

Retraction

Retracted: A Personalized Recommendation Method for Short Drama Videos Based on External Index Features

Advances in Meteorology

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] X. Gong, "A Personalized Recommendation Method for Short Drama Videos Based on External Index Features," *Advances in Meteorology*, vol. 2022, Article ID 3601956, 10 pages, 2022.

Research Article

A Personalized Recommendation Method for Short Drama Videos Based on External Index Features

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Dramatic short videos have quickly gained a huge number of user views in the current short video boom. The information presentation dimension of short videos is higher, and it is easier to be accepted and spread by people. At present, there are a large number of drama short video messages on the Internet. These short video messages have brought serious information overload to users and also brought great challenges to short video operators and video editors. Therefore, how to process short videos quickly has become a research hotspot. The traditional episode recommendation process often adopts collaborative filtering recommendation or content-based recommendation to users, but these methods have certain limitations. Short videos have fast dissemination speed, strong timeliness, and fast hot search speed. These have become the characteristics of short video dissemination. Traditional recommendation methods cannot recommend short videos with high attention and high popularity. To this end, this paper adds external index features to extract short video features and proposes a short video recommendation method based on index features. Using external features to classify and recommend TV series videos, this method can quickly and accurately make recommendations to target customers. Through the experimental analysis, it can be seen that the method in this paper has a good effect.

1. Introduction

With the rapid development of Internet communication technology and multimedia technology in China, the number of new media short videos in China is increasing day by day. By the end of 2019, the total number of video viewing videos of IQIYI and Tencent TIKTOK and short video was 100 million, and the number of monthly users was close to 300 million. The number of videos was up to 1 billion 500 million per day. Using data mining can make research and decision-making, help clarify the complexity of data interaction, understand the uncertainty caused by lack of data, and dig deep into the huge business value behind complex data. In the broad short video market, data mining runs through it, such as market analysis, segmentation, target selection, and finally making plans, which will be inseparable from data mining. It can be said that data mining has opened up a new path for the development of short video.

The prosperity and development of short video mainly depends on the continuous optimization of China's communication infrastructure development and application. The continuous improvement of network environment and the improvement of information transmission speed and stability also provide a strong technical guarantee for the development of short video [1–4]. The popularity of smart phones provides valuable soil for the accumulation of short video users, and the video production in the short video app is simple and easy to learn, the use threshold is low, the integration of production and production is realized, and the operation cost of users is reduced. In the field of visual imaging, the application of AR technology enhances the user's multidimensional experience. Based on the accurate push of data mining, it forms the user's unique personalized label and firmly locks the user.

UGC is the abbreviation of user original content. The positioning of short video platform is content sharing [5]. All users can upload and share their own life short videos.

There is almost no content restriction, which meets the personalized needs of users. Through the UGC content mode, the threshold of user production content is reduced and the number of users of the platform is expanded, so as to occupy the market.

Short video has the characteristics of brevity, rich content, and strong participation and interaction. At the cognitive level, users identify the external rich world through a large number of short videos [6]. At the psychological level, short video occupies most of the scattered time of users, and short video gives users an immersive experience through the three-dimensional form of text, sound, and image senses. At the action level, users' comments and forwarding have become a part of the short video experience, which has also improved and enhanced users' sense of participation.

In recent years, the rapid development of the Internet has increased the convenience of people's access to information. At the same time, thanks to the reduction of production costs of various electronic and digital devices and the progress of production technology, the number of users who use convenient smart phones to shoot and produce videos is growing exponentially [7–9]. A huge user group uploads the captured and produced videos to the Internet, forming a large amount of video data. According to the 38th statistical report on China's Internet development recently released by China Internet Network Information Center (CNIC), as of June 2016, the number of online video users in China had reached 514 million, an increase of 10 million over the end of 2015, and the utilization rate among Internet users was 72.4%. For users, video operators provide rich video data. According to the official data released by YouTube, the world's most famous video social networking website, YouTube has been viewed 2 billion times a day, and users spend an average of 15 minutes browsing YouTube every day. For domestic video operators, the field of Internet video has a sense of competition. Baidu video, Tencent video, LETV, Youku Tudou, Ku6, and other video aggregation and sharing platforms have emerged successively.

Personalized recommendation technology is to recommend content suitable for users' interests according to their previous behavior in huge data. The birth of this technology can well solve the problems of information overload and difficult search. What is more meaningful is that users do not need to go through specific settings. Personalized technology can recommend interest related content for users when users are not aware of their needs, improve user experience, and increase user loyalty. Personalized recommendation technology has become the focus of video website development, and our research in this direction is also of great significance.

The research contributions of the paper are as follows:

- (1) In this paper, external index features are added to extract short video features, and a short video recommendation method based on index features is proposed.
- (2) The paper uses external features to classify and recommend TV series videos, which can be quickly and accurately recommended to target customers. Through the experimental analysis, it can be seen that the method in this paper has a good effect.

2. Related Works

This paper mainly introduces the relevant theoretical knowledge and technology used in the paper, mainly including log data preprocessing method, short video log text model, and classification algorithm [10]. Firstly, this paper will preprocess the short video log and user behavior log. The processing methods include Chinese word segmentation and part of speech tagging. In addition, this paper also introduces the relevant knowledge of noise processing. Next, this paper introduces the models used to represent short video features in detail, mainly including the vector space model used in short video text and the LDA topic model for constructing short video topic features. Finally, the classification algorithm for short video recommendation in this paper is introduced, mainly including factor decomposition machine, gradient lifting decision tree, and logistic regression algorithm.

2.1. Data Preprocessing Technology. Detailed preprocessing work should be carried out before model representation of short video related logs, including Chinese word segmentation, removing stop words, and removing noise in data. Next, it briefly introduces the Chinese word segmentation technology and noise processing of the text.

2.1.1. Chinese Word Segmentation Technology. One of the most important processing links of text data is Chinese word segmentation. The result of word segmentation can determine the efficiency of follow-up research. The purpose of word segmentation is to select the basic units containing complete semantics from the given text. Compared with English words, they are generally segmented with spaces or punctuation marks, and Chinese is much more complex. The purpose of Chinese word segmentation algorithm is to cut the Chinese sentence sequence in the data into a series of words with basic semantics. At present, the main Chinese word segmentation methods include word segmentation based on string matching, word segmentation based on dictionary, and word segmentation based on statistics. The main idea of word segmentation method based on string matching is to use string matching algorithms, such as forward maximum matching method (FMM) [11]. The main idea of Chinese word segmentation method based on dictionary is to build a corresponding Chinese dictionary, compare and match the input Chinese text with the words in the dictionary, and cut the words if the matching is successful, but not anyway. The statistical method is to determine whether the word can be formed according to the frequency of the string in the corpus. If the frequency between adjacent words is high, a word can be formed.

It includes a variety of algorithms, Chinese word segmentation methods, and other Chinese tools, such as part of speech tagging, keyword extraction, and other functions. Bosen is the most authoritative platform in the field of open Chinese semantic tools.

2.1.2. Denoising. Noise data refers to meaningless data in the data set. If the meaningless noise data in the data set is not removed, it will produce deviation and bad results for video description and analysis in the experiment. The noise in the dataset used in this paper mainly includes repeated text data, stop word processing, and semantic noise of short video data itself.

2.2. Short Video Model Representation

2.2.1. LDA Topic Model. The English full name of LDA is latent Dirichlet allocation, that is, implicit Dirichlet distribution. It is a topic model. The main idea is to give each document in the text set in the form of probability distribution. Using this idea, we mine their topic distribution from the text and then cluster or classify them according to the mined topics. LDA topic model needs to manually specify the number of topics K in the training process. At the same time, it is an unsupervised learning algorithm. When training LDA topic model, it does not need to manually label the training set.

LDA is a three-tier generative model, which contains words, documents, and topics. It represents a document as the probability distribution of a certain number of topics, and the topics are represented as the probability distribution of all different words in the document set. Suppose there is a set of documents, marked D . According to the idea of LDA, we believe that document set D is composed of M documents and different words, in which the number of K topics is given manually. The process of document generation by LDA can be represented by graphical model representation, as shown in Figure 1. Firstly, the parameters of LDA are β . The relationship between topic and word is extracted from the Dirichlet distribution Q . When LDA generates a document D , it randomly selects a k -dimensional vector from the Dirichlet distribution with parameter α to represent the topic distribution in document D . According to this distribution, for all words in document D , z_{dn} is randomly selected from the polynomial distribution with parameter θ_d to represent the topic selected by the current word. Finally, the word w_{dn} is extracted from the polynomial distribution with parameter $\phi_{z_{dn}}$.

The box in Figure 1 refers to repeated sampling, where the sampling times are represented by the values of M , N , and K in the lower right corner. Among them, M , N , and K constants represent the number of documents, words, and topics, respectively, and the number of topics is manually set. The gray circle in the figure represents the observable variable, the hollow circle represents the potential variable, and the arrow represents the dependency between the two variables α , β which are the hyperparameters of Dirichlet distribution.

The process of generating a document by LDA is actually to extract the subject information in the document [12]. After obtaining the subject information, the corresponding hidden variables can be deduced by using the word information, so as to obtain the subject probability distribution θ of each document and then mine the potential semantic

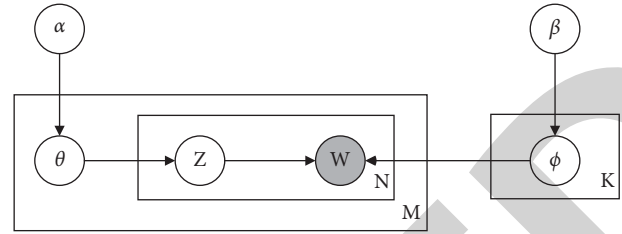


FIGURE 1: Working mechanisms of LDA.

knowledge in the text. In solving LDA topic model, this paper uses Gibbs sampling method to solve the parameters of LDA model and realize topic mining.

2.2.2. Vector Space Model. Vector space model was proposed by Salton et al. in the 1970s [13]. It is an algebraic model taking text content as space vector. Now it is widely used in the fields of information retrieval, data mining, and related sorting.

The vector space model first simplifies the text content into a vector, ignores the order and position of specific semantic units, and only considers their frequency in the text. Then, by taking the spatial similarity as the semantic similarity to measure the text similarity, the processing of text content is simplified into vector operation. The related concepts of vector space model are given below:

- (1) Text: it is the content to be processed by the model, which is composed of one or more complete texts and sentences and usually has systematic meaning.
- (2) Feature item: it mainly refers to the text, words, and phrases in the text content, which can be used as the basic language unit for model processing. They are the basic units of text model.
- (3) Feature item weight: a weight value is used to indicate the importance of a feature item in a text. The higher the weight is, the more important the feature item is. The weighting functions include Boolean weight, word frequency weight, and TF-IDF.

TF-IDF is a statistical method to calculate the importance of a word in the whole text. It is often used in data search and data mining [14]. Term frequency (TF) refers to judging the contribution of a word to the text by counting the number of occurrences of feature items in the document. The higher the frequency, the greater the contribution. If only statistical methods are used, there will be limitations. For example, words that do not contribute to classification in statistical texts without screening, such as prepositions and conjunctions, will affect the accuracy of classification. In addition, for example, if the value of a word with a high statistical characteristic value of F is also high in other documents, the document to which it belongs cannot be judged. In addition, it is often used together with IDF for statistics because of the limitations of using it only. The idea of inverse document frequency (IDF) is to ignore the feature items that appear in multiple documents and retain the feature items that appear in a small number of documents as

a measure of the importance of a word. The IDF statistical method is to divide the total number of documents by the number of documents with feature items and then take the logarithm of the result.

2.3. Text Classification Algorithms. In this paper, our classification algorithms for short video features mainly include three kinds: factor decomposition machine, gradient decision tree algorithm, and logistic regression algorithm. These algorithms are introduced in this section.

2.3.1. Factor Decomposition Machine. Factorization machines (FM) [15] is a machine learning algorithm based on matrix decomposition proposed by Steffen Rendle in 2012. The purpose of this algorithm is to solve the problem of feature combination under sparse matrix. The traditional machine learning problem only considers how to give weight to features without considering the interaction between features. The proposal of FM model solves this problem better.

The factor decomposition machine simulates the factor decomposition model through the eigenvector, can model the interaction between different types of variables, and can predict any real value vector. The factor decomposition machine model can give the prediction results according to the real value characteristics in the data. It uses factor parameter decomposition to build the model between the characteristic variables. Combined with the advantages of SVM, FM can deal the very sparse data well. Meanwhile, compared with SVM, FM has a better performance and its complexity is linear. Suppose x is the inputted feature vector and y is the target variable; we can predict the value of y by the following formula:

$$\hat{y}(x) = \omega_0 + \sum_{i=1}^n \omega_i x_i + \sum_{i=1}^{n-1} \sum_{j=i+1}^n v_i v_j x_i x_j. \quad (1)$$

In this formula, n stands for the dimension of features, v_i, v_j is the interrelationship between the i -th and j -th variable and it can be calculated by $v_i, v_j = \sum_{f=1}^k v_{i,f} v_{j,f}$, k is a hyperparameter, and $\omega_0 \in \mathbb{R}$ is the parameter of the model.

Stochastic gradient descent (SGD) [16], alternating least squares (ALS), and Markov Monte Carlo (MCMC) are three machine learning methods commonly used to solve the parameters of factorization machine. When using the three methods for parameter calculation, it is necessary to select the specified loss function for optimization. The effect is achieved by minimizing the loss function on the specified observed data set. The definition of the loss function minimization optimization function is shown in the following formula:

$$OPT(S, \lambda) = \arg \min_{x,y} \text{loss}(\hat{y}(x|\theta), y). \quad (2)$$

According to the model parameters in practical problems θ to determine the optimization function $\hat{y}(x|\theta)$, the value of $\hat{y}(x|\theta)$ is determined. In order to make the optimization function meet the requirements better, we must use

the appropriate loss function according to the actual problem. For the regression problem, the loss function takes the least square difference, as shown in the following formula:

$$\text{loss}(\hat{y}, y) = (\hat{y} - y)^2. \quad (3)$$

For the binary classification problem, we use the logistic regression function as our loss function, and it can be calculated by

$$\text{loss}(\hat{y}, y) = -\ln \sigma(\hat{y}y). \quad (4)$$

When we find the values of the model parameter θ , they may be overfitting since there are too many parameters. So, in practice, we must optimize the loss function. The commonly used optimization method is to use L_2 normalization, and the formula is

$$OPT(S, \lambda) = \arg \min_{\theta \in \Theta} \left\{ \sum_{x,y} \text{loss}(\hat{y}(x|\theta), y) + \sum_{\theta \in \Theta} \lambda \theta^2 \right\}. \quad (5)$$

In this paper, the stochastic gradient descent algorithm is used to solve the calculation of the loss function of the factorizer. SGD algorithm uses each iteration to calculate the gradient and then updates the parameters of the required solution. SGD can effectively target large data sets, and its algorithm complexity is linear, so SGD has good performance. The updated calculation of parameters by SGD is shown in the following formula:

$$\theta \leftarrow \theta - \eta \left(\frac{\partial}{\partial \theta} \text{loss}(\hat{y}(x), y) \right) + 2\lambda \theta. \quad (6)$$

2.3.2. Decision Tree Algorithm. Decision tree is to train certain sample data to learn decision rules and classify unknown data efficiently. In short, decision tree is a widely used classifier for exploratory knowledge discovery. Decision tree has two advantages: (1) it has good readability, which is helpful for manual analysis; (2) it has high efficiency and can be used many times without repeated construction. The maximum calculation times of each prediction cannot exceed the depth of the decision tree.

The core algorithm of the decision tree is to select the attributes of each node in the tree that are most conducive to the classification of instances. On the basis of ID3 algorithm, the concept of information gain is introduced to determine the attributes used for classification on different nodes at each level of the decision tree through the value of information gain.

Gradient boosting decision tree (GBDT) algorithm is a boosting machine learning idea based on decision tree proposed by Schapire et al. in 1990 [17]. Gradient boosting is an algorithm combination model in which multiple different classification algorithms can be used. Generally, boosting algorithm is an iterative process, and each training is to improve the last result. Each calculation is to reduce the last residual. Because there are many cases where the decision tree is used as the basic model, gradient boosting is often used as the decision tree of gradient promotion.

2.3.3. Logistic Regression Algorithm. Logistic regression is a binary classification model commonly used in machine learning. It is widely used in practice. For example, logistic regression is widely used in statistics and sociology. It is used to analyze the hit rate prediction problem. At present, logistic regression is widely used in the field of computing advertising.

In order to solve the binary classification problem, it is necessary to use logical regression to generate values in the range of 0 to 1. Therefore, sigmoid function is introduced into logistic regression for fitting. The mathematical form of sigmoid function is shown in the following formula:

$$g(x) = \frac{1}{1 + e^{-x}}. \quad (7)$$

The corresponding curve for sigmoid function is shown in Figure 2.

As can be seen from Figure 2, the sigmoid function is a S-shaped curve whose value is between $[0, 1]$, and different input values will result in different output results. Far from 0, the value of the function will quickly approach 0/1, and conversely, near 0, the result will be closer to 0. This property allows us to interpret it in a probabilistic way. Therefore, using logistic regression to predict the hit rate of short videos can solve this problem well, and the parameters in the sigmoid function represent the weights of the features extracted in the short video hit rate prediction problem and their corresponding parameters. A common way to solve for parameters is to use maximum likelihood estimation, i.e., to find a set of parameters, the greater likelihood (probability) of our data under this set of parameters. In this paper, we use logistic regression to solve a binary classification problem. The formula of logical regression can be expressed as shown in

$$f(x) = \frac{1}{1 + e^{-g(x)}}. \quad (8)$$

In this formula, $g(x) = \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n$.

3. The Framework of Short Video Recommendation

This section focuses on the basic framework of short video personalized recommendation and mainly introduces the overall process of short video personalized recommendation, short video data processing module, and short-sighted recommendation module.

Short video is short video, which generally refers to the video transmission content with a duration of less than 5–20 minutes on new Internet media. Short video is different from long video. It has the characteristics of fast propagation speed, timeliness, and hot search. In view of the above outstanding characteristics of short video, this paper focuses on the extraction and analysis of short video features and proposes a short video feature construction method integrating external indexes. Short video recommendation is regarded as a classification problem. LDA topic model is used to construct features, and three different classification

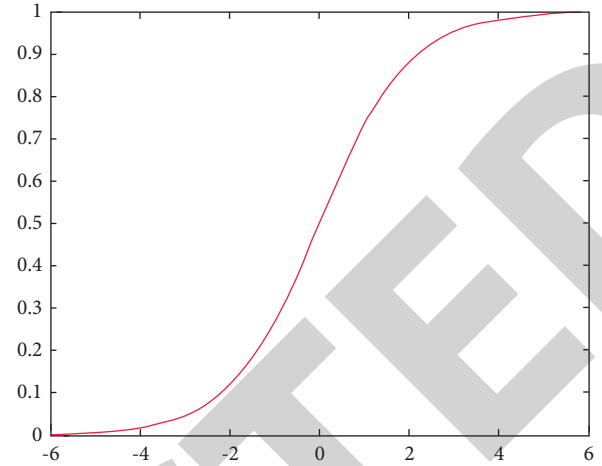


FIGURE 2: The plot of sigmoid function.

algorithms are used to compare, hoping to get more accurate recommendation results.

3.1. Overall Process of Network Short Video Recommendation.

In this paper, short video recommendation is abstracted as a binary classification problem. In the binary classification problem, how to construct the features used in classification is a core work. At present, although the traditional LDA topic features can capture certain implicit semantic information, the topic features obtained by LDA model can not reflect the timeliness and hot search of short video. Therefore, this paper introduces the external index feature into the short video recommendation method and constructs an LDA topic model based on the integration of external index feature, so as to better recommend the network short video with high public attention to users. The overall framework of this work is shown in Figure 3.

As can be seen from Figure 3, the framework mainly includes the preprocessing of short video data sets, the analysis and extraction of short video features, the construction of classifiers, and short video recommendation methods. Among them, the analysis and extraction of short video features and the construction of feature model are the focus of this paper. This paper integrates the relevant features of external index on the basis of traditional topic-based features and applies it to the recommendation method of short video. This approach can effectively improve the shortcomings of short video recommended to users, which is lack of timeliness and hot search.

- (1) In the preprocessing of short video data set, this paper uses the background log data of Baidu video, a well-known aggregated video in China. The log data includes the short video data of the aggregated video app and user behavior data. Firstly, the data are sorted and cleaned according to the technology and method of data preprocessing. Then use the open API provided by boson Chinese semantic tool to segment and label the data. Then cluster the divided words to get the different topics contained in the short video and user search words.

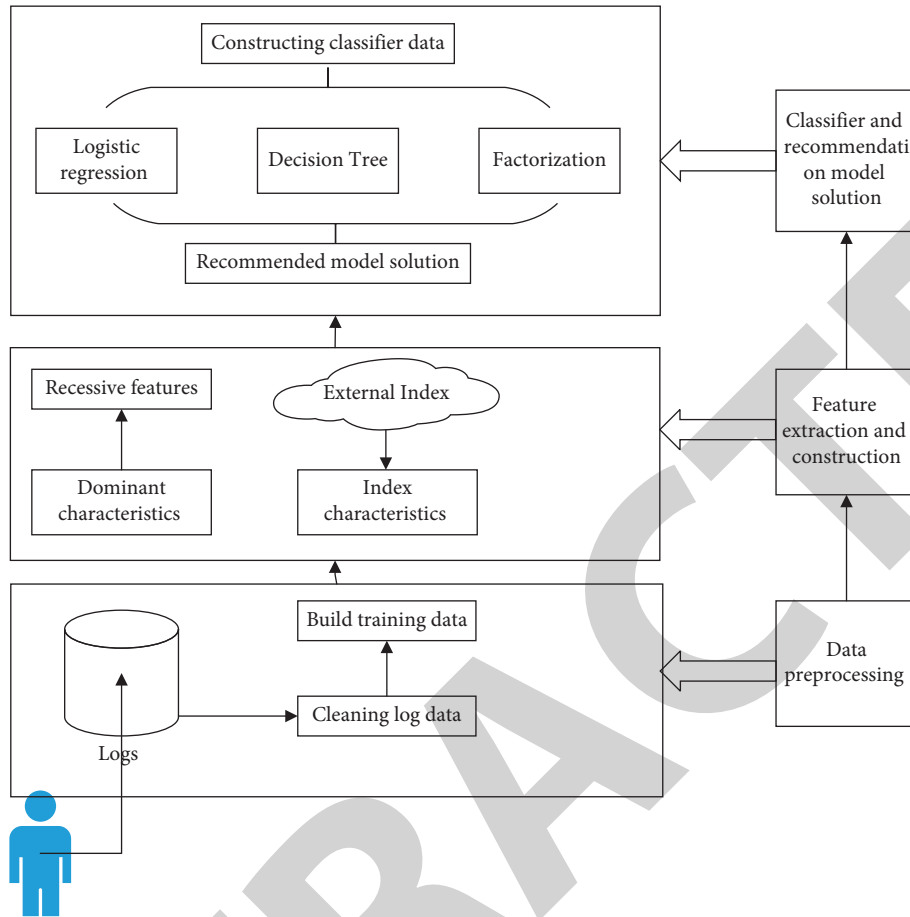


FIGURE 3: Short video recommendation flow chart.

- (2) In the aspect of feature analysis and extraction, the features of short videos are divided into dominant features and recessive features, the two features are statistically analyzed, and the important features are extracted. In the aspect of constructing features, this paper combines the external index features on the basis of the traditional topic features and gives the construction method of constructing the LDA topic feature model which combines the external features.
- (3) In terms of classifier construction and short video recommendation methods, in this paper, we abstract network short video recommendation into a binary classification problem. In the experiment, this paper mainly selects three different classification algorithms such as factor decomposition machine, gradient generation decision tree, and logical regression to realize short video recommendation and compares the performance of three different classification methods in short video recommendation.

defective data. If these garbage data are not handled well, it will affect the construction of feature model. The data preprocessing in this paper includes the following aspects:

- (1) The description text data of short video (positive title, subtitle, description, etc.) and the search words in the user's search log are fused
- (2) Propose useless data in the data set
- (3) word segmentation, de stop words, de symbols, part of speech tagging, etc. for the fused text data
- (4) Filter high-quality users for the user's playback behavior log

The extraction of short video features in this paper comes from the playing log of short video and the user's behavior log. The original basic features of short video can be extracted from the log. This paper defines these features as dominant features. Based on the original features, the features mined by statistical analysis are defined as invisible features in this paper. In addition, this paper also innovatively introduces the characteristics of external indexes, including Tencent Rulan index (TBI), Sina Micro Index, and Baidu Index, three authoritative index platforms of Internet big data. Short video feature categories are shown in Figure 4.

3.2. Network Short Video Data Processing and Feature Extraction Module. Data preprocessing is an important part of constructing training set. There will be a lot of noise data in large data, such as zombie users and repeated and

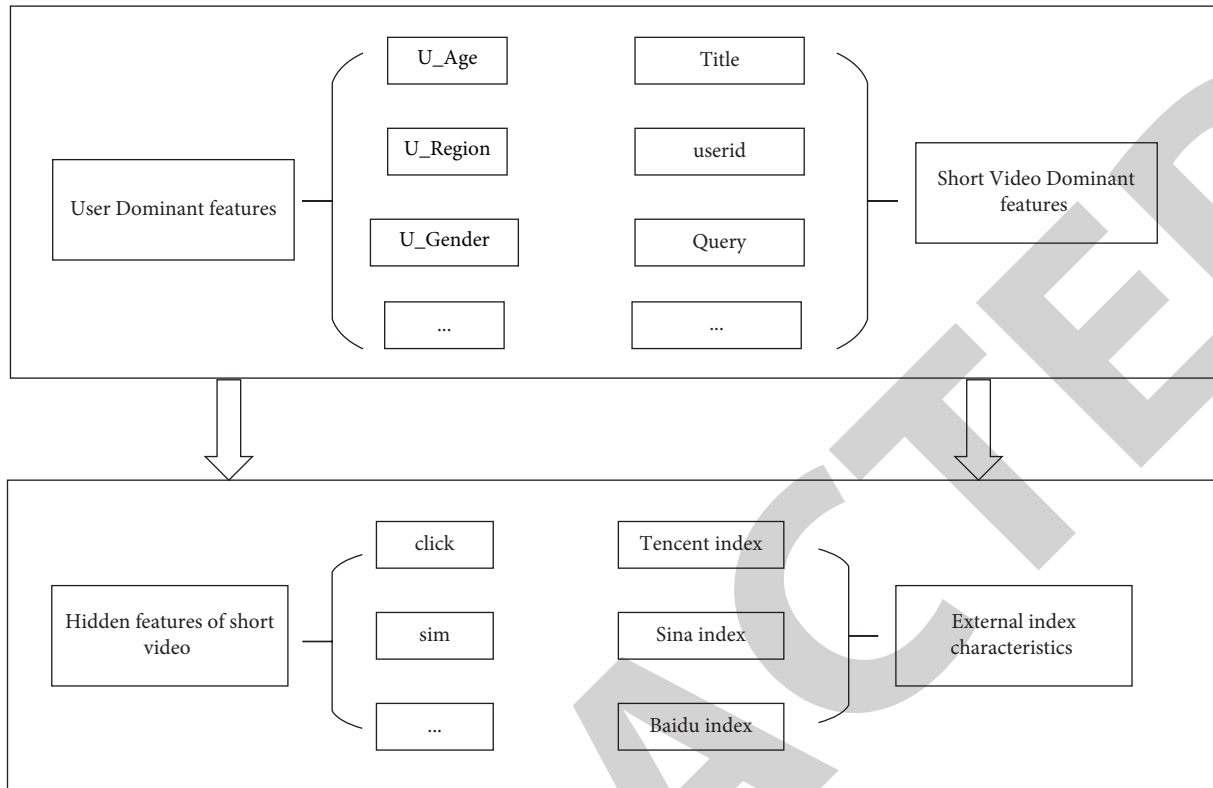


FIGURE 4: Short video features.

3.3. Short Video Recommendation Module. After obtaining the training set and extracting the corresponding features from the training set, this paper uses three different classification algorithms to establish the short video recommendation model, including factor decomposition machine, decision tree, and logistic regression. For the logistic regression algorithm, it belongs to the discriminant model. For the binary classification problem, it has a good effect. For the multicategory features extracted from short video, this paper can give faster results. However, the short video features extracted in this paper have the problem of too large feature space, which makes the performance of logistic regression poor. For the decision tree method, this paper uses the gradient iterative decision tree (GBDT) of boosting method. This paper uses this combination algorithm combined with short video features without detailed feature filtering. For the factorization machine, it can solve the sparsity of short video features. Therefore, these three classification algorithms are used as short video recommendation algorithms in this paper.

4. Experiment and Analysis

4.1. Experimental Corpus and Processing Methods. In terms of data selection, the experimental data used in this paper comes from Baidu video, a well-known aggregation video in China. The data includes the short video log data of Baidu video and the behavior log data of users using it. In terms of time dimension, this paper selects the log data from July to November 2016, a total of 1712460 users watching short

videos and 50 g short video playback logs. In order to ensure the accuracy of the model recommendation results, this paper does not sample the sample data, but selects all the sample data. In this paper, the short video logs in July, August, September, and October 2016 are used as training data, and the short video data in November are used as test data.

In terms of data preprocessing, this paper uses the data preprocessing method proposed in Section 2 to clean the data. The main cleaning work includes deduplication of users, cleaning of duplicate data, screening of high-quality short video users, text segmentation, and part of speech tagging of short video playback logs and user behavior logs, etc.

When constructing topic features, this paper constructs topic features based on the topic model of LDA. In this experiment, we set the number of topics of short video data to 10, 20, 50, and 100, respectively, and finally determine the appropriate number of topics of the data set. At the same time, we select the first 20 subject words in descending order of probability value for the subject words extracted from each subject to prepare for the later integration of external index features. A specific example is shown in Figure 5.

When constructing the theme model integrating the characteristics of external indexes, this paper selects Tencent browsing index (TBI), Baidu Index, and Sina Micro Index, three data sharing platforms with massive data and users on the Internet. They can provide the heat impact index of relevant events in the corresponding time period based on the given keywords and time period. Therefore, this paper

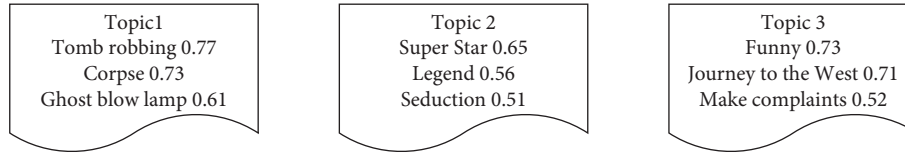


FIGURE 5: The topic of short video.

combines these external exponential features with short video topic model to construct feature model.

4.2. Evaluating Indicator. It is a very important work to evaluate the performance of the classifier. There are many indexes to evaluate the model algorithm, including accuracy (Accuracy), accuracy (Precision), recall (Recall) l , and F-measure (F-value). For two typical two-classification problems, it is very necessary to use AUC as the evaluation index of the classification model. In this paper, the receiver working characteristic curve (receiver operating characteristic, ROC) is used to describe the dynamic performance of the classifier, and ROC can be used to directly represent the performance of the classifier. For the binary classification problem, the classifier will produce a probabilistic prediction for the data, which ranges from 0 to 1. At this time, the classification performance can be seen intuitively by using the ROC curve. The longitudinal coordinate of the ROC curve is the true positive rate (TPR, true positive rate), and the Abscissa is the false positive rate (FPR, false positive rate). The ROC space is formed by TPR and FPR, and the curve is drawn. The larger the area under the curve, the higher the accuracy. Since there are many indicators to evaluate classifiers, why use ROC? This is because the ROC curve has a good characteristic: when the distribution of the positive and negative sample cloth in the test set changes, the ROC curve can remain the same. However, several kinds of uneven phenomena often occur in the actual data set; that is, the proportion of positive and negative samples is very uneven, the distribution of samples in different categories is also very uneven, and the use of ROC curve can solve this problem very well.

To understand the AUC evaluation indicators, you need to introduce the confusion matrix first. The following first gives the relevant knowledge of the confusion matrix: the confusion matrix is a visualization tool in the field of artificial intelligence, which is used to compare the classification results with the real information to get the result matrix. The rows in the result matrix represent the results of the classification, and the columns represent the actual information categories, as shown in Table 1. In the table, positive represents that the prediction instance is from a positive class, and negative represents that the prediction instance is from a negative class. True represents correct prediction and false represents wrong prediction. In the short video click prediction problem, the short video most likely to be clicked by the user is pushed to the user according to the predicted value of the click through rate. AUC is the area under the ROC curve, and its value is between 0.5 and 1.0. The larger its value, the more accurate the prediction of the click through rate of the short video.

TABLE 1: Confusion matrix.

Simplified representation of confusion matrix	Meaning
TP	True positive
TN	True negative
FP	False positive
FN	False negative

ROC index is most concerned with FPR index and TPR index in the confusion matrix. FPR represents the probability of accurate prediction of negative sample distribution, and TPR represents the probability of accurate prediction of positive sample distribution data, as shown in the following formula:

$$TPR = \frac{TP}{TP + FN}, FPR = \frac{FP}{FP + TN} \quad (9)$$

In addition to using ROC as the evaluation index, this paper also uses the accuracy, precision, recall, and F value commonly used to evaluate the performance of classifiers as the evaluation index.

4.3. Experiment and Result Analysis of Network Short Video Recommendation Method. In order to verify the effectiveness of the proposed method, we conducted the following groups of experiments:

- (1) The first group of experiments: we first verify the short video recommendation performance of the feature model constructed using the explicit and implicit features of short video under three different classification algorithms: factor decomposition machine, logistic regression algorithm, and decision tree. It can be seen from Table 2 that the classification results using factor decomposition machine are much better than logistic regression algorithm and decision tree. Next, this paper will use the factor decomposition machine to carry out the next experiment.
- (2) The second group of experiments: in this group of experiments, we mainly verify the impact of the number of topics on the click through rate of short video in the process of algorithm based on LDA-FM. In this experiment, short video text information is tested according to the number of topics to determine the impact of the number of topics. In the process of experiment, we carry out the experiment on different sizes of training sets for the purpose of comparative experiment. The size of the training set is set to 100%, 80%, 60%, and 40%, respectively.

TABLE 2: Comparison of recommended performance of different classifier.

Evaluating indicator	FM		Logistic		GDBT	
	Accuracy rate (%)	F value (%)	Accuracy rate (%)	F value (%)	Accuracy rate (%)	F value (%)
Dominant feature	71.05	73.79	68.33	70.28	70.31	71.34
Dominant + invisibility	74.56	75.83	70.29	72.21	70.79	72.43

TABLE 3: Example of selected topic words and their external index values.

Subject words	Time	Tencent browsing index (average)	Sina Micro Index (average)	Baidu Index (average)	Composite index
Tomb robbing	2016.7	5647	5966	2878	4830
Zombie	2016.7	6380	7621	13604	9201
Ghost blow lamp	2016.7	17700	13035	26247	18994

Subject words	Time	Tencent browsing index	Sina Micro Index	Baidu Index	Composite index
Tomb robbing	2016.12	5088	3089	1473	3216
Zombie	2016.12	4766	5612	8743	6373
Ghost blow lamp	2016.12	7723	9102	13310	10045

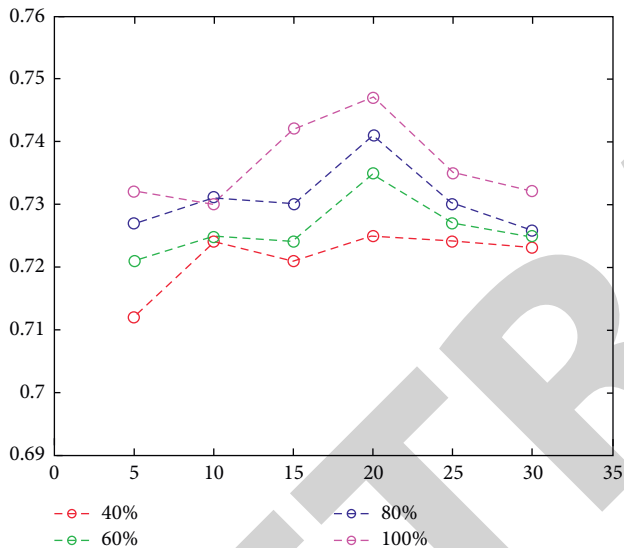


FIGURE 6: The influence of the number of different topics on the click through rate.

As can be seen from Figure 6, the clicks of short videos with different topics are completely different, and the value of AUC gradually increases with the increase of the number of topics. In increasing the number of topics from 10 to 20, the AUC improved significantly. When the number of subjects peaked at 20, the AUC value stabilized after 20. Therefore, the number of subjects selected for subsequent experiments is 20.

- (3) The third group of experiments: the third group of experiments is mainly used to construct the topic characteristics of the fusion external index. This paper generates 20 topics based on the LDA topic model and selects the top 20 words with the largest probability value from each topic. Then input 20 words and corresponding dates into Tencent browsing index, Baidu Index, and Sina Micro Index, respectively, and some results after weighted average of the three index values will be obtained, as shown

in Table 3. The index of zombie related words has a mean value in July and decreased significantly after November. It can be seen that the external index characteristics can reflect the change of theme heat.

5. Conclusion

This paper mainly focuses on short video recommendation methods and proposes a short video recommendation method based on topic model based on external exponential features. The main content of this paper includes the following parts.

- (1) The recommendation framework of network short video is designed. The recommendation framework gives the overall recommendation process from short video log preprocessing to feature analysis and extraction and then to the establishment of recommendation model.
- (2) The features of short video are analyzed, and the explicit and implicit features of short video are extracted. The feature construction method for short video recommendation is studied, and a short video topic feature construction method combining the features of short video itself with external exponential features is proposed.
- (3) The short video recommendation method based on binary classification is studied. In this paper, short video recommendation is abstracted as a binary classification problem, and three different classification algorithms are used to realize short video recommendation: factor decomposition machine, gradient iterative decision tree, and logical regression. Firstly, this paper describes the short video recommendation methods of three different classification algorithms in detail and then verifies the performance of different classification algorithms in short video recommendation through experiments. The experimental data in this paper are from the log data of Baidu video, a well-known aggregate video in China. On this basis, experiments and comparative

analysis are carried out. Firstly, the recommended performance of the three classification algorithms used in this paper is verified. The experimental results show that the performance of the factor decomposition machine is the best. Secondly, experiments verify that the explicit, implicit, and exponential features of short video proposed in this paper are effective features. Moreover, the short video theme feature integrated with exponential feature has the greatest effect. Finally, this paper also gives an experiment of selecting the number of topics when constructing topic features using LDA.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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