Enhancing User Experience in Food Selection through Sentiment Analysis of User Reviews

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Abstrak

Projek ini bertujuan untuk meningkatkan pengalaman pengguna dalam proses pemilihan makanan dengan membangunkan sistem analisis sentimen berdasarkan ulasan pengguna. Menggunakan platform Grab sebagai rujukan, sistem ini membantu pengguna memahami penilaian orang ramai terhadap pelbagai hidangan secara lebih intuitif, supaya dapat membuat pilihan yang lebih sesuai. Memandangkan bilangan ulasan terus berkembang, saringan dan pembacaan manual menjadi tidak cekap, jadi sistem ini menggunakan teknologi pemprosesan bahasa semula jadi (NLP) untuk mengklasifikasikan ulasan secara automatik kepada positif, negatif dan neutral.

Sistem ini menggunakan set data Amazon Fine Food Reviews sebagai sumber ulasan simulasi untuk mencerminkan maklum balas subjektif pengguna tentang pelbagai jenis makanan. Sebelum memasuki proses analisis, data akan dibersihkan untuk menghilangkan bunyi bising dan maklumat yang tidak relevan untuk memastikan ketepatan keputusan analisis. Selepas itu, model analisis sentimen mengekstrak kecenderungan emosi komen dan dimensi penilaian utama, seperti rasa makanan, saiz bahagian dan pengalaman penghantaran. Berdasarkan keputusan analisis sentimen, sistem menjana cadangan makanan yang diperibadikan untuk pengguna, menyerlahkan hidangan yang telah menerima ulasan positif untuk masa yang lama.

Selain analisis sentimen dan fungsi pengesyoran, antara muka sistem juga menyediakan carta aliran sentimen komen, gambar dan penarafan bintang hidangan disyorkan yang popular, serta menyokong pengguna menapis atau mencari ulasan mengikut wilayah dan nama makanan. Pada masa yang sama, sistem menyediakan fungsi pentadbir untuk mengurus data ulasan, memadam komen yang tidak sesuai tepat pada masanya dan memastikan penyeragaman kandungan ulasan. Dengan cara ini, sistem ini bukan sahaja dapat meningkatkan keupayaan membuat keputusan pengguna, tetapi juga membantu platform makanan lebih memahami pilihan pengguna.

Abstract

This project aims to improve the user experience in the food selection process by developing a sentiment analysis system based on user reviews. Using the Grab platform as a reference, the system helps users to more intuitively understand the public's evaluation of different dishes, so as to make more appropriate choices. As the number of reviews continues to grow, manual screening and reading have become inefficient, so this system uses natural language processing (NLP) technology to automatically classify the comments into positive, negative and neutral.

The system uses the Amazon Fine Food Reviews dataset as a simulated review source to reflect users' subjective feedback on various types of food. Before entering the analysis process, the data will be cleaned to remove noise and irrelevant information to ensure the accuracy of the analysis results. Subsequently, the sentiment analysis model extracts the emotional tendency of the comments and key evaluation dimensions, such as food taste, portion size and delivery experience. Based on the sentiment analysis results, the system generates personalized food recommendations for users, highlighting those dishes that have received positive reviews for a long time.

In addition to sentiment analysis and recommendation functions, the system interface also provides comment sentiment trend charts, pictures and star ratings of popular recommended dishes, and supports users to filter or search for comments by region and food name. At the same time, the system sets up an administrator function to manage comment data, delete inappropriate comments in a timely manner, and ensure the standardization of comment content. In this way, the system can not only improve users' decision-making ability, but also help food platforms better understand users' preferences.

1.0 INTRODUCTION

With the rapid development of the mobile Internet and information service industries (such as food delivery, travel, etc.), user experience has become a key factor in market competition. After using the service, users often give feedback on their true feelings through comments, which contain valuable information about customer satisfaction, product quality and service level. However, as the number of comments increases, enterprises find it difficult to efficiently extract the most valuable content from them.

Sentiment analysis, as an important technology in natural language processing (NLP), can automatically identify the emotions expressed in the text, thereby providing support for enterprises to quickly discover aspects that need improvement and adjust services in a timely manner. In the context of food delivery platforms, sentiment analysis can help enterprises understand whether users are satisfied with the taste, portion size, delivery speed and overall service quality of the dishes.

In existing research, early methods mostly adopted traditional machine learning algorithms such as Naive Bayes and support vector machines for sentiment classification; Subsequent research also proposed a theme-based sentiment analysis method, breaking down user feedback into specific aspects such as "dish quality" and "food delivery service". Although deep learning models (such as BERT) have performed well in terms of accuracy in recent years, this project pays more attention to the lightweight, interpret ability and ease of deployment of the system. Therefore, an implementation solution based on Python, scikit-learn and Flask was adopted.

The objective of this project is to design and implement a web-based sentiment analysis and recommendation system for catering reviews. The system can classify the emotions of the comments generated by users, extract relevant topics, and generate personalized dish recommendations based on positive evaluations. Meanwhile, the system also offers functions such as comment filtering, trend visualization, and region-based dish recommendations.

Through this system, users can make more targeted choices of dishes, and merchants can also obtain actionable improvement suggestions from public feedback to enhance service quality. The subsequent chapters will introduce the relevant research, system requirements, architecture design, algorithm principles and implementation processes, and analyze and discuss the experimental results.

2.0 LITERATURE REVIEW

In recent years, sentiment analysis technology has been widely applied in service industries such as food delivery, tourism, and hotels, used to extract valuable information from a large number of user comments, helping enterprises improve service quality and user experience. After using the service, users often post evaluations on the platform. These comments not only contain direct feedback on the product or service, but also reflect their overall satisfaction and potential needs. However, as the number of comments keeps increasing, manual screening and analysis of these data have become time-consuming and inefficient. Therefore, introducing automated sentiment analysis methods has become an effective way to solve this problem.

Early research on sentiment analysis mainly focused on traditional machine learning algorithms. Pang and Lee (2008) proposed models for sentiment classification using methods such as Naive Bayes and Support Vector Machine (SVM), which rely on manual feature extraction (such as bag-of-words model, TF-IDF), and perform stably in basic tasks such as opinion classification. Although its accuracy is slightly lower than that of deep learning methods, its advantages are low computational overhead, easy deployment, and suitability for resource-constrained environments, such as small catering platforms or educational research projects.

At the application level, Medhat et al. (2014) reviewed the application scenarios of sentiment analysis technology, pointing out that public comments in the catering field can effectively reflect users' satisfaction and preferences, providing a reference basis for businesses to improve their services. Feldman (2013) emphasized that extracting user viewpoints from text can not only optimize products but also assist in formulating more precise marketing strategies. These studies provide theoretical support for applying sentiment analysis to the catering recommendation system.

Some studies have refined the granularity of sentiment analysis to the topic level. For instance, Poria et al. (2016) proposed classifying comments by theme, such as the taste of dishes, delivery speed, service attitude, etc., and then making emotional judgments on each theme. This approach enables merchants to optimize specific links in a targeted manner, such as enhancing the quality of meals or improving the logistics process, rather than relying solely on overall ratings to judge user satisfaction.

In terms of technological development, in recent years, deep learning models (such as BERT and XLNet) have demonstrated higher accuracy in sentiment analysis tasks, especially in understanding context semantics and handling polysemous words. However, such models have high requirements for computing resources and deployment environments, and their training and inference speeds are relatively slow. They may not be suitable for online recommendation systems that need rapid responses.

In contrast, this project, based on the above research results and in combination with actual needs, adopted a lightweight machine learning model for sentiment classification and achieved topic recognition through a keyword-based rule method. This solution, while ensuring the accuracy of the analysis results, significantly reduces the computational overhead and is convenient for deployment in ordinary servers or campus experimental environments. In addition, this method has a high degree of transparency, which is convenient for later debugging and expansion.

Existing studies have also shown that combining the results of sentiment analysis with visualization techniques can significantly enhance the interpretability of data. For instance, by drawing emotional distribution pie charts and trend line charts, merchants can quickly grasp the changes in users' emotions at different time periods and promptly identify and solve problems. Meanwhile, integrating emotional outcomes with the recommendation system can provide users with personalized dish recommendations and enhance decision-making efficiency.

The existing research, ranging from algorithm principles, topic identification to visualization applications, has provided a solid theoretical and technical foundation for this project. The design objective of this project is to build a lightweight, efficient and scalable food review sentiment analysis and recommendation system based on the

absorption of mature methods, so that it can ensure accuracy while taking into account practicality and deployment convenience, thereby providing users with more intuitive and reliable references for food choices.

3.0 METHODOLOGY

This project aims to develop an emotion analysis and recommendation system based on the comments of catering users, in order to help users understand the evaluation of dishes more quickly and accurately and make choices. The system development process covers requirements analysis, conceptual model design, system implementation and functional integration, striving to achieve automation, accuracy and user-friendliness.

During the requirements analysis stage, a survey was conducted on the current catering review analysis and recommendation systems on the market. The core functions that the system must have were sorted out, including user registration and login, collection and cleaning of review data, sentiment classification, visual display of sentiment and themes, as well as personalized recommendations based on the results of sentiment analysis. The research results provide a basis for the functional planning and module division of the system.

During the system design stage, modules are divided according to the relationship between functions and data flow, mainly including the user management module, comment processing module, sentiment analysis module, result display module and recommendation generation module. The user management module is responsible for the input and verification of user information to ensure the security of the system and the identification of user identities. The comment processing module is mainly responsible for preprocessing the collected comment data, including text cleaning, denoising, word segmentation and word form restoration, to ensure the accuracy of subsequent analysis. The specific preprocessing process includes converting the text to lowercase, removing punctuation marks, numbers and stop words, and finally performing word segmentation and word form restoration. The sentiment analysis module uses a method combining dictionary and machine learning to determine the sentiment tendency of comment texts, and outputs positive, negative or neutral sentiment labels and corresponding confidence levels. The result display module visually presents the overall emotional distribution and keyword themes through pie charts, bar charts and other forms, helping users quickly understand the comment content. The recommendation generation module, based on the results of sentiment analysis and combined with users' historical behavior data, uses a weighted ranking strategy to generate personalized recommendations, supporting filtering by dish category and region.

The system development adopts the Python language to implement the back-end logic, handling data preprocessing, sentiment analysis and recommendation

algorithms. The back-end framework uses Flask to build API interfaces, which are responsible for handling front-end requests and invoking various functional modules. The front end adopts HTML, CSS and JavaScript technologies to build the user interface, supporting user registration, comment browsing, filtering and recommendation display. In terms of data storage, the system mainly uses CSV files in combination with lightweight databases to ensure timely data updates and stable access. The system as a whole adopts a modular design, which is convenient for subsequent maintenance and functional expansion.

Through the design and implementation of this methodology, the system can automatically handle a large number of comments, achieve accurate emotion recognition and visual display, and help users conveniently filter and browse comment information. Meanwhile, the recommendation mechanism based on emotional scores provides users with scientific and reasonable dining suggestions, enhancing user experience and decision-making efficiency. This system not only meets the project requirements but also provides technical support for the improvement of service quality in the catering industry.

4.0 RESULTS

4.1 Application Development

During the system development stage, we designed and implemented multiple functional modules to meet users' demands for analyzing and recommending food reviews. The comment analysis dashboard module visually presents the emotional distribution of overall user comments through a pie chart, such as the proportion of positive, neutral, and negative comments, helping users quickly grasp the overall evaluation trend of the dishes. Meanwhile, the bar chart shows the frequency of the main topics involved in the comments, such as food taste, delivery speed and service quality, etc., allowing users to understand the feedback from different aspects. The dashboard supports paginated browsing function. Users can filter comments based on emotion or topic for precise viewing, improving the efficiency of browsing and user experience.

The recommendation module rates and ranks the dishes based on the results of sentiment analysis, and selects the recommended dishes that are most highly praised by users. Each recommendation item is presented in the form of a card, including pictures of the dishes, star ratings and brief descriptions, to enhance visual appeal. Users can also use the "View Related Reviews" function to jump to the detailed review page of the dish, making it convenient for them to further understand their specific evaluations of the dish. This function effectively combines sentiment analysis with user feedback to provide users with targeted meal selection suggestions.

In addition, the system has developed a regional browsing module, which provides dish recommendations for the corresponding area based on the geographical location selected by the user. This module not only displays the popular dishes within

the region but also compares the sentiment analysis results of different regions, helping users discover regional differences and word-of-mouth characteristics, and supporting users to make more suitable choices based on their regional preferences.

4.2 Application Evaluation

i. Functional Testing

To ensure the correct realization and stable operation of the system functions, this project has conducted strict functional tests on each major functional module. The test adopts the black-box testing method, focusing on checking the core functions of the system, including the loading and filtering of comment data, the display of sentiment analysis results, the display of dish cards in the recommendation module and the viewing of related comments, regional browsing and sentiment comparison functions, etc.

The specific test steps include:

- Comment pagination and filtering function test: Verify that users can smoothly paginate and browse comments, and filter them based on sentiment categories and topic keywords to ensure the accuracy of the filtering results.

- Chart visualization function test: Check whether the emotion distribution pie chart and the theme frequency bar chart are correctly rendered, and ensure that the chart data is consistent with the background statistical results.

- Recommendation module test: Check whether the card of the recommended dish fully displays the picture, name and star rating, and whether clicking the "View Related Reviews" button redirects to the correct review detail page.

Regional browsing function test: It is confirmed that after users select different regions, both the recommended content and the sentiment analysis results can be updated dynamically, and the regional sentiment comparison data display is normal. No major errors were found in all testing stages. The system's various functions performed stably and met the design requirements.

Test Item	Expected Outcome	Actual Outcome	Result
Page Load	Show navbar and three main modules	Page loaded successfully, layout is normal	√
Navbar Navigation	Button links work correctly	Navigation accurate, username shown when logged in	√

Module Card Style	Icons, buttons, and text all appear, styles are consistent	Display is normal, buttons are clickable	√

Table 1 Home page function test.

Test Item	Expected Outcome	Actual Outcome	Result
Sentiment and Topic Filter	Show only matching comments	Display is correct, filtering accurate	√
Keyword Search	Search results include the keyword	Accurate matching, loads correctly	√
Pagination	Navigate across multiple pages normally	Smooth paging, buttons work	√
Region Filter via URL	Show reviews from the specified region	Correct comments loaded based on region parameter	√

Table 2 Result page function test.

Test Point	Result
Sentiment pie chart renders properly	√ Chart loads normally
Topic bar chart is clearly shown	√ Displays correctly
Chart colors are consistent	√ Uses orange-yellow theme
Charts update with new data	√ Can be re-rendered dynamically

Table 3 Chart display test.

Test Item	Expected Outcome	Actual Outcome	Result
Recommendation Display	Food name, image, and rating shown	Real images display; fallback image shown when original is missing or broken	√
Star Rating Style	Orange-yellow five-star system	Style consistent and neat	√

	used		
Image Loading for Cards	All food images display correctly or fall back	Real images display; fallback image shown when original is missing or broken	√
Region-based Recommendation	Updates results based on region parameter	Display correctly	√

Table 4 Recommendation page function test.

Test Item	Expected Outcome	Actual Outcome	Result
Card Display	Each region shown in consistent style	Cards look good, content is clear	√
Button Navigation	Links to recommendation or results pages	Navigation successful	√
Region Parameter Handling	URL parameter passed to backend correctly	Region data loads as expected	√
Region-Specific Filtering	Only show comments from selected region	Matching reviews shown, filters still work	√

Table 5 Region page function test.

ii. Usability Testing

To evaluate the user experience of the system, the project team organized usability tests for the target user group. The test subjects were 25 users of food delivery services, covering different ages and backgrounds. The usage feedback was mainly collected through questionnaires. The questionnaire content covers dimensions such as operational convenience, interface design, relevance of recommendation results, and overall satisfaction.

The test results show:

Ease of operation: The average score is 4.16 points, indicating that users generally consider the system to be simple to operate and the filtering and browsing processes to be smooth.

Interface design: The average score is 4.19 points. User feedback indicates that the interface is aesthetically pleasing, the charts are clear, and the information layout is reasonable.

Recommendation relevance: The average score is 4.08 points. The recommendation results are relatively consistent with users' expectations, increasing their trust in the system.

Overall satisfaction: The comprehensive score is 4.14 points, reflecting that users are relatively satisfied with the overall performance of the system.

In addition, users have put forward improvement suggestions, such as adding more filtering conditions, optimizing page response speed and enriching recommendation algorithms, which provide important references for the optimization of subsequent versions.

Metric	Score (1-5)
Ease of Use	4.16
Interface Design	4.19
Recommendation Relevance	4.08
Overall Satisfaction	4.14

5.0 CONCLUSION

This project has successfully developed a catering sentiment analysis and recommendation system based on user comments. The system classifies the sentiment of user comments through machine learning methods and combines keyword matching to achieve topic annotation, helping users quickly understand the advantages and disadvantages of dishes from a large number of comments. The system is reasonably designed and can visually display the emotional distribution and topic frequency in the form of charts. It supports users to filter comments based on emotional tendencies and topics, enhancing the user browsing experience. Meanwhile, the recommendation module generates dish recommendations by analyzing positive reviews and is equipped with pictures and rating displays, enhancing the visualization effect of the recommendations. In addition, the system has also realized the function of classified browsing by region, which is convenient for users to understand the differences in catering evaluations and recommendations in different regions, meeting the diverse needs of users.

During the functional testing phase, all functional modules of the system can operate stably and meet the expected design goals. Through usability tests on users, the results show that the system interface is simple and beautiful, and the operation process is smooth. Users have given high praise to the system's ease of use and recommendation relevance, and the overall satisfaction is good. The suggestions put forward by users during the test, such as enhancing the interpretability of recommendations and optimizing the response speed of the interface, have provided valuable references for the improvement of future versions.

This system has realized the practical application value of natural language processing technology in the catering field. It can assist users in more efficiently screening and selecting their favorite dishes, and at the same time provide merchants with an effective tool to understand customer feedback and optimize services.

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