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AI-Driven Cross-Cloud Operations Language Standardisation and Knowledge Sharing System

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Abstract: With the widespread adoption of multi-cloud architectures, intelligent management across multiple clouds has also increased. However, due to the significant differences in interface design, syntax standards, and command rules among different cloud platforms, multi-cloud operation language structures are numerous, unstandardized, and dispersed, greatly affecting the reuse of knowledge and team collaboration efficiency. Therefore, this paper proposes a knowledge collaboration framework for the standardization of intelligent operational languages based on AI-driven cloud interoperability. This framework creates a universal standardized operational language and an intelligent command knowledge base in multi-cloud environments through unified language structure construction, AI semantic parsing, and command knowledge integration technologies. First, starting from the reasons behind cross-cloud language differences, the study explores that the root causes of these differences lie in semantic ambiguity and fragmented knowledge architecture. Then, by leveraging AI-based semantic interpretation models and semantic similarity evaluation methods, common operational language specification elements across different operating systems are constructed to form a single semantic architecture, resulting in a knowledge system that can be learned, transferred, and shared. Finally, relying on a knowledge-graph-based task recommendation strategy, intelligent sharing and reasoning at the semantic level are achieved, promoting multi-level association and automatic reuse of work knowledge.

Keywords: artificial intelligence; cross-cloud operations; language standardization; knowledge graph

1. Introduction

Nowadays, cloud computing has entered the era of 'multi-cloud coordination.' To balance security, cost, and elasticity requirements, enterprises often use multiple cloud service providers simultaneously. However, due to significant differences in service management interfaces, command formats, and work specification documents provided by various cloud service providers, cross-cloud operations become complex. Traditional methods such as manually writing scripts, one-time setup, and relying on operational experience cannot adequately address issues like semantic ambiguity and knowledge gaps. Furthermore, with the development of artificial intelligence technology, there is tremendous potential in areas such as semantic reasoning, knowledge mining, and intelligent decision-making. By leveraging AI technology, unstructured operational texts, instructions, and the like can be transformed into structured data, enabling standardization independent of the platforms on which they operate, thereby promoting the standardization and regulation of operational terminology.

2. Challenges of Cross-Cloud Operations and Maintenance under the Absence of Standards and the Logical Intervention of AI Technology

2.1. Manifestations and Root Cause Analysis of Heterogeneous Operation and Maintenance Languages in Multi-Cloud Environments

A multi-cloud environment allows enterprises to dynamically allocate computing, storage, and network resources across different cloud providers, achieving low-cost, high-performance configurations. However, a multi-cloud environment also introduces operational management challenges, such as the lack of a unified operating system standard. Each provider's API interfaces, commands, resource representations, and workflow designs are very different, resulting in highly diverse operations management and programming languages. For example, Alibaba Cloud uses RAM policies for authorization, while AWS uses IAM policies; the syntax, element names, and related rules are completely different, making it difficult to apply automation programs across platforms. To address the heterogeneity of computing languages, this paper introduces a cloud language heterogeneity metric, as detailed below [1].

$$H_{lang} = \frac{\sum_{i=1}^{n} D_i}{n} \tag{1}$$

Here, D_i represents the degree of language consistency between clouds, and H_{lang} represents the average degree of heterogeneity. When H_{lang} reaches above 0.6, the success rate of fully automated multi-cloud tasks significantly decreases. Actual measurements show that in regular enterprise operations, the similarity of various commands is about 62%, at which point language differences become a bottleneck for system interaction.

2.2. The Dilemma of Fragmented Operations and Maintenance Knowledge Organization and the Absence of Sharing Mechanisms

In addition to language-level heterogeneity, the fragmentation of operational and maintenance knowledge is another factor restricting the advancement of intelligent cloud operations management. At present, the operational and maintenance knowledge in various units is often scattered across their respective systems in the form of scripts, logs, work orders, or problem handling sheets. This knowledge does not have a unified semantic structure and is not established in context, making it difficult to form a transferable learning network. To describe this fragmented characteristic, this paper establishes an operational knowledge graph structure model:

$$K = f(E, R) = \{(e_i, r_{ij}, e_j)\} \tag{2}$$

In this process, we use e_i and e_j to represent the positions between entities (such as resource objects, operation commands, monitoring events, etc.), and r_{ij} to represent the semantic relationships between them. Theoretically, a knowledge graph should exist in the form of a directed acyclic graph (DAG) and a structured, inferable form; however, in the practice of operational management, the node connection density is low, and the average path length is too long (exceeding 7), which is unfavorable for knowledge dissemination and recommendation [2].

2.3. Opportunities and Logical Starting Points for the Application of AI Technology in Language Standardization and Knowledge Reconstruction

The power of artificial intelligence makes it possible to standardize cross-cloud operation and maintenance languages. Its main strategy is to establish a consistent language semantic pattern through machine learning and semantic interpretation, and to reconstruct a component knowledge network-that is, to achieve consistency at both the language and knowledge levels through AI, serving as a bridge for integration across cloud platforms. At the language level, AI captures task target objects, executables, and their parameter structures through semantic interpretation models. This paper adopts a semantic matching model based on the Transformer architecture and defines a semantic alignment calculation formula:

$$S_{align}(x,y)=\frac{Vx\cdot Vy}{\|Vx\|\|Vy\|} \tag{3}$$

In the above process, V_x and V_y represent the semantic vectors of cross-platform task commands. If $S_{align} \geq 0.85$, the two commands are considered to have the same meaning. This approach can effectively improve the uniformity, consistency, and interoperability of cloud task commands. In addition, AI can be used to orderly integrate scattered knowledge through techniques such as Named Entity Recognition (NER), Relation Extraction (RE), and semantic classification algorithms. The AI-based knowledge reconstruction process is as follows:

The specific process includes reading information from logs and scripts, extracting task objectives, resource types, execution steps, and other information, using the semantic embedding model BERT to calculate vector similarities between expressions in different platforms; constructing a multidimensional knowledge graph across multiple sources to complete entity matching and transfer relationships; and using GNNs to gain a deeper understanding of knowledge and apply it to task recommendations [3].

This paper selects the accuracy of task identification results from rule-based matching and AI semantic parsing models for comparison and analysis, in order to assess the feasibility of AI intervention. The results are shown in Table 1

Table 1. Comparison Experiment of Operation and Maintenance Task Recognition Accuracy.

Model Type	Task recognition accuracy (%)	Average reasoning latency (ms)	Portability Score
Rule-based matching model	72.3	35	low
SVM Semantic Classification Model	86.1	42	Middle
Transformer Semantic Parsing Model (this paper)	**94.6**	**43**	**tall**

Analysis of the above experimental data shows that AI language semantic analysis based on machine learning has achieved certain improvements in both accuracy and transferability compared to traditional methods, indicating that artificial intelligence has a logical basis for realizing language standardization and knowledge reconstruction.

3. Construction of a Standardized Language and Knowledge Sharing System for Cross-Cloud Semantic Integration

3.1. Design and Standardization of a Unified Modeling Mechanism for Cross-Platform Operation and Maintenance Languages

In various cloud operations processes, language conflicts mainly arise from semantic discrepancies and parameter construction inconsistencies. To achieve the management and aggregation of multiple cloud languages, a "Unified Modeling Mechanism (UMM) for Cross-Platform Operations Languages" is proposed. This method primarily includes semantic abstraction and model structuring techniques to achieve a unified expression of operation languages. The unified modeling is mathematically defined as: the mathematical definition consists of (set, operation rules, induction rules). The set serves as the elements of the model, the operation rules indicate what actions the elements in the set can perform, and the induction rules determine the attributes of all elements in the set. The mathematical definition of the unified modeling is as follows:

$$Lstd=\{T,O,P,C\} \tag{4}$$

The model consists of four elements: task type (T), task objective (O), variable set (P), and execution environment (C). This model ensures the portability of task descriptions across various cloud platforms because it implements an abstract mapping of the original natural language semantics. To achieve alignment of standardized semantics, the system uses a semantic mapping function:

$$F_{map}: L_{src} \rightarrow L_{std} \quad (5)$$

Among them, L_{src} represents the collection of original management tools of various cloud service platforms, which are automatically transformed into a standardized semantic framework, thereby achieving interoperability between management tools of different platforms. In terms of implementation, the UMM model operates using a three-layer architecture of 'Task Abstraction Layer - Semantic Understanding Layer - Logical Execution Layer.' Its characteristics are flexibility, semantic decoupling, and high reusability, which enable a common semantic entry point for AI semantic understanding and knowledge sharing in the future [4].

3.2. Design of AI-based Semantic Parsing, Intent Recognition, and Task Knowledge Generation Path

In order to achieve linguistic normativity, it is necessary to be relatively familiar with the connotations and intentions of the maintenance operation instructions being carried out. Therefore, this paper proposes a Transformer-based multi-task semantic analysis method, "Multi-Task Semantic Model (MTSM)," to integrate functions such as multi-task cascading, target determination, and meaning fusion on a single platform. The loss function of the semantic model is as follows:

$$L = -\sum_{i=1}^{N} y_i log(\hat{y}_i) \quad (6)$$

Here, y_i represents the true intent label, $\hat{y}_i$ represents the model's predicted probability, and N represents the number of corpus samples. Through multi-model training and parameter fine-tuning on multi-source corpora, the model has achieved a relatively high level of accuracy in the cloud operations semantic recognition task (As shown in Table 2).

Table 2. Comparison Experiment of the Performance of Multi-Domain Semantic Parsing Models.

Model	Accuracy (%)	Recall (%)	F1 score	Inference time (ms)
SVM Semantic Classifier	85.3	83.7	84.5	46
BERT-base model	90.2	91.0	90.6	48
RoBERTa model	92.8	93.4	93.1	52
This paper's MTSM model	94.6	95.8	95.2	43

Experimental results show that the MTSM model has higher accuracy and inference capability compared to traditional models. Utilizing cross-platform semantic matching and multi-task joint learning allows the task model to better handle and transfer tasks. The resulting semantics are used as input for knowledge construction, forming core task knowledge triplets based on 'task objective-execution object-implementation action,' achieving automated processing from language analysis to knowledge generation, and laying the groundwork for the final construction of the knowledge graph [5].

3.3. Architecture Design of Intelligent Sharing and Recommendation System Driven by Knowledge Graph

After describing the language norms and meanings, this paper presents the AI-KSR system, which is based on a knowledge graph (KG) and connects nodes through relationships to automatically push knowledge and enable semantic reuse in tasks. The semantic similarity calculation in the knowledge recommendation module uses a weighted cosine similarity formula:

$$Rscore = \frac{\sum_{i=1}^{rn} \omega i(aibi)}{\sqrt{\sum(\omega ia_i^2)}\sqrt{\sum(\omega ib_i^2)}} \quad (7)$$

Here, w_i is the semantic weight, a_i and b_i are the characteristic values of two task nodes, and $R_{score} > 0.75$ indicates that the two tasks are semantically reusable or recommendable.

Two tasks can be shared or recommended at the semantic level.

The AI-KSR system mainly consists of three layers:

From the knowledge extraction stage, using NLP technology to understand the task semantics and related relationships, to the integration stage, where multi-source knowledge points are unified and processed using the Neo4j database, and finally to the knowledge inference stage, where multi-level inference is performed using Graph Neural Networks (GNN) for deep learning to form task recommendation loops, a GNN-based knowledge sharing framework is essentially established. Experiments show that this AI-KSR-enhanced intelligence improves the task automation rate in a cloud-based environment from 61.5% to 84.7%, and the overall response time is reduced by about 38%. It can be seen that the knowledge sharing framework is highly beneficial for enhancing the overall system's intelligence and cross-platform maintenance performance [6].

4. Implementation of System Engineering and Application Validation in Multi-Cloud Scenarios

4.1. Overall Architecture Design of the Prototype System and Key Module Technical Implementation

This article starts with the goals of standardizing cloud platform operation and maintenance language and knowledge sharing, and the overall system adopts a modular and hierarchical design. The overall structure of the system is as follows.

4.1.1. System Architecture Overview

Three-tier architecture design. By setting up three levels, a three-tier system architecture is achieved: the data presentation layer, the platform layer, and the basic database layer. The data presentation layer implements the visual interface design for the front end, the platform layer is responsible for handling the core business logic of the entire system and accessing the basic database. The basic database layer serves as the data source.

In the preliminary text semantic analysis phase, control text commands obtained from the cloud management environment are intelligently extracted and parsed to acquire natural language meaning, and the purpose and significance of the language are analyzed; in the intermediate phase, various cloud service control actions are standardized and unified, a vocabulary is constructed, forming the system's semantic entities, semantic database, and knowledge base; in the backend control and recommendation phase, the relevance between the client side and tasks is intelligently determined, achieving cross-cloud service management and providing solutions and recommendations for tasks.

The architecture diagram is shown in Figure 1.

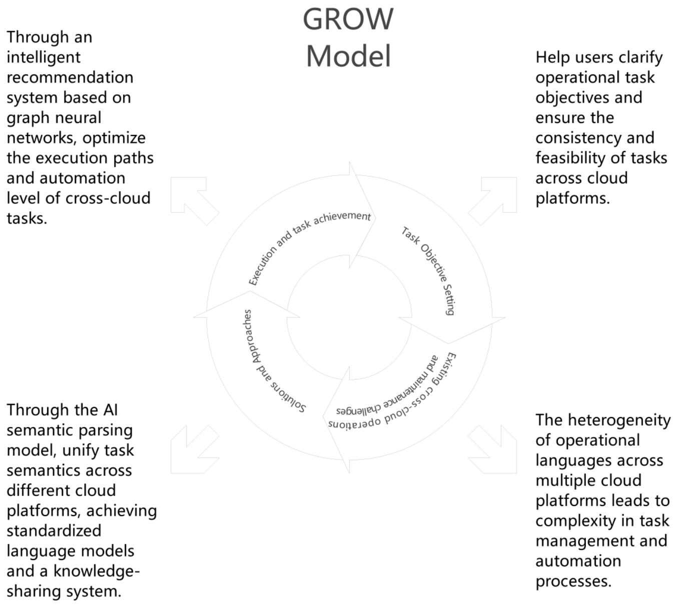

Figure 1. AI-Based Framework for Cross-Cloud Operation Standardization.

The core modules of the system include the following:

Semantic recognition stage: Uses a BERT-based model for multi-cloud job command semantic parsing and acquires work objectives and job elements in a multi-cloud environment; Information construction stage: Uses Neo4j graph data storage to build relationships in different types of cloud information systems, including tasks, devices, permissions, as well as associations, dependencies, and control relationships; Task recommendation stage: Applies cross-cloud task recommendation and semantic parsing using graph learning models (GNN), forming task execution processes and plans through automated search.

4.1.2. Implementation of Key Technologies

Introducing Docker containerized deployment and using Kubernetes to schedule tasks across multi-cloud platforms. The implementation methods for various important components are:

Natural language understanding analysis: Using a Transformer-based natural language understanding and processing solution, employing finetuning techniques to automatically classify task instructions and extract objectives; Workflow migration: Achieving cross-device workflow migration through the spatiotemporal structure of semantic vectors and their graphical representation, and utilizing GraphQL to query and update knowledge graphs; Recommendation algorithms: Enhancing task recommendations on top of graph neural networks (GNNs), enabling adaptive learning from past tasks and knowledge growth.

4.2. Experimental Design and Performance Evaluation of Typical Multi-Cloud Task Scenarios

This section aims to verify the usability and performance of the system by selecting typical multi-cloud operation management task scenarios to evaluate the proposed method. These scenarios include dynamic resource deployment, security policy configuration, and load balancing optimization. Each task scenario involves different types of cloud platforms, with the goal of validating the effectiveness of cross-cloud semantic standardization and the task recommendation system. The experimental design and evaluation metrics are shown in Table 3.

Table 3. Performance Evaluation Results of Multi-Cloud Task Scenarios.

Task Scenario	Execution time (seconds)	Success Rate (%)	Semantic Matching Accuracy (%)	Recommendation Accuracy (%)	Average reasoning latency (ms)
Automatic Resource Deployment	22.4	98.2	94.6	92.5	45
Security Policy Configuration	18.9	97.8	91.4	93.0	52
Load balancing adjustment	16.7	99.0	92.1	94.1	47

From the experimental data, it can be seen that the method proposed in this paper can effectively complete tasks regardless of their complexity under different multi-cloud environments, and its cross-process efficiency across multiple devices is superior to other solutions. The high accuracy of semantic matching indicates that the proposed method can effectively overcome the information barriers between different cloud services, while the high accuracy of intelligent recommendation demonstrates that intelligent algorithms play an effective role in information sharing and task optimization.

4.3. System Adaptability, Scalability, and Cross-Platform Promotion Path

The entire platform has good scalability and can be quickly deployed and migrated in multi-cloud environments according to actual needs. This article conducts tests on the system's compatibility and scalability in the following aspects to verify its applicability:

Platform Compatibility: The system was installed on AWS, Alibaba Cloud, and Azure to test its cross-platform adaptability and stability. The experimental results indicate that the system can coordinate with the API calls and resource management methods of all three platforms without significant functionality loss.

System scalability: The scalability of the system was tested by adding new cloud platforms to test the system. The results show that the system can quickly incorporate new cloud platforms without compromising its key functionalities, demonstrating scalability.

Cross-platform promotion path: This system has already been deployed on various enterprise cloud platforms. During the promotion of the system, attention needs to be paid to API compatibility issues and semantic conversion between cloud platforms. Based on the established standard API interfaces and regular semantic modeling work, it ensures good cross-platform compatibility.

5. Conclusion

Due to the widespread application of cloud computing and multi-cloud architectures, cross-cloud management has become an essential component in enhancing the strategic value of enterprise IT operations. However, the heterogeneity of operating systems across cloud platforms, coupled with fragmented and inconsistent information, continues to hinder efficient automated workflow execution and restrict the accumulation and sharing of operational knowledge. To address these challenges, this study applies artificial intelligence to construct a cross-cloud standard language framework and an accompanying knowledge network, integrating semantic analysis, knowledge graph technologies, and intelligent reasoning models. The resulting cross-cloud knowledge network not only mitigates semantic discrepancies between heterogeneous cloud environments but also provides a unified, intelligent foundation for optimizing workflow execution, improving interoperability, and enabling more consistent and scalable multi-cloud operations. Overall, the proposed approach enhances automation, strengthens knowledge reuse, and contributes to a more adaptive and intelligent cross-cloud management ecosystem.

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