Computer Fraud and Security
ISSN (online): 1873-7056

Sorting Online Reviews of Restaurant Merchants Based on Narrativity

Tianqi Dai *
Shanghai University, Shanghai, China
** Corresponding Author Email: tianqi-dai@shu.edu.cn*

Abstract:
With the rapid development of e-commerce, online reviews have become the core reference information for consumers to make purchase decisions. Traditional review sorting methods mostly rely on the number of likes, timeliness and other factors, ignoring the textual characteristics of the reviews themselves. In this paper, we innovatively propose to take the "narrativity" of reviews as an important dimension of review sorting. We present a measurement method for "narrativity" based on NLP, and combine it with other review metrics (e.g., timeliness, text length, rating deviation, user identity, etc.) to build a comprehensive review sorting model. We crawled 52,500 reviews from 500 stores on the Dianping platform and trained a classification model based on the transformer architecture to categorize these reviews into high-value and low-value groups. Subsequently, we developed a narrative-based sorting model to reorder the reviews of these stores, and observing whether the ranks of high-value reviews have improved relative to the original order. The experimental results reveal that more high-value reviews have been prioritized to the forefront, leading to an overall improvement of 39.4% compared to the original sorting. Our experimental demonstrated that the narrative-based sorting model can optimize the review sorting, so that high-value reviews can get more exposure and improve consumers' shopping experience.

Keywords: Online review sorting; Narrativity; NLP; Transformer.

INTRODUCTION

With the rapid popularization of e-commerce, consumers are increasingly relying on feedback from other users when making purchase decisions. Online reviews, as a channel for consumers to share their shopping experiences and advice, have become an important factor in influencing consumer buying behavior. According to a survey by BrightLocal.com, 90% of consumers read 10 or fewer reviews before making a purchase decision. However, in the face of massive amounts of review information, consumers are often unable to browse through all of them, relying instead on e-commerce platforms to sort reviews based on factors such as the number of likes and the timing of reviews to quickly access key information [1].

Existing review sorting algorithms are mainly based on the number of likes and posting time of reviews, which can help consumers find quality reviews to a certain extent [2]. However, there is a "Matthew effect" in these sorting methods, i.e., highly-liked reviews are displayed in the front row and get more likes, while newly posted reviews, even if they are of high quality, are often buried in the back. Therefore, the traditional review sorting mechanism fails to take into account the quality differences of review contents, especially ignoring the textual characteristics of reviews, such as narrativity [3].

Research has shown that the narrativity of a text can significantly influence consumer perceptions and decision-making. Reviews with strong narratives are often better able to guide consumers into a "story situation", thus enhancing the persuasive power of the reviews[4]. In order to further improve the rationality of review sorting, this paper proposes a review sorting method based on text narrativity, and verifies its effectiveness through experimental analysis.

OVERVIEW OF RELEVANT THEORIES

2.1 Narrativity of reviews

Narrativity refers to the ability of a text to tell a complete story. Narrative texts help readers understand the content of the text by describing the occurrence, development, and outcome of events, and influence their perceptions and judgments through emotional resonance and logical reasoning [5]. In the context of online reviews, narrativity is manifested when consumers tell the story of the process of purchasing a good or service by reviewing their consumption experience. This description usually includes specific details, personal feelings, and evaluations of the merchant's product or service.

Reviews that are more narrative in nature tend to resonate more with readers. Research has shown that narrative texts can influence readers' attitudes by increasing their emotional engagement, even prompting them to take action, such as purchasing recommended goods or services. This kind of emotional engagement is called "Narrative Transportation". Narrative Transportation Theory suggests that when readers are attracted to the stories in a review, they are more likely to be taken into an immersive situation, and thus have a stronger sense of identification and trust in the review. It has been demonstrated that the narrativity of reviews is significantly associated with consumers' purchase decisions. Mukhopadhyay et al. found that reviews with high narrativity not only increase consumers' awareness of products, but also significantly increase merchants' sales [6]. The impact of narrative reviews is especially significant in a competitive market environment. Based on this finding, this paper takes narrativity as one of the core considerations in review sorting [7].

2.2 Current status of review sequencing

Existing review sorting algorithms mainly consider factors such as the posting time of the review, the number of likes, and the identity of the commenter. The main purpose of these algorithms is to increase the value spreading effect of reviews by prioritizing the reviews that users consider "useful" to other users. Common sorting algorithms include:

2.2.1 Timeliness sorting

According to the posting time of the reviews, the latest posted reviews are displayed in the front row. This sorting method ensures the timeliness of reviews, but ignores the quality of reviews. Newly posted reviews may not get likes and interactions due to the short time, making it difficult to evaluate their real value [8].

2.2.2 Likes Sorting

Reviews are sorted according to the number of likes they have received, and reviews with more likes are displayed in the front row. Although the number of likes can reflect the usefulness of the reviews, due to the Matthew effect, reviews with more likes are more likely to get further attention and likes, while newly posted reviews are easily buried.

2.2.3 Machine Learning Sorting

In recent years, review sorting methods based on machine learning have been widely used. These methods automatically adjust the display order of reviews by learning the user's behavioral patterns and preferences. However, machine learning methods are often "black box" models, which make it difficult to explain the specific logic of sorting, and the analysis of text content is also limited [9].

In order to improve the rationality of review sorting, this paper proposes a sorting model that combines text narrativity and other review features. The model aims to provide consumers with a more realistic and effective review sorting by quantifying the narrative nature of reviews and combining other factors such as timeliness and number of likes.

A NARRATIVE-BASED MODEL FOR SORTING REVIEWS

3.1 Definition of Narrative

3.1.1 Definition of concepts

Narrative Transportation is a common expression used by people in describing their personal experiences. When recipients are "transported" into a story, their attention is fully focused on the story itself, and the process of analyzing the information is transformed into a "narrative-driven" mode. Narrative-driven" mode. This concept emphasizes the impact of the story on the listener or viewer, enhancing the authenticity of the experience through a sense of presence, thereby increasing the listener's cognitive and emotional engagement [10]. This sense of engagement can lead to changes in attitudes and beliefs about reality, which can lead to persuasion. Narrative competence is a key element in the narrative transportation process, and there are intricate components woven into the narrative structure, some of which are effective indicators of narrative competence, i.e., "narrativity".

Existing research has shown that texts with a strong narrative can induce readers to make judgments about the information provided by the text based on their own experiences, making the information easier to understand and intuitively more realistic. At the same time, readers can also elicit a strong emotional response from a text's narrative and lead to a reduction in cognitive translation. In contrast to parsed persuasive messages, in which readers tend to refute claims that are inconsistent with their prior beliefs, the combination of truth perception and reduced cognitive response can motivate recipients to adopt attitudes that are consistent with the story even if the narrative-based claims contradict their existing beliefs. The overall process of emotional load associated with narrative processing is also significantly less susceptible to information overload, due to its unique ability to create simplified and coherent imagery by selectively segmenting (or "chunking") the complex stream of events unfolding in a story. It is also known to lead to better understanding and longer retention [11]. Thus, as a result of the combined effects of these factors (i.e., lower sensitivity to information overload, perception of truth, reduced cognitive response, better comprehension, and strong emotional response), recipients tend to be significantly more willing to perform behaviors that are consistent with their changed attitudes. Thus, in the context of reviews, it is often assumed that exposure to a review narrative can lead to a change in attitude that is consistent with the emotional orientation of the narrative. These changed attitudes toward the reviewed product or service can further influence purchase intentions consistent with the value of the story [12].

Past studies have shown that there is a significant monotonic positive correlation between purchase intention and review narrativity, which is a hidden factor that influences consumers to make purchase decisions. Based on that, this paper takes narrative as one of the bases for sorting reviews, combines it with other indicators of information quality to establish a sorting model, and then proves its effectiveness through experiments [13].

3.1.2 Narrative Measures

In accordance with the outlined approach, our initial task was to pinpoint six core elements, largely falling into two primary divisions: the substance of the narrative and the manner of its expression [14]. The substance of the narrative encapsulates the message itself, namely the text, whereas the manner of expression deals with the style of delivery. Under the narrative substance, we identified four key components: Landscape of Affective Consciousness (LAC), Landscape of Cognitive Consciousness (LCC), Spatial Embedding (SE), and Temporal Embedding (TE). The manner of expression is delineated by its two fundamental aspects: Genre and Drama. Drawing from their theoretical underpinnings, each of these elements is then translated into practical application through the analysis of the prevalence of specific word types as categorized by LIWC. The detailed concepts and operational steps are as follows [15].

Table 1 Core elements

LAC & LCC: Narratives of the first incidents in the review depicting characters' feeling or thoughts.	(a). Measure sentence-level intensities of LIWC's "motion", "affective processes", and "insight " dictionaries. (b). Count the motion–affective process motion and motion–insight–motion trigrams across three sequential sentences in each review. (c). The counts obtained from (b) are divided by the total number of words in each review to account for review lengths.
SE: The text's focus is on specific locations and their features.	(a). Find review-level intensities for "space" and "perceptual process" words. (b). Convert the intensities from (a) into an ordinal scale to capture the extent to which a review was spatially embedded as follows: 0 (no space or perceptual process word), 1 (only space words), 2 (space and perceptual process words).
TE: Narrative movement illustrates a series of events following a temporal order, signifying the story's direction and narrative framing highlights the interconnections among various story events.	(a). Measure review-level intensities for "time" and "cause" words dictionaries in LIWC. (b). Convert the intensities from (a) into an ordinal scale to capture the extent to which a review was temporally embedded as follows: 0 (time or causation word are absent), 1 (either causation or time word is present), 2 (causation and time words present).

Genre: The emotional progression depicted in the story can be categorized as follows: Stable, Progressive, Regressive, Comedy and Tragedy.	(a). Measure sentence-level intensities for “positive” and “negative” emotions words in LIWC dictionaries. (b). Find the sentence-level absolute difference between these intensities. (c). Compute sentence ratio(s)- divide the sentence-level scores by the total number of sentences to account for review lengths. (d). Fit a nonlinear quadratic model across the sentence ratio. (e). Interpret the results as follows: Significant positive (negative) linear coefficient along with a significant positive (negative) nonlinear coefficient implies progressive (regressive) genre. A significant positive (negative) linear coefficient with a significant negative (positive) nonlinear coefficient indicates the tragedy (comedy) genre. Non-significant coefficients of this model described stable genres.
Drama: In a narrative, events culminate in an emotional peak, known as the dramatic climax. The placement of this climax within the story's architecture determines the sequence of curiosity.	(a). Find sentence-level intensities of “positive” and “negative” emotions words in LIWC. (b). Take the absolute differences between the intensities obtained from (a) to calculate the sentence-level emotionality. (c). Compute sentence ratio(s)- divide the sentence-level scores by the total number of sentences to account for review lengths. (d). Use the deviations from the emotional polarity ratio of the previous sentence to locate the (emotionally) most extreme sentence ratio per review.

We utilized web scraping to collect reviews from 500 restaurants on Dianping.com, extracting the first 7 pages, totaling 105 reviews per merchant. In the Based on the defined criteria, we six distinct ratings, corresponding to each narrative component, for every evaluation examined. Subsequently, we compiled these ratings across all evaluations and conducted a Principal Component Analysis (PCA) to determine the weight of each rating in the model.

Table 2 Weights in the model

KMO			0.602	
Bartlett's sphericity test			chi-square	80194.869
			df	15
			p	0.000
Variables	Eigenvalues	Explained variance ratio	Cumulative percentage	Weights
LAC	2.274	37.895	37.895	0.1533
LCC	1.155	19.253	57.148	0.1423
SE	0.959	15.986	73.135	0.3084
TE	0.870	14.495	87.630	0.2778
Genre	0.587	9.787	97.417	0.1426
Drama	0.155	2.583	100.000	0.2357

3.2 Narrative-based model for sorting reviews

By using their narrative skills, the reviewer, who is the focal point of the critique, fundamentally outlines their progression from a beginning phase to an end state, experiencing a series of happenings along the way. Therefore, reviews with a strong narrative can offer consumers additional information beyond product quality, such as experiences and contexts, compared to general reviews. For example, excessively long reviews can prevent consumers from quickly obtaining key information, while overly short reviews fail to provide valuable information [16]. Moreover, the timeliness of reviews is also crucial, newer reviews are more reflective of the current state of the product. To more accurately measure the value and effectiveness of reviews, this paper selects five additional characteristics as supplementary metrics: timeliness, text length, reviewer identity, supporting evidence, and scoring deviation.

Timeliness: The timeliness metric of reviews reflects the time interval between the review and the reader's access. Generally, the content of reviews that are closer in time to the reading time is more referential. Generally, the content of reviews that are closer in time to the reading time is more referential. Assuming the cutoff date for obtaining review data is T_0 , if a review is posted at time T_n , then the time difference for this review is $t = T_0 - T_n$. Calculate the time difference t for all reviews, perform normalization and ultimately obtain the timeliness score S_T for each review.

$$S_T = 1 - \frac{t - t_{\min}}{t_{\max} - t_{\min}}$$

Text Length: The length of the review text is another factor affecting the reader's information acquisition. Reading excessively long reviews increases the time cost and energy expenditure for readers to obtain information, while overly short reviews fail to present information. Reading excessively long reviews increases the time cost and energy expenditure for readers to obtain information, while overly short reviews fail to present information comprehensively. In the data obtained, this paper selects the top 5,000 reviews with higher usefulness scores (i.e., likes). Statistical analysis reveals that the text length of these reviews is concentrated between 90 to 110 words. This suggests that texts of this length are more likely to be favored by readers. This suggests that texts of this length are more likely to be favored by readers. Assuming the text length of a review is L , this paper uses the following formula to calculate the text length score S_L for this review. This suggests that texts of this length are more likely to be favored by readers.

$$\begin{cases} S_L = 1 - \dfrac{90 - L}{90} & , L < 90 \\ S_L = 1 - \dfrac{L - 110}{110} & , L > 110 \\ S_L = 1 & , 90 \leqslant L \leqslant 110 \end{cases}$$

Scoring Deviation: Fake reviews have always been a thorny issue for e-commerce platforms. Some merchants' review sections are filled with a large number of fake reviews, where they receive benefits from merchants and give more favorable evaluations of products against the truth. Therefore, it is necessary to incorporate the authenticity of reviews as an important influencing factor into the consideration system. We calculate the difference $r = R_0 - R_n$ between the rating R_n of each review and the total rating R_0 , and We calculate the difference S_R between the rating of each review and the total rating , and obtain the score through normalization.

$$S_R = 1 - \frac{r - r_{\min}}{r_{\max} - r_{\max}}$$

Supporting Evidence: Images or videos of the product are the best supporting evidence for reviews. Generally, reviews accompanied by photos or videos are more likely to be believed by readers than those with text only. Generally, reviews accompanied by photos or videos are more likely to be believed by readers than those with text only. These supporting evidences also provide readers with more information. It is assumed that reviews with images or videos have a score $S_E = 1$, while those without have $S_E = 0$.

Reviewer Identity: Consumers can pay to become VIP members on the platform to access more services. VIP users often have more frequent usage and a deeper understanding of the platform or merchant. Therefore, the reviews from VIP users are more reliable compared to ordinary users. In this paper, if a review is posted by a VIP user, the score , while for ordinary users, is the score of the review. is posted by a VIP user, the score $S_I = 1$, while for ordinary users, $S_I = 0$.

Then, by computing the scores for each review in the dataset across the five indicators and deriving their respective weights using PCA, we obtain the weight coefficients of the first sorting model. This model consists of five variables, representing the two dimensions of the credibility and readability of reviews. The function of this model is to sort reviews based on their information quality, with higher-scoring reviews being placed In subsequent experiments, this model will serve as the control group, being compared with the narrative-based sorting model, to investigate the actual impact of narrative factors. In subsequent experiments, this model will serve as the control group, being compared with the narrative-based sorting model, to investigate the actual impact of narrative factors in the sorting of reviews.

Table 3 The factor weights of no-narrative sorting model

KMO			0.698	
Bartlett's sphericity test			chi-square	6176.608
			df	10
			p	0.000
Variables	Eigenvalues	Explained variance ratio	Cumulative percentage	Weights
Text length	1.439	28.787	28.787	0.2503
Timeliness	1.078	21.552	50.339	-0.0237
User ID	1.007	20.133	70.471	0.2214
Supporting evidence	0.892	17.842	88.313	0.3901
Rating deviation	0.584	11.687	100.000	0.3646

Relying solely on the narrative score of reviews for sorting is not rigorous. Although reviews with strong narrative quality may have a greater sense of authenticity and persuasiveness, we must consider from other angles whether they qualify as acceptable reviews. Although reviews with strong narrative quality may have a greater sense of authenticity and persuasiveness, we must consider from other angles whether they qualify as acceptable reviews. This model consists of six variables, which can provide a comprehensive score for reviews from the perspectives of narrative quality and information quality. Reviews with higher scores will be sorted further up. The weight coefficients of the variables in the model are also determined using the PCA method.

Table 4 The factor weights of narrative-based sorting model

KMO			0.761	
Bartlett's sphericity test			chi-square	10482.982
			df	15
			p	0.000
Variables	Eigenvalues	Explained variance ratio	Cumulative percentage	Weights
Text length	1.666	27.759	27.759	0.2628
Timeliness	1.091	18.178	45.937	0.0279
Source of information	1.036	17.271	63.208	0.2530
Supporting evidence	0.908	15.127	78.336	0.3237
Rating deviation	0.749	12.479	90.815	0.3102
Narrative	0.551	9.185	100.000	0.1671

Next, we will utilize the two aforementioned models to sort the 105 reviews for each merchant individually, and then observe whether the sorted results have been optimized and improved compared to the original sort.

EXPERIMENTAL DESIGN AND DATA ANALYSIS

4.1 Data sources and pre-processing

In order to verify the effectiveness of the above sorting model, this paper obtains the review data of 500 restaurant merchants from Dianping.com. Each merchant crawls the first 7 pages of reviews under the default sorting, about 105 reviews, and obtains a total of 52,500 reviews. The review data includes information such as text content, number of likes, ratings, user identity, and time of review. Since some of the reviews are published for a short period of time and have not yet gained enough likes and interactions, the direct use of the number of likes for sorting may lead to bias. Therefore, in this paper, we use ERNIE (Enhanced Representation through kNowledge Integration) which is a transformer-based machine learning model to predict which reviews are likely to high-value or low-value. ERNIE is a kind of pre-trained language model. Its core characteristic lies in the integration of knowledge enhancement methods, significantly improving the model's language comprehension capabilities by incorporating a vast amount of knowledge into the model.

We select 10,790 reviews from the 52,500 reviews that have been posted for more than one year as the dataset for model training. Then we categorize them into " high-value reviews" (the number of likes is greater than 0) and " low-value reviews " (the number of likes is equal to 0) as data labels. Next, in the Linux operating environment, we utilized Python 3.7 and PaddlePaddle 2.1.2 tools to construct and train the ERNIE model. The key parameters are as follows:

Table 5 Experimental parameters

Learning Rate	Batch Size	Optimizer	Max-Sequence Length	Accuracy
5e-5	32	Adam	128	0.8918

We divided the dataset into training, validation, and test sets in an 8:1:1 ratio. After training, we evaluated the trained ERNIE model on the test set, achieving an average accuracy of 89.18% in predicting and indicating good performance.

4.2 Experiment and Analysis

To validate the effectiveness of the narrative sorting model, we need to establish a criterion for evaluation and then observe whether the re-sorted reviews show improvement according to this criterion. The reviews involved in the sorting are the first 105 reviews from each store, with each reviews's rank ranging from 1 to 105. A higher value indicates that the review is ranked further back. In the previous section, we categorized all reviews into high-value and low-value.

To intuitively compare the effects of different sorting methods, we use the sum of the ranks of low-value reviews as the standard for evaluating sorting performance. If the sum of the ranks of low-value reviews for a store is higher, it demonstrates that the low-value reviews are ranked further back which meaning that more high-value reviews are placed at the forefront. The steps of the experiment are as follows:

Step 1: Use the trained ERNIE model to categorize the remaining 40,000 reviews into high-value reviews and low-value reviews.

Step 2: Re-sort the reviews of each store according to no-narrative sorting model and narrative-based sorting model. Compare the effect of original sorting, no-narrative sorting and narrative-based sorting.

Step 3: Calculate the sum of the ranks of low-value reviews across the three sorting methods.

The experimental data are shown in the figure below:

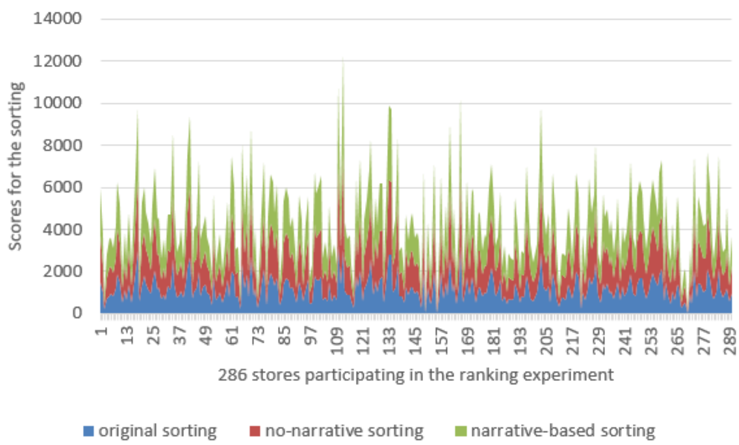

Figure 1 Comparison of results for different sorting

The comparison also shows that narrative-based sorting model shows better results compared to no-narrative sorting across multiple stores. Quality reviews have significantly higher rankings under narrative-based sorting, this indicates that narrativity plays a certain role in the sorting process.

The experimental data are shown in the figure below, which lists the results of the experiment for some stores:

Table 6 The sum of the ranks of low-value reviews

	original sorting	no-narrative sorting	narrative-based sorting
Store1	1526	2198	2506
Store2	995	1326	1461
Store3	210	276	299
…	…	...	…
Store287	582	714	727
Store286	955	1355	1374

The Table 6 shows that the sorting result of narrative-based sorting model is improved by 39.26% compared to the original sorting, and also has a significant advantage compared to no-narrative sorting's 5.70%. This indicates that narrativity, as a new sorting dimension, can significantly improve the effectiveness of review sorting.

It can also be observed from the experimental data that although the number of likes is an important indicator for evaluating the quality of reviews, relying solely on the number of likes for ranking will ignore the deeper information in the review text. By introducing narrativity, the sorting model is able to better capture the emotion and narrative structure in the reviews, which improves the ability to recognize quality reviews.

CONCLUSION

This paper innovatively improves the effectiveness of the existing sorting algorithms by incorporating the narrativity of reviews into the review sorting model. It is experimentally verified that narrative-based sorting model can better sort the high-quality reviews at the top and help consumers make decisions quickly. Meanwhile, this paper also provides new ideas for future review sorting algorithms, i.e., how to improve the accuracy of sorting through finer textual feature analysis. However, the research in this paper also has some limitations. For example, the interference of fake reviews was not analyzed in depth. Future research can further combine text categorization techniques and user behavior data to construct more complex sorting models. In addition, it can also explore how to combine narrative with other natural language processing techniques (e.g., sentiment analysis) to further enhance the effectiveness of review sorting.

REFERENCES

[1] Construction and application of a business competitive intelligence analysis model based on text mining of online reviews [J]. ZHANG Zhenhua; XU Baiming. Intelligence Science, 2019(02)

[2] A method for named entity recognition in Chinese microblogs based on an improved word segmentation and annotation set [J]. WANG Chao; WANG Zheng. Computer and Digital Engineering, 2019(01)
[3] An algorithm for sentiment classification and prediction based on Chinese microblogs [J]. Hao Miaomiao; Xu Xiujuan; Yu Hong; Zhao Xiaowei; Xu Zhenzhen. Computer Applications, 2018(S2)
[4] Research on context-based post-filtering recommendation algorithm based on TF-IDF: A case study of catering industry O2O [J]. Yin Cong; Zhang Liyi. Data Analysis and Knowledge Discovery, 2018(11)
[5] Research on policy text topic recognition based on paragraph information gain [J]. Zhao Yifang; Pei Lei; Kang Lele. Digital Library Forum, 2018(11)
[6] Sentiment analysis of product reviews based on dictionaries [J]. Chang Dan; Wang Yuzhen. Journal of Shaoyang University (Natural Science Edition), 2018(05)
[7] News comment data analysis based on Python-Snownlp [J]. Zhao Zhisheng; Jin Xiaosong; Wen Tongtong; Liang Junhua. Science and Technology Communication, 2018(18)
[8] Hotel service quality evaluation based on TOPSIS multi-objective decision analysis method: An analysis from online review data [J]. Ren Shuo; Yin Hanxiong. Inner Mongolia Science, Technology and Economy, 2018(17)
[9] Research on microblog information recommendation method based on big data and LDA fusion [J]. Cui Jindong; Du Wenqiang; Guan Yang. Intelligence Science, 2018(09)
[10] A review of text feature extraction methods [J]. Xu Guanhua; Zhao Jingxiu; Yang Hongya; Liu Shuang. Software Guide, 2018(05)
[11] Text sentiment analysis based on BERT-BiLSTM-Attention [J]. Zulin Yun; Qu Jinshuai; Fan Jing; Dai Tingting. Journal of Yunnan University for Nationalities (Natural Science Edition), 2023(04)
[12] Research on the influencing factors and countermeasures of consumers' purchase of new energy vehicles from the perspective of online reviews [J]. Pang Qian; Zou Lu; Cheng Mengxue; He Zhiguo. Commercial Exhibition Economy, 2023(04)
[13] Research on consumer satisfaction in the catering industry based on online reviews: taking Xiabuxiabu as an example [J]. Li Zhaotong; Yang Xiao; Xu Yi; Liao Xin. Economic Research Guide, 2023(03)
[14] An affective analysis method based on online reviews and its application [J]. Li Yang; Xu Zeshui; Wang Xinxin. Control and Decision, 2023(02)
[15] Learning needs and response strategies of natural museum users: An empirical analysis based on the perspective of the situational learning model and user online reviews [J]. Huang Yurong; Gong Xiaoqian; Xie Xiaofeng. Shenzhen Social Sciences, 2023(01)
[16] Research on the influencing factors of agricultural product brand building and promotion [J]. Wei Qiufeng; Li Dou; Huang Linghua. Southern Agricultural Machinery, 2023(01)