Improving the Precision of RDF Question/Answering Systems— A Why Not Approach

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ABSTRACT

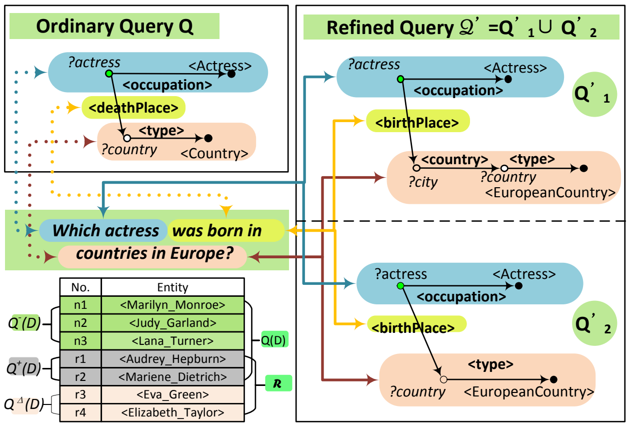
Given a natural language question q_{NL} over an RDF dataset D, an RDF Question/Answering (Q/A) system first translates q_{NL} into a SPARQL query graph Q and then evaluates Q over the underlying knowledge graph to figure out the answers $Q(D)$. However, due to the challenge of understanding natural language questions and the complexity of linking phrases with specific RDF items (e.g., entities and predicates), the translated query graph Q may be incorrect, leading to some wrong or missing answers. In order to improve the system's precision, we propose a self-learning solution based on the users' feedback over $Q(D)$. Specifically, our method automatically refines the SPARQL query Q into a new query graph $\mathcal{Q}'$ with minimum modifications (over the original query Q). The new query will fix the errors and omissions of the query results. Furthermore, each amendment will also be used to improve the precision in answering subsequent natural language questions.

1. BACKGROUND AND MOTIVATION

As more and more RDF Question/Answering (Q/A) systems over RDF knowledge graphs are designed, which allow users to express queries in natural language and translate them into SPARQL queries automatically, RDF is more widely used. Generally, RDF Q/A systems translate a user's natural language question q_{NL} into a SPARQL query graph Q and evaluate Q over the underlying RDF knowledge graph G to find the answers. However, due to ambiguity of natural language question sentences, the translated Q may not be correct, which results in errors and omissions of the query results. According to the analysis of several RDF Q/A systems, we classify the typical errors into three categories:

(1) Entity/Class Linking Error: Systems link the phrase in users' questions with a wrong entity/class, reflected in *subject* or *object*, which is chargeable on the imperfect entity-mapping dictionary. As for the question "Which actress was born in countries in Europe?" *(see Figure 1)*, the system mistakenly links "countries in Europe" with class $\langle$*Country*$\rangle$ instead of the correct one $\langle$*EuropeanCountry*$\rangle$.

(2) Relation Paraphrasing Error: Q/A systems often reply on a relation-paraphrase dictionary to extract relations in users' questions. A paraphrase is to align a natural language relation phrase with the corresponding predicate. However, due to mistakes, noise and incompleteness of the paraphrase dictionary, Q/A systems often extract imperfect relations or even wrong relations, reflected in *predicate* in RDF triples. As shown in Figure 1, the right predicate should be $\langle$*birthPlace*$\rangle$, while the system interprets the relation as $\langle$*deathPlace*$\rangle$ due to one error in the paraphrase dictionary, i.e., mapping "be born (in)" to $\langle$*deathPlace*$\rangle$.



No.	Entity
n1	<Marilyn_Monroe>
n2	<Judy_Garland>
n3	<Lana_Turner>
r1	<Audrey_Hepburn>
r2	<Mariene_Dietrich>
r3	<Eva_Green>
r4	<Elizabeth_Taylor>

Figure 1: Refining Queries based on Users' Feedback.

(3) Incomplete Query Graph Structure: In some cases, the translated SPARQL Q is semantically correct but it cannot match all the expected answers in underlying RDF data graph. See Figure 1, besides Q'_2 with triple "*?actress* $\langle$*birthPlace*$\rangle$ *?country*", another correct SPARQL Q'_1 introduces an additional variable "*?city*" and a triple "*?city* $\langle$*country*$\rangle$ *?country*". Both compose the standard SPARQL $\mathcal{Q}'$ together, while systems usually lose either of them.

Imperfect machine learning methods and costly manual annotation make the entity-mapping dictionary and relation-paraphrase dictionary inconsistent, incomplete and of poor quality, which cause error (1) and (2). The lack of sentence-structure dictionary causes the absence of partial structure, which generates error (3). There are two goals in this work. First, based on the users' feedback over query results $Q(D)$, our method can automatically refine the original query Q into a new query graph $\mathcal{Q}'$ with minimum modifications over Q, where $\mathcal{Q}'$ fixes the errors and omissions of the results. Furthermore, each amendment (from Q to $\mathcal{Q}'$) is used to correct and enrich the dictionaries, which finally improve the precision in answering subsequent natural language questions.

2. PROBLEM DEFINITION AND METHOD

Given a natural language question q_{NL} over an RDF dataset D, an RDF Q/A system generates an original query graph Q. The user acquires an answer set $Q(D)$ and gives judgments. So we receive a new answer set $\mathcal{R}$, where $\mathcal{R}$ includes the right answers $Q^+(D)$ marked by the user and the missing answers $Q^\Delta(D)$ given by the

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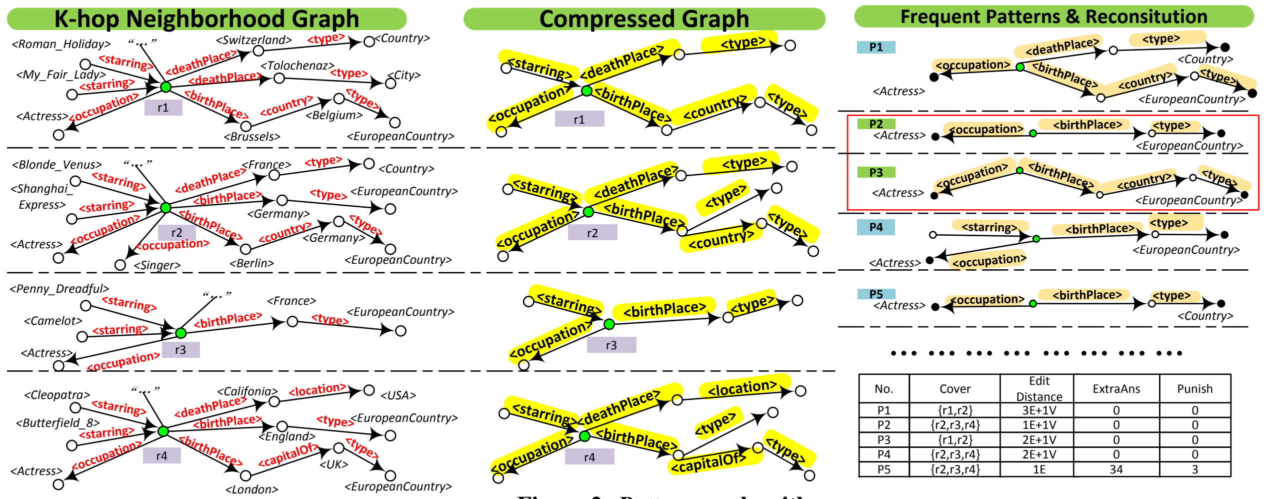

No.	Cover	Edit Distance	ExtraAns	Punish
P1	{r1,r2}	3E+1V	0	0
P2	{r2,r3,r4}	1E+1V	0	0
P3	{r1,r2}	2E+1V	0	0
P4	{r2,r3,r4}	2E+1V	0	0
P5	{r2,r3,r4}	1E	34	3

Figure 2: *Bottom-up* algorithm.

user, excludes the wrong answers $Q^-(D)$ indicated by the user, that is, $\mathcal{R} = Q^+(D) \cup Q^\Delta(D)$, and $Q^-(D) \cap \mathcal{R} = \varnothing$. Our goal is to get a refined query $\mathcal{Q}' = Q'_1 \cup Q'_2 \cup \ldots \cup Q'_s, s \geq 1$, which can cover all the answers in $\mathcal{R}$ and exclude the answers in $Q^-(D)$, also minimize the edit distance between Q and $\mathcal{Q}'$.

The proposed system framework is separated into two parts: *Online Processing* and *Log Dealing*. *Online Processing* stage implements a *Bottom-up* method and a *Candidate-selection* method to ensure the expected modification of this query. And we design a *Rule-Mining* algorithm in *Log Dealing* stage to refine the existing entity-mapping dictionary and relation-paraphrase dictionary, and also build up a sentence-structure dictionary, which will improve existing Q/A systems and subsequent question-answering.

Online Processing During this stage, the new answer set $\mathcal{R}$ after assessments of the user is fed into the *Bottom-up* algorithm. After obtaining candidate graphs, we take them along with Q as input to get the refined SPARQL through the *Candidate-selection* method.

Bottom-up: This part starts from new answer set $\mathcal{R}$ and captures the common feature of accepted answers.

(1) *Get Neighborhood Graphs.* For each answer in $\mathcal{R}$, we find the subgraph induced by its k-hop neighbors.

(2) *Get Compressed Graphs.* We design a method to compress the size of neighborhood graphs. First, we find all simple paths starting from each answer to change the graph into a tree. Then, ignore labels of entities and we can figure out that many paths share same edge label. Insert those paths into a prefix tree, so redundancy vertices and edges are removed. The original neighborhood graphs are compressed obviously while their main structures are still kept.

(3) *Mine frequent patterns.* We devise to extract the common patterns among the Compressed Graphs, so we can deduce the expected query graph. We annotate the nodes on the tree with the label of level, and mine frequent patterns from all these trees using *gSpan* described in [1], altogether denoted by set P.

Figure 2 shows how to apply *Bottom-up* on the example we mentioned in Figure 1, where $Q^+(D)$={r_1,r_2}, $Q^-(D)$={n_1, n_2, n_3}, $Q^\Delta(D)$={r_3,r_4}, and $\mathcal{R}$={r_1,r_2,r_3,r_4}. It displays 3-hop Neighborhood Graphs of answers in $\mathcal{R}$. Take r_2 as an example. Merge paths sharing the same prefix label $\langle$*birthPlace*$\rangle$ into a common edge, also $\langle$*starring*$\rangle$ and $\langle$*occupation*$\rangle$ in the same way. Note that we cannot make edges with $\langle$*type*$\rangle$ as a combination, because they don't share the same prefix. And we mine frequent patterns of these four Compressed Graphs. {P_1,P_2,P_3,P_4,P_5} is a subset of P.

Candidate-selection: Reconstitute candidates in P with labels of entities. By following steps, we can obtain the refined query $\mathcal{Q}'$:

(1) *Calculate Weight* The weight of each graph P_i in P comprises 4 parts: the number of answers covered in $\mathcal{R}$, the edit distance between P_i and original query Q, the number of extra answers introduced by P_i (never show in $Q(D)$ and $\mathcal{R}$), the number of answers in $Q^-(D)$ as punishment. Each part is multiplied by a parameter, determining the significance of either precision or similarity.

(2) *Weighted Set Cover* For all members in P, each with a weight, use a greedy algorithm to find a subset $\mathcal{Q}'$ of P, which can cover all the answers in $\mathcal{R}$, aiming at acquiring minimize weight. Subset $\mathcal{Q}'$ corresponds to the refined SPARQL.

See Figure 2, P_5 covers $\{r_2, r_3, r_4\}$. It's the most similar to Q because only $\langle$*deathPlace*$\rangle$ is changed into $\langle$*birthPlace*$\rangle$. However, it brings in 34 extra answers and 3 known wrong answers. So it has a large weight. Finally, we choose $\{P_2, P_3\}$ as the best cover.

Log Dealing *Rule Mining:* Once modify a graph successfully, analyze the modification log and extract the rules. Discover new knowledge to correct and supplement existing entity-mapping dictionary and relation-paraphrase dictionary, which will avoid error (1) and (2) for future queries (see Figure 1). Also build up a sentence-structure dictionary to record query structures corresponding to specific natural language question(e.g., "be in country" has two corresponding templates:"in . . . country" and "in a city of . . . country"), which will avert error (3) for subsequent queries. In such way we build a mechanism to improve subsequent queries by self-learning.

3. EXPERIMENTS

Our experiment is implemented on a 7.8GB DBpedia dataset. We choose 100 natural questions from QALD-5 whose original answers are not perfect generated by an existing system gAnswer described in [2]. Our algorithm can modify 42 of them and receive correct SPARQL, which solves the three typical errors we proposed before. Among those 42 cases which are solved perfectly, 84% of them are fixed in no more than 2 options. For other 58 cases, the precision improves 30%, recall increases around 80%. After these modifications, entity-mapping dictionary and relation-paraphrase dictionary are rectified and sentence-structure dictionary is built up. When using appeared questions to query the system, the system never shows similar errors and receives perfect answers.

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