Research on Web Query Translation based on Ontology

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Abstract—This paper presents a framework of query translation based on ontology between different query interfaces (forms), which will translate the queries into suitable formats, hiding the differences from underlying sources, and enabling users to access data sources conveniently. Firstly, constructing domain ontology concept model (DOCM), then, finding out predicate matching relationships between source form and target forms based on DOCM, lastly, analyzing query rewrite strategy which contains four type rewriters to construct automatically a set of constraint mapping rules so that the system can use the user-provided input values to fill out the appropriate form fields of different web database forms. Experiment results show that this method is feasible and effective.

Index Terms—Ontology, Query Translation, Predicate Matching, Query Rewrite

I. INTRODUCTION

Large portions of web are buried behind user-oriented interfaces (forms), which can only be accessed by filling out forms. When a user poses all the queries on a global query form, web query translation system will rewrite the queries into suitable formats for the sources, and automatically submit the queries to different underlying physical sources, making the accesses to individual physical sources transparent to the user[1]. Due to integrating multiple heterogeneous data sources to provide users with a unified view, web query translation will be a complex and challenged key point.

One of the earliest efforts at automated form filling was the ShopBot project[2], which uses domain-specific heuristics to fill out forms for the purpose of comparison shopping. The ShopBot project, however, did not propose a general-purpose mechanism of filling out forms for non-shopping domains. Raghavan,S. and Garcia-Molina,H.[3] build Hidden Web Exposer (HiWE), it does this by filling out the searchable form, submitting one or more queries, and after the contents have been extracted, it stores them in a repository and builds an index to support user queries. Shu L et al.[4] propose a method to model the querying capability of a query interface based on the concept of atomic queries. Meanwhile, they also present an approach to construct querying capability automatically. Fangjiao Jiang et al.[5] study the query translation problem of the exclusive query interface and present a novel Zipf-based selectivity estimation approach for infinite-value attribute. Experimental results on several large-scale Web databases indicate that the approach can achieve high precision on selectivity estimation of infinite-value attribute for exclusive query translation. Yongquan Dong et al.[6] propose a novel query interface matching approach based on extended evidence theory for Deep Web. Against the limitations of existing combination methods, their approach considers the credibilities of different matchers and incorporates them into exponentially weighted evidence theory to combine the results of multiple matchers. Tan et al. [7] introduce personalization recommendation to the Deep Web data query, proposed a user interest model based on fine-grained management of structured data and a similarity matching algorithm based on attribute eigenvector in allusion to personalization recommendation.

A few efforts are dedicated to query translation which has responsibility for translating a user’s query from source form to target forms. However, research works related to query translation have mainly fallen into two categories: attribute mapping and constraint mapping. These methods do not consider applying background knowledge, which is important to understand problems and situations. Ontology is an explicit, formal specification of a shared conceptualization in an interesting domain, therefore, we propose a novel method of ontology-assisted query translation between different query forms in this paper.

II. WEB QUERY TRANSLATION ANALYSIS

Web query translation problems can be defined as translating a user’s query from a source form to different target forms (Fig.1), which contains three characteristics:
Characteristic 1: Query-generally: the queries of target forms are similar with the queries of the source form.

Characteristic 2: Domain-generally: the source form and the target forms belong to a domain-specific.

Characteristic 3: Minimum subsumption-generally: web query translation does not miss any correct answer and contains fewest incorrect answers. Simultaneity, it is domain content independent.

**Definition 1** Query Translation: Given a source form $S$ and a set of target forms $T = \{ T_1, T_2, \ldots, T_n \}$, if the user-provided input value is $Q_s$ in the source form $S$, then, the output is the query combination $Q^*_t = \{ Q^*_1, Q^*_2, \ldots, Q^*_n \}$ in the target forms after query translator, $Q^*_i = \delta (q_1, q_2, \ldots, q_n)\}, \quad 1 \leq i \leq n$, which satisfies the following constraints [8][9]:

1. Each query $q_j (1 \leq j \leq n)$ in $Q^*_t$ must be a valid query to target form $T_j$.
2. $Q^*$ is “close” with the source queries $Q_s$ as much as possible in order to minimize the processing costs of target form, and improve the retrieval quality.

**Definition 2** Minimum Subsumption Strategy (MinSS): Given a global query $Q_t$ from source form $Q_s$ and a set of target forms $T = \{ T_1, T_2, \ldots, T_n \}$, $Q^*_i (1 \leq i \leq n)$ is a web query translation using MinSS if the following three conditions are satisfied at the same time:

1. $Q^*_i$ is a valid query of target form, namely, $Q^*_i$ is acceptable to target form $T_i$.
2. $Q^*_i$ semantically subsumes $Q_s$, namely, for any back-end database $D$, $Q_s(D) \subseteq Q^*_i(D)$, it means that the retrieved information of $Q_s$ is a subset of $Q^*_i$.
3. $Q^*_i$ is the minimum subsumption strategy, that is to say, there does not exist any query $Q_t$ which satisfies (1) and (2) and $Q_t(D) \subseteq Q^*_i(D)$.

MinSS can minimize the amount of data to be sent from the web database and minimize the effort to filter out undesired results.

### III. QUERY TRANSLATION FRAMEWORK

In order to realize query translation between different query forms, we need to reconcile the heterogeneities at the predicate-level and value-level, and then generate a query plan expressed upon each target form. The framework of web query translation based on ontology is shown in Fig. 2.

Predicate recognition module is used to find out the attribute(predicate) matching relationships between the source form and the target forms based on ontology; Predicate mapping is used to match the source form and the target forms to determine the mapping type; Query rewrite module is used to match the value translation of mapped predicate; Query submission module is used to trigger button to submit query plans with respective sources, so that the user can immediately receive query results from multiple data sources.

#### A. Ontology Construction

Ontology as the concept model describing information system in semantic and knowledge level, user’s queries and relevant data can be mapped to the concept model, thus, ontology can be seen as a knowledge system which describes concepts and relationships [10][11]. The process of ontology construction is shown in Fig. 3:

The process of ontology construction is as follows:

1. Extracting domain terminologies from searchable forms, simultaneously, capturing the semantic relationships of terminologies.
(2) Extracting domain concepts. The domain concepts need explicit, so there is a need to disambiguate terminology, and describe the terminology with the most common word.

(3) Constructing the hierarchical relationships of concepts, such as Is-A, Part-Of, Synonymous etc.

(4) Refining domain ontology. Ontology engineers revise concepts and semantic relationships under the guidance of ontology engineering standards to ensure that the domain knowledge is shared and consistent.

(5) After constructing the ontology, the semantics of concepts in domain ontology can be enriched by adding concept-level knowledge based on three philosophical notions: identity, rigidity, and dependency.

**Definition 3.** Domain Ontology Concept Model (DOCM): DOCM is a data model that describes a set of concepts and relationships that may appear in a specific domain. It should be understandable by machine so that it can be used to reason about these objects within that domain. Each object can be denoted as Class = \{CM, DT, \{Si\}, \{CAi\}, \{SCi\}\}, which describes the relevant information of object.

- **CM**: It denotes the main class of object, which is universal and easy to understand for users. It can be seen as the keyword of object, e.g. “Author” can be seen CM of name object in Book domain.
- **DT**: It denotes the data type of object, such as “string”, “numerical” and so on, e.g. the DT of “Author” is “string”.
- **\{Si\}**: It denotes the synonyms of CM, namely, the concept aliases, e.g. “Writer” is the aliases of “Author”.
- **\{CAi\}**: It denotes the condition property set of object, which is “Part-Of” relationship to CM, e.g. “First name” and “Last name” are two condition properties of “Author”.
- **\{SCi\}**: It denotes the sub class set of CM, which is “Is-A” relationship to CM. Such as “Author keywords” and “Title keywords” are “Is-A” relationships to CM “Keywords”.

DOCM has a good organizational structure, which represents high-level background knowledge with concepts and relationships. In this paper, the ontology is implemented by Protégé API and represented in the Web Ontology Language(OWL)[12]. In this way, to operate DOCM is equivalent to operate the OWL file.

**B. Predicate Recognition**

Predicate recognition is used to find out the predicate matching relationships among different query forms, an example is shown in Fig.4.

The predicate matching relationships between the source form and the target forms are complex as follows:

1) The predicate labels belong to the same concept are always different, e.g. source form denotes name using “Author”, while target form using “Writer”.

2) The complex predicate relationships are common, e.g. source form denotes time using “data”, while target form using “year, month, day”.

Predicate recognition can be seen as schema matching for different query forms, which are classified attribute-level (predicate-level) matching(Fig.5).

![Predicate Recognition](image)

**Figure 5.** Predicate recognition, which can be divided into simple predicate recognition(SPR) and complex predicate recognition(CPR).

**Definition4** Simple Predicate Recognition (SPR): the predicate of source form and the predicate of target form is 1:1 matching.

**Definition5** Complex Predicate Recognition (CPR): the predicate of source form and the predicate of target form is M:N matching.

**Definition6** Ontology-assisted Predicate Recognition Algorithm: the semantic similarity between two predicate concepts is measured by DOCM, which is the “bridging” to obtain the predicate matching relationships among different query forms. Assume that \(A^*\) is a predicate label from target form, \(A_i\) is the main class of concept node \(C_i\) from DOCM, \(\{S_i\}\) is the synonym set of \(A_i\), \(\{CA_i\}\) is the condition property set of concept node \(C_i\), \(\{SC_i\}\) is the sub class set of concept node \(C_i\), \(\text{Sim}(A^*, A_i)\) denotes the similarity between \(A^*\) and \(A_i\), \(\sigma\) denotes the threshold of matching degree:

- **a)** If \(A^* \in \{S_i\}\) or \(A^* = A_i\), then it is 1:1 matching(SPR) between predicate label \(A^*\) of target form and ontology concept \(A_i\).

- **b)** If \(A^* \notin \{S_i\}, A^* = A_i\), and \(\text{Sim}(A^*, A_i) \geq \sigma\), then it means 1:1 matching (SPR) between predicate label \(A^*\) and ontology concept \(A_i\), we add \(A^*\) to \(\{S_i\}\) as a new synonym of ontology concept \(A_i\).

- **c)** If \(A^* \notin \{CA_i\} \cup \{SC_i\}\), then it is M:1 matching (CPR) between predicate label \(A^*\) of target form and ontology concept \(A_i\).

- **d)** If \(A^* \notin \text{DOCM}\) and \(\forall A_j, \text{Sim}(A^*, A_j) < \sigma\), then it means there is no matching between predicate label \(A^*\) of target form and ontology concept \(A_i\), we add \(A^*\) to DOCM as a new ontology concept.
e) For the other target forms, we do the same above, in this way, we can get ontology-form predicate mapping table, which records the matching relationships between different forms and ontology concepts. The structure of predicate mapping table is shown in Fig.6.

![Figure 6. Predicate recognition, which can be divided into simple predicate recognition (SPR) and complex predicate recognition (CPR).](image)

We exploit the “bridging” effect in the process of matching predicates based on DOCM from a large number of query forms. Through predicate recognition, we can capture the semantic relationships of predicates among different query forms.

C. Predicate Mapping

Predicate mappings are crucial for the system to reformulate a user query into queries on the sources. If we can understand their semantics, we can query in the target forms to find the nearest queries for query optimization. Due to the predicate types are not single from different forms, relying on a single predicate type is not sufficient and the match results of individual types are often inaccurate and uncertain. Literature [13] finds that the most commonly used predicate templates are \{attribute; type\} and \{attribute; value \in \{D\}\} by observing 150 web query forms. Through observation, we found that the predicate type mainly contains “text”, “select”, “numeric”, “data time” and “specific type”. Therefore, we propose a type-based approach for query rewrite by combining multiple type rewriters to obtain the appropriate matching value.

Predicate mapping is used to match source form and target forms to determine the mapping type. The structure of predicate mapping is shown in Fig.7.

![Figure 7. The structure of predicate mapping, which contains text type, select type, numeric type and specific type.](image)

We define a predicate template as a four-tuple \{attribute; type; value; constraint\} in this paper, where attribute denotes the predicate label, type denotes the predicate type, value denotes the filling value of predicate, and constraint denotes the predicate constraint condition. For example, in Fig.4(b), if a user fills out “Deep Web” in the predicate “Title/Keywords” and selects “All Terms” as the constraint condition, then, its predicate template can be expressed with \{Title/Keywords; text; DeepWeb; AllTerms\}. For the target forms, according to different predicate type, predicate template can be divided into text predicate template \{attribute; text; value; constraint\}, select predicate template \{attribute; select; value; constraint\}, numeric and data time predicate template \{attribute; numeric; value; constraint\} and specific predicate template \{attribute; specific; value; constraint\}. When a user fills out query form, it will form the source binding template, and then recognize the corresponding type by predicate mapping, lastly, send to different type rewriters to rewrite queries.

D. Query Rewrite

Query rewrite is responsible for rewriting the query into an equivalent form that one can execute against the physical databases, which is classified as level-value matching. Nowadays, query rewrite based mostly on inefficient keyword matching techniques becomes a bottleneck of the web, therefore, we need to construct automatically a set of constraint mapping rules so that the system can use the user-provided input values to fill out the appropriate form fields of different web database forms[14]. In order to guarantee MinSS, a query of target form field can be seen as a union query Q\_s, which is a union of queries upon the target form to relevant answers from the target database. We want the union query Q\_s to be as “close” to the source query Q\_s as possible so that it retrieves fewest extra answers.

Generally, these requirements of form filling are commonly referred to as access limitations in that access to data can only take place according to given patterns, namely, search space[15].

**Definition 7** Search Space. For a predicate P, we define search space of P is \{t(P), which denotes all possible instances of P.

Query rewrite based on type can be seen as a search problem, its search space can be confirmed by the predicate type. Each type of rewriter implements a search for the type-driven mechanism, if the predicate value is W\_s for source form, then its value is W\_s for the absence of a predefined target value. If there exists a predefined search space in target form, its value can be obtained from predefined values, namely, can be obtained from search space[16]. Each type rewriter has a quite different performance in rewriting queries. To obtain the final matches, we use some heuristics to perform rewriting strategy.

1) Text type rewriter: If the predicate type is “text” in target form, namely, its predicate template is \{attribute; text; value; constraint\}, then filling out this text control of target form with the same value of source form, simultaneity, filling out this constraint value with the
same value of source form. If there does not exist constraint condition for the predicate in target form, then constraint is set null. For select type rewriter, numeric type rewriter and specific type rewriter, we adopt the same approach to obtain the constraint value of target form.

(2) Select type rewriter: If the predicate type is “select” in target form, namely, its predicate template is [attribute; select; value; constraint], we need to compute the matching degree between the source predicate value and the target search space, lastly, selecting the value by using null correspondences strategy[17] as the union query (filling value) of target form, in which we no longer need a threshold to filter out likely incorrect value correspondences. In this union query, the one semantically closest to the source predicate value can be seen as the best translation.

Definition8 Null Correspondence: Given a string s and a set of string \( \{t_i\} (i=1, 2, \ldots, n) \) null correspondence of the string s based on the set of string \( \{t_i\} \) is defined as formula (1):

\[
sim_{n}(s, null) = \prod_{i=1}^{n}(1 - \text{simp}(s, t_i))
\]

Where \( \text{simp}(s, t_i) \) denotes the semantic similarity between the string s and the string \( t_i \). When we get the value of null correspondence, \( \sim_{n}(s, null) \) will compare with all \( \text{simp}(s, t_i) \) \( (i=1, 2, \ldots, n) \). If \( \text{simp}(s, t_i) \) is the maximum value, then it means the string s is mostly similar with the string \( t_i \), so \( t_i \) will be selected as the filling value; If the maximum value is \( \sim_{n}(s, null) \), then it means the string s is not similar with all string \( t_i \) \( (i=1, 2, \ldots, n) \), so null or default value will be filled into the query field.

There are two cases for “select” types:

1) If the predicate type is “select” in source form, namely, its predicate template is [attribute; select; value; constraint], the predicate type in target form is also “select”. Since the set of select values is fixed, there is no possibility of mismatched for users. In this case, we can use the ontology-assisted similarity algorithm to obtain the desired union query.

2) If the predicate type is “text” in source form, namely, its predicate template is [attribute; text; value; constraint], the predicate type in target form is “select”. While not all the users are professional, they may not know how to exactly describe what they want and sometimes they type a wrong word into the query field. Therefore, query system may possibly return some results the user doesn’t want or even no result at all. Such a query is called failed query and this will bring on some uncertainties. In order to obtain a fixed quantity of results satisfying the query to the user, a query strategy is proposed: firstly, computing similarity based on edit distance matcher which is explained in definition 10, if the similarity does not exceed a threshold, then it means the two phrases are not shaped in font, in this case, switching to call ontology-assisted similarity algorithm.

Definition9 Edit Distance Matcher: Given two character strings \( S_1 \) and \( S_2 \), edit distance between \( S_1 \) and \( S_2 \) is measured by the number of edit operations, including insertions, deletions and substitutions, necessary to transform one string into another. We define the similarity based on edit distance between two strings (phrases) \( S_1 \) and \( S_2 \) as formula (2):

\[
\text{Sim}(s_1, s_2) = \frac{1}{1 + ed(s_1, s_2)}
\]

Where \( ed(S_1, S_2) \) is the edit distance of string \( S_1 \) and \( S_2 \).

(3) Numeric type rewriter: the predicate type is “numeric” in target form, namely, its predicate template is [attribute; numeric; value; constraint]. Numeric and data time have very similar nature in that they all form a linear space, and have similar operators, therefore, the mapping techniques for the two types are generally the same.

For the choice of numeric or data time can be divided into two ways, one is the discrete data selection, the other is the continuous data selection. For the discrete data selection method, we call discrete numeric data matcher which is explained in definition11.

Definition9 Discrete Numeric Data Matcher: If the user-provided input value in source form is \( q \), a discrete data. The corresponding search space in target form is \( D = \{q_1, q_2, \ldots, q_n\} \), where, \( q_1, q_2, \ldots, q_n \) are discrete data, then the similarity between \( q \) and \( q_i \) \( (1 \leq i \leq n) \) can be defined as formula (3):

\[
\text{Sim}(q, q_i) = 1 - \frac{|q - q_i|}{\max(q, q_i)}
\]

Assume \( \sigma \) is the threshold of MD, if \( \text{Sim}(q, q_n) = \max(\text{Sim}(q, q_1), \text{Sim}(q, q_2), \ldots, \text{Sim}(q, q_n)) \geq \sigma \), \( 1 \leq m \leq n \), then we select \( q_n \) as the union query of target form.

Example1 If the user-provided input value in source form is “100” for predicate label “Price”, the corresponding search space in target form is \( \{90,95,98\} \), \( \delta = 0.8 \), then through the similarity formula (2), we can infer that \( \text{Sim}(100,90) = 0.9 \), \( \text{Sim}(100,95) = 0.95 \), \( \text{Sim}(100,98) = 0.98 \), thus, the value “98” of search space is the most greatest similarity with “100”; thus, we should select “98” as the union query of target form.

In query forms, the user is likely to be given ranges of values to choose(Fig.8), to help the query rewriter understand different ranges, we need to let the system know the meanings of the range modifiers. For this purpose, we build a semantic dictionary that keeps commonly used range modifiers for numeric domains (Table1).

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After converting the range modifiers, we need to select the advisable value as the filling value. In order to reduce the undesired intermediate results to the minimum, we ought to choose the minimum target range, namely, the target range is exactly a minimum subsumption of the original one. The most appropriate value can be easily found out by projecting the original value to the number or time axis, which is explained in definition 12.

**Definition 10** Continuous Numeric Data Matcher: If the user-provided input value in source form is \( q \), which is a continuous data with range \( [a,b] \), the corresponding target range is \( q_t \), whose selective values are continuous ranges \( S_t = \{[n_1,n_1'],[n_2,n_2'],...,[n_m,n_m']\} \), \( n_i \leq n_i' \), \( 1 \leq i \leq m-1 \), the overlap grade between \( q \) and \( S \) reflects the MD. There are four cases for the overlap grade between \( a, b \) and \( n_i, n_i' \):

- a) \( n_i \leq a \) and \( a \leq n_i' \leq b \)
- b) \( a \leq n_i \) and \( n_i \leq b \)
- c) \( n_i \leq a \) and \( n_i' \geq b \)
- d) \( n_i \leq a \) and \( n_i' \geq b \)

In this condition, the union query is the conjunction of the above four cases, namely:

\[ q_t = \bigcup Condition_i \bigcup Condition_{i+1} \bigcup Condition_{i+2} \bigcup Condition_{i+3} \]

If the source query range becomes large, the cost of MinSS will be high because the number of targets queries to the web database will increase. An example for minimum subsumption strategy is shown in Fig. 9.

<table>
<thead>
<tr>
<th>Range modifiers</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>More than</td>
<td>&gt;</td>
</tr>
<tr>
<td>Less than</td>
<td>&lt;</td>
</tr>
<tr>
<td>under</td>
<td>&lt;</td>
</tr>
<tr>
<td>from</td>
<td>&gt;=</td>
</tr>
<tr>
<td>Any</td>
<td>All range</td>
</tr>
</tbody>
</table>

Table I. THE SEMANTIC DICTIONARY FOR RANGE MODIFIERS, AND WITH THE INFORMATION AND AN APPROPRIATE SEMANTIC DICTIONARY FOR RANGE MODIFIERS, WE CAN INFER THE CORRESPONDING NUMERIC RANGES FROM RANGE SEMANTICS TABLE.

![Figure 9](image)

Figure 9. An example for minimum subsumption strategy: For the predicate label “Price range” (Fig.9), if the filling value is “under 35” in source form, whose meaning is the value of less than 35 by range modifiers table. The search space in target form contains five selective values “0-25”, “25-45”, “45-65”, “65-85”, “85-”, we can observe that the projection area in source form contains two target search space “0-25” and “25-45” by numeric projection, that is to say the minimum subsumption using MinSS in target form is (“0-25”, “25-45”), namely, the conjunction of target form which contains the source projection area.

(4) Specific type rewriter: The above type rewriters can only deal with 1:1 mapping to find corresponding filling values, which can not handle complex mapping. Complex mapping binds a source schema element to a target schema element through an appropriate mapping expression. Therefore, we need specific type rewriter to realize the complex mapping by DOCM, which the user-provided input values will be stored to corresponding class. If the predicate type is “text”, then, according to a predefined order, specific type rewriter will assign the value of source form to target form; if the predicate type is “numeric”, then, according to a predefined format, specific type rewriter will assign the value of source form to corresponding field of target form.

**E. Query Submission**

After query rewrite, user’s suggested queries have been filled out each target forms, then the system will automatically trigger button to submit these query plans. As we know, when a form is submitted, the web browser will code the data which the user fills out source form, the final query forms for sending web server are in accordance with the “variable name 1 = value & variable name 2 = value & ...”, the data format as URL parameters affixing to this basic URL address to realize the complete URL address for web server. To sum up, we can see that to complete the automatic submission of each target form, it needs to achieve this function of simulating browser, namely, constructing URL address with parameters and triggering this URL. In this case, the query posted to the source form can be precisely translated to a query against the target form.

**Example 2**

Given a URL http://www.abbeys.com.au/search.asp, we can observe that the base URL is http://www.abbeys.com.au, and the action path is /search.asp, the form fields are “Author”, “Keywords”, “Category”, “Price Range”, “ISBN” and “Publication data”, if we fill out this form with value “Bing Liu”、“web mining”、“Computing and information technology”、“All Prices”、“After the year 2000” respectively then, the query is thus constructed as: http://www.abbeys.com.au/search.asp?Author=Bing+Liu&Title/Keywords =web+mining&Category=Computing+and+information+technology&PriceRange=All+Prices&ISBN=&Publication data=After+the+year+2000. If we send this query directly to the web site, we will get the desired results from the target site[18].

**IV. EXPERIMENTS**

Though the above analysis, we implement the graphical interface for web query translation which is shown in Fig.10.
To evaluate our approach, we select the Book-Domain query interfaces from UIUC[19] as the test samples. The evaluation metric for query translation is measured by Precision, Recall and F-measure. Precision denotes the percentage of the correctly query translation templates over all the query translation templates, Recall denotes the percentage of the correctly query translation templates over all the query form, and F-measure is a comprehensive assessment of Precision and Recall. The formulas are defined as (4), (5) and (6):

\[
\text{Precision} = \frac{\text{the correctly query translation templates}}{\text{all query translation templates}} \times 100% \quad (4)
\]

\[
\text{Recall} = \frac{\text{the correctly query translation templates}}{\text{all the query form}} \times 100% \quad (5)
\]

\[
F\text{- measure} = \frac{(1 + \mu^2) \times \text{Precision} \times \text{Recall}}{\mu^2 \times \text{Precision} + \text{Recall}} \times 100% \quad (6)
\]

Where \(\mu\) denotes the weight coefficient, which is used to measure the importance between Recall and Precision. The results are shown in Table.2:

<table>
<thead>
<tr>
<th>Form number</th>
<th>Predicate template number</th>
<th>Predicate template number correctly</th>
<th>Recall</th>
<th>Precision</th>
<th>F-measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>132</td>
<td>123</td>
<td>0.884</td>
<td>0.932</td>
<td>0.907</td>
</tr>
<tr>
<td>50</td>
<td>256</td>
<td>235</td>
<td>0.869</td>
<td>0.922</td>
<td>0.895</td>
</tr>
<tr>
<td>75</td>
<td>364</td>
<td>337</td>
<td>0.867</td>
<td>0.926</td>
<td>0.896</td>
</tr>
<tr>
<td>average</td>
<td></td>
<td></td>
<td>0.873</td>
<td>0.927</td>
<td>0.899</td>
</tr>
</tbody>
</table>

From the results of Table3, we can see that the predicate type “text” occupies the largest number in all predicate types, and the precision is also the best. The main reason for “text” type translation mistake is the predicate matching error, and the text field does not rationally combine with corresponding constraints in the process of schema extracting. The mistake reason for “select” type is to mistakenly input dissimilarity value and not to fill in the real similarity value in computing similarity based on edit distance. The inconsistent representation for “numeric” type content is the main reason to cause mistake. The “specific” type is more complicated, the mistake is mainly due to unreasonably split or combine source query, partly to schema extraction and predicate matching. The statistical results show that the precision of four types predicates mapping have reached a higher level, but the precision of “specific” type query translation would be further improved.

V.CONCLUSION

We presented a novel approach to query translation based on ontology automatically, which can transform queries from source form into queries that address the underlying physical databases. The experiment results show that our approach is feasible and effective.

For our future work, we plan to enrich the domain ontology and continually improve query translation algorithm, we will also further research on the complex matching problem. We believe that our approach, with appropriate extensions, can achieve better results.

REFERENCES