Application of Neural Network Based Knowledge Graph in Vertical Industry

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Abstract. Knowledge graph was mentioned first by Google, now is used to refer to a wide variety of large-scale knowledge bases, in both general areas and vertical industry areas. Techniques such as knowledge fusion, knowledge extraction, knowledge reasoning and knowledge expression are key techniques in knowledge graph which need to be researched urgently. Neural network technologies have achieved hugely these years, the technique has been readily applied to a variety of practical engineering problems such as pattern recognition, signal processing and control systems. In this work, we represent how to implement the neural network technique to knowledge reasoning technology, to achieve the completion of knowledge base, to predict hidden relationships among entities through reasoning inside a specific knowledge base. We also show the possibility of knowledge graph applied to one vertical industry, namely the electrified power grid industry. This paper shows that knowledge graph can apply to the whole power processing procedures, such as electric power producing, operating and marketing procession, and electric power equipment operation and maintenance, as well as customer service.

1. Introduction

Knowledge graph was first mentioned by Google [1] for improving the ability of searching engine, as well as enhance user search experience. Knowledge graphs can be used to formally describe things and their relationships in the real world, which now has been used to refer to a wide variety of large-scale knowledge bases. In knowledge graphs, triplets are viewed as a general representation method usually expressed as (Entity, Relationship, Entity).

Work [2-4] represents entity with one vector. Work [5] each entity is showed as the average of its word vectors, by improving vector representing, it allows the sharing of statistical strength between words to describe each entity.

Knowledge graphs can be used in general areas and vertical industry areas, general constructed knowledge graphs focus on knowledge breadth and integrates more entities, typically applied in areas such as intelligent search engine, in-depth question & answering system, social networks, machine translating. Vertical industry knowledge graphs rely on industry-specific data, in the vertical industry areas, knowledge graph has taken its way into financial, medical & healthcare industry, as well as e-commerce industries.

There are two ways to build a knowledge graph: the top-down construction and the bottom-up construction. Either way, ontologies and knowledge bases bear the incompleteness and the lack of reasoning capability.
2. Several typical knowledge graphs
Freebase [6] is a large-scale collaborative repository of metadata, with contributions coming from community members, it incorporates online resources, including content from some wiki sites. The basic model of its data structure includes: Topic, Type, Domain, and Property.

DBpedia[7] as a multi-language knowledge base, extracting structured information from Wikipedia, is a community effort, it is created by researchers from the Germany, DBpedia also publish its information on the Web, making it accessible for online networking applications, social networking sites and other online repositories. Domains DBpedia covers include: geographic information, people, companies, films, music, genes, drugs, books and scientific publications.

YAGO [8] is a large ontology with high coverage and high precision built by Max Planck Institute(MPI). YAGO derived automatically from Wikipedia and WordNet. Facts in YAGO have been extracted from category system and infoboxes of Wikipedia, and also have been combined with taxonomic relations from WordNet. YAGO has been used in multiple major ontology projects.

3. Key technology
Construction and application of knowledge graph need the support of various AI technologies, for example: knowledge extraction, knowledge fusion, knowledge reasoning and knowledge expression.

3.1 Knowledge reasoning with neural network
Patterns and classifiers are usually applied to large text corpora to solve problems of how to extending existing knowledge bases, but the results are not obviously better applied to knowledge expression, predicting truth or knowledge reasoning in the knowledge base are not achieved well. The goal of knowledge reasoning is to predict additional truth accurately or expressions by use of the existing database or known facts. Knowledge reasoning can be used in entity attributes, entity relationships, the structure of concepts in the ontology base.

Methods of knowledge reasoning are categorized into: logic-based reasoning and graph / vector-based reasoning. Logic-based reasoning includes mainly method based on first order logic, as well as description logic. Graph-based reasoning involves relation Path based method. Knowledge reasoning also contains the following techniques: knowledge graph completion technique / knowledge base completion technique, knowledge graph refinement techniques, which involving operations such as link prediction, entity prediction, relation prediction, attribute prediction.

![One-layer neural network](image)

**Figure 1.** One-layer neural network

One-layer neural network is shown in Figure 1, in which \( p_1, p_2, p_3, p_R \) are multiple inputs, which also can be presented as input vector \( P \). \( w_{1,1}, w_{5,R} \) are the weight of each input to each accumulator, \( b_i \) is the bias of each neuron, each neuron has its own transfer function \( f \), and the \( a_i \) is the output of each neuron, which also can be taken together as the output vector \( a \). Weight elements \( w_{ij} \) are also
be represented as matrix $W$:

$$W = \begin{pmatrix} w_{1,1} & w_{1,2} & \ldots & w_{1,R} \\ w_{2,1} & w_{2,2} & \ldots & w_{2,R} \\ \vdots & \vdots & \ddots & \vdots \\ w_{S,1} & w_{S,2} & \ldots & w_{S,R} \end{pmatrix} \quad (1)$$

Vector $a$ is as the follow equation:

$$a = \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_s \end{pmatrix} \quad (2)$$

In recent years, deep learning technologies have achieved hugely these years, semantic information of entities can be represented as dense low-dimensional real value vectors, the calculation and their complex semantic relations of entity relations can be efficiently achieved, which is of great significance to the construction, reasoning, fusion and application of knowledge base. Representative models of knowledge representation mainly include distance model, bilinear model, neural tensor model, matrix decomposition model, and Trans model.

Neural Network is definitely a hands-on approach to the knowledge reasoning technology, in the neural tensor model, article [5] represents each entity as a vector, in order to capture facts about that entity and show the probability of it as part of a certain relation, with each relation defined by parameters of a neural tensor network (NTN) which can explicitly relate two entity vectors. The NTN provides a more powerful way than a statistical model. They use large unlabeled text as the training triplets to obtain a more accurate performance when predicting underlying knowledge relationships.

By learning vector representations, the neural tensor network reasons over database entries, each relation triple is described by a neural network and pairs of database entities, which are given as inputs to that relation’s model, the model returns a high score if they are in that relationship and a low one otherwise. This allows any fact, whether implicit or explicitly mentioned to be answered with a certainty score in the database [5].

$$g(e_1, R, e_2) = u^T_{Rf} \left( e_1^T W^{[1:k]}_R e_2 + V_R \left[ e_1 \right] + b_R \right) \quad (3)$$

Where $f = \tanh$ is a standard nonlinearity transfer function, $W^{[1:k]}_R \in \mathbb{R}^{d \times d}$ is a tensor, $u^T_{Rf}$ is the vector representation of the entity relation, $e_1^T W^{[1:k]}_R e_2$ is the bilinear tensor product, it results in a vector $h$, $h \in \mathbb{R}^k$.

The work carries experiments on both WordNet and FreeBase, the above model can obtain knowledge by learning relationship classifiers and entity representations jointly. Each triplet uses a specific related neural network to do the learning, the head entities and tail entities are used as input, with the relationship tensor, formed a bilinear tensor for third-order interaction. At last, the model returns the confidence of the triplet.

The work [9] introduces a similar neural tensor network model to predict new possible relationships, to predict the relationships of entities that take no appearance in the knowledge graph by initializing the entity representation of the word vectors learned from the unsupervised text.

Neural network based knowledge reasoning is trying to apply the great learning ability of neural network to build triplets, so as to obtain reasoning ability. At present, neural network based knowledge reasoning research is relatively less than other methods, but the high expression ability has proved great when applied to other research areas, especially in social network which focus on graph structured data, the outstanding performance of neural network method inspired further application in the knowledge graph area.

### 3.2 Other key techniques

Knowledge extraction mainly direct at open linked data, by using automatic technology, to extract available knowledge units, which include three basic elements: entity, relationship and attribute. Entity extraction stands as the most basic and critical step in knowledge extraction process, as the extraction
completeness, extraction accuracy and extraction recall rate of entity extraction will directly affect the quality of knowledge base.

The goal of relationship extraction is to solve problems existed in the semantic links between entities. Open information extraction (OIE) [10] is a relation extracting method which makes a huge improvement in the extraction model. However, the performance of OIE method is low in the extraction of the implied relation of entities, researchers propose a deep implied relation extraction method based on Markov logic net and ontology reasoning [11].

Attribute extraction forms the complete picture of the whole entities, and large amounts of attribute data exists mainly in large-scale open domain data sets which are full of semi-structured and unstructured data, extracting these properties can emerge with methods of relation extraction.

4. Application of knowledge graph in vertical industries

Knowledge graph has been typically applied in areas such as intelligent search engine, in-depth question & answering system, social networks, machine translating, and vertical industry platforms. In the intelligent search area, Google has come out with the product of Knowledge graph and Knowledge Vault, Facebook proposed Graph Search, Microsoft launched Bing Satori, Sogou takes out the Zhilifang, Baidu also applied Knowledge graph to the use of its search engine. It can better understand user's search intention, providing in-depth search results which can parallel with the marvelous vertical search results. In the question & answering area, Watson from IBM, Siri from APPLE, AMAZON’s echo device Alexa are the recent representative applications which have revealed extremely high intelligence.

In the vertical industry areas, Knowledge graph has taken its way into financial, medical & healthcare industry, as well as e-commerce industries. By integrating structured and unstructured data from different sources, analyze complex relationship network, Knowledge graph is able to build anti-fraud engine to effectively identify fraud related cases. Knowledge graph could also help Anomaly Detection, as well as precision marketing.

Vertical industries also need to introduce Knowledge graph to its uses, such as electrified power grid industry.

In the producing, operating and marketing procession, the electric power grid has accumulated various types of large volume operational data with high value, which possess close and strong correlation with each other. Deployment of knowledge graph can enhance/improve the capacity of the grid operation, operational management as well as first-rate custom service in the area.

In electric power producing, the accessing of a large number of new of energy type forms, such as wind electricity, photovoltaic energy, energy reservation have broken the traditionally relative static power producing, as a result, power production measurement and power production management becoming more and more complex. How to intelligently manage each unit of electric power production by knowledge graph is a topic worth pursuing.

In power operational process, with the gradual evolution of power grid system, highly flexible data-driven and relation-driven electric power supply chain will replace traditional power supply chain, the supply chain will become more automatic and quicker in response. How to use knowledge graph to deduce the possible changes is a topic worth exploring.

In the electric power equipment operation and maintenance of all kinds, how to use knowledge graph to accurately predict and analyze the equipment state and the equipment fault feature, and predict the equipment faults in different voltage levels in each region per day or per month in the future, so as to effectively shorten equipment breakdown repair time and improve the reliability of electric supply.

In the customer service, how to construct knowledge graph of traffic volume, user behavior, so as to improve the prediction accuracy and deviation rate of traffic volume, and improve the scientificalness of the scheduling of telephone operators.

Knowledge graph is also needed in other vertical industries such as education and research, librarianship, biomedical, banking, which are in urgent need of data resources for integration and
relevance. Knowledge graph can provide with more accurate and standardized data and relation expression, helping the acquirement of industry knowledge more easily.

5. Conclusion
In the future, Knowledge graph will be the frontier of AI research area, technologies such as knowledge acquisition, knowledge extraction, knowledge representation, knowledge reasoning, knowledge fusion and other related technologies still need to be perfected by the joint effort of Academia and industry. Skills of large open domain based knowledge acquisition, hidden and implicit knowledge extraction, trans-language knowledge extraction are still in its very early stages. When encountered complex entity relations, multiple sources information fusion, the ability of knowledge extraction should to be further developed.

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