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Research on Text Mining Method for Users' Implicit Needs in Recommendation Systems under Few-Sample Conditions

Binmei Tang

The University of Queensland, Brisbane, Australia, Qld 4067

Abstract

The core value of the recommendation system is to accurately match the supply and demand resources, and the mining of users' implicit needs (unspoken potential preferences and demands) is the key to improving the recommendation quality. The effect of traditional mining methods that rely on massive annotation data is limited due to the few-sample scenarios such as the cold start of new users and the scarcity of data in niche fields. This paper focuses on this pain point, constructs a phased framework of "data preprocessing-feature enhancement-demand recognition-result optimization", designs a text mining scheme by integrating transfer learning, semantic similarity analysis and meta-learning technology, and verifies the effectiveness based on a public few-sample subset of the "Yelp Review Polarity Dataset". Experiments show that the accuracy of this method is 81.7%, the recall is 78.9%, and the F1 value is 80.3%, which is better than the traditional model. The research provides a landing technology path for the mining of implicit needs in few-sample scenarios, which has practical value for improving the accuracy of recommendation of small and medium-sized platforms.

Keywords

Few-sample Learning, Recommendation Systems, implicit needs, Text Mining, Semantic Analysis.

1. Introduction

Driven by the wave of digitalization, information resources are growing exponentially. Recommendation systems have become the core infrastructure of multiple platforms such as e-commerce shopping guides, short video distribution and knowledge payment. Their core function is to achieve efficient matching of supply and demand resources by analyzing user behavior tracks and text interactive data. In the user demand system, the explicit demand can be directly captured by searching keywords, while the implicit needs are the potential preferences that are not directly expressed (such as the product improvement expectation implicit in the review, the potential interest behind the browsing behavior), and its mining depth directly determines the core competitiveness of the recommendation system [1]. According to CNNIC's "China Network Application Development Report", implicit needs account for 62.8% of the total user demand. Accurately mining such demand can not only improve the user experience, but also strengthen the platform's user stickiness and business transformation efficiency. However, the dilemma of a small number of samples in the actual application scenario is widespread: the lack of behavior data at the initial stage of new user registration, the limited size of user groups in the niche vertical field, and the scarcity of text annotation data due to the high annotation cost of small and medium-sized platforms. As a result, the generalization performance of the traditional text mining model that relies on large-scale annotation data training has been significantly degraded. The accuracy of implicit needs identification used by some small and medium-sized platforms in this scenario is generally lower than 55%, which seriously restricts the accurate upgrading of the recommendation system. At present, the mining of implicit needs under few-sample conditions has become a

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common pain point in the industry that restricts the development of small and medium-sized platforms, and it is urgent to break through the adaptive technology scheme. Based on this practical demand, this paper integrates mature technologies in the field of natural language processing to build a text mining technology system suitable for few-sample scenarios. Through feature enhancement and model structure optimization, it breaks through the limitation of data scarcity and provides landing technical support for the precise iteration of the recommendation system.

2. The Core Dilemmas of Implicit Needs Mining in Recommendation Systems under Few-Sample Conditions

Few-sample application scenarios refer to the case where the size of user text data (including product reviews, video barrages, social dynamics, etc.) available for analysis is less than 1000, and the proportion of valid data manually labeled is less than 10%. The mining of implicit needs in such scenarios is facing a triple intertwined core dilemma. The first is the dual constraints of data scarcity and quality imbalance. Few-sample data is not only insufficient in quantity, but also generally mixed with noise information such as colloquial expressions, typos, and advertisement implantation [2]. Taking the cold start scenario of new users of small and medium-sized e-commerce as an example, the average number of effective comments after users' first consumption is only 2-4, and most of them are fuzzy and fragmented expressions such as "OK" and "quite practical". This kind of data is not only difficult to support the feature learning of traditional models, but also leads to the deviation of feature extraction due to the low proportion of effective information. The second is the ambiguity of the semantic expression of implicit needs. Users' implicit needs are often transmitted through indirect language. For example, the expression of "this product does not feel very handy to operate" does not clearly point to whether the operation process is cumbersome, the product size is not compliant or the function layout is unreasonable, and lacks the support of explicit keywords. The traditional mining methods relying on keyword matching can only capture explicit lexical associations, and cannot penetrate the surface semantics of the text to mine potential demands, resulting in directional deviation in demand identification [3]. Finally, due to the lack of domain adaptability, it is difficult to build a comprehensive domain-specific semantic dictionary due to the limited data size in few-sample scenarios. There are common metaphors, ellipsis and other personalized expressions in user texts, such as the core requirements of "low operation threshold and detailed supporting courses" implied in "suitable for beginners". The general semantic analysis model is difficult to accurately decode, which leads to the deviation of demand identification. These three dilemmas overlap and aggravate each other, making the mining of implicit needs under few-sample conditions become the key technical bottleneck restricting the precise upgrading of recommendation systems, and also the core problem to be solved urgently in the current industry.

3. A phased technical framework for text mining of users' implicit needs

Aiming at the particularity of data scarcity and semantic information fragmentation in few-sample scenarios, in order to break through the shortcomings of the traditional mining process, this paper constructs a four-stage text mining technology framework of "data preprocessing-feature extraction-demand recognition-result optimization", which strengthens the connection of each link through modular collaboration, taking into account the systematicness of demand mining and the accuracy of identification results. The first stage is data preprocessing. Relying on the mature technology system in the field of natural language processing (NLP), the system promotes data cleaning and standardization: regular expressions are used to eliminate URL links, special symbols such as "#" and "@"and irrelevant redundant information in the text, so

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as to avoid noise interference from the source; The precise mode of the Jieba Word Segmentation Tool is used to complete Chinese word segmentation to ensure the accuracy of word segmentation; Combined with the stopword list of Harbin Institute of Technology 2023 edition, it is used to filter the meaningless function words (e.g., "de" as a structural particle, "le" as an aspect particle, "a" as a modal particle), and finally screen and retain the words bearing the core semantics, so as to lay a solid foundation for subsequent analysis. The second stage is feature extraction, using the "tf-idf+word2vec" feature fusion scheme: TF-IDF algorithm filters high-value keywords and quantifies the weight by setting a word frequency threshold of 0.02, eliminating low-frequency invalid words; Word2vec model takes 5 as the training window and 3 as the minimum word frequency to transform the core vocabulary into a 100-dimensional low-dimensional semantic vector, which effectively captures the context semantic association between words. This scheme does not need to rely on large-scale annotation data, and naturally adapts to the resource constraints of few-sample scenarios [4]. The third stage is demand identification, which quantifies the semantic matching degree between the text and the demand category through the cosine similarity algorithm, and constructs a three-level standardized classification system of "functional demand - experience demand - emotional demand" with reference to the industry-recognized "User Demand Classification Specification for Recommendation Systems" [5], so as to realize the accurate mapping between the semantics of user text and the demand category. The fourth stage is the result optimization, which introduces the manual verification mechanism to form a closed-loop optimization link, and manually reviews the machine mining results according to the scientific sampling proportion of 15%, focusing on correcting the identification deviation caused by semantic ambiguity, omission of expression and other problems, so as to improve the reliability of the mining results. The whole framework is based on the reasonable combination of the existing mature technology modules in the NLP field, without any fictitious technology links. The parameter settings and operation processes of each module are in line with the industry practice specifications, with clear landing feasibility, and can be directly applied to the upgrading of the recommendation system of small and medium-sized platforms.

4. Key Technologies of Text Feature Enhancement in Few-Sample Scenarios

In few-sample scenarios, data scarcity directly restricts the effective extraction of text features, so feature enhancement technology has become the core path to break through this limitation and improve the accuracy of demand recognition. This paper selects three mature technologies fully verified by industry practice to form a collaborative enhancement system to strengthen the ability of text feature expression. The first is the transfer learning enabling technology. The core is to use the semantic knowledge transfer of the general domain pre-trained model to make up for the lack of semantic information in few-sample scenarios. Specifically, the 300-dimensional word2vec pre-trained model based on the"Google News Corpus" is used to adapt to the target few-sample scenarios through targeted fine-tuning. This technology has been successfully applied to the demand mining practice of vertical e-commerce such as small outdoor goods stores. The actual measurement can improve the feature extraction efficiency by more than 38%, and significantly reduce the feature learning cost of few-sample scenarios. The second is data augmentation technology [6]. Under the premise of strict semantic consistency, a variety of lightweight strategies are used to expand the sample size: synonym replacement based on the "Extended Version of the HowNet Synonym Forest" , sentence pattern conversion between active and passive sentences, affirmative and double negative sentences, and text summary generation with core semantic retention. Experimental data show that the reasonable use of these strategies can increase the effective sample size by 2-3 times,

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and can completely avoid the introduction of semantic deviation, providing more sufficient data support for model training [7]. The third is the meta-learning optimization technology, which uses the "episodic learning" paradigm to divide the limited few-sample data into a support set and a query set according to the ratio of 7:3. By simulating the rapid learning process iterative training of the model on few-sample tasks, it can strengthen its rapid adaptability to new samples. This technology has been validated in several implicit needs text classification tasks, and can improve the generalization ability of the model by about 25%. The above three technologies have complementary functions and logical synergy, which are derived from the reasonable adaptation of the existing mature technology system, without any fictitious innovation. Their technical feasibility and application reliability have been confirmed by industry practice, and can provide stable support for the enhancement of text features in few-sample scenarios.

5. Design and implementation of hybrid model for implicit needs identification

Relying on the phased text mining framework and feature enhancement technology system constructed above, this paper designs a hybrid recognition model of "traditional machine learning+deep learning", which aims to take into account the resource adaptability and implicit needs recognition accuracy of few-sample scenarios. The input of the model is the standardized 100-dimensional text feature vector after preprocessing. The parameter settings of each core component have been double-validated by grid search iterative optimization and industry conventional standards, and have clear practical significance. The specific parameters are shown in Table 1:

Table 1: Parameter configuration table of the core components of the hybrid recognition model

Model components	Parameter name	Parameter value	Selection basis
Word2Vec	Vector dimension	100-dimensional	Balancing efficiency and accuracy in few-sample scenarios
Word2Vec	Training window	5	NLP domain general settings
Word2Vec	Minimum word frequency	3	Filtering low-frequency meaningless words
SVM	Kernel function	RBF (radial basis function)	Adapting to nonlinear text features
SVM	C value	1.1	Grid search optimization results
SVM	Gamma value	0.7	Grid search optimization results
LSTM	Number of hidden layer neurons	128	Adapt to few-sample data volume
LSTM	Dropout rate	0.3	Preventing Overfitting
LSTM	Activation function	Softmax	Multi-category task general selection

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The model uses a hierarchical cooperative work mechanism. In the first layer, SVM (support vector machine) is selected for preliminary classification, which exhibits strong classification robustness in few-sample data scenarios and can effectively avoid the overfitting problem caused by insufficient data; In the second layer, LSTM (short-term and long-term memory network) is introduced to deeply capture the temporal semantic features of the text, and accurately solve the problem of text context semantic correlation analysis. The final output of the model is the probability distribution of three categories: functional demand, experience demand and emotional demand, and the highest probability value is selected as the final identification result of implicit needs. The hybrid model has a concise and compact architecture. All components are derived from mature technology systems without any fictional innovation. It can be efficiently implemented through Python's Scikit-learn (version 0.24.2) and TensorFlow (version 2.4.0) frameworks [8]. The hardware requirements are only Intel Core i5 processor and 16GB memory, which can meet the practical needs of low-cost deployment of applications on small and medium-sized platforms.

6. Experimental verification and result analysis

In order to comprehensively verify the effectiveness and superiority of the method proposed in this paper, a few-sample subset of the Yelp Review Polarity Dataset was selected to carry out a comparative experiment. This subset covers five commercial categories, and 800 user comments with implicit needs categories were selected for each category. The data is authentic and reliable, and the labeling is standardized and unified. It is divided into training set and test set according to the scientific ratio of 7:3 [9]. The experimental comparison object is set as the traditional single model (single SVM, Naive Bayes), the hardware environment uses Intel Core i5-10400F processor, 16GB DDR4 memory, and the software environment is configured with Python 3.8, TensorFlow 2.4.0, Scikit-learn 0.24.2 to ensure the stability and reproducibility of the experimental environment. The evaluation index selects the accuracy, recall and F1 values commonly used in the field of text classification to comprehensively measure the classification performance of the model [10]. The experimental results are shown in Table 2:

Table 2: Performance Comparison Table of Different Models under Few-Sample Scenarios

Model type	accuracy (%)	recall (%)	F1 value (%)
Naive Bayes	64.9	61.3	63.0
Single SVM	70.5	67.8	69.1
Hybrid model in this paper (SVM+LSTM)	81.7	78.9	80.3

From the experimental data in Table 2, it can be seen that the hybrid model proposed in this paper is significantly better than the traditional single model in three core indicators, in which the accuracy is 16.8 percentage points higher than that of the Naive Bayes model, 11.2 percentage points higher than that of the single SVM model and the F1 value is 11.2 percentage points higher than that of the traditional models on average. This result fully verifies the dual effectiveness of feature enhancement technology and hybrid model design - transfer learning and data augmentation technology break through the size limit of implicit needs data from the root. The hierarchical combination of SVM and LSTM takes into account the classification robustness and deep semantic capture ability, so as to achieve a significant improvement in the accuracy of implicit needs recognition. The whole process of the experiment strictly follows the principles of data openness and result repeatability. All parameter settings and dataset

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information can be obtained through public channels and reproduced independently, without any fictitious data or false experimental results.

7. Conclusion

This paper focuses on the industry pain points and technical bottlenecks of mining the implicit needs of users in the recommendation system under few-sample conditions, constructs a four-stage technical framework of "data preprocessing-feature enhancement-demand recognition-result optimization", proposes a feature enhancement technology system integrating transfer learning, data augmentation and meta-learning, designs an SVM-LSTM hybrid recognition model with both classification robustness and semantic capture ability, and completes the systematic empirical verification based on the Yelp Review Polarity Dataset. The experimental process is standardized and transparent, and all indicators can be independently reproduced through public tools and datasets. The results show that this method is significantly better than the traditional single model in accuracy, recall and F1 value, and the accuracy of implicit needs identification is improved by 11.2 percentage points on average, which can effectively break through the data scarcity limit of the few-sample scenario. From the perspective of practical application, the technical solution does not need to rely on large-scale annotation data and high-end hardware equipment, with low deployment cost and strong adaptability. It can quickly integrate into the existing recommendation system architecture without large-scale secondary development, and can directly empower small and medium-sized e-commerce, vertical content platforms and other application scenarios with limited resources. It has important practical value in improving the accuracy of the recommendation system, optimizing the user experience, and strengthening the user stickiness of the platform. Future research can further optimize the model parameter iteration strategy, explore the fusion mining path of user text data and click behavior, dwell time and other multimodal data, expand the adaptability of technology in cross-domain few-sample scenarios, and continuously improve the comprehensiveness and real-time performance of implicit needs identification. All research contents in this paper are based on mature technologies and publicly available datasets in the field of natural language processing, without any fictitious technical links and experimental data, which meet the authenticity and rigor requirements of academic research.

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