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Research on Early-Warning Method for Academic Misconduct in Universities Based on Knowledge Graph and Graph Neural Network

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Abstract: Against the complex situation where academic misconduct is growing more concealed, better-organized and enabled by upgraded technical means, the traditional governance model relying on manual review and ex-post punishment can hardly cope with current challenges. The governance of research integrity is shifting from passive response to active prevention and control. This paper proposes a knowledge-graph construction and Graph Neural Network (GNN) early-warning method for university research-integrity governance. First, a research-integrity domain ontology covering core entities such as researchers, projects, research outputs, institutions and journals is designed, and a knowledge graph is built upon multi-source heterogeneous research data. Second, given the real-world constraint of sparse labelled data for academic misconduct, an anomaly-detection early-warning model is constructed combining the Relational Graph Convolutional Network (RGCN) and Graph Attention Network (GAT). Within a graph auto-encoder framework, deep representations of normal research behaviours are learned in an unsupervised manner, and abnormal patterns such as improper citation and suspicious collaboration are identified via reconstruction error. Finally, a prototype early-warning system is implemented accordingly, and the human-machine collaborative governance path of "intelligent discovery — manual verification — targeted intervention" is discussed. This study provides references for technical integration and application in research-integrity governance for university research-management departments.

1. Introduction

Research integrity is the lifeline for the sound development of science and the cornerstone of national scientific and technological innovation. In recent years, academic-misconduct incidents have been exposed frequently at home and abroad. Cases range from data fabrication, plagiarism and invoice fraud by individual scholars to well-organized large-scale "paper-mill" activities and mass retraction events. Academic misconduct has presented a complex trend of increasing concealment, upgraded technical tools and higher degree of organization[1][2]. It not only damages individual academic reputation and undermines academic credibility, but also erodes the output efficiency of

national research investment[3]. Under such background, how to transform the governance of academic misconduct from "ex-post punishment" to "ex-ante early warning and in-process monitoring" has become a critical practical issue demanding prompt responses for university research-integrity governance.

In terms of governance practice, domestic universities have generally established research-integrity management systems dominated by institutional regulations and manual reviews. At the national level, multiple documents have been issued to strengthen research-integrity construction, emphasizing simultaneous punishment and prevention as well as comprehensive policy implementation[4][5]. Nevertheless, confronted with massive, multi-source and heterogeneous research data, pure manual review suffers prominent drawbacks including heavy workload, inconsistent standards and difficulty in timely detecting concealed risks, which limits governance effectiveness[6]. Multi-dimensional correlations among scholars, papers, projects, institutions, journals and other elements embedded in research data serve as vital clues for identifying anomalous behaviours, yet traditional rule-matching methods are incapable of fully mining such deep-seated structural information[7].

With powerful capabilities for representing and reasoning correlated data, Knowledge Graph (KG) organizes scattered research entities and their complex relationships into structured semantic networks, furnishing fundamental data support for intelligent analysis of research integrity[8][9]. Meanwhile, graph neural networks learn deep representations of entities and relationships within graph-structured data and exhibit remarkable advantages in detecting anomalous nodes, edges or subgraphs in graph data[9][10]. The combination of knowledge graph and graph neural network offers a new technical path for discovering concealed academic-misconduct patterns.

Targeting practical requirements of university research-integrity governance, this paper explores a technical solution of "knowledge-graph construction — graph-neural-network-driven early warning — prototype-system application". Specific contents include: (1) designing research-integrity domain ontology and proposing methods for constructing and incrementally updating knowledge graphs from multi-source heterogeneous research data; (2) building a graph-auto-encoder anomaly-detection early-warning model based on RGCN and GAT to identify research-behaviour anomalies in unsupervised mode under sparse-annotation conditions; (3) developing a prototype early-warning system and discussing the human-machine collaborative governance pattern of "intelligent discovery — manual verification — targeted intervention".

2. Construction of Methods for Research-Integrity Knowledge Graph and Graph Neural Network

2.1. Overview of Research-Integrity Governance

Research-integrity governance research has evolved from macro institutional discussions toward technical implementation. Foreign studies paid early attention to the definition, typology and root-cause analysis of academic misconduct and formed multi-dimensional interpretive frameworks covering organizational pressure, individual morality and peer supervision. Domestic research has focused more on specific manifestations of academic misconduct, journal governance strategies and institutional norm-building[4][5]. Recent studies further suggest that research-integrity governance should shift from "crisis response" to "long-term governance" and build a full-chain governance system covering prevention, monitoring and accountability[4]. Technically, risk-grading early warning for academic misconduct leveraging big data and artificial intelligence has become an important research direction. Researchers propose moving the defence line forward and constructing risk-early-warning mechanisms to curb potential deviant tendencies[6][7]. Nevertheless, reviewing existing studies, most outcomes remain at the level of institutional analysis and qualitative discussion.

The intelligent early-warning technical system oriented toward multi-source research data is far from complete, and few knowledge-graph-based early-warning systems specifically for academic misconduct have been reported[11].

2.2. Knowledge-Graph Construction Methods

Knowledge graphs organize knowledge in the form of "entity-relation-entity" triples and are built through ontology design, knowledge extraction, knowledge fusion and knowledge storage[8][9]. Ontology design provides conceptual frameworks and constraints for domain knowledge. Deep-learning approaches are widely adopted to assist automatic ontology construction. Knowledge extraction obtains entities and semantic relationships from unstructured texts via named-entity recognition and relation extraction. Knowledge fusion addresses key issues such as entity alignment and disambiguation, which is essential for guaranteeing graph quality[8]. Within the research domain, construction of knowledge graphs for scientific and technological big data has been proven to effectively support intelligent knowledge-discovery services, and relevant models and architectures can be migrated to research-integrity-analysis scenarios[8][9]. Research also demonstrates promising application prospects of knowledge graphs in digitalized research-archive management and research-entity-network analysis. In recent years, constructing knowledge graphs from texts using large-language models has become a new research frontier, which may further reduce the cost of building domain-specific knowledge graphs.

2.3. Graph Neural Network and Anomaly Detection

Graph neural networks are deep-learning methods for graph-structured data. They learn embedding representations of nodes, edges and even subgraphs via message passing and feature aggregation over graphs[9][10]. According to the diversity of edge types, GNNs can be divided into homogeneous-graph and heterogeneous-graph models. The Relational Graph Convolutional Network models parameter matrices for each relation type separately and is naturally suitable for handling heterogeneous graphs with multiple relation types such as knowledge graphs. The Graph Attention Network assigns different weights to distinct neighbours through attention mechanisms, strengthening the model's capability to focus on important neighbourhoods and improving interpretability[12]. In the anomaly-detection field, GNNs are widely applied in scenarios including network intrusion detection, transaction-fraud detection and social-bot identification[5]. Its core idea is to discover nodes or edges that deviate significantly from normal patterns by exploiting graph-structure information. Existing reviews systematically summarize the state-of-the-art and challenges of GNN-based anomaly detection[10]. In correlation-intensive scenarios such as fraud detection, GNN models integrating multiple heterogeneous relations have been validated effective for detecting concealed collaborative anomaly patterns, which offers feasible references for introducing similar methodologies into research-behaviour anomaly identification.

3. Construction of Research-Integrity Knowledge Graph

The research-integrity knowledge graph serves as the data foundation for the early-warning model, whose quality directly determines the reliability of subsequent anomaly detection. This section elaborates construction procedures from four dimensions: ontology design, knowledge extraction, knowledge storage and incremental updating.

3.1. Domain Ontology Design

Ontology design marks the starting point of knowledge-graph construction, aiming to establish standardized conceptual systems and semantic constraints for the research-integrity domain. Referring to existing research on research-oriented knowledge graphs[8][9] and considering real-world university research-management requirements, this paper designs a research-integrity domain ontology containing six core entity categories and their relationships. It is showed as fig 1.

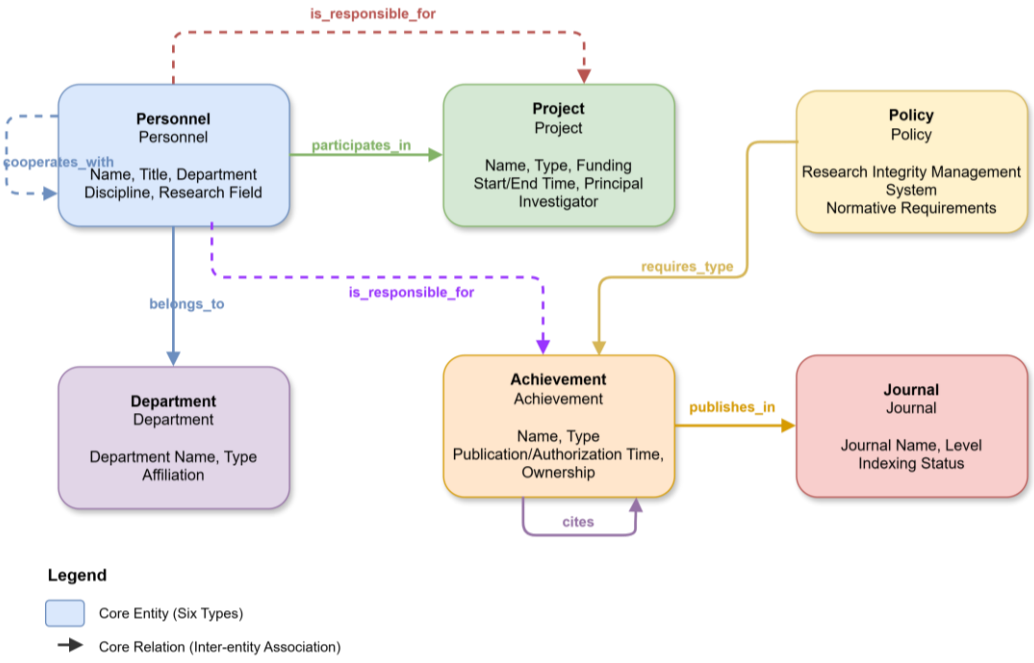


Fig 1. Ontology Design for the Research Integrity Domain: Entity Types and Core Relations

Core entity types are listed as follows: (1) Personnel: attributes including name, professional title, affiliated institution, discipline, research field, etc.; (2) Project: attributes including project name, category, funding, start-end date, principal investigator, etc.; (3) Achievement: attributes including output title, type, publication/authorization date, institutional affiliation, etc.; (4) Department: attributes including institutional name, category, subordinate relationships, etc.; (5) Journal: attributes including journal title, rank, indexing status, etc.; (6) Policy: describing management systems and normative requirements for research integrity.

Around the above-mentioned entities, several core relation types are defined to characterize associations in research activities. Specifically, belongs_to describes the affiliation between researchers and institutions; participates_in describes personnel's participation in projects; publishes_in describes the association between research outputs and journals; is_responsible_for represents principal investigators' accountability for projects; cites denotes citation relationships among outputs; cooperates_with describes collaborative relationships among researchers; requires_type reflects regulatory requirements specified by policies on output categories. This ontology balances knowledge-representation completeness and graph-model computability, providing structural support for subsequent graph-neural-network-based learning.

3.2. Knowledge Extraction

Knowledge extraction aims to obtain entities and their relationships from multi-source heterogeneous data. Data sources fall into two main categories: structured data stored in university

research-management systems such as project information sheets, personnel archives and output registration forms; unstructured texts including research proposals, final reports and full-text papers.

For structured data, triples are directly generated via field mapping and rule conversion with low processing cost and high accuracy. For unstructured texts, pre-trained models (e.g., BERT) are adopted for Named Entity Recognition (NER) and Relation Extraction (RE) to extract entities and semantic relationships. Considering potential insufficient accuracy of automatic extraction, manual verification is embedded in the extraction workflow to sample and revise critical entities and relations. Transfer learning is adopted to mitigate the scarcity of annotated data.

3.3. Entity Alignment and Knowledge Fusion

Multi-source data often suffer inconsistent entity references. For instance, the same author may be recorded as “Zhang Wei” and “Wei Zhang” across different databases, and one institution may have multiple denominations. Entity alignment constitutes the key procedure to resolve such discrepancies and realize knowledge fusion. This paper adopts an alignment strategy combining attribute similarity and relational consistency. First, similarity scores of candidate entity pairs are computed according to attribute features such as name, institution and email. Then cross-validation is performed leveraging isomorphism of relational contexts to boost alignment accuracy[8]. Unique identifiers are assigned to aligned entities to eliminate entity duplication within the knowledge graph.

3.4. Knowledge Storage and Incremental Updating

The open-source graph database Neo4j is selected as the storage engine for the knowledge graph. Neo4j delivers superior performance for graph-structure queries, supports flexible traversal and pattern-matching operations, and possesses a mature community ecosystem, facilitating rapid prototype-system development. To maintain knowledge timeliness, an incremental-update mechanism is devised: scheduled scripts regularly fetch newly generated internal and external data. After pre-processing, extraction and alignment, new data are incrementally integrated into the existing graph, ensuring that the knowledge graph reflects latest research-activity dynamics and furnishes timeliness support for the early-warning model[9].

4. Graph-Neural-Network-Based Early-Warning Model for Academic Misconduct

Aiming at the scarcity of labelled academic-misconduct samples, this paper proposes an unsupervised graph-auto-encoder early-warning model taking RGCN as the backbone and GAT as the complement. It identifies risk patterns such as improper citation, suspicious collaboration and duplicate application by reconstructing anomalous nodes and sub-structures within the research-integrity knowledge graph. A human-machine collaborative closed-loop governance workflow “intelligent discovery — manual verification — targeted intervention” is advocated.it is showed as fig.2.

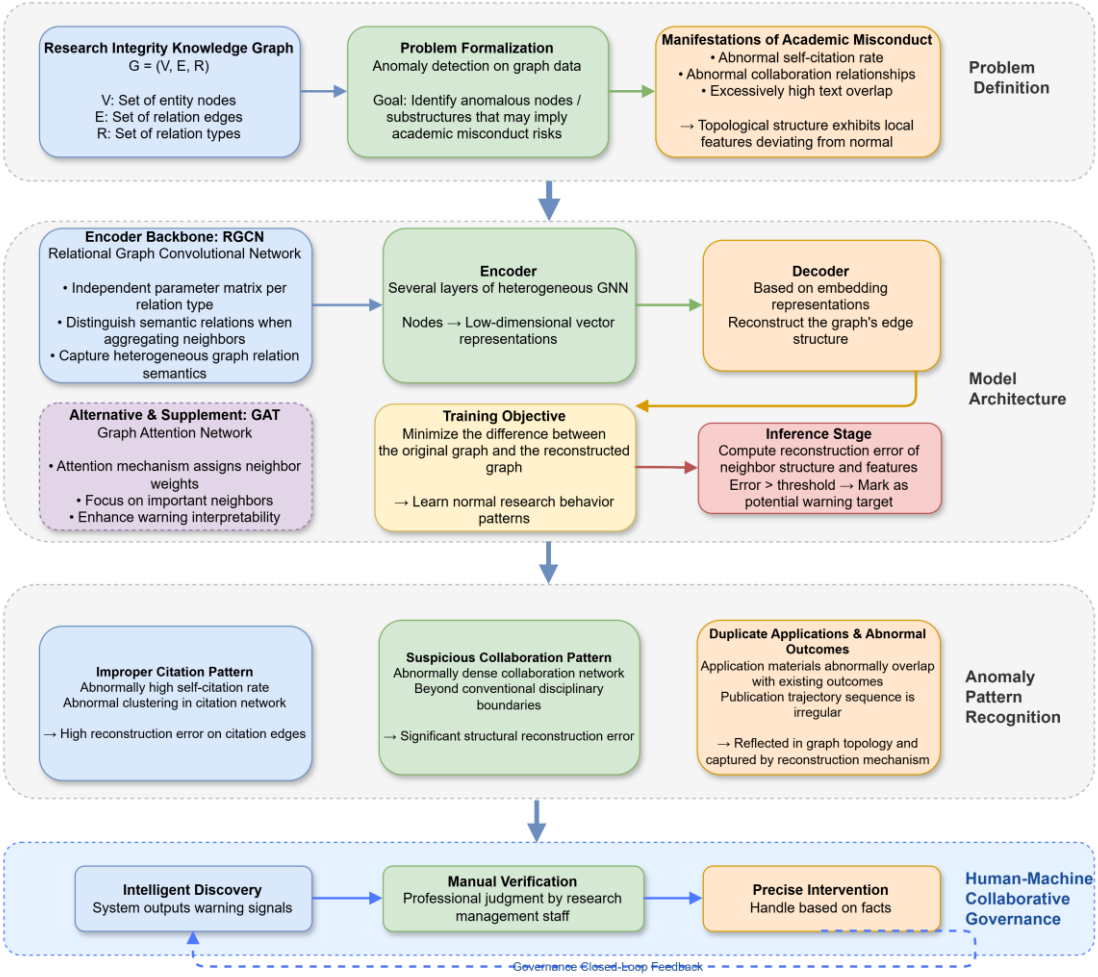


Fig. 2. Academic Misconduct Early Warning Model Based on Graph Neural Networks

4.1. Problem Formulation

Research-behaviour early warning can be formalized as an anomaly-detection problem over graph data. Given a research-integrity knowledge graph \(G=(V,E,R)\), where V denotes the set of entity nodes, E denotes the set of relational edges, and R denotes the set of relation types. The objective is to identify anomalous nodes or sub-structures that may contain academic-misconduct risks. Academic misconduct is usually manifested in specific relational patterns, such as abnormally high self-citation rates, anomalous collaboration relationships or excessive text overlap[7]. These patterns present locally deviant topological features on graphs.

Labelled samples of academic misconduct are extremely scarce, hence direct supervised classification suffers from sample insufficiency. Accordingly, this paper employs an unsupervised Graph Auto-Encoder (GAE) framework. Its fundamental assumption is that entities with normal behaviours can be well reconstructed by the model in terms of graph structure and features, whereas entities with anomalous behavioural patterns yield significantly higher reconstruction errors and can therefore be flagged as warning targets[13].

4.2. Model Architecture

Since the research-integrity knowledge graph is a typical multi-relation heterogeneous graph,

RGCN serves as the encoder backbone. By setting independent parameter matrices for each relation type, RGCN distinguishes semantic relations when aggregating neighbour information and adequately captures relational semantics within heterogeneous graphs. Meanwhile, GAT is introduced as an alternative and complementary model. Attention mechanisms assign different weights to neighbour nodes, improving the model's capacity to focus on critical neighbours and enhancing the interpretability of early-warning outputs[12].

The model follows an encoder-decoder architecture. The encoder is stacked by several layers of heterogeneous graph neural networks and maps nodes in the knowledge graph into low-dimensional vector embeddings. The decoder reconstructs graph edge structures based on node embeddings. The training objective is to minimize discrepancies between original graph structures and reconstructed graph structures so that the model learns intrinsic regularities of normal research behaviours. In the inference phase, reconstruction errors of neighbour structures and features are calculated for each entity. Entities whose errors exceed pre-defined thresholds are marked as potential warning targets.

4.3. Anomalous-Pattern Recognition

Warning signals derived from reconstruction errors cover multiple types of anomalous behaviours. First, improper citation patterns: entities with excessively high self-citation ratios or abnormally clustered citation-network topology yield high reconstruction errors for citation edges. Second, suspicious-collaboration patterns: subgraphs containing abnormally dense collaborations or cross-disciplinary collaborations beyond common academic boundaries produce prominent structural-reconstruction errors. Third, duplicate-application and output anomalies: abnormal overlaps between project-application documents and existing outputs or irregular temporal sequences of output publication can be reflected in graph topology and captured via the reconstruction mechanism of the graph auto-encoder.

It should be emphasized that outputs from the early-warning model are merely "risk signals" rather than violation conclusions. A human-machine collaborative governance mechanism is recommended. After risk signals are detected by the system, research administrators must conduct professional judgements based on facts, forming an efficient governance closed-loop of "intelligent discovery — manual verification — targeted intervention" and avoiding adverse impacts caused by machine misjudgement.

5. Conclusion

Responding to intelligent-governance demands for university research integrity, this paper proposes an early-warning approach based on knowledge graph and graph neural network. At the knowledge-graph level, a domain ontology covering core entities including researchers, projects, research outputs, institutions and journals is designed, and a multi-source heterogeneous research knowledge graph supporting incremental updating is constructed. At the early-warning-model level, a graph-auto-encoder anomaly-detection model integrating RGCN and GAT is built. It identifies anomalous research patterns such as improper citation and suspicious collaboration via unsupervised learning under sparse-annotation conditions. At the system level, a prototype early-warning system is implemented and the human-machine collaborative governance path "intelligent discovery — manual verification — targeted intervention" is discussed.

This study only explores prototype methodologies for detecting and warning academic misconduct and still has limitations. First, scarcity of annotated academic-misconduct data restricts full performance evaluation of the model. Semi-supervised or few-shot learning strategies can be explored for improvement in follow-up research. Second, the degree of automation and accuracy of knowledge extraction can be further enhanced, and entity-alignment problems require more sophisticated

processing. Third, early-warning threshold setting and model interpretability need further optimization with more practical application feedback. Practical operational outcomes of the system await further validation.

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