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Application of Semantic Analysis Technology in Natural Language Processing

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Abstract: With the evolution of intelligent technology, especially in the field of natural language processing, semantic analysis has become a powerful tool for studying users. It is good at processing and interpreting numerous unformatted information texts produced in user interactions. This article takes an in-depth look at how to improve the user experience design process using intelligent semantic analysis technology, which can quickly and accurately extract important information from user feedback through automated analysis. Although some current semantic analysis technologies face accuracy tests when analyzing data rich in contextual information, by integrating algorithms such as TF-IDF and Word2vec with deep learning models, the accuracy and efficiency of analysis and interpretation can be achieved significantly improved. In particular, this study developed a semantic clustering analysis technology for short texts, confirming its significant effect in classifying user feedback and assisting product design decision-making. In the future, with technological advancement, artificial intelligence is expected to be routinely used in consumer research, thereby making product design closer to user needs.

Keywords: Artificial intelligence Semantic Analysis, User Research, Natural Language Processing, User Experience Design.

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1 INTRODUCTION

In an era where the economy focuses on experience, product creation is increasingly focused on consumers' emotional satisfaction, and the conception and creation of user experience has become particularly important. User experience design focuses on the user's full experience during the use of a product. Therefore, in-depth research on users becomes particularly critical. The goal is to grasp the real needs of users by analyzing their behavior and satisfaction. User research relies on indispensable language materials, such as interview records, user feedback, etc., but the processing of this information is time-consuming and full of challenges. With the rapid progress of intelligent technology, especially in natural language processing, the analysis technology of language meaning has ushered in a major breakthrough. With the help of artificial intelligence technology, in-depth semantic analysis of text can effectively filter out key information from massive language data, and subtleties that may be overlooked by traditional means can also be revealed one by one, thus greatly improving the speed and efficiency of user research and analysis [1].

2 INTRODUCTION OF ARTIFICIAL INTELLIGENCE SEMANTIC ANALYSIS METHOD

2.1 Natural Language Processing and Semantic Analysis

Natural language processing is a technology that processes human language through computers [2,3,4]. It integrates multiple disciplines such as linguistics, computational linguistics, and machine learning. It is an important part of the field of artificial intelligence. With semantic analysis as the core, we build an analysis framework covering mathematical statistics and deep learning to achieve automatic analysis of vocabulary, sentence patterns and overall text meaning, aiming to gain in-depth insight into the substantive meaning conveyed by language. The complexity and variety of natural language, such as illogical emotions and thinking patterns, make computer understanding of language a huge challenge. In the academic research process of natural language processing, the symbolic school and the

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stochastic school constitute the two mainstream schools. The symbolic school focuses on analyzing the logic of language rules, while the stochastic school focuses on using statistical methods to process massive language data. The booming development of deep learning has greatly promoted natural language processing technology, especially in the field of semantic analysis, making it a reality to automatically mine language patterns from massive data [5,6]. Compared with old methods, this technology is both more efficient and more accurate. There has been a significant improvement, especially when faced with a language like Chinese that lacks obvious vocabulary boundaries. Deep learning can automatically identify and analyze words and their characteristics, providing a strong impetus for the advancement of language processing technology.

2.2 SEMANTIC ANALYSIS TECHNOLOGY AND APPLICATIONS

With the support of deep learning, semantic analysis technology has made significant breakthroughs [7,8,9,10,11,12,13]. Recent advancements in GPU-based parallel computing have further enhanced the efficiency of complex data processing tasks [14,15,16,17]. For instance, Yi and Qiao's (2024) research on GPU-based parallel computing for medical photoacoustic image reconstruction significantly reduced processing times from 118 seconds to approximately 20 seconds, a sixfold improvement. This breakthrough not only accelerates medical imaging processes but also enables real-time iterative reconstruction, crucial for applications like hemodynamic monitoring and clinical disease diagnosis. Their work underscores the potential of GPU technology to handle vast data volumes and complex algorithms, revolutionizing medical imaging by facilitating faster and more accurate diagnostics [18,19].

2.3 Analysis methods of user research language materials

In the field of user research, the analysis of language materials includes both numerical quantitative analysis and in-depth qualitative discussion [20,21,22]. Researchers use diversified social science research methods such as diary records, questionnaires, eye tracking and face-to-face conversations to Uncover the deeper meaning behind your data. Hu Fei applied "ethnology" to the process of software simplification and made systematic innovations in user research. He integrated a variety of text analysis techniques including affinity diagrams, and refined every aspect of user interviews. In particular, the importance of precise screening, in-depth interpretation, reasonable exclusion of invalid information, and careful preparation of abstracts in research is pointed out. In addition, seven key research approaches covering group discussion, laboratory operations, phenomenon observation, etc. are also widely used. By integrating diversified means architecture and semantic parsing technology of artificial intelligence, the efficiency and depth of user research in processing language materials have been significantly improved, as shown in Table 1:

parsing technique	Application method	application object	Application effect
Quantitative and qualitative studies	Including diary, questionnaire, observation and interview methods	user study	Improve the coverage and depth of user research
Affinity graph method	Systematically summarize and summarize the text in design and user studies	User Experience Design	Structured data analysis to improve decision support capabilities
Hu Fei's interview process	Extract and code the coded corpus, interpret the annotated corpus, eliminate the irrelevant language, and write the interview summary	Design user research	Improve the efficiency of data analysis and deepen the application value of the results

Table 1: Intelligent semantic analysis of user research language materials

3 ANALYSIS PROCESS OF USER RESEARCH TEXT MATERIALS USING INTELLIGENT SEMANTIC ANALYSIS TECHNOLOGY

3.1 PRINCIPLES OF ANALYSIS PROCESS AND RELATED PROCESSING METHODS

Apply advanced semantic understanding technology to deeply mine the language data involved in the user research process [23]. This process is divided into several steps: first, create a professional vocabulary library, and at the same time filter out unnecessary or misleading words, and analyze the text [24,25]. Carry out deep purification, and then use a strategy that combines dictionary and context to precisely cut the Chinese text to ensure that the meaning of each word is accurately captured. After word segmentation processing, the TF-IDF model and the NB, RF, SVM, and KNN algorithms in machine learning are used to evaluate the similarity between texts, and then perform cluster analysis on the texts [26,27,28,29,30,31,32]. Sentiment classification and text summarization are two powerful tools for analysis work. Sentiment classification relies on the advancement of deep learning to accurately identify, while text summarization screens out sentences with high information content. Both of them jointly promote in-depth research [33].

Recent advancements in transformer-based architectures have further demonstrated their versatility and effectiveness across different domains [34,35]. Wang and Qiao's (2024) study on network intrusion detection using TabTransformer is a prime example of this progress. Their research achieved an impressive F1-score of 98.45%, significantly higher than traditional models like SVM and MLP. Utilizing a simulated military network environment with over 25,000 samples, they demonstrated how the self-attention mechanisms inherent in transformer architectures can significantly enhance the accuracy and robustness of network security systems. This breakthrough not only highlights the scalability of transformer-based models for real-time threat detection but also underscores their potential to revolutionize the field of artificial intelligence by providing more reliable and efficient solutions to complex security challenges. Wang and Qiao's contributions exemplify the transformative impact of advanced AI methodologies in enhancing cybersecurity measures, paving the way for more secure and resilient network infrastructures [36].

This process not only integrates traditional mathematical modeling methods, but also combines deep learning technology to cope with various analysis needs, thereby improving product design quality and functional updates [37]. The in-depth analysis process from vocabulary to text is like an onion analyzed layer by layer, which effectively improves the ability to deal with complex data and enhances the accuracy and efficiency of work.

3.2 Introduction to the Analysis and Application Development of Artificial Intelligence Semantics

Typically, semantic analysis technology applications of artificial intelligence develop systems based on deep learning engines, or open platform interfaces that rely on natural language processing [38,39]. The flexibility given allows the selection or innovation of algorithms according to the characteristics of specific corpus [40]. This method has the possibility of technological development; the "latter" mentioned above is more suitable for daily business operations, and its investment cost is relatively less. Mainstream open platforms such as Baidu AI, Alibaba Cloud, Tencent AI, and iFlytek provide interfaces that support natural language processing and can implement complex functions such as word segmentation, sentiment judgment, and refining of comments and opinions in Chinese text. In the process of applying these technologies, it is necessary to select appropriate algorithms according to actual business requirements and enrich vocabulary resources in a timely manner to improve recognition accuracy and operation efficiency.

4 APPLICATION EXAMPLES

With the help of artificial intelligence semantic analysis tools, I conducted in-depth exploration and improvement of the interaction design of a well-known brand's kitchen appliances that integrate microwave, steaming, and baking functions [41,42,43]. This plan contains a large amount of unorganized user research text information, such as maintenance service feedback, questionnaire records, face-to-face interviews, and user reviews on the Internet. Reading and analysis using old methods is both time-consuming and Inefficient [44]. In-depth analysis with the help of intelligent technology greatly improves the efficiency of data processing and promotes humanized improvements to the interactive interface [45,46].

Analysis Category	Data Volume	Positive Feedback	Neutral Feedback	Negative Feedback
Open-ended Questionnaire Responses	5000	2700	1200	1100
Online User Reviews	113281	61200	21480	30501

Table 1: Intelligent Semantic Analysis Results of User Feedback Language Materials

Based on the data in the table, the volume of online user reviews is significantly higher than that of open-ended questionnaire responses. Positive feedback constitutes a large proportion in both types of feedback, with online user reviews having a higher positive feedback rate of 54.1%. Negative feedback is less prominent in the questionnaire responses, accounting for only 22%. This difference might be due to the varying data sources and the mindset of users when providing feedback.

4.1 Preprocessing

For the four data tables containing 169,197 records, during the preliminary data processing, we focused on removing data impurities to enhance the accuracy and reliability of the data. This step involves clearing all blank and invalid entries in the data table, as well as those records that only contain modal particles; eliminating various technical fault records that are irrelevant to the research in the "Repair Feedback" form; filtering and removing "Questionnaire Records" Unnecessary redundant option fields in the form; clean up user evaluation files, remove invalid blank comments and unified standardized responses. After filtering and sorting out regular and stop words, the amount of data was reduced to 113,281 items, adding precision and efficiency to the subsequent analysis process.

4.2 Supplement the Professional Vocabulary and Test the Accuracy of Word Segmentation

Introducing a business-specific vocabulary library to optimize the effectiveness of semantic analysis. In this study, we made personalized enhancements to the Jieba word segmentation library and incorporated self-defined vocabulary to improve the performance of word segmentation. After randomly sampling the data for word splitting and manual verification, it was confirmed that the accuracy of the word splitting tool reached 96.7%, which shows that the tool can efficiently handle work in related research fields. This strategy not only improves the accuracy of text segmentation, but also enhances the quality and credibility of data analysis results.

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4.3 Analyze the open-ended question response corpus of the "Questionnaire Survey" data table

When processing the large amount of data generated by the "questionnaire survey", the TF-IDF weighted text similarity algorithm is applied, which significantly improves the accuracy and processing speed of data screening. First, the text is normalized and impurities are removed, and then the Word2vec model is used to generate word vectors [47]. On this basis, the TF-IDF algorithm is combined with the TF-IDF algorithm to give corresponding weights to the word vectors. Finally, the vector representation of the sentence is obtained by calculating the weighted average. The expression for vector calculation is defined as follows:

$$V = \sum_{i=0}^{n}\left(tfidf\left(d, v_w \right) \cdot W_i \right) \quad (1)$$

Here, d represents the document, vw represents the vocabulary, and W represents the vectorized expression of the vocabulary. Further, calculate the cosine similarity of the two sentence vectors, the expression is:

$$\text{Similarity} = \cos(\theta) = \frac{V_1 \cdot V_2}{V_1 V_2} \quad (2)$$

Among them, $V1$ and $V2$ represent the vectors of the two sentences respectively.

4.4 Analysis of the corpus of the "Online User Evaluation" data table

In the process of analyzing user evaluation data on e-commerce platforms, we are faced with a large number of online user reviews of varying quality. Use semantic understanding methods to extract data with exploratory significance based on user evaluations and emotional tendencies. The specific methods are as follows: giving a neutral or negative evaluation of 3 to 4 stars is regarded as a rational evaluation method; giving 1 to 2 stars Star positive reviews were identified as anomalies and flagged; other positive reviews were assessed as having no research significance. Sentiment analysis technology was used to intelligently classify text materials: positive reviews accounted for 54.1%, neutral views accounted for 18.9%, negative reviews accounted for 27.0%, and the average confidence index exceeded 90% [48]. Using this screening method, the burden of manual review is reduced by 27% compared with the original one, and materials with greater research significance can be reviewed first.

Maintenance Feedback Category	Data Volume	Main Issue Category	Related Proportion
Complex Operations	2000	45%	900
Water Removal	1500	30%	450
Water Tank Application	800	15%	120
Wireless Network Connection	700	10%	70

Table 2: Application of Intelligent Semantic Analysis Technology in Maintenance Feedback and User Interviews

Based on the data in the table, complex operations are the most common issue in user feedback, accounting for 45%. Other issues such as water removal and water tank application also have significant proportions. These data indicate that users encounter frequent issues with operational complexity during actual product use, highlighting the need for product design optimization in this area.

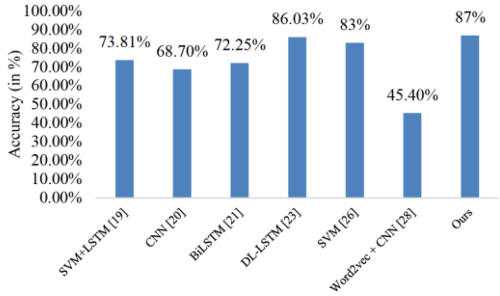

Figure 2. Comparative State of Art

4.5 Analyze The Corpus of The "Maintenance Feedback" and "User Interview" data tables

When studying the data sets formed by "maintenance feedback" and "user interviews", we encountered the challenges of data colloquialism and content diversity [49]. The traditional "opinion extraction" and "summary" technologies failed to perform their best in this situation. Desirable functionality. When processing the "Maintenance Feedback" data form, the conventional analysis method of TF-IDF weighted synthetic vector was not used, but a training classification model under manual supervision was used for information processing. The processing process includes: splitting Chinese words and removing impurities from the text data, carefully screening to retain important actions and specific nouns, extracting digital representations of various types of words and recording their responses, comparing and analyzing the similarity of words with each other and automatically grouping them into groups. Extract information for manual annotation, use the annotation data to train the intelligent classification system, and continue to adjust until valuable results are output. Using this method, the main maintenance feedback issues are subdivided into "complex operations", "removing accumulated water", "water tank application" and "wireless network connection", providing accurate data support for product development. In the actual application process, after testing the performance of multiple algorithms, we found that for data in the field of user research, "Chinese word segmentation", "short text similarity" and "emotional tendency" analysis can be done without relying on contextual information [50]. Under this condition, higher accuracy can be achieved. This finding provides strong support for subsequent application development and strategy formulation.

In line with these challenges, Su et al. (2024) conducted a systematic literature review on the use of large language models (LLMs) for forecasting and anomaly detection. Their review identifies critical challenges such as the reliance on extensive historical datasets, issues with generalizability, model hallucinations, and significant computational resource demands. The review also discusses potential solutions, including the integration of multimodal data and advancements in model explainability and computational efficiency. These insights are highly relevant for improving methodologies in diverse data analysis, as they highlight both the potential and the limitations of current AI technologies in complex and varied data environments [51].

5 CONCLUSION

In the process of exploring user needs, artificial intelligence has shown great potential, especially in taking over tasks that require in-depth human intelligence analysis, showing unparalleled advantages. With the help of AI technologies such as "Chinese word segmentation", "short text similarity", and "emotional tendency", work efficiency can be significantly improved, the burden of corpus analysis can be reduced, and new analysis methods can be developed. Use automated semantic classification methods to classify large amounts of data to improve the generation of innovative ideas. Although some current semantic analysis technologies still have shortcomings in handling context and logical relationships, their effectiveness has been proven, indicating that they will play a key role in future user research and product development, which is in line with the development pace of the big data era. fit together.

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CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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