CS520: KNOWLEDGE GRAPHS
How Should AI Organize Knowledge?
for
Searching, Learning, Reading, Explaining
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CS520

Knowledge Graphs

What should AI Know ?

How to Create a Knowledge Graph from Data?

1. Introduction

Large organizations generate lot of internal data, and also consume data produced by third party providers. Many data providers obtain their data by processing unstructured sources, and invest significant effort in providing it in a structured form for use by others. To make an effective use of such external data, it must be related to company's internal data. Such data integration enables many popular use cases such as 360 view of a customer, fraud detection, risk assessment, loan approval etc. For this chapter, we will discuss the problem of creating a knowledge graph by integrating the data available from structured sources. We will consider the problem of extracting data from unstructured data sources in the next chapter.

When combining data from multiple sources into a knowledge graph, we can undertake some upfront design of schema as we discussed in the previous chapter. We can also begin with no schema as it is straightforward to load external data as triples into a knowledge graph. The design of the initial schema is typically driven by the specific business use case that one wishes to address. To the degree such an initial schema exists, we must determine how the data elements from a new data source should be added to the knowledge graph. This is usually known as the *schema mapping* problem. In addition to relating the schemas of the two sources, we also must deal with the possibility that an entity in the incoming data (e.g., a Company) may already exist in our knowledge graph. The problem of inferring if the two entities in the data may be the same real world entity is known as the *record linkage* problem. The record linkage problem also arises when third party data providers send new data feeds, and our knowledge graph must be kept up-to-date with the new data feed.

In this chapter, we will discuss the current approaches for addressing the schema mapping and the record linkage problems. We will outline the state-of-the-art algorithms, and discuss their effectiveness on the current industry problems.

2. Schema Mapping

Schema mapping assumes the existence of a schema which will be used for storing new data coming from another source. Schema mapping then defines which relations and attributes in the input database corresponds to which properties and relations in the knowledge graph. There exist techniques for bootstrapping schema mappings. The bootstrapped schema mappings can be post corrected through human intervention.

We will begin our discussion on schema mapping by outlining some of the challenges and arguing that one should be prepared for the eventuality that this process will be largely manual and labor-intensive. We then describe an approach for specifying mappings between the schema of the input source and the schema of the knowledge graph. We will conclude the section by considering some of the techniques that can be used to bootstrap schema mapping.

2.1 Challenges in Schema Mapping

The main challenges in automating schema mapping are: (1) difficult to understand schema (2) complexity of mappings, and (3) lack of training data available. We next discuss these challenges in more detail.

Commercial relational database schemas can be huge consisting of thousands of relations and tens of thousands of attributes. Sometimes, the relation and attribute names do not have semantics (e.g., segment1, segment2) which do not lend themseves to any realistic automated prediction of the mappings.

The mappings between the input schema and the schema in the knowledge graph is not always simple one-to-one mapping. Mappings may involve calculations, applying business logic, and taking into account special rules for handling situations such as missing values. It becomes a tall order to expect any automatic process to infer such complex mappings.

Finally, many automated mapping solutions rely on machine learning techniques which require large amount of training data to function effectively. As the schema information, by definition, is much smaller than the data itself, it is unrealistic to expect that we will ever have large number of schema mappings available against which a mapping algorithm could be trained.

2.2 Specifying Schema Mapping

In this section, we will consider one possible approach to specify mappings between input data sources and a target knowledge graph schema. We will take an example in the domain of cookware. We can imagine different vendors providing products which an E-commerce site may wish to aggregate and advertise to its customers. We will consider two example sources, and then introduce the schema of the knowledge graph to which we will define mappings.

We show below some sample data from **the first data source** in a relational table called *cookware*. It has four attributes: *name*, *type*, *material*, and *price*.

cookware			
name	**type**	**material**	**price**
c01	skillet	cast iron	50
c02	saucepan	steel	40
c03	skillet	steel	30
c04	saucepan	aluminium	20

The second database shown below lists the products of a manufacturer. In this case, there are multiple tables, one for each product attribute. The `kind` table specifies the type of each product. The `base` table specifies whether each product is made from a corrosible metal (aluminum or stainless), a noncorrosible metal (iron or steel), or something other than metal (glass or ceramic). The `coated` table specifies those products that have nonstick coatings. The `price` table gives the selling price. There is no material information. The company has chosen not to provide information about the metal used in each product. Note that the `coated` table has only positive values; products without nonstick coatings are left unmentioned.

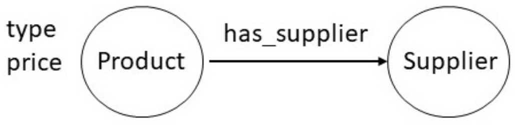
kind	
id	**value**
m01	skillet
m02	skillet
m03	saucepan
m04	saucepan

base	
id	**value**
m01	corrosible
m02	noncorrosible
m03	noncorrosible
m04	nonmetallic

coated	
id	**value**
m01	yes
m02	yes

price	
id	**value**
m01	60
m02	50
m03	40
m04	20

Suppose the desired schema for the knowledge graph expressed as a property graph is as shown below. We have two different node types: one for products, and the other for suppliers. These two nodes are connected by a relationship called *has_supplier*. Each product node has properties "type" and "price".



To specify the mappings, and to illustrate the process, we will use a triple notation so that a similar process is applicable regardless of whether we use an RDF or property graph data model for the knowledge graph. For an RDF knowledge graph, we will need to create IRIs which is a process orthogonal to relating the two schemas, and hence omitted from here. The desired triples in the target knowledge graph are listed below.

knowledge graph		
subject	**predicate**	**object**
c01	type	skillet
c01	price	50
c01	has_supplier	vendor_1
c02	type	saucepan
c02	price	40
c02	has_supplier	vendor_1
c03	type	skillet
c03	price	30
c03	has_supplier	vendor_1
c04	type	saucepan
c04	price	20
c04	has_supplier	vendor_1
m01	type	skillet
m01	price	60
m01	has_supplier	vendor_2
m02	type	skillet
m02	price	50
m02	has_supplier	vendor_2
m03	type	saucepan
m03	price	40
m03	has_supplier	vendor_2
m04	type	saucepan
m04	price	20
m04	has_supplier	vendor_2

Any programming language of choice could be used to express the mappings. Here, we have chosen to use Datalog to express the mappings. The rules below are straightforward. Variables are indicated by using upper case letters. The third rule introduces the constant *vendor_1* to indicate the source of the data.

```
knowledge_graph(ID,type,Type) :- cookware(ID,TYPE,MATERIAL,PRICE)
knowledge_graph(ID,price,PRICE) :- cookware(ID,TYPE,MATERIAL,PRICE)
knowledge_graph(ID,has_supplier,vendor_1) :- cookware(ID,TYPE,MATERIAL,PRICE)
```

Next, we consider the rules for mapping the second source. These rules are very similar to the mapping rules for the first source except that now the information is coming from two different tables in the source data.

```
knowledge_graph(ID,type,Type) :- kind(ID,TYPE)
knowledge_graph(ID,price,PRICE) :- price(ID,PRICE)
knowledge_graph(ID,has_supplier,vendor_2) :- kind(ID,TYPE)
```

In general, it may not make sense to reuse the identifiers from the source databases, and one may wish to create new identifiers for use in the knowledge graph. In some cases, the knowledge graph may already contain objects equivalent to the ones in the data being imported. We will consider this issue in the section on record linkage.

2.3 Bootstrapping Schema Mapping

As noted in Section 2.1, a fully automated approach to schema mapping faces numerous practical difficulties. There is a considerable work on bootrapping the schema mappings based on a variety of techniques and validating them using human input. Bootstrapping techniques for schema mapping can be classified into the following categories: linguistic matching, matching based on instances, and matching based on constraints. We will consider examples of these techniques next.

Linguistic techniques can be used on the name of an attribute or on the text description of an attribute. First and most obvious approach is to check if the names of the two attributes are equal. One can have greater confidence in such equality if the names were IRIs. Second, one can canonicalize the names by processing them through techniques such as stemming and then checking for equality. For example, through such processing, we may be able to conclude the mapping of *CName* to *Customer Name*. Third, one could check for the mapping based on synonyms (e.g., car and automibile) or hypernyms (e.g., book and publication). Fourth, we can check for mapping based on common substrings, pronunciation, and how the words sound. Finally, we can match the descriptions of the attributes through semantic similarity techniques. For example, one approach is to extract keywords from the description, and then check for similarity between them using the techniques we have already listed.

In matching based on the instances, one examines the kind of data that exists. For example, if a particular attribute value contains dates, it can only match against those attributes that contain date values. Many such standard data types can be inferred by examining the data.

In some cases, the schema may provide information about constraints. For example, if the schema specifies that a particular attribute must be unique for an individual, and must be a number, it is a potential match for identification attributes such as an employee number or social security number.

The techniques considered here are inexact, and hence, can be only used to bootstrap the schema mapping process. Any mappings must be verified, and validated by human experts.

3. Record Linkage

We will begin our discussion by illustrating the record linkage problem with a concrete example. We will then give an overview of a typical approach to solving the record linkage problem.

3.1 A Sample Record Linkage Problem

Suppose we have data in the following two tables. The record linkage problem then involves inferring that record a_1 is the same as the record b_1, and that record a_3 is the same as the record b_2. Just like in schema mapping, these are inexact inferences, and need to undergo human validation.

	Table A		
	Company	**City**	**State**
a_1	AB Corporation	New York	NY
a_2	Broadway Associates	Washington	WA
a_3	Prolific Consulting Inc.	California	CA

	Table B		
	Company	**City**	**State**
b_1	ABC	New York	NY
b_2	Prolific Consulting	California	CA

A large knowledge graph may contain information about over 10 million companies. It may receive a data feed, that was extracted from natural language text. Such data feeds can contain over 100,000 companies. Even if the knowledge graph had a standardized way to refer to companies, but this new data feed that was extracted from text will not have those standardized identifiers. The task of the record linkage is to relate the companies contained in this new data feed with the companies that already exist in the knowledge graph. As the data volumes are large, performing this task efficiently is of paramount importance.

3.2 An Approach to Solve the Record Linkage Problem

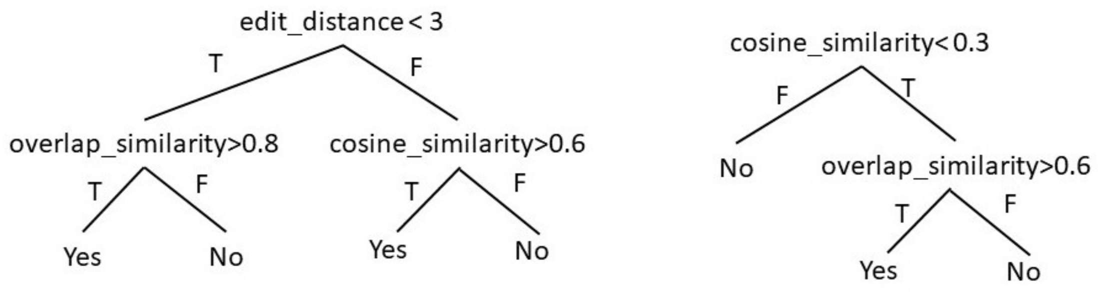
Efficient record linkage involves two steps: *blocking* and *matching*. The blocking step involves a fast computation to select a subset of records from the source and the target that will be considered during a more expensive and precise matching step. In the matching step, we pairwise match the subset of records that were selected during blocking. // In the example considered above, we could use a blocking strategy that considers matching only those records that match on the state. With that strategy, we need to consider matching only a_1 with b_1, and a_3 with b_2, thus significantly reducing the comparisons that must be performed.

Both blocking and matching steps work by learning a random forest through an active learning process. A random forest is a set of decision rules that gives its final prediction through a majority vote returned by individual rules. Active learning is a learning process that constructs the random forest by actively monitoring its performance on the test data, and selectively choosing new training examples to iteratively improve its performance. We will next explain each of these two steps in a greater detail.

3.3 Random Forests

Blocking rules rely on standard similarity checking functions, such as, exact match, Jaccard similarity, overlap similarity, cosine similarity, etc. For example, if we were to check the overlap similarity between "Prolific Consulting" and "Prolific Consulting Inc.", we will first gather the tokens in each of them, and then check which tokens are in common, giving us a similarity score of 2/3.

We show below a snippet of a random forest for blocking. A random forest can also be viewed as a set of set of rules. The random forest shown below is a set of two sets of rules. The arguments of each predicate are two values to be compared.



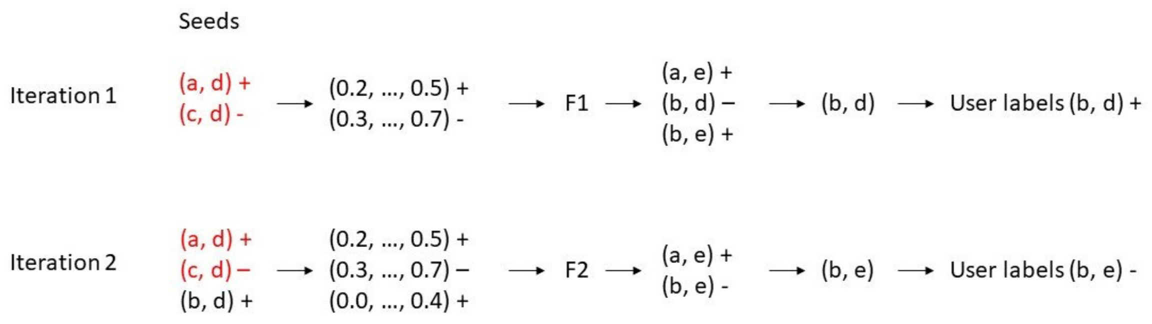
r_1: (edit_distance ≥ 3) and (cosine_similarity > 0.6) $\rightarrow$ match
r_2: (edit_distance < 3) and (overlap_similarity > 0.9) $\rightarrow$ match

r_3: (cosine_similarity > 0.6) and (overlap_similarity < 5) $\rightarrow$ match

Several general principles exist for automatically choosing the similarity functions for blocking rules. // For example, for a numerical valued attributes such as age, weight, price, etc., candidate similarity functions are: exact match, absolute difference, relative difference, and Levenstein distance. / For string valued attributes, it is common to use edit distance, cosine similarity, Jaccard similarity, and TF/IDF functions.

3.4 Active Learning of Random Forests

We can learn the random forest for the blocking rules through the following active learning process. // We randomly select a set of pairs from the two datasets. -> By applying the similarity functions on each pair, we obtain a set of feautres for each pair. -> Using these features, we learn a random forest. -> We apply the resulting rules to new pairs selected from the data set, and evaluate their performance. -> If the performance is below a certain threshold, we repeat the cycle, by providing additional labeled examples until an acceptable performance is obtained. We illustrate this process using the following example.



We assume that our first dataset contains three items: a, b, and c, and our second dataset contains two items, d and e. From this dataset, we pick two pairs (a,d) and (c,d) which are labeled by the user as similar and not similar respectively. On this pair, we apply the similarity functions each of which results in a feature of the pair. We then use those features to learn a random forest. We apply the learned rules to the tuples which were not in the training set, and ask the user to verify the result. The user informs us that the result for the pair (b,d) is incorrect. We add (b,d) to our training set, and we repeat the process for another iteration. Over several iterations, we anticipate the process to converge, and give us a random forest that we can effectively use in the blocking step.

Once a radom forest has been learned, we present each of the learned rules to the user. Based on the user verification, we choose the rules that will be used in the subsequent steps.

3.5 Applying the Rules

Once we have learned the rules, the next step is to apply them on the actual data. When the data size is huge, it is still not possible to apply the blocking rules to all the pairs of objects. Therefore, we resort to indexing. Suppose, one of the rules requires that the Jaccard index should be greater than 0.7, and we are looking to match the movie *Sound of Music*. As the length of the movie name is 3, we need consider only those movies in our data whose length is between 3*0.7 and 3/0.7, ie, between 2 and 4. If we have indexed the dataset on the size of the movies, it is efficient to choose only those movies whose sizes are between 2 and 4, and filter the set even further through the application of the blocking rule.

3.6 Performing the Matching

The blocking step produces a much reduced set of pairs which must be tested for whether they match. The general structure of the matching process is very similar in that we first define a set of features, learn a random forest, and through the active learning process refine it. The primary difference between the blocking and the matching step is that the matching process needs to be more exact and can require more computation. That is because this is the final step in the record linkage, and we need to have high confidence that the two entities indeed match.

4. Summary

In this chapter, we considered the problem of creating a knowledge graph by integrating the data coming from structured sources. The integrated schema of the knowledge graph can be refined and evolved as per the business requirements. The mappings between the schemas of different sources can be bootstrapped through automated techniques, but they do require verification through human input. Record linkage is the integration of the data at the instance level where we must infer the equality between two instances in the absence of unique identifiers. The general approach for record linkage is to learn a random forest through active learning process. For applications requiring a high accuracy, automatically computed record linkage may eventually need to undergo human verification.

Exercises

Exercise 4.1.Two popular methods to calculate similarity between two strings are edit distance (also known as Levenshtein distance) and the Jaccard measure.

We can define the Levenshtein distance between two strings a, b (of length |a| and |b| respectively), given by lev(a,b) as follows:

- lev(a,b) = a if |b| = 0
- lev(a,b) = b if |a| = 0
- lev(tail(a),tail(b)), if a[0] = b[0]
- 1 + min{lev(tail(a),b), lev(a,tail(b)), lev(tail(a),tail(b))} otherwise.

where the tail of some string x is a string of all but the first character of x, and x[n] is the nth character of the string x, starting with character 0.

We can define the Jaccard measure between two strings a, b as the size of the intersection divided by the size of the union between the two.

$$J(a,b) = |a \cap b| / |a \cup b|$$

(*a*) Given the strings "JP Morgan Chase" and "JPMC Corporation", what is the edit distance between the two?

(*b*) Given the strings "JP Morgan Chase" and "JPMC Corporation", what is the Jaccard measure between the two?

(*c*) Given three strings: x = Apple Corporation, CA, y = IBM Corporation, CA, and z = Apple Corp, which of these strings would be equated by the edit distance methods?

(*d*) Given three strings: x = Apple Corporation, CA, y = IBM Corporation, CA, and z = Apple Corp, which of these strings will be equated by the Jaccard measure?

(*e*) Given three strings: x = Apple Corporation, CA, y = IBM Corporation, CA, and z = Apple Corp, what intuition you would use to ensure that x is equated to z?

Exercise 4.2. A commonly used approach to account for the importance of words is a measure known as TF/IDF. Term frequency (TF) denotes the number of times a term occurs in a document. Inverse Document Frequency (IDF) denotes the number of documents containing a term. The TF/IDF score is calculated by taking the product of TF and IDF. Use your intuition to answer whether the following is true or false.

(*a*) Higher the TF/IDF score of a word, the rarer it is.

(*b*) In a general news corpus, TF/IDF for the word *Apple* is likely to be higher than the TF/IDF for the word *Corporation*

(*c*) Common words such as stop words will have a high TF/IDF.

(*d*) If a document contains words with high TF/IDF, it is likely to be ranked higher by the search engines.

(*e*) The concept of TF/IDF is not limited to words, and can also be applied to sequence of characters, for example, bigrams.

Exercise 4.3. To check if two names might refer to the same real-world organization, one strategy is to check the similarity between two documents that describe them. Cosine similarity is a measure of similarity between two vectors, and is defined as the cosine of the angle between them. Highly similar documents will have a cosine score closer to 1. Which of the following might be a viable approach to convert a document into a vector for calculating cosine similarity?

(*a*) Word embeddings of the words used in a document.
(*b*) TF/IDF scores of the words used in a document.
(*c*) TF/IDF of bigrams used in a document.
(*d*) None of the above.
(*e*) Any of (a), (b) or (c).

Exercise 4.4. Which of the following is true about schema mappings?

(*a*) Schema mapping is largely an automated process.
(*b*) It is usually straightforward to learn simple schema mappings.
(*c*) Complete schema documentation is almost never available.
(*d*) Examining the actual data in the two sources can provide important clues for schema mapping.
(*e*) Database constraints play no role in schema mapping.

Exercise 4.5. Which of the following is true about record linkage?

(*a*) Blocking can be an unnecessary and expensive step in the record linkage pipeline.
(*b*) A random forest is a set of set of rules.
(*c*) Blocking rules must always be authored manually.
(*d*) Active learning of blocking rules minimizes the training data we must provide.
(*e*) Matching rules are as expensive to apply as the blocking rules.