Research on Internet Financial Personalized Services Based on Big Data Analysis

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Abstract: With the advent of the era of big data, the massive accumulation of data and the continuous improvement of data processing capabilities have promoted the development of the Internet finance industry. Internet finance is not a simple combination of the Internet and the financial industry. It is a new model and new business generated by the users after they are familiar with the network technology level, such as security and mobile. This paper analyzes the application of big data in Internet finance precision and personalized service, and takes customer behavior analysis as an example to establish a customer accurate recommendation model based on convolutional neural network. Experiments show that customer behavior is analyzed through big data to achieve personalization. And precise customer service helps companies to better understand and deeply understand customer needs and make pre-judgments in innovative business models, thereby improving business operations and improving operational efficiency.

1. Introduction

With the development of society and computer Internet, the data has been well preserved. With the accumulation of data, we have also entered the era of big data. Big data can be summarized as large data volume, fast speed, multiple types, and low value density. Big data is not simply a fact of big data. Big data contains potentially valuable information that we don't know. The value of the data is not the size of it, but how much valuable information we can mine based on the data. For big data, the most important thing is to analyze it and get a lot of intelligent, in-depth and valuable information through analysis. Big data analysis methods are particularly important in the field of big data, and can be said to be the decisive factor in determining whether the final information is valuable. Big data analysis refers to the analysis of large-scale data and the extraction of potentially valuable information from large amounts of data. Commonly used big data analysis techniques include data acquisition, data access, infrastructure, data processing, statistical analysis, data mining, model prediction, and result presentation.

Internet finance is a concept developed on the basis of the Internet and big data. With the advent of the era of big data, the accumulation of data and the continuous improvement of data processing capabilities have promoted the development of the Internet finance industry. Internet finance is not a simple combination of the Internet and the financial industry. It is a new model and new business generated by the users after they are familiar with the network technology level, such as security and mobile. At present, the main Internet finance models are: traditional finance provides services for everyone through Internet channels; p2p model is peer-to-peer; through interactive marketing, full use of Internet means to closely integrate traditional marketing channels with online marketing channels; The financial industry has realized the transformation from “product-centricism” to “customer-centrism”; adjusted the relationship between the financial industry and other financial institutions, and jointly established an open and shared Internet financial platform.

2. Big Data Personalized Service Application

For the large amount of data accumulated in the financial industry, big data analysis can just use its unique data analysis functions to mine valuable information, develop new models of the financial industry and new businesses to meet the new needs of customers. Personalized and precise services are mainly customer-centric, through comprehensive customer service and in-depth customer analysis to meet the different needs of different customers. With the development of the market economy, the competition in the financial market is becoming more and fiercer, the needs of consumers are becoming more diversified and tend to be personalized. Enterprises must change the traditional single sales model and use computer technology and information technology to Demand-oriented, priced separately according to different consumer demand and price elasticity. To meet the needs of different groups of people. This research combines big data analysis with Internet finance, and uses big data analytics technology and business processes to link and guide customer-centric personalized and accurate services to enhance customer value.

2.1 Customer segmentation

Since different types of customer needs are different, and if different customers are satisfied with the same company, they are required to provide targeted products and services that meet the needs of customers, and to meet this diverse heterogeneity. Demand requires customer segmentation based on different criteria for the customer base.

Customer segmentation is to segment customers into groups with different needs and trading habits according to their gender, income, transaction behavior characteristics, etc. Customers in the same group have similarities in product demand and trading psychology, but different There are large differences between groups. Customer segmentation enables companies to develop the right marketing strategy in marketing, and to provide customers with differentiated products and services to improve customer satisfaction with the company and products in order to obtain greater profits.

Customer segmentation can be done by classification or by clustering. For example, customers can be divided into high-value and low-value customers, and then determine the factors that have an impact on the classification, and then extract the customer data with relevant attributes, select the appropriate algorithm to process the data to obtain classification rules. Using the clustering method, it is not known before those customers can be divided into several categories. After clustering the data, the result data is analyzed to summarize the similarities and commonalities.

Each category of customers has similar attributes, and different categories of customers have different attributes, thereby determining the interests, consumption habits, consumption propensities and consumer demands of specific consumer groups or individuals, and inferring the corresponding consumer groups or individuals in the next step. Consuming behavior. Segmentation allows users to view the data in the entire database from a higher level, and enables companies to adopt different marketing strategies for different customer groups and effectively utilize limited resources. Reasonable customer segmentation is the foundation for implementing customer relationship management.

2.2 Cross-selling

Cross-selling refers to the marketing process in which a company sells new products or services to its original customers. It is not only an effective means to increase profits by expanding sales to existing customers, but also to enhance corporate image, cultivate customer loyalty, and protect enterprises.

The business relationship between the company and its customers is a continuous, evolving relationship. After the customer establishes this two-way business relationship with the company, there are many ways to optimize this relationship and extend the relationship. During the maintenance of this relationship, increase mutual contact and strive to obtain more profits in each contact. Cross-selling is the tool that provides new products and services to existing customers.

In cross-selling activities, big data analytics can help companies analyze the optimal sales match. The customer information held by the company, especially the information about the previous purchase behavior, may contain the key or even the determining factor for the customer to decide his next purchase behavior. Through correlation analysis, big data analysis can help analyze the best and most reasonable sales match. The general process is like this, first analyze the purchasing behavior and consumption habit data of existing customers, and then use some algorithms of big data analysis to model individual behaviors under different sales methods; secondly, use the established forecasting model to predict future consumption of customers. The behavior is predictively analyzed, and each sales method is evaluated. Finally, the established analysis model is used to analyze the new customer data to determine which cross-selling method is most suitable for the customer. There are several big data analysis methods that can be applied to cross-selling. Correlation rule analysis can find out which customers are inclined to purchase related products; cluster analysis can find users who are interested in specific products; neural network, regression and other methods can predict the possibility of customers purchasing this new product.

The results of the correlation analysis can be used in two aspects of cross-selling: on the one hand, for the combination of goods with a high frequency of purchase, find out those customers who have purchased most of the products in the portfolio, and sell them the “missing” goods; The aspect is to find out the relevant laws that are applicable to each customer and sell them the corresponding product series.

3. Customer Behavior Case Study

Through big data analysis of customer behavior, personalization and precise customer service will help companies to better understand and deeply understand customer needs and make pre-judgments in innovative business models, thereby improving business levels and improving operational efficiency. When analyzing customer behavior, we must first collect customer behavior information, analyze customer's individual behavior, establish appropriate mathematical models, set appropriate parameters, and accurately analyze customer behavior. This paper uses the improved hybrid recommendation model of convolutional neural networks to accurately recommend movies to customers.

3.1 Recommended model

The first layer of the text convolutional network is the word embedding layer, which is an embedding matrix composed of the embedding vectors of each word. The next layer is a convolutional layer that is convolved on the embedded matrix by using multiple convolution kernels of different sizes (window size), which refers to each convolution covering several words. The pooling layer extracts the main features from the convolutional layer to construct fixed-length feature vectors. Finally, through the output layer, the feature vector is mapped into a specific dimensional space.

(1) Embedded layer

This layer transforms the preprocessed movie name text into a dense matrix representing the next convolutional layer movie name. Specifically, as for l is the sequence text of a word, represented by a vector that connects the words in the text.The word vector is pre-trained through the word bag model.w_i Represents the word vector, then the text matrix d$\mathbf{E}$$\mathbf{R}^{p\times l}$ can be expressed as:

$$D = [\cdots \quad w_{i-1} \quad w_i \quad w_{i+1} \quad \ldots]$$

Among them$l$ indicates the length of the movie name text, p is the word vectorw_i is the size of the embedded dimension.

(2) Convolutional layer

The convolution layer is used to extract context features. By using multiple convolution kernels of different sizes (window size) to convolve on the embedded matrix, this article useswsIndicates the size of the convolution window.

Defining context feature vectorsc^j : a vector used to extract the context information of the movie name, indicating the first in the movie name.j Is the contextual characteristics of the word. After convolution operation, obtained in the convolution layer$l - ws + 1$Context feature vector c_i^j, i represents the context feature vector sequence number and each context feature vectorc^j share a weightW_c .

Specifically, the context feature vectorc_i^jE**R** by the first$j$shared weightW_c^jE$\mathbf{R}^{p \times ws}$, where p is the word vector in the embedded layer w_i context feature vectorc_i^jcan be expressed as:

$$c_i^j = f(W_c^j * D_{(:,i:(i+ws-1))} + b_c^j)$$

Where * represents a convolution operator,b_c^jshared weight W_c^jdeviation,$f$representing the nonlinear activation function here, this paper uses the ReLU nonlinear activation function to effectively avoid the problem of gradient disappearance. In summary, the context feature vector of the movie name c^j E$\mathbf{R}^{l-ws+1}$That is, it can be expressed by the following formula:

$$c^j = [c_1^j, c_2^j, \dots, c_i^j, \dots, c_{l-ws+1}^j]$$

(3) Pooling layer

The pooling layer extracts the characterized features from the convolutional layer and processes the variable length of the text by a pooling operation that constructs a fixed length feature vector.

Movie name context feature vector generated by convolutional layer processingc_i^jE**R** have different lengths and it is difficult to construct the next layer, so the text representation needs to be reduced to a fixed length vector. In this paper, the max-pooling method is used to reduce the representation of text to only the maximum context feature from each context feature vector.n_c Is the fixed length vector is obtained, so that the corresponding pooled vector is obtained. This article uses d_f represents a pooled layer output, where f that is, the dimension of the text vector output from the pooling layer, there are:

$$d_f = [max(c^1), \dots, max(c^j), \dots, max(c^{n_c})]$$

Among them c^j is from the first$j$Shared weight W_c^j is the length of the extraction is$l - ws + 1$context feature vector.

(4) Output layer

The output layer maps feature vectors into a specific dimension space.

This article is used twice $Tanh$ the transformation maps the pooled layer output to a specific dimensional space, specifically, the pooled layer output on the k-dimensional space of the movie hidden model d_f , get the movie name text feature vector s_i:

$$s_i = Tanh(W_{f2}\{Tanh(W_{f1}d_f + b_{f1})\} + b_{f2})$$

Among them: W_{f1} E $\mathbf{R}^{f \times nc}$, W_{f2}E$\mathbf{R}^{k \times f}$ represents a spatial projection matrix, b_{f1}E$\mathbf{R}^f$, b_{f2}E$\mathbf{R}^k$separatelyW_{f1},W_{f2}offset vector,$f1, f2$are different spatial dimensions, ands_iER^k.

Through the above process, the text convolutional network of this article will return the feature vector of each movie name as output:

$$s_i = \mathrm{cnn}(\mathrm{W}, X_i)$$

Where w represents the weight of ownership and offset variables in the convolutional network, $X_i$indicates the name of the movie i,$s_i$represents the movie name text feature vector.

3.2 Experimental setup

This article uses the Movie Lens public dataset. The mean absolute error (MSE) and the root mean square error (RMSE) were used as the evaluation criteria for measuring the performance of the model.

MSE: For a given test data set, the user's rating set for the project R = {r_1, r_2,..., r_k}, the set of predicted scores calculated by the recommendation algorithm P = { p_1, p_2, ... p_k}, then:

$$MSE = \frac{1}{k}\sum_{i=1}^{k}(r_i - p_i)^2$$

In the model training, the RMSE of the true score and the predicted score is minimized. RMSE calculates the deviation between the predicted value and the true value, and squares the difference, and finally calculates the square root of the ratio of the magnitude n of the predicted data. The mathematical formula is as follows:

$$RMSE = \sqrt{\frac{\sum_{i,j}^{m,n}(r_{ij} - r'_{ij})^2}{N}}$$

Among them n indicates the number of users,m represents the number of movies, n is the number of ratings in the test set.r_{ij}Represents the true score of user i on movie j,r'_{ij}represents the predicted score of user i for movie j.

In the data processing, the UserID, Occupation, and MovieID fields remain unchanged; the Gender field needs to convert 'F' and 'M' to 0 and 1; the Age field is converted to 7 consecutive numbers 0~6; the Genres field is a classification field. This article treats it as a number. First, the category in Genres is converted into a string-to-number dictionary. Since some movies are a combination of multiple Genres, the Genres field of each movie is converted into a number list, and the number list is equal in length; the Title field is processed in the same way as Genres. Like a field, first create a text-to-number dictionary and then convert the description in the Title into a list of numbers. It should be noted that the Genres and Title fields need to be uniform in length, which is convenient for processing in the neural network; the processing of the blank portion is filled with the number corresponding to '<PAD>'.

3.3 Experimental results

In this paper, the probability matrix decomposition model PMF is selected for comparison. The following figure compares the benchmark model PMF with the RMSE loss of the model. Taking the MovieLens-1M dataset as an example, in terms of iteration speed, the PMF achieves convergence at 100 steps of iteration, and the model can be converge in 50 steps. In terms of accuracy, PMF eventually reached 0.98, and this model can reach 0.85, which is significantly improved compared with the benchmark model. It can be seen that the model can effectively improve the performance of the model by adding user and movie auxiliary information.

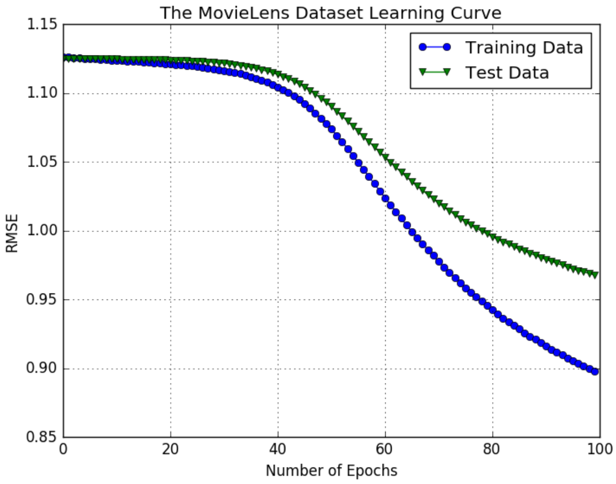

Figure 1. PMF loss graph

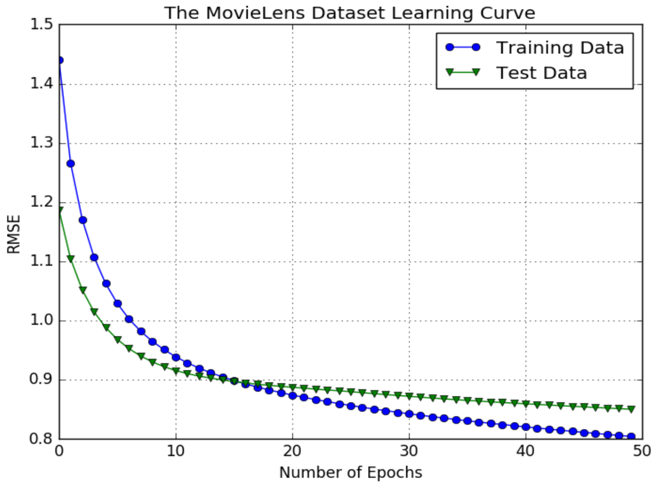

Figure 2. The Model loss graph

4. Conclusion

In the analysis of customer behavior, we must first collect customer behavior information, analyze the individual behavior of the customer, establish appropriate mathematical models, set appropriate parameters, and accurately analyze the customer's behavior. This paper uses the improved hybrid recommendation model of convolutional neural networks to accurately recommend movies to customers. In view of the data sparsity and cold start problem of the recommendation system, this paper introduces additional information and uses the convolutional neural network to extract relevant features, and integrates deep learning into the recommendation model. This research helps companies to better understand and deeply understand customer needs and make pre-judgments in innovative business models.

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