CS520

Knowledge Graphs

What should AI Know ?

What are some High Value Use Cases of Knowledge Graphs?

1. Introduction

Knowledge graphs are being used for a wide range of applications from space, journalism, biomedicine to entertainment, network security, and pharmaceuticals. We cannot do justice to discussing the full range of knowledge graph applications in this short chapter. Therefore, we have chosen the financial industry vertical for which we will describe three different flavors of knowledge graphs: analytics, tax calculations and financial reporting. The use of knowledge graphs for analytics is probably the most common usage. The use of knowledge graphs in tax calculations (or, more generally, for financial calculations), is similar to their usage in compilers and programming languages. Use of knowledge graphs for exchanging reporting data is an emerging area of application that will likely become increasingly important in the future.

2. Knowledge Graphs for Financial Analytics

Consider a large financial organization such as a bank that must deal with millions of customers some which are companies, and some are individuals. Such organizations routinely face questions that can be instantiated from the following templates.

1. If a company goes into financial trouble, which of our clients are its suppliers and vendors? Are any of those applying for a loan? How much of their business depends on that company?
2. In a supply chain network, is there a single company that connects a group of companies?
3. Which startups have attracted the most influential investors?
4. Which group of investors tend to co-invest?
5. Which companies are most similar to a given company ?
6. Which company might be a good future client for us?

To answer the first question above, we need data about suppliers and vendors of a company. Such data are usually available through third party data providers and must be purchased. The external data about the suppliers and the vendors must be combined with a company's internal data. Doing so leverages the techniques of schema mapping and entity linking that we considered in Chapter 4 for creating a knowledge graph from structured data. Increasingly, institutions are starting to leverage data from the daily news for market intelligence. To leverage the financial news, we will need to extract information from the text using the entity extraction and relation extraction techniques described in Chapter 5. Once a knowledge graph is built, we can use path finding algorithms considered in Chapter 6 to answer this query. Assuming our knowledge graph represents the supplier and vendor relationships between the companies, the traversal algorithms need traverse those relationships to answer the query. The query results may benefit if we use a simple visualization of the supply chain. To answer the second question, we can leverage the centrality detection techniques. In particular, the betweenness centrality is one possible approach for identifying the company that plays a central role in a supply chain.

The third question above is clearly relevant to the valuation of a startup. Just as in the first question, the answer requires getting data about investments from a third-party provider, and integrating it with the internal customer data. Answering the query requires using centrality detection techniques that we considered in Chapter 6. In particular, the graph adaptation of the page rank algorithm is an appropriate technique for answering this question. The answer presentation will benefit by showing a graphical visualization of how the influential investors are connected to various startups they are involved in. The fourth question is an example of community detection. In a knowledge graph that captures the investment relationships, the investors who co-invest in a company often will form a community.

The fifth and sixth questions are examples of reasoning techniques based on graph embeddings that were briefly introduced in chapter 1. Fifth question can be answered using techniques for calculating similarity based on the embedding vectors for the nodes of interest. Sixth question is an instance of the link prediction problem in a graph which is very similar to the problem addressed in language models. Here, instead of predicting the next word, we are interested in predicting the most likely links from a given node.

3. Knowledge Graphs for Income Tax Calculations

The income tax law in United States consists of more than 80,000 pages of text. Every year, more than 150 million income tax returns are filed. The US tax law includes thousands of forms and instructions that can appear in an income tax return. The requirements change every year, and sometimes, can even change in the middle of a tax filing year. With the advent of the income tax preparation software, this difficult to understand body of law has been made accessible to end-users so that they can prepare and file their income tax return on their own.

Some income tax preparation tools represent the income tax law using a set of rules. Once the law is represented as rules, it can not only be used for calculations, but also for generating user dialogs, providing explanations, checking completeness of input, etc. While the calculation of income tax requires rule-based reasoning similar to what we considered in Chapter 6, but many of the supporting operations such as generating user dialogs, determining the effect of changing a rule to the rest of the system, are achieved by modeling the rules as graphs, and using graph-based algorithms to perform those computations. To illustrate such use of the knowledge graphs, consider the following rule from the income tax law.

A person is qualified for a tax benefit if:

- the person is a resident of California, and
- the age of the person is greater than 18 years.

We can express this rule as a Datalog rule as shown below.

```
qualified_for_tax_benefit(P) :-
          resident_of(P,CA) & age(P,N) & min(N,18,18)
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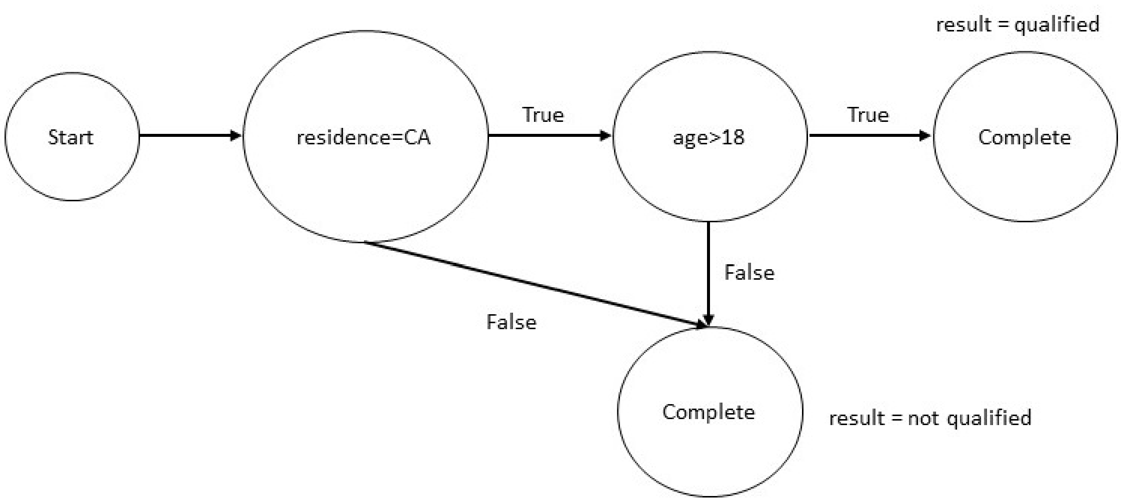
Given the rule above, we can construct a knowledge graph shown below.



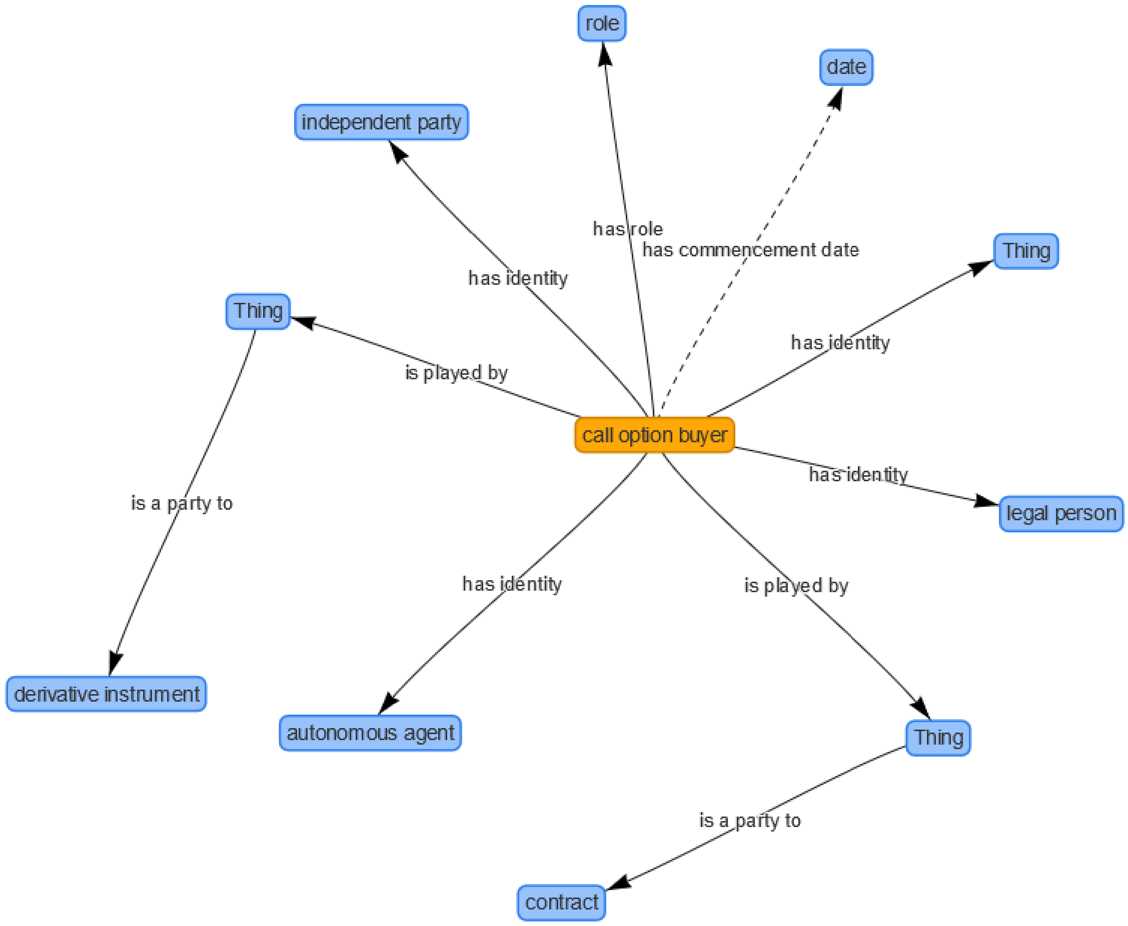
If we are preparing the tax return for a person whose age is 17 years, through a reachability analysis on the above graph, we can determine that in all cases, the person will not be qualified, and hence it is not even necessary to determine their residence. The above example is small as it involves only a single rule. But, as stated earlier, thousands of rules are applicable to a person, and in practice, such analysis needs to be performed on a very large and complex graph.

3. Knowledge Graphs for Financial Reporting

The financial institutions are required to report the derivative contracts that they currently hold. The examples of such contracts include interest rate and commodity swaps, options, futures and forwards, and various asset-backed securities. Such reports are of interest to the compliance teams within an organization, brokers and dealers who need to understand and manage such portfolios, and regulators who need to analyze and oversee these markets. If each financial institution provides such reports in a different format, it becomes challenging for these diverse set of stakeholders to process, aggregate and make sense of these reports. This problem is a classic instance of the data integration problem that knowledge graphs are meant to address.

An industry-wide initiative to address this problem has taken the approach of defining a common semantic model, called, Financial Industry Business Ontology (FIBO). FIBO is defined using a formal language called Web Ontology Language (OWL). FIBO defines things that are of interest in financial business applications and the ways those things can relate to one another. In this way, FIBO can give meaning to any data (e.g., spreadsheets, relational databases, XML documents) that describe the business of finance. FIBO concepts have been developed by a community of users coming from multiple financial institutions and represent a consensus of the common concepts as understood in the industry and as reflected in industry data models and message standards.

FIBO provides the concepts and terminology required for reporting on derivatives. To help users in getting started with FIBO, the developers have provided examples to get started with modeling basic concepts such as a Company, its global legal identifier, the derivatives, etc. For example, FIBO defines that a *Derivatives Contract* could have *has part* one or more *Options*. An *Option* can have a *call option buyer*. We show below a graphical view of connections from a *call option buyer* to related entities in the diagram below.



The graph shown above is an ontology graph in the sense that it does not capture the relationship between data values but the relationships that exist at the schema level. For example, it captures that a call option buyer has to be an independent party, a legal person and an autonomous agent. When a financial institution uses the terms and definitions from FIBO for the financial reports it generates, it provides the foundation for integrating its reports with reports coming from other providers. Use of FIBO can lead to significant streamlining and reduction of costs in aggregating and understanding the information about derivatives contract.

The development of FIBO is being driven by a set of motivating use cases. Derivatives contracts are only one of the several use cases under consideration. Other use cases include counter party exposure, index analysis for ETF development, and exchange instrument data offering.

4. Summary

Knowledge graphs have wide-ranging applications across multiple industries. In this chapter, we chose to focus on three different uses of knowledge graphs in financial industry: analytics, calculations and reporting. Use of knowledge graph for analytics is the most mainstream and wide-spread use of knowledge graphs as it has the potential to offer novel insights into data that an organization may already have. Use of knowledge graph for computations has been around for quite some time as it is similar to the use of graphs in compilers and rule engines for various reasoning and analysis tasks. Finally, the use of ontologies in data exchange is an emerging area for knowledge graphs with tremendous potential that will be increasingly important and mainstream in the future.

Exercises

Exercise 9.1. Suppose, you are facing the problem of finding alternative routes in the face of a traffic jam. Which of the following graph algorithms might be a good choice for this use case?

(*a*) A* Search

(*b*) Minimal Spanning Tree
(*c*) Random walk
(*d*) All pairs shortest path
(*e*) Depth-first Search

Exercise 9.2. Suppose, you are facing the problem of deciding the location of a branch office in a city, and you need to choose the most accessible location. Which graph algorithm might you use to help you make this decision?
(*a*) Degree centrality
(*b*) Closeness centrality
(*c*) Betweenness centrality
(*d*) Page rank
(*e*) Public opinion survey

Exercise 9.3. Suppose, you are working on fraud analysis, and you need to check if a group has a few discrete bad behaviors or is acting as a systematic collection of entities, which of the following graph algorithms might be ideally suited?
(*a*) Triangle count
(*b*) Connected components
(*c*) Strongly connected components
(*d*) Page Rank
(*e*) Fast unfolding algorithm

Exercise 9.4. An income tax application can use as knowledge graph in which of the following ways?
(*a*) Analyze the graph of rules to determine what inputs are required
(*b*) Create a taxonomy of classes to better organize the tax calculation rules
(*c*) Connect customer data with different investment opportunities
(*d*) All of the above
(*e*) None of the above

Exercise 9.5. Which of the following could not be achieved by financial ontologies such as FIBO?
(*a*) Stock recommendations that will outperform the market
(*b*) A standard vocabulary to exchange information
(*c*) Index analysis for ETF development
(*d*) Analysis of counter party exposure
(*e*) Exchange instrument data offering