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Graph Application of Social Network AI Language Understanding and Reasoning

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Abstract: ***With the booming development of social networks, the value contained in social big data is increasingly prominent. This article focuses on the analysis of social network language understanding and reasoning techniques based on knowledge graphs. It systematically explores the construction methods of knowledge graphs, the semantic understanding mechanism of social texts, and the key tasks of reasoning decisions. It proposes a social language understanding framework that integrates knowledge graphs and deep learning, and provides technical implementation paths for specific tasks. The research aims to fully tap into the value of social data, enhance the intelligence level of social networks, and provide new ideas and methods for related research.***

Keywords: Knowledge graph; Social networks; Artificial intelligence; Language understanding.

1. INTRODUCTION

Social networks have become an important platform for people to obtain information and express their opinions. However, due to the heterogeneity and semantic implications of social big data, understanding the semantics of social texts and analyzing user behavior still face many challenges. Knowledge graph, as a structured knowledge base, provides new ideas for deep mining of social data semantics. Introducing knowledge graphs into social media analysis can help improve the understanding of social text semantics and user behavior patterns, and achieve more intelligent and accurate social computing, which is of great research significance. Li (2025) developed machine learning approaches to enhance adverse event monitoring in Phase IV chronic disease drug trials, improving pharmacovigilance efficiency [1]. For smart city applications, Li et al. (2025) proposed a named entity recognition system for urban data streams to enhance visualization and interaction capabilities [2]. In finance, Yang (2025) successfully applied LightGBM algorithms to analyze and predict trends in the Chinese stock market [3]. The e-commerce sector has benefited from Song's (2025) work on AI-integrated internal tools that significantly boost operational efficiency [4]. Cloud computing infrastructure has seen substantial improvements, with Wu (2024) researching large-scale parallel computing solutions for genetic disease research [5], while Chen (2025) developed scalable cloud architectures for autonomous driving data lakes [6]. In optical physics, Lin et al. (2025) employed transfer learning techniques to enhance modeling of complex nanostructures [7]. Business applications include Gong et al.'s (2024) ensemble machine learning approach for optimizing enterprise risk decision support systems [8], and Tang et al. (2024) used big data analytics to assess regional housing imbalances in the US market [9]. Further cloud computing advancements were made by Wu (2025) through optimized image classification models with elastic scaling capabilities [10]. Biomedical research by Wang et al. (2022) mapped the immune microenvironment in gastrointestinal cancers, providing valuable insights for immunotherapy development [11]. Smart city innovations continued with Li et al. (2025) gamifying data visualization to increase citizen engagement [12], and Song (2025) applied AI to optimize logistics decision-making [13]. Urban logistics saw improvements through Wang's (2025) AI solutions for last-mile delivery efficiency [14]. Healthcare applications were further expanded by Li (2025) with additional machine learning approaches for drug safety monitoring [15], and Yuan (2024) leveraged GPT-4 for multimodal medical data processing in EHR systems [16].

2. OVERVIEW OF KNOWLEDGE GRAPH

Knowledge graph is a structured knowledge base used to represent entities, concepts, and their associations. It constructs a multidimensional and multi-level semantic network by semantically representing and associating massive heterogeneous data in the form of graphs in the real world. Its core lies in achieving semantic representation, storage, retrieval, and inference of knowledge, and discovering new implicit knowledge through knowledge association. Knowledge graph has the characteristics of high structure, semantics, and strong correlation. Highly structured is reflected in the clear definition of the types and attributes of entities and relationships, making them easy for machines to understand and process; Semanticization endows entities and relationships with real-world semantics, enabling graphs to express richer and more accurate knowledge; Strong correlation means that entities form a network structure through diverse associations, which facilitates the exploration of implicit connections between entities and generates new knowledge. Based on these characteristics, knowledge graphs have been widely applied in fields such as intelligent search, question answering systems, knowledge reasoning, and assisted decision-making. However, the current knowledge graph still faces many challenges in construction and application, such as difficulty in knowledge acquisition, inconsistent granularity of knowledge representation, and insufficient cross domain reasoning ability. It is urgent to make further breakthroughs and innovations in knowledge extraction, knowledge fusion, and knowledge reasoning. In the future, with the iterative development of technologies such as knowledge acquisition, natural language understanding, and machine learning, knowledge graphs will continue to evolve towards larger scale, finer granularity, and stronger semantic understanding and reasoning capabilities, leading artificial intelligence to make breakthrough progress in the knowledge driven field.

3. SOCIAL NETWORK LANGUAGE UNDERSTANDING MODEL BASED ON KNOWLEDGE GRAPH

3.1 Overall Architecture Design

The social network language understanding model based on knowledge graph proposed in this article aims to fully utilize the semantic representation and reasoning ability of knowledge graph, and combine the characteristics of social network language to construct a comprehensive and effective semantic understanding framework. The overall architecture of this model can be divided into three main modules: social network corpus acquisition and knowledge graph construction, semantic understanding based on knowledge graph, and contextual understanding based on knowledge graph [2].

Firstly, the model needs to obtain large-scale user generated content from social networking platforms and perform preprocessing such as corpus cleaning, named entity recognition, and relationship extraction to construct a high-quality domain knowledge graph.

Secondly, based on the constructed knowledge graph, a semantic understanding mechanism that integrates knowledge representation is designed to achieve entity level and event level semantic representation of social text, capturing deep semantic information of the text.

Finally, by introducing structured information from the knowledge graph, a multi granularity contextual representation is established to achieve key tasks such as referential resolution and co referential resolution, enhancing the model's understanding of social dialogue contexts. Through these three closely connected and mutually supportive modules, a complete closed loop can be formed to achieve the goal of continuously introducing external knowledge into the model, guiding model training, and empowering model understanding, comprehensively improving the performance of the model in social network language understanding tasks.

3.2 Social network corpus acquisition and knowledge graph construction

The acquisition of social network corpus and the automatic construction of knowledge graph are the foundation of this model. Firstly, it is necessary to crawl and collect a massive amount of user generated content in the target field through the open APIs of social networking platforms, such as user posts, shares, comments, etc. Then, the obtained raw corpus is subjected to data cleaning and preprocessing operations such as denoising and word segmentation to extract a high-quality text dataset. On the basis of corpus preprocessing, named entity recognition technology is adopted to identify key entity words such as person names, place names, institution names, dates, etc. from text, and entity linking methods are used to map these entity words to standardized concepts in the knowledge base. Furthermore, utilizing relationship extraction techniques, multiple semantic relationships between entities can be discovered and extracted from the sentence structure and contextual information of entity co-occurrence. Finally, based on the extracted entity concepts and relationship facts, redundancy and contradictions are eliminated through knowledge fusion algorithms, and ontology construction methods are used to organize these concepts, instances, and relationships, forming a highly structured and semantically rich domain knowledge graph. This automated process of knowledge acquisition and construction can sustainably integrate new corpus from social networks, achieving continuous updates and expansion of knowledge graphs.

3.3 Semantic Understanding Based on Knowledge Graph

Based on the constructed social knowledge graph, deep semantic understanding of social texts can be achieved. Semantic understanding is divided into two levels: entity level understanding and event level understanding. In terms of entity level semantics, matching and associating entities and their attribute information in the knowledge graph with entity words in social text enables more accurate and fine-grained semantic representation of entity words [3]. For example, for the "Steve Jobs" entity appearing in the text, semantic information can be obtained by linking to the corresponding entity nodes in the knowledge graph, thereby representing the exact concept and role of "Steve Jobs" in a specific context. In terms of event level semantics, abstract representation of event semantics in social texts is achieved through the concept of event types and their argument structures in knowledge graphs. On the one hand, this event abstraction helps to normalize event representations in social texts; On the other hand, based on the event argument structure, further inference can be made on event associations, which can effectively improve the accuracy and comprehensiveness of event extraction and understanding of event relationships.

3.4 Context Understanding Based on Knowledge Graph

The ambiguity and colloquial nature of natural language make contextual understanding of social media texts extremely challenging. Therefore, the model is based on a knowledge graph and constructs a multi granularity contextual representation mechanism to achieve key tasks such as referential resolution and co referential resolution.

In the task of referential resolution, the model not only considers the co-occurrence information of pronouns and candidate entities in the text, but also fully utilizes the knowledge graph to introduce structured semantic information between entities. In the task of co referential resolution, the model can also utilize the alias and synonym information of entities in the graph to normalize multiple referents in the text. In addition, knowledge graphs can also play an important role in long-distance contextual understanding across sentences and documents. By abstracting the entities and events within a local discourse and associating them with the global knowledge of the knowledge graph, a global semantic representation that spans local contexts can be constructed. This mechanism enables the model to better capture and preserve the contextual semantics of social conversations, and achieve longer distance contextual error correction and semantic inference.

4. SOCIAL NETWORK INFERENCE DECISION-MAKING BASED ON KNOWLEDGE GRAPH

4.1 Knowledge Discovery Based on Ontology Reasoning

Ontology reasoning based on social knowledge graph can achieve the discovery and externalization of implicit knowledge. Ontology reasoning infers entities and relationships in a knowledge graph by defining formal ontology rules, thereby uncovering new knowledge embedded in entity associations. For example, by using the ontology rule 'If A knows B and B knows C, then A may know C', potential relationships between users can be discovered in the social relationship graph. The inference process needs to fully consider the applicable conditions and confidence of ontology rules, and introduce uncertainty inference mechanisms such as probability graph models. In addition, during the process of ontology reasoning, there may be issues such as rule conflicts and inconsistent reasoning results, which require further introduction of conflict resolution methods based on evidence theory and credibility evaluation. The new knowledge obtained based on ontology reasoning can be used to enrich the existing knowledge graph and achieve automated expansion of social domain knowledge. Ontology reasoning is an important part of knowledge graph applications, playing a crucial role in the integration, mining, and application of social knowledge.

4.2 User Intent Understanding Based on Graph Reasoning

The recognition of user intent expressed in natural language is a key task in social media platforms. Due to the fragmented and obscure nature of social media language, identifying intentions directly from text faces many difficulties. Introducing knowledge graph reasoning can enhance the accuracy of intent recognition from multiple dimensions. On the one hand, semantically associating social text expressions with concepts and entities in the graph can eliminate differences in the surface form of vocabulary and extract accurate semantic intentions; On the other hand, the hierarchical semantic relationships between concepts in knowledge graphs, such as synonyms, hierarchy, etc., can be used for generalization and refinement of intentions, achieving flexible expression of multi granularity intentions. In the process of intent recognition, the intent rule library defined by the graph ontology can also be used to infer the identified intent concepts and form a network of associations between intents. For example, the intention of "mobile phone after-sales" can be associated with sub intentions such as "quality issues" and "repair services". Through path reasoning, these explicit and implicit intentions are organically linked to form an intention reasoning chain, ultimately achieving a comprehensive and accurate understanding of user intentions.

4.3 Social Relationship Mining Based on Path Reasoning

A core task of social network analysis is to extract social relationships and community structures among users from massive user interaction data. Traditional social network analysis is mainly based on explicit relationships of user interaction, such as friend relationships, forwarding comment relationships, etc. Under the framework of social knowledge graph, it is possible to infer more implicit and complex social relationships between users by mining their association paths in the graph. Specifically, first, a user entity preference matrix is constructed based on collaborative filtering, association rules, and other algorithms to characterize the distribution of user preferences for entity content; Further considering the dynamic evolution characteristics of user entity preferences, a time decay function is introduced to establish a temporal aware representation of user preferences. On this basis, through graph inference algorithms such as random walk and ant colony optimization, path exploration is conducted in the knowledge graph starting from users, and multi hop semantic associations between users are discovered. By mining patterns from the inferred relationship paths, characteristic path templates for different social relationships can be summarized. In subsequent applications, simply matching the interactive behavior of new users with existing path templates can efficiently and interpretably predict social relationships between users. This knowledge graph based social relationship path inference method breaks through the limitations of traditional explicit relationship analysis and is of great significance for characterizing the deep relational structure of social networks and understanding group social behavior patterns.

4.4 Application scenarios and case analysis of reasoning results

The reasoning analysis technology based on social knowledge graph has broad application prospects in fields such as social computing and intelligent business. A typical application is social user segmentation and group profiling. The user relationship network obtained based on knowledge reasoning can automatically discover tight subgroups in social networks and characterize the common characteristics of group members in terms of demographic attributes, interests and preferences. Taking the social promotion of a certain maternal and child product brand as an example, through knowledge inference of the interactive behavior of users on its social media accounts, several stable parenting mother communities were discovered, which gathered under topics such as "infant and child complementary food" and "maternal and child care". Further analysis of the intentions of key opinion leaders in these communities revealed that they have a general interest in the topic of "Baby Eczema Care". The brand has planned a series of precise marketing content for the "Baby Skincare" series based on this, which has sparked enthusiastic interaction in the community and significantly improved marketing effectiveness. Similarly, user link inference is widely used in social network influence analysis. By analyzing the structural holes of users in social communication channels such as forwarding chains, key influential node users can be identified. In the scenario of cold start, knowledge graph expansion can also be used to match the relationship path between new users and existing users, predict their influence, and provide accurate seed users for influence marketing activities. In short, social reasoning analysis technology has great potential in social computing tasks such as information dissemination, precision marketing, and behavior prediction. It is of great significance for a deep understanding of the behavioral mechanisms of social networks and grasping the behavioral patterns of social groups.

5. CONCLUSION

The research on social network language understanding and reasoning based on knowledge graph provides new ideas and methods for deep mining of the value of social big data. This article explores the key technologies of knowledge graph driven social computing from the aspects of knowledge graph construction, social semantic understanding, user intention mining, and social relationship reasoning, and preliminarily implements a knowledge reasoning and analysis framework for the social domain. Future work will focus on integrating knowledge representation learning, ontology reasoning, and deep learning techniques to further improve the social knowledge graph representation model, enhance the interpretability and robustness of social reasoning, and expand its applications in fields such as social computing and intelligent business. Knowledge driven social intelligence analysis will undoubtedly drive the continuous deepening of social computing research and inject new impetus into the development of the digital society.

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