Design and Implementation of an Intelligent Data Analysis Platform Combining Large Models and Cloud Computing

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Abstract: The design and implementation of an intelligent data analysis platform combining large models and cloud computing will effectively solve the problem of large-scale heterogeneous data processing. In this paper, the platform is designed and implemented, which will improve the efficiency of data processing based on the distributed architecture of cloud computing, and improve the accuracy of data analysis by combining large models. In the process of research, this paper gradually builds a complete platform from data collection and processing, storage, analysis and prediction. The final experimental data shows that the platform has low latency when processing massive data, and at the same time, the prediction accuracy is 96%, which has high reliability and scalability. Research has shown that the platform not only addresses the challenges of today's data growth and complexity, but also provides extremely powerful technical support for tomorrow's intelligent data analysis.

1 INTRODUCTION

Because of the rapid development of big data, how to effectively process and analyze massive heterogeneous data has become a hot research topic. Some researchers have proposed that these problems can be solved based on enhanced computing power and traditional data processing tools, but due to the large amount of data, traditional methods cannot adapt to complex application scenarios. Some researchers have also proposed that data can be decomposed based on distributed intelligent data for parallel computing, but this method is not efficient enough to deal with real-time data and cannot effectively handle the problem of sudden data surge. This paper uses the combination of intelligent algorithms and cloud computing to solve these problems based on the scalability of cloud computing and the deep learning ability of large models. This method can achieve efficient data processing and accurate analysis, and can adapt to complex data scenarios to provide truly effective and intelligent support for urban management and business analysis.

2 RELATED WORKS

2.1 Large Model Theory

Large models are a new technology that has emerged in the field of data analysis and artificial intelligence in recent years, which is mainly reflected in its excellent performance in processing large-scale data and complex pattern recognition (Ata, Gökce, et al. 2024). Based on a large number of parameters and hierarchical structures, large models can capture deep features in the data, so as to play a significant role in tasks such as image recognition and natural language processing. The training of large models generally requires a large dataset and powerful computing resources (Fei, Jiang, et al. 2024), which is also an advantage that cloud computing can perform. In the intelligent data analysis platform, large models can improve the accuracy of data processing, and based on deep learning algorithms, potential correlations in data can be mined to achieve more complex analysis tasks (Feng and Ji, 2024). For example, in traffic forecasting, large models can accurately predict traffic flow changes based on the combination of historical data and real-time data, and provide decision support for traffic management.

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2.2 Cloud Computing Theory

Cloud computing is a key component of modern information technology, which emphasizes the virtualization of computing and storage resources based on the network and the provision of services to users (Gao, Qiu, et al. 2024). Cloud computing features high scalability, flexibility, and high availability, making it a good choice for large-scale data analysis. In an intelligent data analysis platform, cloud computing will provide powerful computing power, distributed computing, and large-scale data storage (Guo, Mu, et al. 2024). Based on cloud computing, intelligent data can dynamically allocate resources to effectively respond to changes in data volume and fluctuations in computing tasks. In addition, it supports parallel computing and multi-node collaboration, which is very conducive to the training and inference of large models (Li, Wu, 2024). For example, in a real-time data analysis of intelligent data, cloud computing can quickly process real-time streaming data from multiple large models, and conduct real-time analysis and response, thereby improving the response speed and processing efficiency of intelligent data.

3 METHODS

3.1 Description of the Intelligent Data Analysis Process

The intelligent data analysis platform has as many as 6 main modules, each of which is responsible for a specific task, so that the data can be processed and analyzed efficiently. The data acquisition module is responsible for obtaining raw data from a variety of sources. It supports real-time and batch data streams, based on API interfaces, cloud computing servers, and database connections to obtain data (Li, Ma, et al. 2024). In addition, it can also realize data cleaning and format conversion to ensure that the input data can meet the analysis needs. The data storage module is responsible for managing and storing all the data on the platform. It can be beneficial for both structured and unstructured data storage, such as databases, distributed file intelligence data, etc. In addition, it also has a data backup and recovery mechanism, which can effectively ensure the security and durability of data. The data processing module is responsible for preprocessing and formatting the collected data. It provides parallel computing and distributed processing capabilities to address the analysis needs of large-scale datasets. The model training module is responsible for using the data from the platform (Su and Yang, 2024) to complete the training of the machine learning model. It enables distributed training, automatic hyperparameter tuning, and flexible switching of model types based on task requirements. In addition, the module provides the evaluation function of training results, which makes the model highly stable, valid, and correct. The model prediction module is responsible for making real-time predictions on new input data. It can use the trained model in a production environment and complete the steps to output the predictions. The module supports high-volume concurrent forecasting and automatically adjusts compute resources to respond to potentially fluctuating forecasted demand (Yang, 2024). The Visualization & Reporting module is responsible for presenting the results of the analysis and generating reports. The module provides a variety of charts and dashboards to visually display the operation of the model and its prediction results. The module also supports automatic report generation and export functions for decision support.

3.2 The Process of Cloud Computing

In this paper, we apply large model and cloud computing to process complex datasets in intelligent data analysis. The model can represent the intelligence of data as a graph structure and cluster based on the spectral decomposition of the graph, which is suitable for various types of intelligent analysis tasks, such as classification, recommendation, and cluster analysis. In intelligent data analysis, a similarity matrix should be constructed based on the similarity between the intelligences of the data. Whether the intelligence of the data refers to user behavior and device cloud server data, or different categories of documents, their similarity can reflect the correlation and connection between the data and the data. For the calculation of similarity, see Eq. (1).

$$W_{ij} = exp\left(-\frac{|x_i - x_j|^2}{2\sigma^2}\right) \quad (1)$$

In this formula,W_{ij} the elements representing the first row and$i$ column in the matrix $j$refer to the intelligence of the two data, that is,x_i the similarity of the andx_j. High similarity means that the intelligence of the two data has similar characteristics, and low similarity means that the intelligence of the two data is very different. For example, in data analysis, if the similarity between the intelligence of two data is high, it means that they have the same trend and performance in some specific characteristics. $x_i - x_j$Represents the intelligence of the datax_i and $x_j$the distance between them, commonly used is the Euclidean distance. The larger the distance, indicating that they are significantly different; The smaller distances indicate that they have similar characteristics. σA parameter representing the Gaussian kernel that controls the decay rate of the similarity value. If it $\sigma$is relatively large, it means that even if the distance is large, its similarity will not decay too quickly; If the σcomparison is small, the similarity will decay rapidly. For example, if you analyze different categories of documents, the larger ones σwill make the smart data more tolerant of small differences and identify larger groups. The construction of Laplace matrix based on similarity matrix can reveal the graph structure relationship between data intelligence and data intelligence, and is conducive to subsequent clustering operations. The formula for calculating the Laplace matrix is given in Eq. (2).

$$L = D - W \tag{2}$$

In this equation, $L$the Laplace matrix is depresented, which can be calculated based on the degree matrix$D$ and the similarity matrix$W$. This value mainly reflects the structural characteristics of the graph, and is used to describe the relationship between the intelligence of the data, so as to provide a solid basis for the decomposition of the eigenvalues in the future. For example, in a certain intelligent monitoring intelligence data, the Laplace matrix can help researchers identify which data intelligence, such as which device signals, belong to similar activity patterns. Based on the spectral decomposition of the Laplace matrix, the$k$ eigenvectors corresponding to the minimum eigenvalues will be obtained to form the eigenmatrix (U). Subsequently, the rows in the feature matrix can be clustered k-means. See Eq. (3) for this.

$$\text{Cluster}(X) = k\text{-means}(U) \tag{3}$$

In this formula, $k$the number of clusters is described, that is, the number of clusters to be divided into different clusters for the intelligence of the data. This value can be automatically selected based on the nature of the data. For example, in the intelligent data analysis platform, it may be necessary to divide the cloud computing server data into several categories, based on which different working states and anomaly detection can be represented. (U)The representative feature matrix is obtained from spectral decomposition, containing the previous $k$feature vector, which is mainly used to map high-dimensional data to a new, low-dimensional space to complete clustering. For example, in a financial risk analysis intelligence, a feature matrix identifies the behavior patterns of different users and divides them into groups based on risk.

3.3 Model Training and Optimization

In the cloud computing environment, the training process of the model is mainly to construct the phase degree matrix, calculate the Laplace matrix, and perform spectral decomposition. Based on parallel computing, these calculations can be greatly accelerated, allowing intelligent data to process massive amounts of data. For example, in a monitoring intelligent data, the intelligent data can process the signals of multiple devices in parallel to quickly identify the working status of the equipment.

During the optimization of the model, the number of clusters needs to be determined automatically$k$, which requires the application of the maximum spectral gap method. This method is based on observing the eigenvalues of the Laplace matrix to find the natural cluster division points, without manual setting. Eigenvalue gaps represent natural groupings in the data based on the differences between the observed eigenvalues. For example, when analyzing the data in a logistics intelligent data, the number of clusters is automatically selected, so that the intelligent data can divide the freight volume into different intervals, which is convenient for optimizing scheduling.

In the clustering process, the final impact of noise can be suppressed based on regularization to avoid the interference of clustering results. At the same time, the robustness of the model can be improved. See Eq. (4) for this.

$$min \quad _H \text{Tr}(H^T L H) + \alpha |H|_F^2 \tag{4}$$

In this formula, αit can be used to control the strength of the regularization term, which determines the sensitivity of the model to noise. If the value is large, then the noise can be suppressed, and if the value is small, then the model is allowed to cluster more closely.

4 RESULTS AND DISCUSSION

4.1 Improvement Cases of Cloud Computing and Large Model Integration

The large-scale smart city project in the eastern province introduces the intelligent data analysis platform that combines the large model and cloud computing designed this time, aiming to solve the increasingly severe traffic congestion problem and improve the operational efficiency of urban traffic. The processed data are unstructured data, qualitative data and quantitative data, and there is no correlation between the data, and the data are all mapped and processed, and the data correlation is strong. In order to simplify the complexity of data processing, improve the feasibility of data, take the traffic flow and the travel demand of citizens as the research field, because there is also a sharp increase in the problem in this field, the city manager now needs to use the intelligent data, based on the data analysis platform to do accurate traffic flow prediction, traffic accident warning, road condition monitoring and signal optimization, as shown in Table 1.

Table 1: Statistics of core data collected on a daily basis

data type	Data volume (TB)
Traffic monitoring	180
Road condition sensing	130
Meteorological data	90
Vehicle dynamics	100
Citizen feedback	40
Emergencies	60
environmental monitoring	50

Table I shows the amount of data collected by Smart Data from multiple domains on a daily basis, reflecting that traffic monitoring and road condition sensing are the main data sources. The intelligent data continuously obtains data from tens of thousands of cloud computing servers, surveillance cameras, and citizen feedback channels every day, covering real-time traffic flow, traffic accidents, and emergencies. With more than 500 terabytes of data streaming per day, this intelligent data needs to be efficiently stored, distributed, and analyzed in real time using cloud computing technology. The platform processes more than 500 terabytes of data per day, covering a number of key areas, mainly traffic monitoring, road condition sensing, weather data, and vehicle dynamics, as shown in Figure 1.

As can be seen from Figure 1, intelligent data is the comprehensive result of large models and cloud computing, and is at the top of data processing. Among them, traffic monitoring data accounts for the largest proportion, reaching 180 terabytes per day, which indicates that traffic flow is the core content of the platform's key monitoring. Based on the real-time processing of this data, intelligent data can accurately predict future traffic conditions and propose signalable optimization schemes to improve road efficiency.

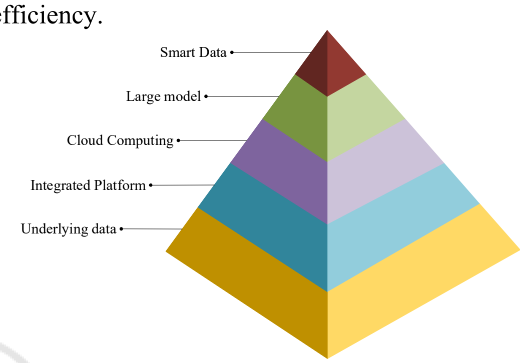

Figure 1: Intelligent data processing process of large model and cloud computing

4.2 The Degree of Optimization of Key Indicators in the Platform

The core of intelligent data correlation is to ensure that all modules can work together efficiently with each other. Using standardized interfaces and APIs, there will be a seamless data flow between each module, and then all aspects of the entire intelligent data will be closed. Intelligent data will use middleware to manage the communication between modules and ensure that information can be delivered in a timely and accurate manner for specific metric optimization, as shown in Table 2.

Table 2: Key performance indicators after intelligent data association

Performance metrics	Numerical optimization quantity
Average response time (ms)	350
Data processing speed (TB/s)	1.8
Prediction Accuracy (%)	96
Anomaly Detection Accuracy (%)	93
Equipment failure early warning rate (%)	90
Traffic Signal Optimization Improvement Rate (%)	88

Table II illustrates the key performance of smart data, from response time to prediction accuracy and other key performance indicators for efficient operation. From the data reflection, the intelligent data has a strong data processing ability, which can use the speed of 1.8TB/s to process large-scale data in real time, and the prediction accuracy of the intelligent data is 96%, indicating that its application in traffic prediction and traffic management is very significant. Moreover, the anomaly detection accuracy rate of intelligent data is 93%, and the early warning rate of equipment failure is 90%, which means that it can effectively identify traffic anomalies, such as accidents, congestion, and sudden road closures. At the same time, it also shows that the intelligent data can show high reliability in equipment monitoring and maintenance management, and timely detect and prevent potential equipment failures to ensure the continuous and stable operation of the intelligent data, as shown in Figure 2.

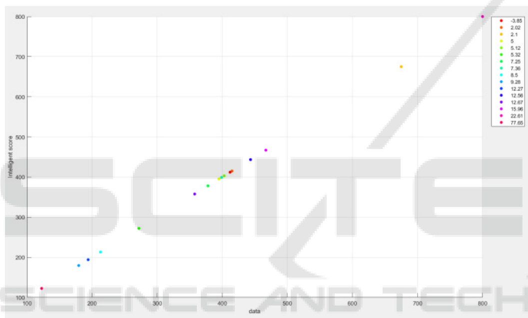

Figure 2: Levels of intelligent data analysis

As shown in Figure 2, the support of the cloud computing platform will make data analysis very intelligent and flexible to adapt to the needs of concurrent data processing, and further enable the intelligent data to still operate intelligently when processing massive amounts of data. In addition, intelligent data association also attaches great importance to security management, such as encrypted transmission, access control, and logging, which can ensure the reliability and data security of intelligent data (Zhao, Wu, et al. 2024). In addition, with the automatic scaling function of the cloud, intelligent data can flexibly allocate computing resources according to changes in business needs, so as to achieve high availability and dynamic scalability.

4.3 Statistics on the Effect of Intelligent Data Processing in Different Months

In a predictive analytics intelligence data, a larger regularization coefficient can make the intelligence more stable when it finds anomalous data. The parallel computing capability based on the cloud computing platform can accelerate the process of matrix factorization and clustering, especially the process of similarity matrix and eigenvalue calculation. For example, in a smart city management intelligent data, the intelligent data can process a large amount of cloud computing server data based on parallelization to make real-time judgments and optimize resource allocation, and the specific statistical results are shown in Table 3.

Table 3: Statistics on the number of monthly processing events of intelligent data

Month	Data processing capacity (TB)
January	1200
February	1350
March	1400
April	1550
May	1600

Table 3 shows the amount of data processed by the smart data in different months, showing that the data processing demand for the smart data continues to grow over time. From the perspective of monthly data processing, it can be seen that the amount of data processed by this intelligent data has increased over time. The amount of data processed in January was 1,200 TB, and in May it has increased to 1,600 TB, as shown in Figure 3.

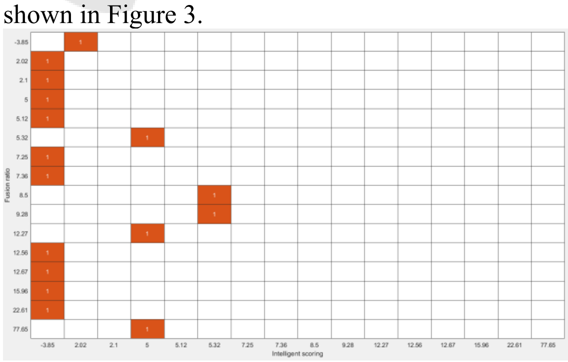

Figure 3: Intelligent scoring and statistical ratio

As can be seen from Figure 3, with the access of more cloud computing servers and large models, the load of intelligent data gradually increases, and the platform has good scalability to adapt to the growing demand for data processing. On the whole, the intelligent data analysis platform has excellent performance in various aspects such as traffic flow prediction and anomaly detection, and intelligent data scalability for equipment failure warning. The platform can provide city managers with intelligent traffic management and optimization solutions, and has high flexibility and scalability to cope with future data growth.

5 CONCLUSIONS

This paper designs and implements an intelligent data analysis platform that combines large models and cloud computing, and demonstrates its strong ability to process large-scale, multi-source heterogeneous data. Based on the combination of cloud computing technology and large models, the platform has intelligent parallel processing, distributed computing capabilities, and can ensure fast response and stability when dealing with massive data. In addition, the application of large models in the platform can improve the accuracy and prediction ability of data analysis, and then cope with complex data environments. In short, in this paper, the elastic expansion capability provided by cloud computing can ensure the continuous and dynamic expansion of the platform, and provide a strong technical guarantee for future intelligent data analysis. At the same time, it lays the foundation for the future intelligent development. Although this article has been improved in many aspects, there will still be errors and omissions, and I hope that the data analysis part can be expanded in the future. There are some limitations in this study, mainly because the application time of large models is short, and more practical cases are needed to support it, and related research will be focused on in the future.

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