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# A Survey on Application of Knowledge Graph

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**Abstract.** Knowledge graphs, representation of information as a semantic graph, have caused wide concern in both industrial and academic world. Their property of providing semantically structured information has brought important possible solutions for many tasks including question answering, recommendation and information retrieval, and is considered to offer great promise for building more intelligent machines by many researchers. Although knowledge graphs have already supported multiple “Big Data” applications in all sorts of commercial and scientific domains since Google coined this term in 2012, there was no previous study give a systemically review of the application of knowledge graphs. Therefore, unlike other related work which focuses on the construction techniques of knowledge graphs, this present paper aims at providing a first survey on these applications stemming from different domains. This paper also points out that while important advancements of applying knowledge graphs' great ability of providing semantically structured information into specific domains have been made in recent years, several aspects still remain to be explored.

## 1. Introduction

In recent years, knowledge graphs (KGs) have become the base of many information systems which require access to structured knowledge. The concept of Semantic Web can be traced back to Berners-Lee's [1] research in 2001. In his work, Berners-Lee suggested that the technical standards such as Uniform Resource Identifier (URI), Resource Description Framework (RDF) and Web Ontology Language (OWL) should be promoted and developed.

Some researches contributed to promote the graph-based representation of knowledge by employing the RDF standard in early days. Nodes in such graphs represent entities and they are connected by edges which represent relations. The sets of relations can be organized in a schema or ontology which defines their correlativity and restrictions of their usage.

The concept of Linked Data [2] came out in 2009. It is proposed to link different datasets to each other in the Semantic Web to make them be treated as one large, global knowledge graph. Until 2014, approximately 1,000 datasets are linked with each other in the Linked Open Data cloud, most links between them connect identical entities [3].

In 2012, Google proposed a new technology, called Knowledge Graph, to use semantic knowledge in web search. Google's knowledge graph is used to identify and disambiguate entities in text, to enrich search results with semantically structured summaries, and to provide links to related entities in exploratory search, for the purpose of improving the ability of the search engine and enhancing the search experience of users. After that, many other companies started to develop their own knowledge graphs. For example, Bing, a search engine developed by Microsoft, has integrated with Satori, a similar knowledge graph. Nowadays, “Knowledge Graph” is also referring to semantic web knowledge bases such as DBpedia [4], YAGO [5], Wikidata or Freebase [6].



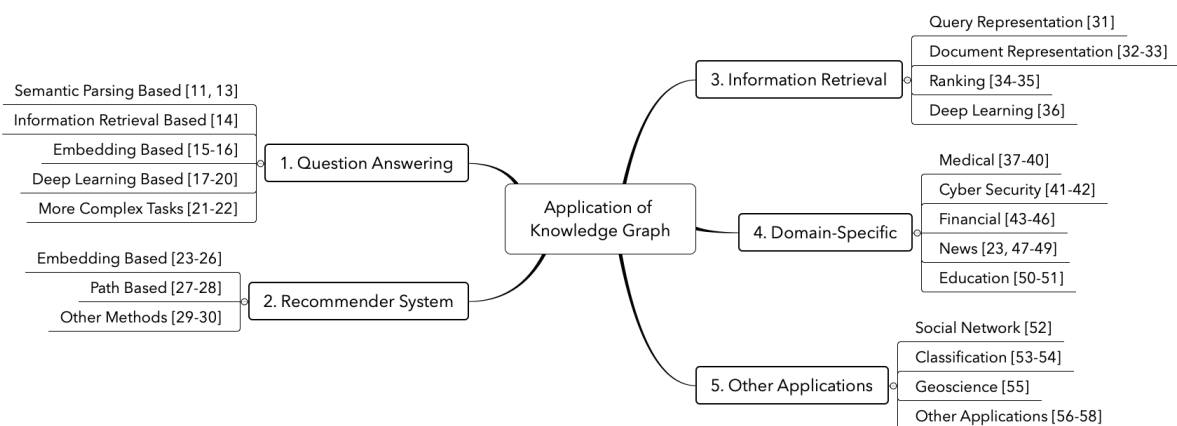
Knowledge graphs have caused wide concern in both industrial and academic world. They provide semantically structured information which can be interpreted by computers, and such property is considered to offer great promise for building more intelligent machines by many people. Many reviews about knowledge graphs focused on the construction techniques [7-8], however, although knowledge graphs have already supported multiple “Big Data” applications in a variety of commercial and scientific domains, there is no review about the application of knowledge graphs. Therefore, the main contribution of this paper is to give a first survey on applications of knowledge graphs.

This paper is organized as the follows. Section 2 introduces the applications which KGs have been employed in. Section 3 presents our conclusions.

## 2. Application

Knowledge graph technology has drawn a lot of research attentions in recent years after being proposed by Google. Researches on KGs can be classified into two categories, researches on construction techniques of KGs and application of KGs. Studies on construction techniques focus on the extraction, representation, fusion, and reasoning of the knowledge in the graphs [7], such as linking entities and relations to KG correctly after extracting them from unstructured text and reasoning new facts from such KG. While studies on application stress applying KGs to practical systems and specific domains. This paper gives a systematic survey on applications of knowledge graphs.

According to our current survey, most papers devoting to applying KGs into specific areas have put their interests on question answering system, recommender system and information retrieval system, which will be introduced in from section 2.1 to section 2.3 in this paper. Section 2.4 describes some specific domains in which KGs have wide application prospects such as medical, financial, cyber security, news and education. Section 2.5 introduces some other possibilities of application for KGs like social network or classification. A taxonomy of the application fields of KGs in this paper is given in figure 1.



**Figure 1.** Application fields of KGs.

### 2.1. Question Answering System

Semantic information from KGs can be used to enhance search results in semantic-aware question answering (QA) services. Watson, a question answering system using several knowledge bases such as YAGO and DBpedia as its data source, is developed by IBM to defeat human experts in the program of Jeopardy, which can be used to show such value of KGs [9]. Structured knowledge is also an important component of social chatbots and digital assistants such as XiaoIce [10], Cortana and Siri.

Many researches on question answering system use Freebase as source of knowledge and test their systems on WebQuestion including 5,810 question answering pairs [11] or SimpleQuestion containing

more than 100k simple questions which can be answered by the extraction of a single fact [12]. Traditional QA systems over KG can be classified into three groups: semantic parsing based, information retrieval based and embedding based. And in recent years, deep learning methods are combined with tradition methods to improve the performance of KG based QA systems.

*2.1.1. Semantic Parsing Based.* Semantic parsing based QA systems work on transforming natural language questions into logic forms which can express the semantics of the whole queries. Then, the parse results are used to generate structured queries (e.g. SPARQL) to search knowledge bases and obtain the answers. Bercant et al. [11] use Freebase to construct a coarse mapping between phrases and predicates. Then they employ all predicates, including neighboring predicates and additional predicates which are generated based on them by a bridging operation, in a given question to generate an exact query and obtain the right answer. Fader et al. [13] factor questions into a set of smaller, related problems and map each small problem to a query in order to find its corresponding answer. Then they combine all answers together to answer the given question. Semantic parsing method shows a good performance when dealing with complex questions. However, it depends on large hand-crafted features for semantic parsers, which limits the application domains and scalability of their method.

*2.1.2. Information Retrieval Based.* Information retrieval based QA systems try to automatically translate natural language questions into structured queries. Then they retrieve a set of candidate answers from the knowledge base. Finally, features of the question and candidates are respectively extracted to rank these candidates with the proposed of identifying the right answer from them. This kind of method concerns little about the semantics of natural language questions and achieved good results only in dealing with simple queries. For example, in [14], linguistic information such as question words, question focuses, question verbs and question topics are extracted from a given question in order to transform this question to a question feature graph. Then, a topic graph which composed with topic nodes and other relative nodes in Freebase is formed, each node in topic graph is considered as a candidate answer. Finally, features extracted from both candidate answers and topic graph are combined to identify the right one from candidate answers. This method relies on rules and dependency parse results to extract hand-crafted features for questions.

*2.1.3. Embedding Based.* The research work [15] is an example of embedding based QA systems. The authors start by learning low-dimensional vector embeddings of given question and of entities. Then, they relate types of Freebase to calculate the similarity score between the question and candidate answers. Finally, the candidates with the highest similarity score will be considered as the final answers. The research work [16] also uses embeddings as its core. It exhibits enticing adaptability on imperfect labeled training data. Besides, it proposes an approach to fine-tune embedding-based models and then improve the performance consistently. Such achievement depends on careful optimization of a matrix parameterizing the similarity adopted in the embedding space. Compared to the semantic parsing method and the information retrieval method, the vector modeling method achieves a competitive performance without any hand-crafted features or additional systems for part-of-speech tagging, syntactic or dependency parsing during training. However, it ignores word order information and cannot process complicated questions.

*2.1.4. Deep Learning Based.* With the rapid development of deep learning in the field of natural language processing, many researches started to improve the performance of traditional methods by using deep learning method and achieved good results. Dong et al. [17] use multi-column convolutional neural networks (MCCNNs) for information retrieving without relying on hand-crafted features and rules. They employ a score layer to rank candidate answers according to the representations of questions and candidate answers. Hao et al. [18] provide an end-to-end neural network model with cross-attention mechanism which considers various candidate answer aspects to represent the questions and their corresponding scores. Yih et al. [19] suggest that traditional

approaches for semantic parsing are largely decoupled from the knowledge base. Inspired by information retrieval method and embedding method, they reduce semantic parsing to query graph generation and formulate it as a staged search problem to make full use of the knowledge in knowledge bases. They also apply a deep convolutional neural network (CNN) model to leverage the knowledge base in an early stage to prune the search space and thus simplifies the semantic matching problem. Zhang et al. [20] propose an attention based bidirectional long short-term memory (BiLSTM) to learn the representations of the questions when using embedding approach. The experimental results show that their approach is effective and has a better ability of expressing the proper information of questions.

*2.1.5. More Complex Tasks.* In recent years, some researches also focused on more complex QA tasks. Unlike other work which focuses on fact-finding extractive QA, the research work [21] focuses on multi-hop generative task. According to this work, a model with multi-attention mechanism is used to perform multiple hops of reasoning and the answer is synthesized by a pointer-generator decoder. This work also presents a method to fill in gaps of reasoning between context hops by using grounded multi-hop relational commonsense information selected from ConceptNet. The work [22] focuses on Code-Mix Simple Questions QA which contains two languages. It proposes a Triplet-Siamese-Hybrid CNN (TSHCNN) to re-rank candidate answers and uses K-Nearest and bilingual embedding for language transformation.

## *2.2. Recommender System*

With the advance of internet technology, the overwhelming volume of online content such as commodities, movies and news become a serious problem to users. Recommender systems which is arising in this environment alleviate the information overload faced by individuals. Collaborative filtering (CF) is a traditional recommendation method performing the recommendations based on users' common preferences and historical interactions. However, this method usually suffers from the sparsity of users' data, such as user-item interactions, and the cold start problem. Therefore, solving such problems in order to make improvement in recommender systems by using side information is of great importance.

Recent studies start to consider KGs as the source of side information. The relations with various types in a KG help to improve the recommender accuracy and increase the diversity of recommended items. KGs also brings interpretability to recommender systems. In general, most existing method of building KG based recommender systems can be classified into embedding based and path based approaches.

*2.2.1. Embedding Based.* One feasible way of taking advantage of KGs in recommender systems is embedding based method, which preprocesses the KG by knowledge graph embedding (KGE) algorithms and applies the learned entity embeddings to a recommendation framework. DKN [23] is a method based on CNN proposed to combine entity embeddings with word embeddings for news recommendation. Zhang et al. [24] present a unified Bayesian framework, in which a CF module is combined with text embedding, image embedding and knowledge embedding of items. The work [25] develops several networks of social, profile and sentiment by using a deep autoencoder for recommendations. Wang et al. [26] designs a cross & compress unit to automatically share latent features between KGE task and recommendation task, and learn high-order interactions between items in recommender systems and entities in the KG.

Although embedding-based methods have exhibited their high flexibility in applying KGs in recommender systems, they can hardly contain side information expect for texts. Also, commonly-used KGE algorithms of embedding-based methods are not suitable enough for recommendation.

*2.2.2. Path Based.* Another more natural and intuitive way called path based method is to design a graph algorithm directly to explore a variety of patterns of connections among nodes in KG to provide

additional information for recommendations. KG is considered as a heterogeneous information-based network in the research work [27]. In this work, meta-graph/meta-path based latent features are extracted from KG to represent the link between items and users along different types of relation graphs/paths. Wang et al. [28] adopt a LSTM network to generate representations of path by composing the semantics of both entities and relations and allows effective reasoning on paths by leveraging the sequential dependencies within a path.

Although this method makes use of KG more naturally and intuitively, it seriously depends on hand-crafted designed meta-paths that is hard to optimize in practice and is not possible to be designed in some special scenarios where entities and their relations are not within one domain such as news recommendation.

*2.2.3. Other Work.* RippleNet [29] is a method trying to combine the advantages of the aforementioned two types of methods. It propagates users' potential preferences in the KG and discovers their hierarchical interests. It incorporates the KGE approaches into recommendation system naturally by propagating the preference information and does not need any hand-crafted design. However, this method pays less attention on relations. Also, with the increasing size of KG, the size of ripple set may become unpredictable, which will lead to a large amount of computation and storage overhead.

Cao et al. [30] notice it is very common that a KG has missing entities, relations, and facts. Therefore, they complete the missing facts in KG based on the enhanced user-item modeling after utilizing the facts in KG as auxiliary data to augment the modeling of user-item interaction.

### *2.3. Information Retrieval*

Because of the emergence of KGs, more and more commercial web-based search engines today are incorporating entity data from KGs to improve their search results. For instance, Google incorporates data from Google Plus and Google Knowledge Graph, while Facebook perform the search tasks over entities with Graph Search.

KGs' property of containing human knowledge about real-world entities assist search systems with improving their ability of understanding queries and documents. Some researchers are focusing on exploring KGs' potential for information retrieval. The entity-oriented search develops with the development of large-scale KGs. There are many possible ways to utilize KGs' semantics in different components such as query representation, document representation and ranking of a search system.

Query representation can be improved by introducing related entities and their texts to expand the query. For example, the work [31] provides features from entities themselves and links between entities to knowledge bases, such as structured attributes and text, are used to enrich the query.

Document representation can be enriched by adding the annotated entities into the document's vector space model. In the research work [32], bag-of-entities vectors are generated from entity annotations of queries and documents to represent them. Then, the output matches between documents and queries in the entity space are used to rank documents. The work [33] models queries and documents as a set of semantic concepts obtained from running them through an entity linking system.

Another way is to build the additional connections from query to documents through related entities to improve ranking model. Liu et al. [34] map both queries and documents to a high-dimensional latent entity space, in which each dimension corresponds to one entity, and then estimate the relevance between query and document based on their projections to each dimension in the latent space. Xiong et al. [35] contribute to capturing more semantic relevance patterns. In their work, cross matches between entity and word representations are incorporated with a four-way interaction.

While entity-oriented search which incorporates human knowledge from KGs is showing promising results in information retrieval system, deep learning techniques make it possible to learn more complex ranking models from large-scale training data. The research work [36] introduces KGs to neural search systems. It integrates semantics from KGs in distributed representations of their entities and ranks documents by interaction-based neural ranking networks.

## 2.4. Domain-Specific

*2.4.1. Medical.* While healthcare information is growing explosively, textual medical knowledge (TMK) is occupying a more and more important position in healthcare information systems. Therefore, some researches develop and integrate the TMK into knowledge graphs to provide computers with retrieving and interpreting medical knowledge in a correct and quick way. Ernst et al. [37] propose a method to construct a large biomedical science knowledge graph automatically. Their data source is the entity thesaurus from UMLS and input sources from a variety of scientific publications and postings in different health portals, which were unable to integrated with health data. Shi et al. [38] are success to integrate health data into heterogeneous textual medical knowledge. They also provide an algorithm to prune the meaningless inference over the knowledge graph to improve the performance of inference results. Goodwin et al. [39] focus on incorporating the belief state of the physician for assertions in the medical record using the framework proposed by the i2b2 challenge in 2010. Rotmensch et al. [40] propose an approach to generate a graph mapping diseases to the symptoms, which might cause from electronic medical record (EMR) data automatically. Their data source includes emergency department medical records of over 270,000 patient visits.

These approaches for constructing medical KGs depend on authentic standard medical terminology, which is lacking in some languages such as Chinese. Therefore, attempts to build medical KGs on such languages always receive a result with relatively low accuracy. Construction algorithms still need to be improved to solve such problems in future work.

*2.4.2. Cyber Security.* As the development of information technology, information security is concerned more by society and industry. KG can be combined with cybersecurity in order to detect and predict dynamic attacks and safeguard people's cyber assets. Jia et al. [41] build a cybersecurity knowledge base using machine learning and present a quintuple model to obtain the new knowledge via the path-ranking algorithm. Qi et al. [42] demonstrate cyber-attacks steps and define the relationship between attacks, events, and alarms by adding event ontologies when building the KG. Then they propose an association analysis algorithm based on the idea that some attack steps have many combinations but they are related to the same alarm.

The aforementioned works focus more on the construction of cyber security KG. However, how to effectively detecting the cyber security events by using the inherent knowledge reasoning ability of KG and update KG quickly with the new discoveries of analysts still need further research in future.

*2.4.3. Financial.* Liu et al. [43] build an enterprise KG by crawling the news of each company, identifying named entities and extracting business relations between relevant stocks. They combine news sentiment of correlated stocks via Gated Recurrent Unit (GRU) model in order to predict stocks' price movement. Their approach uses relations between stocks for prediction, so how to identify the stocks with strong correlation between them in a large KG is a problem to be solved. The work [44] proposes an open, fine-grained, freely-accessible scheme for company identifiers in KGs.

Cybersecurity insurance (CI), which mainly provides service to the financial industry and assists financial companies with reducing cybersecurity risks, also has been booming. The difficulty for insurance vendors when classifying cyber incidents caused by complicated relations between insurance items is a problem in CI. Elnagdy et al. [45] suggest that combining knowledge graph with ontology is an efficient method for identifying the complicated relations between entities in CI field. The work [46] proposes a taxonomy model for cyber incidents called SCIC, which links all ontologies in semantic web to generate knowledge representation.

*2.4.4. News.* In general, news is dynamic and change over time, and news language is highly condensed, as well as full of knowledge entities and common sense. Therefore, some researches apply KGs in news field to deal with such characters. DKN [23] employs knowledge graph representation in news recommendation to fully discover latent knowledge-level connections among news in order to

extend the recommended results for users reasonably. The work [47] develops a tool to construct event-centric KGs from news reports describing changes in the world in various languages including English, Italian, Dutch and Spanish automatically. The work [48] aggregates unstructured news articles and structured Wiki data which describes events to retrieve news articles describing events.

On the other hand, the widespread of fake news may exert a great deal of negative influence on society. Fake news detection problem is viewed as a link-prediction task in a KG by the research work [49]. This work mines heterogeneous connectivity patterns from a factual statements network to examine the authenticity of an assertion.

Considering that news always spread quickly between countries, improving the performance of some key tasks such as entity resolution and semantic role labelling is extremely necessary, especially in multilingual environment.

*2.4.5. Education.* In education domain, some studies have adopted KGs for learning resource recommendation and concept visualization. KnowEDU [50] is a system to construct KG for education automatically. Unlike general KGs in which nodes represent entities of common real world, desired nodes in educational KGs represent instructional concepts that learners should master. Therefore, this study applies recurrent neural network (RNN) models on pedagogical data to extract instructional concept. Then, the educational relations which interlink instructional concepts are identified through the probabilistic association rule mining algorithm by using students' performance data. Grévisse et al. [51] present a tool to recommend and integrate learning material in popular authoring software. They exploit additional information from open KGs through expansion and filtering strategies to build a semantic representation and identify the most important concepts for teachers, then they use these concepts to pinpoint and retrieve related learning resources from an open corpus.

Current researches always focus on basic relationship extraction only. A more in-depth and accurate relationship extraction may help to show more latent information of data in educational KGs.

## *2.5. Other Applications*

Depicting the social network de-anonymization and privacy inferring process is a further application where KGs have been applied. Such application helps to determine and measure privacy disclosure [52]. In this scenario, nodes represent users, while links represent users' relations. The problem of de-anonymization is transformed into the maximum weighted bipartite matching problem and Locality-Sensitive Hashing (LSH) is used for privacy inferring.

Some researchers also consider about using KGs for classification. Zhang et al. [53] take full advantage of the knowledge graph that is closer to the biological visual information-processing model to study the relationship between categories in the image, and combine the semantic calculation method to guide the image classification task. Ma et al. [54] improve the classic LSTM cell with adding components integrating with external knowledge, which directly contributes to the identification of aspects and sentiment polarity for sentiment analysis.

While mainly geoscientific research work focuses on processing georeferenced quantitative data, some researchers are trying to extract information and knowledge discovery from the textual geoscience data. The work [55] processes geological documents and extract knowledge directly through an unsupervised learning approach. Then it builds a KG by using documents processing and dictionary expanding technology with linked open data. However, these work does not implement the information retrieval between the knowledge graph and the original literature.

KGs can also help to combat human trafficking. In order to assist related organizations with finding traffickers and helping victims, Szekely et al. [56] build a large KG for the human trafficking domain. They use ads of sex trafficking industry continuously crawled from web sites as their data source and reconcile these data from different sources via semantic technologies.

The work [57] suggests that KGs can be applied to machine translation and this insight is supported by the research work [58] which contribute to aligning entities across languages by generates multilingual knowledge graph embeddings.



### 3. Conclusion

To the best of our knowledge, this paper is the first to systemically review about different applications of knowledge graphs stem from different fields like question answering, recommendation, information retrieval and other domains. Overall, we conclude that while knowledge graphs have great ability of providing semantically structured information and important advancements of applying such ability into specific domains have been made in recent years, several aspects remain to be explored.

In future work, we plan to extend this survey by integrating not only applications, but also methodological extensions of the KG-based algorithms.

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