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Key Technologies of Talent Portrait Based on Big Data Analysis

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Abstract. This paper studies a talent comprehensive quality platform based on big data analysis, including: unified data collection layer, which gathers talent data from various data sources to HDFS storage in an adaptive way; At the basic data platform layer, the talent data from the unified data collection layer is analyzed with big data to form a talent comprehensive quality evaluation report, which provides publishing and query; The application display layer displays the talent comprehensive quality evaluation report published or queried by the basic data platform layer. This paper realizes the comprehensive quality evaluation and management of talents, with high accuracy, convenience and security. In addition, this paper proposes a multimodal information fusion method, including image, text, and audio data, to comprehensively describe and predict the characteristics of talents. The experimental results show that the user portrait modeling method based on multi-modal information in this paper has achieved better performance in the talent feature prediction task.

Keywords. Big data, data collection, multimodal information, user portrait modeling

1. Introduction

Usually, the talent evaluation is based on paper evaluation papers or online evaluation questions, and the evaluators are usually colleagues or superiors.[1] Due to the artificial evaluation, it is inevitable that subjective bias will be mixed, which will lead to distorted results, and it is difficult to be fair.[2] At the same time, the evaluation data that colleagues or superiors can use are generally experience or some personnel files in irregular record and storage status.[3] The searchability of evaluation data is low, and there is no systematic classification of talent data.[4-6] It is difficult for evaluators to comprehensively understand the evaluated person.[7] At the same time, the efficiency of

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paper evaluation papers or online evaluation papers is too low, which will consume too much time for both parties.[8] Therefore, it is particularly important to form an objective and accurate talent comprehensive quality evaluation report through big data analysis.[9] In this process, there are many data sources, and data mining is required to form the comprehensive quality evaluation data of talents. Therefore, it is necessary to build a basic data center, a unified data storage and release system, and a unified data modeling to lay the foundation for the presentation of data value. The purpose of this paper is to provide a talent comprehensive quality platform based on big data analysis to realize the evaluation and management of talent comprehensive quality, with high accuracy, convenience and security.

In addition, with the increasing importance of human resources, various enterprises and organizations are facing challenges in recruiting, selecting and managing talents. Traditional resume and interview methods can no longer meet the needs of comprehensive evaluation and precise matching of talents. Therefore, constructing accurate talent user portraits has become an important research and application task. Talent user portrait modeling can help companies better locate and attract suitable talents and improve the hit rate of recruitment. At the same time, by analyzing the characteristics and interests of talents, it can provide enterprises with personalized training and development plans to improve employees' job satisfaction and performance. In addition, talent user portrait modeling can also provide a reference for the balance of the talent market and help talents rationally plan career development and resource allocation. Our goal is to use deep learning techniques to comprehensively utilize multimodal information, such as image, text, and audio data, to construct accurate user portraits of talents. By fusing information from different modalities, our approach can more fully describe talent characteristics and needs, and provide more accurate talent assessment and matching.

2. Talent Portrait System Based on Big Data Analysis

With reference to Figure 1, Figure 2, Figure 3 and Figure 4, the talent comprehensive quality platform based on big data analysis in this paper includes the unified data collection layer, basic data platform layer and application display layer.

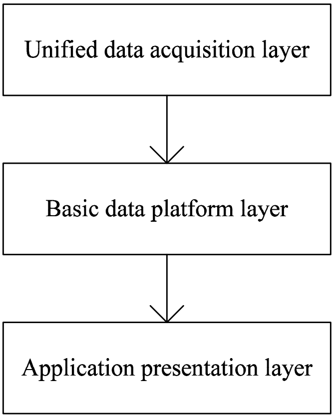

Fig. 1. Structure of talent comprehensive quality platform based on big data analysis

The unified data collection layer aggregates talent data from various data sources to HDFS storage in an adaptive way.[10] The adaptation methods include SQL acquisition adaptation, file acquisition adaptation and HDFS acquisition adaptation. The unified data collection layer uses Kafka as the message management layer of the unified collection platform, flexibly connects and adapts to various data source collection (integrated Flume), provides flexible and configurable data collection capabilities, and uses HAProxy+Keepalived+Flume NG to achieve high-performance and highly available distributed data collection.

Data sources include: school basic information, class information, student basic information, curriculum information, student performance information, student health information, student activity information, student activity practice records, student rewards and punishments records, student research project records, student self-evaluation records, teacher evaluation records, student training records, and student reading records.[11]

The unified data collection layer sends talent data to Flume NG cluster through file interface, and Flume NG cluster collects the received data to the basic data platform layer in real time through HDFS through memory data transmission.

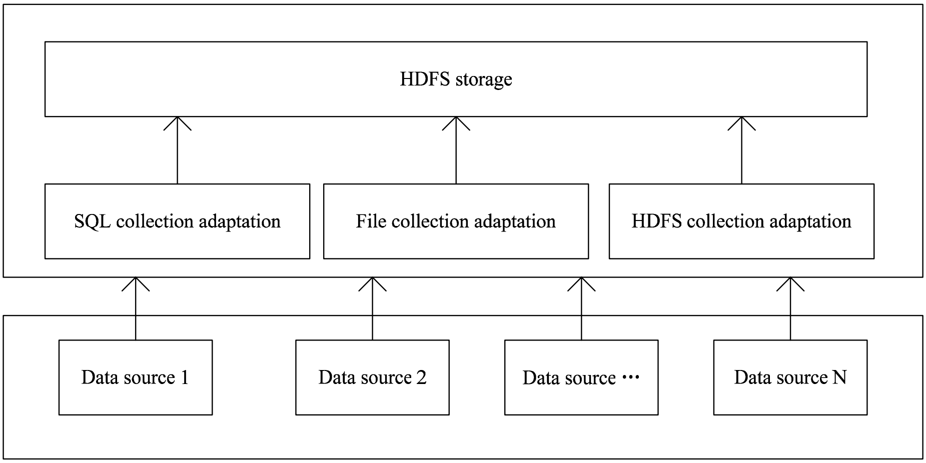

Fig. 2. Structure of unified data acquisition layer

The basic data platform layer conducts big data analysis on talent data from the unified data collection layer, forms a talent comprehensive quality evaluation report, and provides publishing and query.[12] Specifically, the basic data platform layer includes the comprehensive quality evaluation big data release and query module and the data mining module.

The data mining module uses HIVE as the data cleaning engine, provides Petabyte level data preprocessing, processing, integration services, and forms a wide feature table. For data based on the wide feature table, SparkR is used to call clustering, classification and other algorithms for data mining model development, model evaluation, and model application.[13] SparkR provides an API (Application Programming Interface) for elastic distributed data sets in Spark. Users can run tasks interactively on the cluster through the command line. The data mining model builds a big data analysis engine in the cluster mode of SparkOnYarn. Big data analysis of talent data through data mining model.

The big data publishing and query module of comprehensive quality evaluation first stores the statistical information of the talent comprehensive quality evaluation documentary report and the original detailed result set in HBASE, and creates a new HBASE table in HBASE to store the result set.[14-18] After the generated files are warehoused, they can be queried by opening the HBASE API. Using HBASE technology can provide efficient publishing and query of massive data. The massive detailed data after sorting and classifying the original details are statistically analyzed and stored in RDBMS, providing highly summarized statistical data of talents' comprehensive quality and talent comprehensive quality evaluation report to meet the needs of conventional statistical reports and reduce the threshold for using the platform.

The talent comprehensive quality evaluation report includes statistical information and detailed information. The on-the-spot report of talent comprehensive quality evaluation consists of two parts: student report and school report. Student reports are recorded and presented from the perspective of individual students, including self-evaluation (comprehensive evaluation, ideological and moral education, etc.) that students actively fill in, student course scores (including the final examination, unified examination, expansion course, research course, awards, etc. of basic courses), special records of various research topics, records of practical activities (which can be related to the application records of electronic student cards), etc. The school report records and presents the school's teaching activities from the perspective of student class, including the basic information of the school, the class opening situation (basic courses, expansion courses, research courses, etc.), the teacher allocation (head teachers, teachers), the school's practice activities, and the activities highlighting the list of students; The similar contents in the student report and the school report can correspond to each other and support each other.

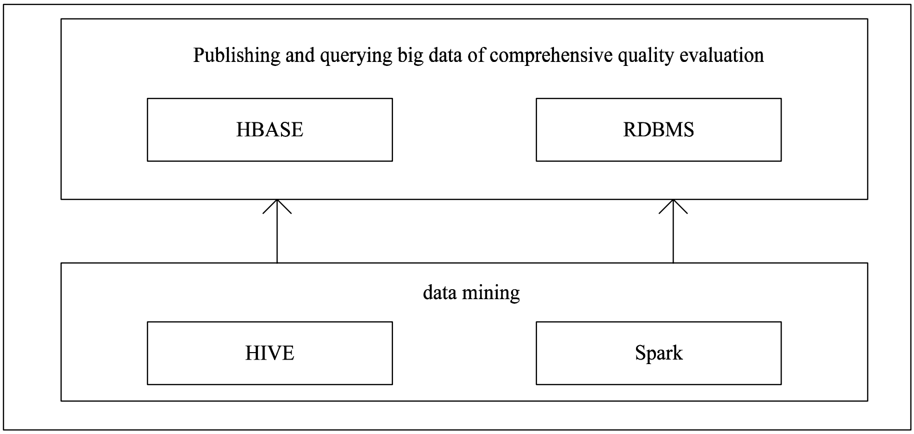

Fig. 3. Structure of basic data platform layer

The application display layer displays the talent comprehensive quality evaluation report published or queried through the basic data platform layer. It is divided into comprehensive quality statistics information and comprehensive quality details information, which respectively display the statistical data and detailed data of the talent comprehensive quality evaluation documentary report.

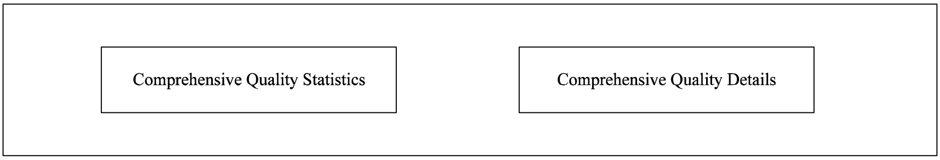

Fig. 4. Structure of application display layer

3. Portrait Modeling Based on Multimodal Information

In this section, we clarify the task and goals of persona modeling for multimodal information, and define the types of multimodal data used and the representation of output personas.

The user portrait modeling task of multimodal information is to construct a comprehensive feature representation of users by comprehensively utilizing data from different modalities (such as images, text, audio, etc.). Our goal is to transform multi-modal data into user portraits, which contain the characteristics and preferences of users in different modalities, so as to perform tasks such as personalized recommendation and behavior prediction.

The multimodal data types we use can include but are not limited to the following:

- Image data: such as user avatars, photos, etc.
- Text data: such as user's personal description, social media text, comments, etc.
- Audio data: such as the user's voice recordings, music preferences, etc.

The representation of the output user portrait can be determined according to specific needs, such as a vector representation, multi-dimensional feature representation, etc., to express the user's multi-modal characteristics and preferences.

For data of different modalities, we use corresponding methods for feature extraction. For image data, we can use a Convolutional Neural Network (CNN) as a feature extractor. By stacking convolutional, pooling and fully connected layers in the network, we can extract important visual features from images. A commonly used CNN model is VGGNet, and its feature extraction formula is as follows:

$$\boldsymbol{F}_{cnn} = VGGNet(I_{img}) \tag{1}$$

where I_{img} is the input image data, and F_{cnn} is the extracted image features.

For text data, we can use word embedding (Word Embedding) technology to convert the text into a vector representation. Commonly used word embedding models include Word2Vec, GloVe, Bi-LSTM, etc. By mapping each word in the text to a vector, we can capture the semantic relationship between words. The formula for text feature extraction can be expressed as:

$$\begin{aligned} \overrightarrow{\mathbf{H}}_t &= \phi(\mathbf{X}_t \mathbf{W}_{xh}^{(f)} + \overrightarrow{\mathbf{H}}_{t-1} \mathbf{W}_{hh}^{(f)} + \mathbf{b}_h^{(f)}) \\ \overleftarrow{\mathbf{H}}_t &= \phi(\mathbf{X}_t \mathbf{W}_{xh}^{(b)} + \overleftarrow{\mathbf{H}}_{t+1} \mathbf{W}_{hh}^{(b)} + \mathbf{b}_h^{(b)}) \end{aligned} \tag{2}$$

$$\mathbf{F}_{text} = \mathbf{H}_t \mathbf{W}_{hq} + \mathbf{b}_q \tag{3}$$

where $\mathbf{X}_t$ is the input text data and $\mathbf{F}_{text}$ is the extracted text features.

For audio data, we can use sound signal processing technology to extract the spectral features or acoustic features of the audio. For example, the Short-time Fourier Transform can be used to obtain the spectral information of the audio, or the Mel-frequency Cepstral Coefficients (Mel-frequency Cepstral Coefficients) can be used to extract the acoustic features. The formula for audio feature extraction can be expressed as:

$$\boldsymbol{F}_{audio} = STFT(A_{audio}) \tag{4}$$

where A_{audio} is the input image data, and $\boldsymbol{F}_{audio}$ is the extracted image features.

After obtaining the feature representations of different modal data, we need to fuse them to obtain a comprehensive user portrait representation. A common approach to multimodal data fusion is to use neural networks for fusion. We can design a fusion network, take the features of different modalities as input, and learn the fused comprehensive feature representation through the neural network. Fusion networks can be modeled using fully connected networks or recurrent neural networks (RNN). The fusion formula can be expressed as:

$$\boldsymbol{F}_{fusion} = FusionNet(\lambda_1 \boldsymbol{F}_{cnn}, \lambda_2 \boldsymbol{F}_{text}, (1 - \lambda_1 - \lambda_2) \boldsymbol{F}_{audio}) \tag{5}$$

We need to define a loss function suitable for the multimodal persona modeling task. This loss function can include multiple parts, which measure the prediction accuracy of the model on different modalities. For example, for the age prediction task in user portraits, Mean Squared Error (Mean Squared Error) can be used as the loss function. The formula of the loss function can be expressed as:

$$L = \sum_{i=1}^{N} (Y_{\text{age}}^{(i)} - \hat{Y}_{\text{age}}^{(i)})^2 \tag{6}$$

where $Y_{\text{age}}^{(i)}$ is the true age label and $\hat{Y}_{\text{age}}^{(i)}$ is the age label predicted by the model. Through the above methods, we can comprehensively utilize multi-modal information for user portrait modeling, so as to obtain a more comprehensive and accurate representation of user characteristics. Such a modeling method can be applied to fields such as personalized recommendation and precision marketing to provide users with better-personalized experience and services.

4. Experiments

We first collect multimodal data related to user portraits, such as avatars, personal descriptions, user recordings, etc. Then data cleaning, missing value filling and data normalization preprocessing are performed on the data. In addition, we collected the user's age as the label, and the age distribution is shown in Figure 5.

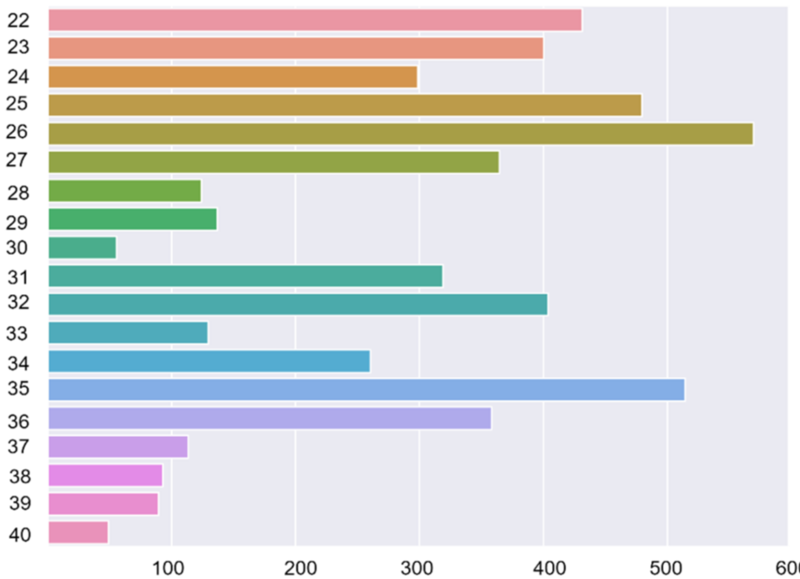

Figure 5. Data distribution.

Table 1 displays the user portrait prediction results based on multi-modal information fusion, demonstrating the usefulness of our proposed model in user portrait modeling and achieving good prediction outcomes. Furthermore, the hidden layer dimension in the Bi-LSTM model used for text features is a key hyperparameter that affects the model's prediction ability and training efficiency. In general, the bigger the dimensionality of the hidden layer, the greater the expressiveness of the model, but this also increases training time and computational resource consumption. As a result, the dimensions of the hidden layers must be evaluated and optimized. As indicated in Table 1, we believe it is fair to set the hidden layer dimension to 256 in order to ensure prediction accuracy and efficiency.

Table 1. Performance results

Hidden Size	AUC	MAE	RMSE
16	0.8085	0.3812	0.3048
32	0.8202	0.3442	0.2855
64	0.8354	0.3377	0.2564
128	0.8461	0.3101	0.2442
256	0.8475	0.3146	0.2453
512	0.8480	0.3112	0.2461

We conduct an analysis of the hyperparameter λ for multimodal information fusion. In the experiment we set both λ_1 and λ_2 to be 0.3. In order to observe the influence of λ on the experimental results, we conducted two sets of experiments. First, let λ_2=0.3, and then adjust the size of λ_1, the result is shown in Figure 6; let λ_1 =0.3, adjust the size of λ_2, and the result is shown in Figure 7. From these two sets of experiments, we can observe that image information and text information are very important for age prediction of user portraits, because as λ increases, the performance of prediction improves again. It can be seen that it is necessary to fuse multimodal information to help model user portraits.

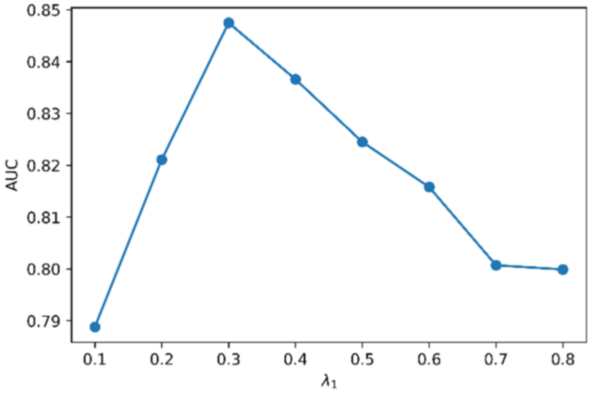

Figure 6. The influence of λ_1 on the experimental results.

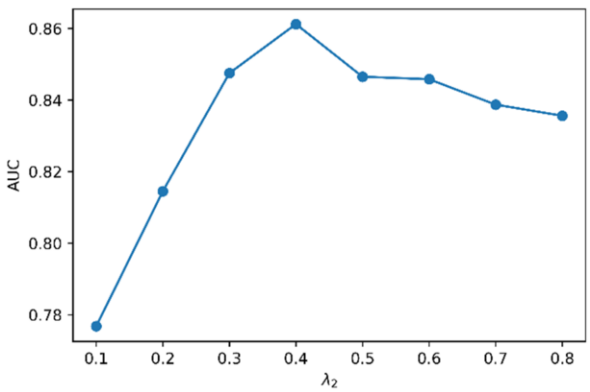

Figure 7. The influence of λ_2 on the experimental results.

5. Conclusion

The positive effects of the talent evaluation system based on big data algorithm are: This paper adopts database, evaluation algorithm module and evaluation output module; By connecting the database with each major data platform, and after filtering, classifying and evaluating the data, the visual chart is output through the evaluation output module. The evaluation is carried out by the machine in the whole process, and the evaluation results are more fair and authentic. Through the research of this paper, we successfully explored the method of user portrait modeling based on multi-modal information. Using a combination of image, text, and audio data, we built a deep learning model for predicting a user's age. Our experimental results show that the fusion of multimodal data can significantly improve the performance and accuracy of user profile modeling.

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