Comparative Study and Optimization Proposals for Knowledge Graph Construction Management Systems: Postprint

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Abstract

Purpose/Significance: Knowledge graphs serve as a crucial cornerstone in the era of artificial intelligence, providing a novel form of organization and representation for knowledge. How to efficiently construct and reasonably manage knowledge graphs has become an urgent need for current knowledge graph researchers. This research focuses on existing knowledge graph construction and management systems, aiming to summarize new ideas for the development of current knowledge graph construction and management systems after conducting a comprehensive and in-depth comparison of multiple existing systems, and to provide references for the research and development of more universal, practical, and user-friendly knowledge graph construction and management systems.

Method/Process: Currently, numerous scholars have proposed advanced algorithms and techniques for the core construction processes of knowledge graphs, and many knowledge graph-related institutions have also developed various types of knowledge graph construction and management systems. This paper selects six representative mainstream knowledge graph construction and management systems from both domestic and international sources for investigation, analyzes the distinctive features of each system in their business processes, conducts a comparative summary in terms of system construction process support, technology selection, and usability, and summarizes the limitations of existing systems based on the latest user requirements for knowledge graph construction and management systems.

Results/Conclusion: Based on in-depth comparative analysis, this paper investigates the construction model of integrated knowledge graph collaborative construction and management systems, and summarizes and proposes optimization concepts for the construction of knowledge graph construction and management systems, including distributed collaborative construction, multi-graph parallel

management, multi-path knowledge extraction, multi-type graph storage engines, and cross-media and multi-modal knowledge graphs.

Full Text

Comparative Study and Optimization Framework for Knowledge Graph Construction Management Systems

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Abstract: [Purpose/Significance] Knowledge graphs, as a cornerstone of the artificial intelligence era, provide a novel form of knowledge organization and representation. Efficient construction and rational management of knowledge graphs have become urgent needs for researchers in this field. This study focuses on existing knowledge graph construction management systems, aiming to provide comprehensive and in-depth comparisons of multiple systems, summarize new ideas for constructing such systems, and offer references for developing more universal, practical, and user-friendly platforms. [Method/Process] Currently, numerous scholars have proposed advanced algorithms and technologies for the core construction processes of knowledge graphs, and many related institutions have developed various types of knowledge graph construction management systems. This paper selects six representative mainstream systems from domestic and international markets for investigation, analyzing their distinctive features in business processes, summarizing and comparing their support for construction workflows, technology selections, and usability, and identifying limitations based on users' latest requirements. [Results/Conclusions] Based on in-depth comparative analysis, this paper investigates the construction model of integrated knowledge graph collaborative management systems, and proposes optimization concepts including distributed collaborative construction, parallel management of multiple graphs, multi-path knowledge extraction, multi-type graph storage engines, and cross-media multimodal knowledge graphs.

Keywords: knowledge graph; collaborative parallelism; multi-path extraction; multi-graph engine; management system

1 Introduction

Knowledge graphs have emerged as a major research hotspot in artificial intelligence due to their powerful information retrieval capabilities, semantic analysis abilities, and knowledge representation and reasoning capacities, serving as a crucial technological approach for semantic network development. Since Google introduced the Knowledge Graph in 2012, it has played a significant role in improving search efficiency and refining search engine results. Following the introduction of CiteSpace in 2009, scientific knowledge graphs primarily focused on visualization analysis have quietly risen in the library and information science field in China. Simultaneously, with the development of linked data and large-scale open knowledge bases, semantic knowledge graphs have gained tremendous momentum domestically. Nowadays, knowledge graphs have been deeply researched and applied in various domains including medicine, information science, military science, and library science, with most fields having constructed their proprietary knowledge graphs.

However, the current landscape presents several challenges. The volume of internet data and scientific information is growing rapidly, characterized by large scale, diverse types, and wide distribution across domains. Due to factors such as non-uniform underlying data sources, inconsistent construction processes, and lack of collaboration among construction personnel, the building process of such semantic knowledge graphs remains cumbersome, time-consuming, and resource-intensive. Most existing knowledge graph systems are designed for specialized domains, lacking unified research knowledge graphs. In particular, the vast resources of literature and archives within the library and information science field are difficult to transform into more standardized structured knowledge bases. This is partly because most documentation workers focus on the analytical application of knowledge graphs while paying insufficient attention to the construction and research of related graph tools. Consequently, how to use an adaptable, unified, and universal graph system to efficiently construct, manage, and store domain-focused semantic knowledge graphs has become an urgent problem to solve.

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2 Investigation and Analysis of Mainstream Knowledge Graph Construction Management Systems

With AIGC technology becoming a global research focus, knowledge graphs, as the foundation supporting AIGC, have also experienced rapid development. Numerous institutions at home and abroad have developed their own Knowledge Graph Construction Management Systems (KGCMS) to help organizations quickly achieve knowledge graph development, construction, and subsequent applications. Based on industry standards and rankings, combined with research requirements, this paper selected six mainstream KGCMS from domestic and international markets for systematic investigation: PoolParty, Hume, RelationalAI, Huawei Cloud Knowledge Graph Service, Baidu Knowledge Graph Platform, and gBuilder. The analysis covers system characteristics in supporting knowledge graph construction business processes, technical selections, and usability, summarizes the advantages and disadvantages of each system, and explores future development directions for KGCMS in the industry.

2.1 Basic Overview

PoolParty adopts a modular architecture design and serves as a platform for enterprise knowledge graph implementation and digital transformation. Its semantic suite provides necessary tools and algorithms, including multiple processors for knowledge extraction, enabling efficient processing of multiple graph tasks. A distinctive feature of PoolParty is its PoolParty GraphEditor, which manages the entire knowledge graph lifecycle, provides visual graph operation processes, and supports batch and inline large-scale graph query functions. Additionally, PoolParty allows defining multiple GraphEditors for each project with different data access methods and user permissions, effectively improving knowledge graph construction efficiency and quality. Currently, PoolParty primarily serves enterprise-level knowledge graph construction, text mining, graph exploration and analysis, and intelligent Q&A.

Hume, developed by GraphAware, is a graph exploration and analysis tool that includes schema design, data mapping, data annotation, and knowledge graph construction modules. Its main characteristic in knowledge graph management is allowing different users at various stages of the graph lifecycle to collaborate in building knowledge graphs. Hume can connect to extensive and dispersed data sources to establish a comprehensive and authentic data collection, with each user having different operation permissions. Every knowledge graph managed by users can become an asset for all members within their organization, facilitating collaborative construction and data sharing among enterprise departments. Hume provides out-of-the-box natural language processing technology, machine learning method integration, and graphical visualization technology. It primarily uses property graphs as storage format, managed through the Neo4j graph database, and serves fields such as finance, law, enterprise-level knowledge graph construction, and text mining.

RelationalAI is a next-generation intelligent data application database system based on relational knowledge graphs. It provides a knowledge graph construction management system that treats knowledge graphs as an executable model combining data and logic, enabling model management through declarative programs. The system features domain knowledge modeling, heterogeneous data conversion and integration into graphs, and knowledge graph incremental updates. Users can specify their intentions using simple Rel statements without handling various logic and control flows in the process. The constructed graph models can directly import various types of data according to established rules to build large-scale knowledge graphs, simplifying user development programming complexity. RelationalAI currently serves intelligent data applications in telecommunications, life sciences, finance, and other domains.

Huawei Cloud Knowledge Graph Service Platform is a full-process knowledge graph construction and application platform that integrates multiple graph technologies and provides specific applications for knowledge graphs, enabling users to quickly implement knowledge graphs from development to deployment. The platform supports collaborative construction of knowledge graphs among different users, provides extraction templates that can be recycled across different modules, simplifies the construction operation process, and enhances user-friendliness. It offers two construction approaches: zero-code programming-based graph building and intelligent one-click graph construction, with pre-trained information extraction models. Completed graphs can be stored in Huawei Cloud's proprietary Object Storage Service (OBS) buckets for subsequent applications. The platform primarily serves semantic search and recommendation systems, industry scenario analysis, intelligent Q&A, clinical decision support, and travel assistants.

Baidu Knowledge Graph Platform, part of Baidu's AI Open Platform, is query-performance-oriented and supports multi-source heterogeneous data processing. It features knowledge extraction and mapping, multi-form knowledge large-scale automatic mining, multi-graph management, heterogeneous knowledge storage, and other functions. The platform has launched various services for the graph construction process on Baidu's AI Open Platform, such as knowledge graph schema design, allowing users to customize graph design models, import local data, train extraction models, and systematically complete knowledge graph construction and management processes. Baidu has also launched the Baidu Knowledge Graph Open Platform and EasyData intelligent data service platform, allowing users to access data and complete data annotation and processing operations on Baidu's data platform, improving upstream data processing in the knowledge graph construction workflow. The platform primarily serves intelligent dialogue, intelligent search and recommendation, financial and medical industries, and legal sectors.

gBuilder, developed by Peking University, is a knowledge graph automation construction platform that adopts a microservices architecture and combines machine learning, natural language processing, graph databases, and other technologies. The platform is divided into two management modules: graph projects and graph asset libraries. The graph project module is used for building knowledge graphs, while the asset library contains user-built ontology libraries and model libraries. gBuilder features visual schema design through drag-and-drop, direct connection to relational databases through mapping, pipeline construction processes for extracting and transforming unstructured data into graphs, and is equipped with a natural language Q&A system (gAnswer) and a native graph database system (gStore). It primarily serves domain graph construction, medical knowledge graph building, and correlation analysis.

2.2 Comparative Analysis

Based on collected literature and technical documentation, as well as the authors' hands-on experience with the six KGCMS, this section compares and analyzes their support for knowledge graph construction and management workflows, technology selections, and usability.

2.2.1 Comparative Analysis of Support for Knowledge Graph Construction Management The ability to fully support the entire knowledge graph construction workflow is an important criterion for measuring KGCMS construction. Current construction methods include top-down and bottom-up approaches, with conventional workflows roughly comprising: ontology construction for knowledge modeling, knowledge extraction from different data sources, knowledge fusion to resolve contradictions and ambiguities, knowledge reasoning to discover new knowledge for graph completion, and quality assessment through manual and machine methods.

PoolParty supports the complete graph workflow, including text data extraction and mapping, graph data management, thesaurus management, and semantic queries. It can receive and parse external ontology files or build original ontologies through the system, providing metadata management and data governance services. Hume supports complete graph workflows from traditional ETL construction to text-based search and data science applications, using high-availability connectors to ensure real-time data reading from any source. RelationalAI supports multiple paths for knowledge extraction and can integrate labeled property graph data, triple data, and relational database data into its internal standardized relational graph data model, minimizing data redundancy through declarative semantics and incremental computing. Huawei Cloud provides one-stop full lifecycle management, including ontology visualization construction, automated graph pipeline construction, and graph Q&A and reasoning applications. Baidu Knowledge Graph Platform divides various functions into services for different roles, supporting cross-media and multimodal knowledge graphs. gBuilder supports complete extraction processes for structured and unstructured data based on the D2RQ platform, with visual modules and task centers for real-time monitoring.

Beyond complete construction, features like distributed collaboration, parallel management, and multi-path capabilities are also important considerations. PoolParty provides multiple PoolParty GraphEditors with different data access methods and user permissions for each project. Hume's core feature is collaborative graph building, allowing different users to have different operation permissions. RelationalAI can effectively provide workload isolation for different graph construction tasks through its cloud-native architecture, demonstrating good performance in multi-graph management. Huawei Cloud's resource library allows different users to share models. However, most systems still lack sufficient user collaboration during development, making multi-user collaborative development difficult.

2.2.2 Comparative Analysis of Technology Selection and Usability In terms of technology selection, users focus on whether KGCMS employs advanced machine learning and deep learning algorithms and supports multiple graph storage engines. PoolParty combines advanced machine learning, natural language processing, and knowledge graph technologies, supporting mainstream graph databases like GraphDB and RDF4J, but primarily for RDF format storage. Hume uses property graphs as the main storage format through Neo4j, allowing free deployment of trial versions and local secondary development, but only supports English. RelationalAI is commercially oriented, providing some open-source SDKs, but currently only supports English interfaces and requires its declarative language Rel for some operations. Huawei Cloud integrates knowledge graph construction, natural language processing, and big data storage, offering four storage modes, but charges by functional permissions and provides limited access for ordinary users. Baidu Knowledge Graph Platform uses self-developed big data processing technology, supports Chinese and English interfaces, but primarily serves single users with limited multi-user collaboration. gBuilder requires license server approval, supports only Chinese, and has limited graph storage engine options.

Usability concerns include whether KGCMS is easy to deploy and develop secondarily, and language applicability across different platforms. Most KGCMS have relatively single underlying graph storage engines. Currently, knowledge graph storage mainly includes property graphs and RDF triples, corresponding to different mainstream graph databases. When the underlying graph storage engine is monolithic, users cannot select appropriate engines based on data characteristics, graph scale, and subsequent services. Additionally, most systems are designed for graph builders only, lacking consideration for data annotators and graph quality inspectors, making parallel management of multiple graphs impossible.

2.3 Summary Analysis

Through investigation and comparative analysis of the six mainstream KGCMS, several trends and limitations emerge. Most enterprise KGCMS are commercial, offering only a few predefined construction routes for ordinary users. In graph storage, user access permissions are limited. Some research institution KGCMS are mainly developed for specific domains, making it difficult to support cross-media and multimodal fields. The underlying graph storage engine choices are relatively single.

Current limitations include: insufficient collaboration among users during graph development, with most systems following traditional design concepts oriented toward single users; difficulty for ordinary users to obtain platform usage permissions or deploy platform functions locally; unified requirements for data storage formats in systems like RelationalAI that hinder collaborative co-construction and sharing; and most KGCMS lacking support for cross-media and multimodal domains. With current data characteristics, there are already large amounts of video, audio, and image data that have become important sources for knowledge graphs. If KGCMS cannot support multimodal data extraction and transformation, it will affect the quality of constructed graphs.

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3 Optimization Framework for Integrated Knowledge Graph Construction Management Systems

Current domestic and international research on KGCMS has reached considerable depth, with systems gradually maturing in construction processes, application technologies, and theoretical methods, creating domain-specific solutions. However, users still have numerous requirements regarding functional modules, technology selection, and application scenarios. Based on analysis of the six KGCMS and industry standards, this paper proposes optimization concepts from five perspectives for more universal and applicable integrated knowledge graph collaborative construction management systems. [Figure 1: see original paper] illustrates the system model diagram for KGCMS under new requirements.

3.1 Distributed Collaborative Construction

Knowledge graphs often require massive multi-source heterogeneous data and complex processes for construction, making it difficult for individual users to efficiently and accurately build large-scale graphs. Modern KGCMS should enable multi-user collaborative, stage-divided graph construction. In teams, different functional modules can be handled by personnel with different responsibilities: graph managers oversee construction process details, data annotation personnel handle labeling of various input data, and system administrators manage daily operations and services. This enables distributed construction of the same knowledge graph, with system modules that can be separated or combined as needed. Subsequent users can reuse graph models or extraction templates predefined by other users, or train existing models directly using other users' annotation data, promoting information sharing between different graph projects within teams. Distributed multi-user graph construction allows specialized users to focus on core processes, significantly improving overall system efficiency and enabling operators to specialize in specific modules, thereby simplifying complex construction workflows and improving accuracy.

3.2 Multi-Graph Parallel Management

Knowledge graphs from different domains require different types of graph storage engines, different sources of graph data, and different construction workflows. Therefore, different graph projects need separate management, with each having a complete construction strategy from knowledge extraction to final storage, clear project identification, reasonable resource allocation, and well-defined personnel permissions. KGCMS must enable unified parallel management of all graphs under a user's responsibility, ensuring rigor during construction and facilitating resource transformation between projects. The system should provide real-time feedback on project progress, allowing users to manage multiple graphs simultaneously based on specific functional modules and construction process details.

3.3 Multi-Path Knowledge Extraction

Common data types for knowledge graph construction include structured, semi-structured, and unstructured data, as well as RDF triple data and graph database data. A complete KGCMS should have multiple knowledge extraction paths to transform different data types into graphs. For structured and semi-structured data, traditional ETL tools or template/rule-based machine learning extraction methods can be used. For unstructured data, data annotation personnel should mark raw data, followed by pre-training and transformation using machine learning or deep learning extraction technologies. The system should provide pre-trained extraction models based on different domain data, allowing users to select and reuse models according to their data characteristics, saving training costs. Additionally, KGCMS should directly accept RDF triple data and graph data from other systems, parsing and translating them for storage in various adapted graph storage engines. Multi-path knowledge extraction enhances user flexibility when facing different data types and effectively addresses data fusion and transformation issues.

3.4 Cross-Media and Multimodal Support

Beyond traditional text data, current electronic resources have diversified into video, audio, and image data. Many institutions now treat such cross-media, multimodal data as important sources for knowledge graphs. KGCMS should include preprocessing stages like feature alignment and fusion for multimodal data, enabling complete feature tagging and filtering chaotic multimodal data into effective and standardized graph inputs. The system should provide multimodal fusion strategies and knowledge graph construction methods for different modalities, including machine learning models with multimodal information and various cross-media data fusion algorithms. Cross-media graph model representation mechanisms allow users to clearly extract semantic information from video and audio data. KGCMS should possess storage engines for different modal data to ensure high-speed read/write of large-scale data, establishing massive text, image, and video knowledge bases to support subsequent cross-media applications.

3.5 Multi-Type Graph Storage Engines

Graph storage engine management is the foundation supporting upper-layer knowledge graph construction. Current knowledge graph storage methods include RDF triples, graph databases, and relational databases, with representative systems including Virtuoso, GraphDB, Neo4j, Nebula-Graph, and relational databases like MySQL and SQL Server. Different databases have varying storage strategies, data organization structures, query languages, and read/write standards. KGCMS should provide multiple graph storage engines, allowing users to select appropriate engines based on graph data sources, scale, types, and subsequent services. The system should also pre-process data transformation between different engines to facilitate rapid migration and transformation of constructed graphs. Deploying multi-type graph storage engines enables dynamic and efficient distributed storage of multiple data formats in KGCMS, with more rational allocation of underlying storage resources and better support for diverse graph application development.

4 Conclusion

This paper systematically studied six mainstream knowledge graph construction management systems domestically and internationally, investigating their main characteristics and conducting comparative analysis on functional support, technology selection, and usability. The study identified overall trends and existing limitations of current KGCMS in the industry. Based on existing construction standards and analysis of mainstream systems, this paper explored future construction models for KGCMS under new requirements from graph users. The paper proposes optimization concepts for an integrated, full-process knowledge graph construction management system supporting distributed collaborative construction, multi-graph parallel management, multi-path knowledge extraction, multi-type graph storage engines, and cross-media multimodal knowledge graphs, aiming to provide new ideas and reference solutions for developing more advanced KGCMS in the industry.

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Note: Figure translations are in progress. See original paper for figures.