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Knowledge Engineering With Big Data (BigKE): A 54-Month, 45-Million RMB, 15-Institution National Grand Project

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ABSTRACT Starting in July 2016, the Ministry of Science and Technology of China, along with several other national agencies, sponsors a 54-month 45-million RMB (Chinese Yuan) project on knowledge engineering with Big Data (www.bigke.org) for 15 top research and development institutions to study the fundamental theory and the applications of BigKE, a big-data knowledge engineering framework that handles fragmented knowledge modeling and online learning from multiple information sources, nonlinear fusion on fragmented knowledge, and automated demand-driven knowledge navigation. The project seeks to provide petabyte-scale data and knowledge services in identified application domains. In this paper, we discuss our BigKE framework, and present a novel application scenario for BigKE services.

INDEX TERMS Knowledge engineering, data mining.

I. INTRODUCTION

Knowledge engineering [6] was defined as applied artificial intelligence with three fundamental scientific issues: knowledge representation, knowledge utilization/inference, and knowledge acquisition. In the big data era, these three fundamental issues have to change with the essential characteristics of heterogeneous, autonomous information sources for complex and evolving relationships [15] among data objects. With big data, knowledge does not rely only on domain expertise, but also fragmented knowledge pieces from multiple information sources. Hence we need big knowledge to provide knowledge engineering services with big data.

With the 54-month, 45-million RMB, 15-institution project on Knowledge Engineering with Big Data (BigKE) sponsored by the Ministry of Science and Technology of China and several other national agencies, there are three key research issues to be investigated in this grand project: 1) fragmented knowledge modeling and online learning, 2) nonlinear fusion of fragmented knowledge, and 3) automated demand-driven knowledge navigation.

The major contribution of this paper is to address these issues. With 1), we will study fragmented knowledge and knowledge cluster representation, online collaborative learning of fragmented knowledge, and modeling of evolving knowledge with spatial and temporal characteristics. For issue 2), association and emerging pattern analysis in fragmented knowledge, and dynamic fusion of knowledge subgraphs will be concerned. Interactive context awareness computing, demand-driven knowledge navigation and path discovery, and optimization of interactive knowledge adaption will be under key topics for issue 3).

II. FROM BIG DATA TO BIG KNOWLEDGE

Wu et al. proposed a HACE theorem in 2014 [15] to formulate the essential characteristics of big data: big data derives from **h**eterogeneous, **a**utonomous sources and aims at exploring **c**omplex and **e**volving relationships among data objects. Due to these characteristics of multiple sources, traditional offline data mining methods are clearly incapable for streaming data since the data are required to be reformed. Online learning methods can help solve this challenge and swiftly adapt to drifting in streaming data. But conventional online learning methods are designed mainly for single source data. Thus handling these characteristics simultaneously bring forward great challenges and opportunities for big knowledge generated from big data.

Big knowledge starts with big data, deals with streaming data, including data streams and feature streams, and integrates fragmented knowledge from multiple data sources as well as domain expertise, for personalized demand-driven knowldge services. In the big data era, multiple data sources are usually heterogeneous and autonomous and contain complex and evolving relationships among data objects. These characteristics are considered by big knowledge. Meanwhile, big knowledge services provide personalized and real-time demand-driven services by big-data knowledge engineering [16].

Because of the characteristics of multiple data sources, processing fragmented knowledge [17] is the key in multi-source knowledge processing. Local knowledge pieces from individual data sources should be integrated to generate global knowledge. In order to acquire fragmented knowledge from local data sources, existing online learning algorithms often use linear fitting [5]. However, linear fitting cannot perform fragmented knowledge fusion efficiently, and may even cause over-fitting problems [9]. Numerous studies have been carried out for improving the quality of fragmented knowledge acquisition and representation [12], and there is an advantage of using machine learning for analyzing big data: most data samples are available, which reduces the possibility of overfitting to some degree [19].

Unlike traditional knowledge engineering which relies on domain experts, big-data knowledge engineering acquires knowledge mainly from user-generated contents in addition to authoritative sources of knowledge, like expert knowledge bases. User-generated contents provide a new kind of data sources that could be seen as an important carrier of human knowledge, and it also helps to solve the knowledge bottleneck problem in traditional knowledge engineering. User-generated contents are massive and heterogeneous which result in difficulties for storing and indexing [7], and the knowledge base should have abilities of self-evolving and propagation to establish concrete relationship models of data. For instance, clinical data in survey trials are probably incomplete and inconsistent for several reasons and preprocessing is needed to improve data for analysis [1]. These two abilities are essential for generating personalized services of the knowledge base, since the knowldge base should adjust itself according to individual user's requirements. Big knowledge intensifies fragmented knowledge to strengthen the two abilities. In order to solve personalized problems from the users, big-data knowledge engineering also needs to learn based on user's interactions.

III. BigKE: A FRAMEWORK FOR BIG-DATA KNOWLEDGE ENGINEERING

BigKE aims at fragmented knowledge modeling from multiple data sources, nonlinear knowledge fusion for fragmented knowledge, and demand-driven knowledge services.

A. KNOWLEDGE MODELING

Fragmented knowledge is a special topic in a particular field, and it hides in multi-source, heterogeneous data. This presents real-time dynamics of fragmented knowledge. For example, social networking produces numerous data with different structures, like tweets. When users look for information or express their views on an interesting topic, a number of real-time tweets are produced. Facing such a huge amount of information, we also need to distinguish emotional tendencies in user behaviors from complex semantic relationships. A user's behavior is independent, but the information they have published affects each other.

How to analyze and process user behaviors and the impact of other's behaviors among them are challenges for big knowledge analytics. Corresponding to this problem, the first step of BigKE is to design appropriate models for fragmented knowledge modeling. In this step, we need to consider data streams and feature streams. We seek to realize fragmented knowledge modeling through online learning from multiple data sources. From online learning with data streams and feature streams, we can evaluate data reliability as well as building models for data and feature streams with spatial and temporal characteristics.

1) SEMANTIC ENCAPSULATION OF FRAGMENTED KNOWLEDGE

Besides real-time dynamics of streaming data, in terms of data quality, fragmented knowledge in user-generated contents varies greatly in different sources. There are quality problems in authenticity, completeness and autonomy. Therefore, the aim of evaluating data reliability is to improve the quality of data we have processed. Meanwhile, concept drifting reduces data accuracy and the overall value of different data sources [13]. Incremental real-time data processing needs a dynamic model to update data modeling according to new data in order to assure that the acquired fragmented knowledge from multiple sources is useful and valuable.

For example, when we ask a question on a search engine, we hope to obtain relevant information as close as possible to the topic of our concern. However, multiple sources will likely provide different information pieces on different aspects of the topic, hence big-data knowledge engineering should integrate them and provide an overall picture of the different formation pieces for the user. Fragmented knowledge from multiple sources cannot integrate and show global and systematical information. BigKE aims at co-learning to distinguish relationships among data objects [10]. These data objects can evaluate and invoke mutual information [11].

Due to the characteristics of multiple sources in big data, there is redundancy during extracting fragmented knowledge. The authenticity of data sources is also manifested in this process. For example, in order to make a recommendation for its user, a mobile phone application may need to combine various aspects of its user's information, such as diet, exercise capacity, personal medical history, and other aspects of the user. However, these information pieces could violate privacy concerns, hence a tradeoff problem between privacy protection and data credibility is necessary to consider [3].

B. NONLINEAR KNOWLEDGE FUSION

After semantic encapsulation of fragmented knowledge, in order to acquire global knowledge of big data, BigKE requires a nonlinear knowledge fusion process. We represent fragmented knowledge using knowledge graphs [14], to provide an easy to understand representation of fragmented knowledge. Traditional knowledge engineering depends on domain experts, hence the knowledge bottleneck problem and the lack of user feedback and self-learning mechanisms. Big-data knowledge engineering extracts user-generated contents in addition to domain expertise. Therefore, traditional linear fusion is no longer sufficient to big-data knowledge engineering. By making inferences on fragmented knowledge, nonlinear fusion is expected to generate useful information that does not yet show in existing fragmented knowledge.

1) KNOWLEDGE GRAPH FOR FRAGMENTED KNOWLEDGE REPRESENTATION

There are reasons that BigKE adopts knowledge graph to represent fragmented knowledge. First of all, due to the evolving and dynamic nature of relationships among fragmented knowledge pieces, traditional linear fusion can not get associations among local knowledge fragmentations. The complexity of data representation from different sources can not be solved. Secondly, a path on a knowledge graph can be seen as a relationship of different local knowledge pieces. We can find a most matching path from the starting node to the destination node of a particular problem. This provides the possibility for the realization of personalized services.

When performing nonlinear fusion of fragmented knowledge, we focus on semantic associations. For example, the emotional tendencies in different social media comments on the same news event may be the same. Looking at comments on Weibo (a popular microblog in China), Wechat (an instant communication application), and Facebook, the same user could have the same emotional tendency. Therefore, BigKE considers additional information such as behavior information of the users. When the information from different sources of the same user conflicts, we will distinguish which emotional tendency is right.

Although there are various applications of personalized recommendations, such as social software to recommend people you may know, it is necessary for big-data knowledge engineering to update the contents and structures of knowledge graphs. For this purpose, BigKE analyzes the associations among fragmented knowledge by evaluating the reliability of subgraphs, which depends on the evolution of data relationships that can be represented as edges of a knowledge graph. Evaluating the reliability of subgraphs is expected to improve the quality of a knowledge graph and the accuracy of personalized navigation.

C. PERSONALIZED DEMAND-DRIVEN KNOWLEDGE SERVICES

The ultimate purpose of big-data knowledge engineering is to provide personalized demand-driven knowledge services. After nonlinear fusion of fragmented knowledge, we obtain a reliable knowledge graph. BigKE uses social and personalized information to model user's queries in conjunction with context awareness [8]. The accurate provision of a knowledge service in a knowledge graph is to find a best path between two nodes.

An example for personalized services is that different patients with the same disease may have different causes for the disease hence need different treatments. Therefore, we need to take a full account of each patient's daily activities, eating habits and other personal information to ensure a correct treatment. We should stand at the forefront of the development of scientific data, and actively explore ways to apply data analysis to personalized services.

1) KNOWLEDGE NAVIGATION

There is another characteristic of fragmented knowledge which is the lack of ordering. Autonomous data sources result in an implicit and sparse relationship among fragmented knowledge. This is to say, it is difficult to find and represent relationships among fragmentations of knowledge. How to represent fragmented knowledge dynamically and provide an adaptive formation of fragmented knowledge is another challenge for BigKE efforts. Would it be possible to use navigation to accommodate user demands?

Owing to the lack of integrity of personal information, it is often difficult to fully and accurately understand the real requirements of a user. A more integrative approach is needed to complement existing information fusion methods for path recommendations of big-data knowledge engineering. Knowledge navigation and path discovery in BigKE seek to predict the future behavior of a user. We can improve the quality of existing knowledge and the structure of a knowledge graph through modeling a user's future behavior. This is another difference between traditional knowledge engineering and big-data knowledge engineering. For the purpose of predicting a future behavior, some existing techniques can be applied, such as context awareness and collaborative filtering [2]. These techniques have been used in various studies. One advantage is to obtain and understand a user's demand accurately. However, in the era of big data, the large amount of streaming data makes the scale of knowledge graphs out of control, and therefore, inference and prediction on a large knowledge graph requires complex computing. Also, multidimensional data may result in a complex structure of a knowledge graph, and also reduce the reliability of the updated knowledge graph and the quality of navigation services.

During path discovery, BigKE provides knowledge navigation through a web-based learning system. To adapt to the graphical form of a knowledge graph, this learning system is an online system, where nodes and links correspond to a knowledge graph [4].

2) KNOWLEDGE COMPILATION AND PUBLICATION

One of the components in BigKE is to compile and publish knowledge from a knowledge graph. According to a user's personal needs, an effective knowledge service is to provide a straightforward and concise form to show relevant contents from a knowledge graph for the user in order to increase the availability and operability of the knowledge graph. It would be more attractive if a news recommendation system recommends news information of a specific theme with various types of media, such audio, video and pictures rather than just a long text.

IV. CHALLENGES OF BIG KNOWLEDGE

BigKE has its uniqueness when compared with existing big data models, and in the meanwhile, brings its own challenging problems.

- The challenge of nonlinear fusion of fragmented knowledge lies on the lack of an uniform representation of fragmented knowledge. BigKE deals with various types of data, such as (long and short) text messages in social networks, video, emails, and so on. Non-uniform data formats make it difficult to form a uniform logic of fragmented knowledge which is hidden in these data formats. Therefore, analyzing and inferring these data sources is challenging. It is necessary to abstract some details of the data which may sacrifice the accuracy of the global knowledge.
- The relationships among data objects can be seen as links in a knowledge graph. When new data or features arrive, the relationships may change. To extract real-time knowledge, the corresponding knowledge graph should be updated accordingly. There are two key problems in the dynamic updating of a knowledge graph: 1) how to set an appropriate time interval of the updating, and 2) how to determine whether a data item, or a link in the previous knowledge graph, should be modified.
- The main theme of BigKE is to discover and integrate fragmented knowledge from big data sources, and generate global knowledge from fragmented knowledge for personalized demand driven knowledge services. However, fragments are not of a uniform size. The granularity of division determines whether a data source provides sound fragmented knowledge. We would need to adjust the granularity according to actual application scenarios.
- Big data is not just data with a large amount, but the large amount of data needs to be stored and managed appropriately, and offer the possibility of simplifying the representation of the storage, access, and use of information fragmentations [18]. One example is manifold learning which is used to reduce dimensions of data and not reduce the quality of data characteristics.
- For improving the computing effectiveness, BigKE needs to adopt new distributed approaches. Current approaches include the Map-Reduce framework and the latest Spark framework. We need to split big data into many blocks and then assign them to different nodes. However, when fusing the results calculated in different nodes, the statistical value may be incorrect. Therefore, BigKE needs to process data blocks by taking consistency into consideration.
- Big knowledge from big data offers information to realize personalized knowledge services, and we need to model personal information. BigKE infers big knowledge on knowledge graphs which need filtering and selection algorithms with real-time characteristics. The knowledge graph structure is changing with new data, and user's requirements may also change. We should integrate emotional tendencies in BigKE to improve the quality of knowledge services.

V. BigKE SERVICES: A PROSPECT APPLICATION

BigKE seeks to provide tools and utilities for knowledge services in different application domains. Pervasive health, e-learning, and Internet+ are three identified areas for practical applications. We have Baidu (http://www.baidu.com/) and Ding XiangYuan (http://www.dxy.cn/), two of the largest search and healthcare companies in the world, are among the 15 collaborating institutions for the project. Within the 54-month project period, we will demonstrate 6-million users with PB-scale data and knowledge services. Below is a prospect application.

When a parent from a remote area in China has a medical problem, a child in the US can visit our BigKE website,[1] to

1) check what the problem is about based on the parent's available information (interactive context awareness computing);
2) find which hospitals and doctors can possibly provide medical treatment (demand-driven knowledge navigation and path discovery);
3) check and advise what a local hospital can possibly do if the patient is not willing or able to go to one of these recommended hospitals, by
    a) understanding what medical background and expertise the local hospital already has (fragmented knowledge modeling and online learning),
    b) map the information from (a) with the knowledge from (2) to see what Big Knowledge is required for the local hospital to treat the parent's medical problem (knowledge fusion and navigation),
    c) train the local hospital by compiling and navigating the Big Knowledge to implement the Big Knowledge at the local hospital (knowledge navigation and e-learning),
4) watch the patient's progress and update the Big Knowledge when necessary (context aware computing and knowledge adaption),

[1] This case assumes that the child cannot go back to China or find a proper delegate to assist her/his parent in real time.

5) update our patient databases and give feedback (knowledge navigation and adaption), and
6) connect the parent with other patients (knowledge fusion).

The above prospect illustrates the key techniques that are being developed with the BigKE grand project.

VI. CONCLUSION

This paper introduced the Chinese national grand project, i.e. Knowledge Engineering with Big Data (BigKE), for 15 top research and development institutions to study the fundamental theory and applications of BigKE. To explore the essential generation mechanisms underlying fragmented data, BigKE combines fragmented knowledge from multiple sources and domain expertise to provide reliable and personalized solutions to users. This could prove to be the most useful way of answering user queries, given the world's fragmented nature. We also presented a prospect application of BigKE in pervasive health.

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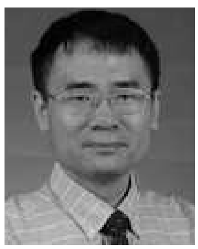

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