COLLABORATIVE SCHEDULING OF WORKLOAD TASKS IN A CLOUD-EDGE HYBRID ARCHITECTURE

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Abstract:

Task scheduling in a cloud-edge hybrid architecture is a challenge in research and industry. The task scheduling algorithm needs to consider restricted resources and service requirements. The restricted resources include hardware resources, network topology and latency, storage resources and data placement. Service requirements include service latency, data transmission time, etc. In the last few years, we not only design a dynamic collaborative scheduling method under the heterogeneous cloud-edge architecture but also propose a data placement and retrieval mechanism under the cloud-edge hybrid architecture in order to cooperate with the execution of the scheduling method. It reduces the response time of the entire system and improves the user's application experience. Besides, a collaborative training method of models under the cloud-edge hybrid architecture is proposed and designed. According to the types of tasks it handles, appropriate model deployment is selected and personalized model training is performed.

Why we need collaborative scheduling for workload tasks?

Recently, in academia and industry, the collaborative scheduling of workload tasks in the cloud-edge hybrid architecture is a key area of research at home and abroad. The latest research results have carried out joint research on task service deployment and task scheduling, but they are for applications with a large amount of data and a large amount of transmission. More importantly, the current joint scheduling mostly stays in the design of the model, the resource utilization method is relatively rough, and the data placement, retrieval and model coordination need to be considered when the scheduling method is implemented.

In the heterogeneous cloud-edge hybrid architecture, the same task type may be deployed on different edge servers, and different edge servers may deploy different type of services. There are various task scheduling schemes, and different scheduling schemes have a significant impact on the completion time of tasks. When a user task request arrives at the edge layer, the system should be able to select a suitable instance on the edge server to respond to the task calculation according to the task attribute and the resource attribute at the location of the edge node (including the parameter configuration and data cache of the edge node), so as to ensure the real-time and validity of the calculation.

There are three problems involved here: 1. The edge server itself has limited resources and cannot deploy all types of tasks. The system should be able to perform edge-edge coordination according to the changing characteristics of user requests, support refined resource joint scheduling of hardware, and select appropriate resources to adjust service deployment to utilize the limited edge resources to meet the needs of user services. 2. The execution of tasks requires data support, and the unloading, placement and retrieval of data need to be reflected in the entire architecture, which can more comprehensively support the work tasks. 3. In the process of executing tasks interactively with the edge cloud, users need to consider the data security of the execution model and the wishes of the actual stakeholders, which is also one of the limitations of task coordination and scheduling. In the dynamic collaborative training of the model, the training results of each model in the node and the training data are used to jointly train the model, and the cloud computing power and edge node computing power have also been effectively used, realizing the dynamic collaborative scheduling of the edge cloud model, thus greatly improving the training efficiency and resource utilization of the model under the heterogeneous edge-cloud architecture.

How we make collaborative scheduling for workload tasks?

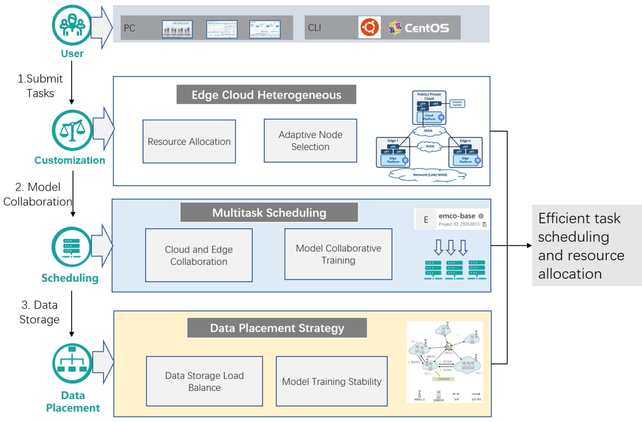

Figure 1: Technical route of our researches

In the last few years, we make some tries to solve the problem of low efficiency of the workload collaborative scheduling mechanism in the cloud-edge hybrid architecture. By proposing and implementing the collaborative scheduling method, combined with the innovation of the data placement and retrieval mechanism, it will be deployed in the cloud-edge hybrid architecture. The model in the system is collaboratively trained on multiple nodes, so that it can not only realize the refined joint scheduling of hardware resources in the system and improve the efficiency of resource utilization, but also meet their requirements for response time and data security from the user's point of view. We take into account the heterogeneous work task resource application characteristics of multi-edge nodes and the data storage and computing resource deployment of the cloud-edge hybrid system. Based on some open-source edge computing frameworks, a dynamic collaborative task scheduling algorithm is designed to fully integrate and utilize the system. It can reduce the average processing delay of tasks, improve user service quality, and meet the high real-time processing requirements of massive edge tasks. The data placement and retrieval mechanism under the cloud-edge hybrid architecture are proposed, and the data required for task scheduling is efficiently and safely used in an environment with high privacy protection requirements, and the computing power of heterogeneous edge nodes is effectively utilized to realize edge cloud. Model dynamic scheduling improves training efficiency and resource utilization, and improves system security and privacy protection capabilities. To express the content of these studies more intuitively, the technical route of our research is shown as Figure 1.

A. Dynamic collaborative scheduling methods

We propose some dynamic collaborative scheduling methods under the heterogeneous cloud-edge architecture. On the basis of sensing the deployment status of services and data on edge nodes, select the corresponding edge nodes that can meet the task request delay submitted by users. The node with the smallest requirement and the smallest average completion time performs the cooperative processing of the task. By virtue of the fact that edge nodes are located at the edge of the network and are close to mobile terminal equipment, they can effectively reduce the delay of data transmission and better support the real-time nature of local services. At the same time, due to its strong computing power, the cloud system can command and dispatch the task deployment and computing resource allocation of edge nodes at the macro level. Our goal is to deploy the collaborative scheduling method in the KubeEdge, relying on its powerful container orchestration and scheduling capabilities to deploy tasks, support refined joint scheduling of resources at the hardware level, and improve computing resource scheduling performance.

We allocate the required computing resources for different user tasks, maximize the use of heterogeneous cloud-edge distributed characteristics, and processes tasks in parallel in the form of multi-task dynamic coordinated scheduling, reducing the response delay when edge computing processes jobs submitted by multiple users, optimize the processing efficiency of heavy tasks in heterogeneous cloud-edge networks. Based on the task processing model and resource management model, we design a task scheduling dynamic coordination mechanism and the task coordination scheduling mechanism. For the user's high concurrency and heavy workload requests, the cloud makes task scheduling decisions for incoming requests based on the resource capacity information of the edge server, the instance information of the services deployed on the edge server, and the instance running time.

First, according to the feature information of concurrent requests, the request-response sequence is calculated to form priority scheduling based on service deployment. In the case of meeting the time and resource requirements of the task itself, the edge nodes that can meet the delay requirements and can reduce the task completion time are selected from the edge nodes to perform task scheduling processing. When the edge node cannot respond to the task request, the service configuration recommendation algorithm is used to generate the relevant service configuration recommendation according to the spatiotemporal distribution characteristics of the task request, and the edge node is selected to deploy the relevant service. At the same time, a timing mechanism is designed. The edge nodes periodically send metadata to the central nodes for tasks and resources in the system, so as to realize task rescheduling, that is, to dynamically schedule tasks. Finally, a prototype verification system based on the scheduling component Dispatcher of the open-source project is designed to verify the effectiveness of the proposed cooperative scheduling algorithm.

The main function of the Dispatcher is divided into two parts: the first part is to schedule task requests generated by edge devices and find the optimal edge node for task processing; In the second part, when the required service is missing or cannot meet the user's QoS guarantee, select the appropriate edge node for service deployment. The performance reference indicators of the verification system include delay, deadline, QoS, energy consumption, economic indicators and other aspects. For the delay analysis, the service delay of the task can be obtained by weighting the processing delay of different nodes according to the distribution probability, and the delay optimization effect of the collaborative scheduling algorithm can be judged by analyzing the weighted average delay and the processing of time-sensitive tasks. In addition to minimizing the delay, the task deadline also indicates the urgency of the task. The delay sensitivity of different tasks is different. If some tasks are not completed before the deadline, there will be serious consequences, so they are defined as hard deadline-constrained tasks. Otherwise, Soft deadline-constrained tasks. In addition to minimizing the delay, the task deadline also indicates the urgency of the task. The delay sensitivity of different tasks is different. If some tasks are not completed before the deadline, there will be serious consequences, so these tasks are defined as hard deadline-constrained tasks. Other tasks are defined as soft deadline-constrained tasks. If the completion time is greater than the deadline, there is a delay. The verification system describes the requirements of the task completion time according to the time-related efficiency function, and performs the final collaborative scheduling algorithm effect verification. The verification system also needs to consider QoS. According to the user's expectations for the application and the state of edge computing resources, it supports the refined joint scheduling of resources of the system hardware and improves the performance of computing resources.

B. A data placement and retrieval mechanism

We propose a data placement and retrieval mechanism under the cloud-edge hybrid architecture, which greatly reduces the response time of the entire system and improves the user's application experience. By considering the resource heterogeneity and dynamic variability of edge nodes, combined with the respective advantages of cloud data centers and edge nodes, a more reasonable data placement and retrieval mechanism is proposed, which fully considers the scalability of edge nodes. The speed of data placement and retrieval is improved, and the error rate of data retrieval is reduced.

The actual execution of the task is inseparable from the placement and retrieval of the corresponding data, which is often realized through heterogeneous edge computing systems. In our study it consists of a controller and several edge nodes. The controller manages the edge nodes in the system network and is generally not used to store data or indexes. An edge node consists of a network access point and its edge server, and the edge server deploys the network access point. In order to meet the differentiated demands of different regions of the edge layer, the distribution of resources among edge nodes is often uneven. Edge nodes can play the roles of storage server and index server at the same time. A storage server refers to a server that stores data items, and an index server refers to a server that stores indexes. Given an index key, it is easy to find an index server and find the corresponding index value in the DIT record of the index server that stores the data item.

C. A collaborative training method

We design a collaborative training method under the cloud-edge hybrid architecture. In heterogeneous edge nodes, according to the types of tasks they process, select appropriate model deployments and conduct personalized model training to achieve a trade-off between training speed and security. Refine the consensus on the training results of each model to collaboratively train intelligent models deployed on different edge nodes to improve model training efficiency and accuracy. When dealing with complex intelligent learning tasks, according to tasks of different difficulty, the models that have been deployed in the edge cloud are reasonably scheduled, the complex model in the cloud handles the more difficult tasks, and the lightweight model on the edge node handles the simple tasks, reducing the task processing delay and improving throughput.

Model collaborative training in traditional federated learning requires edge nodes to deploy the same model, which cannot be applied to the needs of heterogeneous edge nodes to deploy heterogeneous models for different tasks in the context of the Internet of Things. At the same time, for different types of tasks, complex models deployed in the cloud will increase communication overhead and task processing delays. Lightweight models deployed entirely by edge nodes are generally less accurate and efficient when dealing with complex tasks. Our research proposes and designs a model dynamic co-scheduling method in a heterogeneous edge-cloud environment. In the heterogeneous edge nodes, according to the type of processing tasks, select the appropriate model deployment, and carry out personalized model training. At the same time, the consensus on the training results of each model is refined to collaboratively train heterogeneous models deployed on different edge nodes to improve model training efficiency and accuracy. When dealing with complex tasks, according to tasks of different difficulty, the models deployed on the cloud edge are reasonably scheduled. The complex model on the cloud handles the more difficult tasks, and the lightweight model on the edge node handles the simple tasks, reducing the task processing delay and improving the throughput.

The method proposed in our research makes full use of the training results of each model in the heterogeneous edge nodes and the collaborative training model, and the computing power of the cloud and the computing power of the edge nodes are also effectively used, realizing the dynamic collaborative scheduling of the edge-cloud model. It greatly improves the training efficiency and resource utilization of the model under the heterogeneous edge-cloud architecture.

What we have done for collaborative scheduling?

In our research, the paper ORHRC [1] (IEEE ICWS'20) placed the performance prediction module in the cloud layer based on the cloud-fog hybrid architecture, and placed the configuration selection module in the nodes of the edge layer. ORHRC processes the workload in the fog nodes and sends the characteristics of the workload to the cloud layer for modeling. The paper ARVMEC [2] (JPDC’20) uses an ensemble learning algorithm based on XGBoost to make accurate predictions on the workload performance of various VM types according to the objectives of different user needs. The paper [3] focuses on the application of edge service distribution strategy and proposes a novel edge service distribution strategy based on intelligent prediction, which reduces the bandwidth consumption of edge service providers and minimizes the cost of edge service providers. Based on the edge-cloud computing paradigm, Reference [4] not only constructs a data placement model that includes shared datasets within the individual and among multiple workflows across various geographical regions, but also proposes a data placement strategy (DYM-RL-DPS) based on algorithms of two stages. In [5], we design a microservice-based service deployment strategy to reduce the average latency of IoT devices in a mixed environment. Aiming at the heterogeneity of edge server capacity, dynamic geographic information of IoT devices, changes in device preferences for applications, and complex application structures, we first propose a method based on heterogeneity and dynamic characteristics in an edge-cloud hybrid environment. Reference [6] proposes an adaptive mechanism (ADST) for dynamic collaborative service deployment and task scheduling under a heterogeneous edge-cloud architecture. In the process of task scheduling and service deployment, in order to meet the request delay requirements, ADST uses a greedy way to make decisions, and selects edge nodes and instances to reduce the average completion time. [7] (IEEE ICWS’20) considers the existence of multiple scientific workflows and multiple cloud data centers when building the data placement model, and constructs a new data placement model. [8] (IEEE JIOT’21) proposed a blockchain empowered secure and incentivized federated learning (BESIFL) paradigm. [9] (IEEE ICWS’22) designs a novel blockchain-based intelligent edge cooperation system to make CEC effective, among which incentive and trust mechanisms and performance optimization are crucial for latency-sensitive service provision. [10](JDPC'22) takes into account the heterogeneity and scalability of edge nodes in real scenes when formulating an efficient indexing mechanism, and adopts a method that maps all edge nodes to points in a two-dimensional coordinate system according to the network distance. [11] (IEEE Access'22) propose an Online Pre-filtering Task Offloading System (OPTOS) that is able to mitigate the impact of vehicle mobility on task offloading performance in the edge network.

What is the next?

In the future, we will combine with some existing open-source frameworks and design fine-grained scheduling of resources and computing models. The data placement and indexing will be fully considered in the design, which lays the foundation for the collaborative training of the model in the architecture.

The corresponding collaborative scheduling algorithm, data placement strategy and specific retrieval mechanism will be proposed around the dynamic scheduling model and data placement model in the heterogeneous cloud-edge hybrid architecture. In addition, from the perspective of landing, the methods will support the refined resource joint scheduling of hardware and improve the performance of computing resources.

Finally, we will realize the prototype system based on the heterogeneous cloud-edge hybrid architecture, the dynamic scheduling method of resources and data, and the collaborative training strategy of the model, and ensure the security and accuracy of the model training.

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