QiboGraph: A Knowledge Graph for Traditional Chinese Medicine

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Abstract. Existing knowledge graphs often impose substantial modification constraints due to stringent accuracy requirements, and there are few multimodal graphs in Traditional Chinese Medicine (TCM), hindering timely incorporation of cutting-edge domain knowledge. To resolve these challenges, we propose QiboGraph, a multimodal TCM knowledge graph featuring crowdsourced collaborative modification. We also introduce a two-stage alignment pipeline assigning images initial weights, to accelerate the convergency of the graph. Finally, a practical system is developed to demonstrate two typical use cases of QiboGraph.

Keywords: Multimodal Knowledge Graph · Traditional Chinese Medicine · Crowdsourcing · Multimodal Alignment

1 Introduction

Challenges in Updating Knowledge Graphs. Recently, numerous knowledge graphs (KGs) have been constructed to support various downstream applications [3]. The rapid evolution of domain-specific knowledge often outpaces the update cycles of existing KGs, resulting in an expanding gap between cutting-edge knowledge and graphs, which may compromise the accuracy and reliability of the graph. Furthermore, the inherent constraints of conventional KG architectures in integrating multimodal information [4], hinder their capacities to model intricate real-world relationships and contextual nuances.

Our Approach. We present the QiboGraph, a multimodal Traditional Chinese Medicine (TCM) knowledge graph, which features the dynamic crowdsourcing mechanism and incorporates expertise-weighted validation to ensure that contributions from experts are valued. Specifically, we introduce a two-stage pipeline, consisting of text-image alignment and initial weight assignment, which enables the system with the ability to process multimodal information and unknown images.

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2 QiboGraph Overview

Figure 1 illustrates the architecture and key components. Further details about the components are given as follows.

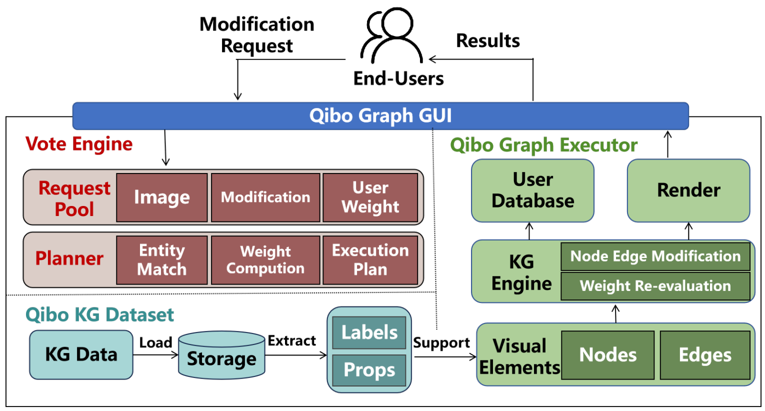

Fig. 1. **The architecture of QiboGraph**

2.1 QiboGraph Dataset and Ontology

The dataset is principally constructed from ancient Chinese medical classics, comprising more than 80,000 traditional prescriptions and treatments for various diseases. The related images are curated from the Web and then aligned manually. The ontology of QiboGraph adheres to the empirical rules of TCM, as illustrated in Fig. 2, where properties of the corresponding ontology are surrounded by dashed lines.

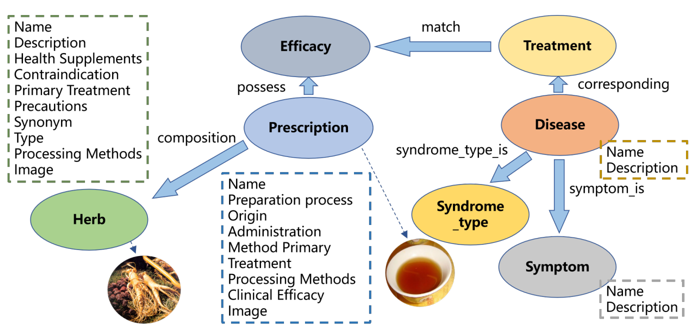

Fig. 2. **The ontology of QiboGraph**

2.2 Vote Engine

Each node is assigned a credibility score determining its preservation or elimination. Users are also assigned their own weights, which represents their expertise and affects the rate of score change when they downgrade or upgrade the credibility score. The node whose threshold is reached, will be deleted or materialized, and the weights of users participating in voting on this node will be re-evaluated. The weights of users whose modifications are in favor of the result (e.g., downgrading the node before deletion) will be increased; otherwise, their weights will be decreased. This mechanism enables quantifiable expertise qualification via historical voting consistency and dynamic role transitions between experts and end users.

2.3 Multimodal Alignment

Users may only upload the image, and the system will align it with the graph automatically. Firstly, the system matches the unknown image to the entity. Then an initial weight is assigned, which is calculated as follows. Let $I_{1 \cdots n}$ represent other images aligned with the same entity, and I_{n+1} represent the new image. Note that E is the entity and w_i is the weight of the image I_i. We introduce semantic association coefficient (SAC) to represent the semantic similarities between $I_{1 \cdots n}$ and I_{n+1} regarding E, which is defined as follows:

$$\mathrm{sac}(i, E) = f(\mathrm{abs}(\mathrm{cov}(i, E) - \mathrm{cov}(n+1, E))), i = 1 \cdots n \tag{1}$$

$\mathrm{cov}(\cdot, \cdot)$ is the similarity between the image and entity (e.g., CLIP [2] score). Let $\mathrm{range}(E) = \max(\mathrm{cov}(\cdot, E) - \min(\mathrm{cov}(\cdot, E))$, then $f : [0, \mathrm{range}(E)) \to [0, 1]$ is a linear interpolation which satisfies $f(0) = 1$ and $f(\mathrm{range}(E)) = 0$. Then the initial weight of I_{n+1} is calculated as follows:

$$w_{n+1} = \frac{1}{n} \sum_{i=1}^{n} w_i \cdot \mathrm{sac}(i, E) \tag{2}$$

3 Demonstration

Based on the methods above, we have developed QiboGraph. Two typical use cases are given as follows.
Use Case 1: Knowledge Graph Query and Visualization. Within the system, users can query using SPARQL [1]. Nodes with lower confidence are rendered in orange whereas high-confidence entities are rendered in blue. This feature helps to identify potential knowledge inconsistencies within the knowledge graph and establish a cognitive error analytics systems.
Use Case 2: Crowdsourcing and Automatic Update. The nodes of graph can be upgraded, downgraded or issued qualified opinion, of which each vote type will slightly change the node score based on the weight of the voter. When a node is confirmed to be deleted or materialized, all voters will receive their shares of weight which they are able to check in their profiles.

The Fig. 3 shows the GUI of aforementioned use cases.

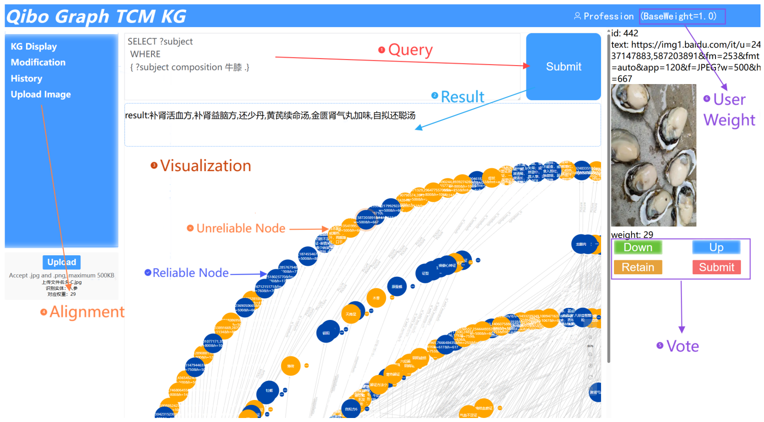

Fig. 3. GUI of QiboGraph.

4 Conclusion

This paper presents a multimodal knowledge graph QiboGraph for TCM, which introduces a crowdsourcing mechanism and expertise-adaptive system to enable collaborative editing by both experts and end users, ensuring the experts are valued and end users are taken into account as well. In order to align images with texts and accelerate the convergence of the credibility score of the untagged image, QiboGraph develops a two-stage pipeline, which assigns the image a rational weight based on its semantic similarity between other images regarding the entity, which can improve the usability and reliability effectively.

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