

Article

AI-Empowered Technical Knowledge Modelling and Transformation Mechanism in Cross-Cloud Environments

Zhengrui Lu ^{1,*}¹ Oracle, Seattle, WA, 98101, USA

* Correspondence: Zhengrui Lu, Oracle, Seattle, WA, 98101, USA

Abstract: For technical knowledge in multi-cloud and cross-cloud environments, there exist characteristics such as structural diversity, meaning differences, and dynamic continuity. The existing knowledge management methods cannot adapt to this form of cooperation. This study focuses on proposing and answering how to establish and transform technical knowledge in a cross-cloud environment. It has established an AI modeling system of "extraction - matching - integration - update", proposed quantitative expressions suitable for cross-cloud knowledge, and developed strategies for automatic model extraction, semantic matching, and dynamic knowledge network construction. In terms of knowledge transformation, a cross-cloud technology knowledge transformation model centered on AI has been established, and a reasoning and decision-making mechanism has been introduced to accelerate the transformation efficiency. The effectiveness of the proposed method has been proved through typical cases, providing technical path support for cross-cloud knowledge organization and intelligent management.

Keywords: cross cloud environment; artificial intelligence; knowledge modeling; knowledge transformation

1. Introduction

With the rapid development of cloud computing, enterprises and research institutions have shifted from single cloud platform services to multiple cloud platform services and cross cloud environments that interact across clouds. Cross cloud environments can fully utilize the optimal utilization and effective sharing of various infrastructure and service resources of various cloud service providers. However, the data isolation and knowledge closure brought about by diverse structures have become increasingly prominent, and traditional data storage and model construction models cannot meet the needs of real-time response and intelligent decision-making in constantly changing environments. The fundamental problem is how to achieve a unified representation, fast transmission, and efficient conversion of information across various cloud platforms, which is a challenge in promoting the development of intelligent systems. With the development of artificial intelligence technology, new technological support has been provided to solve this problem for us [1].

2. The Foundation of Technical Knowledge Modeling in Cross-Cloud Environments

2.1. Characteristics and Modeling Requirements of Cross-Cloud Knowledge Structure

In a cross-cloud environment, there are differences in the recording structure, element definitions, and metric definitions of logs on various cloud platforms, which leads to diversity in technical understanding, namely structural ambiguity, semantic ambiguity, and temporal ambiguity. Among them, structural ambiguity causes inconsistencies among knowledge units, with features such as homonymous synonyms and different temporal overeffects, while temporal differences result in consistent

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association problems of cross-cloud events [2]. To achieve the goal of establishing model consistency construction, it is necessary to first conduct a mathematical quantitative analysis of the differences in knowledge among various cloud platforms, thereby supporting the subsequent semantic matching and standardization process to be based on a computable foundation. The structural differences of cross-cloud knowledge can be expressed as:

$$D_{struct} = \sum_{i=1}^n w_i \cdot \|S_i^{(a)} - S_i^{(b)}\| \tag{1}$$

Among them, $S_i^{(a)}$ is the structural code of the i-th field of cloud platform a; $S_i^{(b)}$ is the encoding of the corresponding field of cloud platform b; w_i represents the field difference weight; n represents the number of fields; D_{struct} represents the overall structural difference degree. This quantitative approach provides fundamental support for the standardization of cross-cloud knowledge and subsequent modeling.

2.2. Core Mechanism of AI-Driven Cross-Cloud Technology Knowledge Modeling

Based on AI capabilities, by leveraging automated extraction, semantic description, and vector matching, a homogeneous representation of multi-cloud knowledge is achieved. Logs, events, metrics, etc. on various platforms can be processed and mapped to the same semantic space, reducing structural and semantic differences among different cloud platforms. This enables cross-cloud knowledge to be combinable, deductive, and updatable. It is also conducive to further achieving knowledge integration and dynamic network construction [3]. The unified semantic representation can be obtained by minimizing the differences between embedding vectors, in the following form:

$$z^* = \arg \min_z \sum_{k=1}^m \|E_k(x) - z\|^2 \tag{2}$$

Among them, $E_k(x)$ is the embedding of entity x by the KTH cloud platform; z is the candidate unified representation; z^* represents the final unified representation; m represents the number of platforms. This mechanism provides a unified semantic basis for cross-cloud knowledge modeling.

3. Knowledge Modeling Methods for AI Empowerment Technology in Cross Cloud Environments

Before delving into the specific components of the modeling and transformation pipeline, present the workflow of the entire modeling and transformation process. Figure 1 below Outlines the main steps of technical knowledge modeling and transformation in a cross-cloud environment, including data collection, fusion, representation, and knowledge integration, etc.

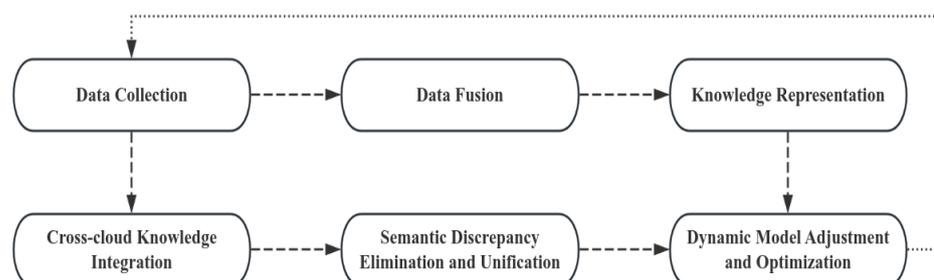


Figure 1. workflow of technical knowledge modeling and transformation in a cross-cloud environment.

3.1. Framework and Methods for Modeling Technical Knowledge

The core task of technical knowledge modeling is to transform scattered and multi-source data and information into ordered information. The modeling of technical

knowledge in cross cloud environments should take into account multi-source data and solve the problem of data isolation between clouds. In general, AI based knowledge modeling architecture consists of three steps: data collection, data fusion, and knowledge representation [4].

Data collection: It is necessary to gather discrete data from various sources, which can be in different formats of files or of different types (such as logging, databases, text, videos, etc.). Text can be automatically extracted through artificial intelligence technology, natural language processing (NLP) technology, or real-time capture and extraction of sensor readings, detection results, and other data can be achieved through machine learning methods [5].

Data Fusion: Data fusion is the core process of aggregating and standardizing data from different cloud platforms. Artificial intelligence uses deep learning methods such as convolutional neural networks and recurrent neural networks to achieve adaptive matching and synchronization of different forms of information [6]. In this process, knowledge graph, as a form of knowledge relationship, plays the main role of connecting and aggregating cross cloud information.

Knowledge representation: Knowledge representation refers to the structure of model data that can be inferred and applied. AI uses image embedding, text embedding, and other techniques to map data into a high-dimensional vector space for deep inference and analysis.

Through the above steps, technical knowledge in cross cloud environments can be integrated, modeled, and optimized.

$$K \text{ model}(t) = \sum_{i=1}^n f_i(D_i(t), \theta_i) \quad (3)$$

Among them, $d_i(t)$ represents the data of the i -th cloud platform, θ_i represents the corresponding parameters, and is a knowledge modeling in the form of a dynamic function model.

3.2. Application of AI Technology in Knowledge Modeling

Cross-cloud knowledge models need to adapt to the log formats, call link structures, resource activity processes of different platforms, as well as the semantic differences among multi-cloud nodes. The traditional processing methods of manual features cannot depict the structural relationships and correlations of cross-cloud knowledge. Therefore, it is necessary to introduce AI technology to provide support for the encoding, aggregation and update of cross-cloud knowledge entities, so as to obtain a consistent knowledge system that can be inferred and calculated. Graph Neural Network (GNN) is a tool that can depict the relationships among knowledge nodes of various cloud platforms under the graph structure and then aggregate knowledge from various sources across platforms [7]. At the same time, it can discover the implicit semantic connections among nodes from the learning of feature fusion.

In the cross-cloud knowledge graph, the update of knowledge node v can adopt the representation method based on neighborhood aggregation [8]. The structural information fusion is achieved through the feature weighted summation of cross-cloud neighbor nodes, as follows:

$$H_v^{k+1} = \sigma\left(\sum_{u \in N(v)} W_k H_u^k + b_k\right) \quad (4)$$

Among them, H_v^k is the representation of node v at the KTH layer; H_v^{k+1} represents the updated representation; $N(v)$ is the set of cross-cloud neighborhood nodes of node v ; W_k is the feature transformation matrix of the KTH layer; H_u^k is the representation of the neighbor node u ; b_k is the bias term; σ is the activation function, which is used to enhance the nonlinear expression ability [9]. This update method integrates the knowledge structures from different cloud platforms layer by layer into a unified vector space through neighborhood feature aggregation.

Considering the expression situation when modeling cloud knowledge, further introduce the historical state of the node itself and the attention coefficient across

platforms to improve the modeling effect of the knowledge model. The improved update method can be expressed as:

$$H_v^{k+1} = \sigma(\alpha_v W_s H_v^k + \sum_{u \in N(v)} \alpha_{u,v} W_n H_u^k) \quad (5)$$

Among them, α_v is the importance weight of node v itself; W_s is the node self-characteristic transformation matrix; $\alpha_{u,v}$ is the cross-cloud attention coefficient of neighboring node u to node v , which is used to measure the importance of knowledge relationships among different cloud platforms. W_n is the neighbor feature transformation matrix; The meanings of the remaining symbols are consistent with the above formula. The degree of knowledge fusion of this mechanism can be dynamically adjusted according to the semantic inconsistency of the cloud platform, making the model pay more attention to the knowledge paths where semantics are more important and improving the semantic consistency of knowledge prediction [10].

By combining these two feature update methods, AI can repeatedly integrate and represent knowledge entities in multi-cloud environments in a consistent form [11]. This endows scattered and diverse technical knowledge with characteristics such as formalization, reasoning ability, and transferability, thus enabling it to be used for later knowledge transformation, unified reasoning, and the construction of dynamic knowledge networks.

3.3. Data Integration and Intelligent Analysis in Cross Cloud Environments

Data integration in cloud environments requires obtaining data from different platforms and applications, and converting it into a unified data format. AI enabled intelligent analysis has improved the effectiveness and efficiency of data integration through the following methods:

Integrating heterogeneous data sources: The data formats served and displayed by cloud platforms may vary, and AI uses technologies such as natural language understanding (NLU) and image recognition to unify and label heterogeneous text, images, videos, and other data.

Data cleaning and feature selection: Data quality is a prerequisite for ensuring prediction accuracy, and artificial intelligence technology can use methods such as detecting outliers and filling in blanks to ensure data accuracy and completeness. Machine learning methods such as L1 regularization or decision tree methods can also be used to filter important features from the data, making it easier to use high-quality data as a prerequisite for subsequent modeling [12].

Intelligent prediction: fitting and analyzing data in the dataset through deep neural networks and time series analysis models, conducting trend prediction and pattern analysis based on historical data, and assisting in technical knowledge modeling and decision-making. See Table 1 below:

Table 1. Technical solutions for data integration in cross cloud environments.

integration method	advantage	challenge	Applicable scenarios
Data Warehouse Integration	Unified storage and query	Data redundancy and high storage costs	Large scale static data storage
Real time stream processing integration	Real time data analysis and response	Delay issues and high complexity	Scenarios with high timeliness requirements
Data virtualization integration	Seamless integration of heterogeneous data sources	Performance bottleneck, system complexity	Cross platform data linkage and access

3.4. AI Based Automatic Generation and Optimization of Technical Knowledge

To ensure consistency in the generation and optimization of technology across cloud environments, it is necessary to use artificial intelligence (AI) to achieve automated extraction and automatic adjustment [13]. The application of AI can enable expression learning from log data, API request channels, and resource condition processes, forming structured and inferable structural items, and continuously adjusting model parameters to adapt to multi-cloud changes. To ensure that the generated text achieves an optimal balance between accuracy and stability, regularized optimization objectives are usually employed and parameters are constrained, as shown in the following form:

$$L_{opt} = \min_{\theta} (\sum_{i=1}^N (y_i - f(x_i, \theta))^2 + \lambda \|\theta\|^2) \quad (6)$$

Among them, x_i is the i -th cross-cloud input sample; y_i represents the corresponding knowledge label; $f(x_i, \theta)$ is the output of the model under the parameter θ ; θ is the parameter to be learned; λ is the regularization coefficient; N represents the total sample size; L_{opt} is the overall optimization objective. This optimization approach can prevent the model from overly relying on the data structure of a certain cloud platform when generating knowledge, thereby enhancing cross-cloud adaptation capabilities [14].

After the initial generation is completed, it is also necessary to optimize the consistency of the structure and semantics of the knowledge entries to ensure that the generation results remain interpretable and technically relevant across different cloud platforms. By introducing a lightweight update strategy, the smooth evolution of knowledge entries can be achieved in the form of

$$K_{new} = K_{old} + \alpha(\hat{K} - K_{old}) \quad (7)$$

Among them, K_{old} represents the original knowledge; \hat{K} is the candidate knowledge generated by the AI model; α is the step size coefficient for adjusting the update scale; K_{new} for the optimized new knowledge representation [15]. This generation process and improvement process can gradually introduce new meanings of new knowledge while maintaining the original knowledge system unchanged, avoiding language jumps or structural shifts. Through this generation and evolution process, the relevant knowledge of cross-cloud technology can be automatically generated, self-updated, and always ensure semantic coherence, providing a reliable foundation for subsequent knowledge transformation, cross-cloud logical operations, and system collaboration.

4. AI Empowered Technology Knowledge Transformation Mechanisms

4.1. Framework for Technology Knowledge Conversion in Cross Cloud Environments

In a cross-cloud environment, knowledge on different platforms varies in structure, semantics and processes. Therefore, it is necessary to build a unified technical knowledge transformation framework to ensure consistency among explicit knowledge, tacit knowledge and cross-domain knowledge during the migration process. This framework models the functional relationship among input knowledge, expected expression and strategy output, endowing the transformation process with reasoning and dynamic adjustment capabilities. Figure 2 presents the cross-cloud knowledge transformation model adopted in this study [16].

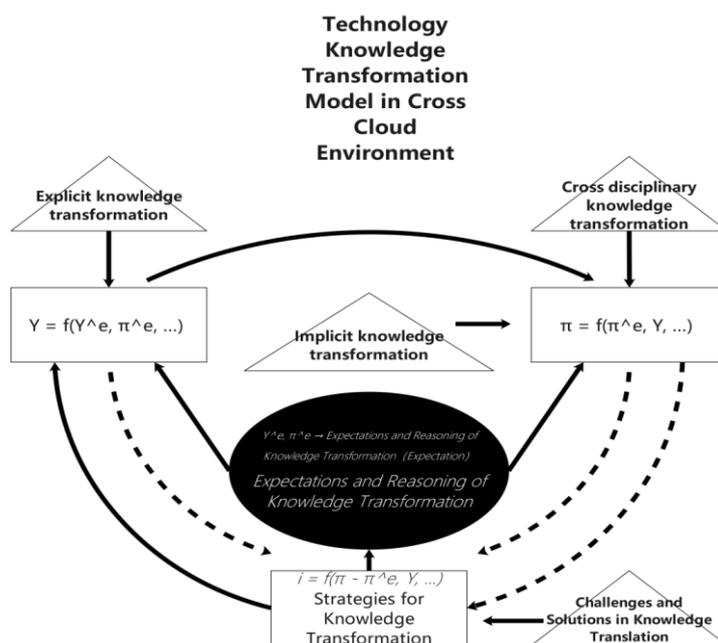


Figure 2. Model of technical knowledge transformation in cross-cloud environments.

In the model, explicit knowledge and cross-domain knowledge respectively generate the output Y and the policy vector π , and jointly act on the transformation of tacit knowledge. The system forms Strategy i by comparing expectation deviations to coordinate cross-cloud conversion paths.

4.2. AI Technology and Knowledge Transformation Efficiency Improvement

4.2.1. Automated Mapping Knowledge Generation

With the help of artificial intelligence, especially natural language technology and deep learning, organized knowledge is automatically generated and the relationships between knowledge clouds are described. By utilizing semantic registration technology and semantic web technology, AI technology can connect knowledge from various cloud platforms between clouds and transform them into forms suitable for specific purpose platforms. With the help of AI, the process of knowledge transfer has been automated. By utilizing deep neural network learning, AI can automatically extract key information from various file formats (such as PDF or Word) and transfer it to other platforms. For example, AI can automatically convert product manuals from one cloud platform into process specification guidelines from another platform to avoid human interference.

4.2.2. Tools Based on Intelligent Reasoning Decision-Making

The intelligent reasoning system based on artificial intelligence can make real-time decision support systems (DSS) based on data mining and knowledge models on cross platform clouds, helping enterprises flexibly transform knowledge between multiple clouds. In complex decision-making environments, artificial intelligence can make optimal decision recommendations for users based on its powerful data processing capabilities. To describe this decision-making process, it can be represented by the following weighted prediction model:

$$D(t) = \sum_{i=1}^n W_i \cdot Model_i(t) \tag{8}$$

Among them, $D(t)$ is the decision result, $Model_i(t)$ is the model decision result for each cloud platform, and W_i is the weight.

4.3. Knowledge Sharing and Collaboration Mechanisms in Cross Cloud Environments

In a cross-cloud environment, to ensure the unified description, real-time response and elastic operation of knowledge transfer and collaborative work among groups, a unified language is needed to describe cross-platform information and facilitate the interaction among work instructions, group collaboration and decision-making actions. However, due to the inconsistent data structure and data refresh cycle of cloud-to-cloud, the coordination system needs to have the ability to self-organize and accept information from different sources and maintain its own dynamic stability. To achieve this goal, cross-cloud knowledge can be uniformly calculated through a collaborative update method based on consistency inference, which takes the following form:

$$K_{t+1} = \beta \cdot K_t + (1 - \beta) \cdot \frac{1}{m} \sum_{i=1}^m K_i \quad (9)$$

Among them, K_t represents the current global knowledge representation; K_{t+1} is the updated knowledge representation; K_i is the local knowledge state of the i -th cloud platform; m represents the number of platforms participating in the collaboration; β is the weight coefficient for maintaining the original state of cross-cloud knowledge. This mechanism balances local knowledge contribution with global consistency, enabling cross-cloud collaboration to maintain stable and controllable knowledge sharing effects even in the presence of structural differences.

4.4. Case Analysis of Technology Knowledge Transformation Empowered by AI

To verify the effectiveness of the knowledge transformation mechanism, this study selects cross-cloud task chain reconstruction as an example scenario. By comparing the differences between traditional methods and AI-enabled methods in terms of indicators such as knowledge update speed, semantic consistency, and task chain recovery rate, the performance improvement of AI technology in the knowledge transformation process is evaluated. The experiment constructed knowledge samples based on log sequences and operation events from three cloud platforms, and compared the quantitative results using a unified evaluation index (see Table 2).

Table 2. Comparison of technical knowledge conversion Effects between Traditional methods and AI-enabled methods.

Indicator	Traditional Method	AI-Enabled Method	Improvement
Knowledge update latency (s)	118	36	↓69%
Semantic alignment accuracy	0.71	0.92	↑30%
Task-chain reconstruction success rate	64%	86%	↑22%
Cross-cloud dependency recognition accuracy	0.68	0.89	↑21%

It can be seen from the results that the AI model has significant advantages over traditional technologies in word meaning recognition, node association construction, and integration of multi-platform information. The short delay time for data updates indicates that it can quickly generate and supplement knowledge items. Enhanced semantic consistency and the identification of dependency relationships mean higher stability and interpretability of cross-cloud information transformation. The increase in the resilience of the task chain means that AI models have a greater chance of building a complete knowledge system and supporting future inferential decisions. Overall, this case demonstrates the role of AI in cross-cloud knowledge transformation, providing a feasible basis for system deployment and application promotion.

5. Conclusion

This article explores the application and role of AI in cross cloud computing from the perspective of technical knowledge transfer. In this section of the paper, a corresponding theoretical model is first established; Discuss how to improve efficiency; Some application experiments were also conducted to provide evidence. This article provides a detailed introduction to the process of AI enhancing technological knowledge on the cloud, as well as the conversion, sharing, collaboration, and application between clouds, thereby improving the intelligence level of intelligent systems. The knowledge transformation mechanism of AI can effectively achieve knowledge transfer across clouds in the system, which is not only beneficial for intelligent decision-making, but also has irreplaceable contributions to intelligent manufacturing and cloud computing resource optimization management.

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