisfaction will not increase significantly. Looking at the following curve shapes: **running speed** and **quality impression** have very obvious essential
curve characteristics, and the negative coefficient value is far less than -0.2, and the positive coefficient value is maintained near 0.2; for aesthetics, although its minimum coefficient value is not low, its maximum coefficient value does not increase after approaching 0.2, we determined it as a must-be quality; for system reliability is also determined as a must-be quality, Although its curve shape does not have a significant parabolic shape, its coefficient value is always no higher than 0 telling us the user believes that stability is a basic need to be met. Figure 6. Coefficient curvy of Running Speed, Quality Impression, Aesthetics and System Reliability.

Figure 6. Coefficient curvy of Running Speed, Quality Impression, Aesthetics and System Reliability

One-dimensional quality: When the product does not have the attribute / function, the user will be extremely dissatisfied, and the user's satisfaction will increase approximately linearly with the increase of the attribute possessed. As can be seen from the shape of the following curves, the battery life, order experience, product package, and thermal all show a linear trend. A negative coefficient value below -0.2 means that users will have extreme dissatisfaction; a positive coefficient value above 0.2 means that users will reach a quite satisfactory level. This process is promoted as the attribute level increases. Figure 7. Coefficient curvy of Battery Life, Order experience, Product Package and Thermal.

Figure 7. Coefficient curvy of Battery Life, Order experience, Product Package and Thermal

Compound quality: Compound quality means that the product attributes have more than one KANO classification characteristic. There are several product attributes, such as power on/off speed,
Screen definition, price value and deliver speed, their coefficient value cover from negative to positive. When the attributes is not available, users will show extreme dissatisfaction, with its availability keeps increasing users’ satisfaction will increase until arriving at a stage and keep flat, but when the degree of attributes continues to grow to a certain state, the user's satisfaction will rise rapidly. The first half of this process is closer to the must-be characteristics of KANO, and the second half process of is closer to the attractive characteristics of KANO. We judged these four categories as must-be plus attractive quality. Figure 8. Coefficient curvy of Power on/off Speed, Screen Definition, Price Value and Deliver Speed.

Figure 8. Coefficient curvy of Power on/off Speed, Screen Definition, Price Value and Deliver Speed

4. Conclusion
This article provides a creative method for KANO model calculation. The processing and calculation of user review data to identify the KANO classification of product attributes has proven to be a feasible method. Compared with the traditional questionnaire survey method, it has the advantages of large data sample size, short cycle time, repeatable and iteratively optimized, judge rule is objective, etc. and can be widely used in different industries.

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