Light-weight Domain-based Form Assistant: Querying Web Databases On the Fly*

Zhen Zhang Bin He Kevin Chen-Chuan Chang

University of Illinois at Urbana-Champaign
{zhang2, binhe}@uiuc.edu, kcchang@cs.uiuc.edu

Abstract

The Web has been rapidly "deepened" by myriad searchable databases online, where data are hidden behind query forms. Helping users query alternative "deep Web" sources in the same domain (*e.g.*, Books, Airfares) is an important task with broad applications. As a core component of those applications, dynamic query translation (*i.e.*, translating a user's query across dynamically selected sources) has not been extensively explored. While existing works focus on isolated subproblems (*e.g.*, schema matching, query rewriting) to study, we target at building a complete query translator and thus face new challenges: 1) To complete the translator, we need to solve the *predicate mapping* problem (*i.e.*, map a source predicate to target predicates), which is largely unexplored by existing works; 2) To satisfy our application requirements, we need to design a customizable system architecture to assemble various components addressing respective subproblems (*i.e.*, schema matching, predicate mapping, query rewriting). Tackling these challenges, we develop a *light-weight domain-based form assistant*, which can generally handle alternative sources in the same domain and is easily customizable to new domains. Our experiment shows the effectiveness of our form assistant in translating queries for real Web sources.

*This material is based upon work partially supported by NSF Grants IIS-0133199, IIS-0313260, and an 2004 IBM Faculty Award. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of the funding agencies.

**Proceedings of the 31st VLDB Conference,
Trondheim, Norway, 2005**

1 Introduction

Recently, we have witnessed the rapid growth of databases on the Web, or the so-called "deep Web." A July 2000 survey [1] estimated 96,000 "search cites" and 550 billion content pages in this deep Web. Our recent study [4] in April 2004 estimated 450,000 online databases. On the deep Web, numerous online databases provide dynamic *query-based* data access through their *query forms*, instead of static URL links. For instance, amazon.com supports a query form for searching books on author, title, subject, *etc.*. To help users explore the deep Web, it becomes increasingly important to facilitate users' interaction with query forms. Therefore, this paper proposes to build a *form assistant* to help querying databases on the Web.

In particular, with the proliferation of sources in various domains, we often need to query "alternative" sources in the same domain (*e.g.*, Books, Airfares). We observe that such a domain-based integration scenario is useful with broad applications. For instance, we may build a MetaQuerier [6] to integrate dynamically selected sources relevant to user's queries, where on-the-fly translation of user's queries to these sources is necessary; we may build a domain portal (*e.g.*, pricegrabber.com) to provide a unified access to dynamic online sources in the same domain with general translation techniques; or we may build a form assistant toolkit to suggest users with potential queries they are likely to issue in query forms, *e.g.*, if a user fills the query form in amazon.com, the toolkit can suggest potential queries in bn.com. (Section 6 will discuss the implementation of such a form assistant toolkit.)

A core component of these applications is a *dynamic query translator*, which translates user's queries between dynamically selected query forms in the same domain. In particular, we define the query translation problem as *translating a user's query from a source query form to a target one*, which we believe is a foundation of many translation tasks in various applications. (Section 2 will present our formal definition of the query translation problem.) Existing works mainly focus on isolated subproblems of translation (*e.g.*, schema matching, query rewriting) to study. The goal of our work, *i.e.*, building a complete dynamic query translator, has thus not been extensively investigated.

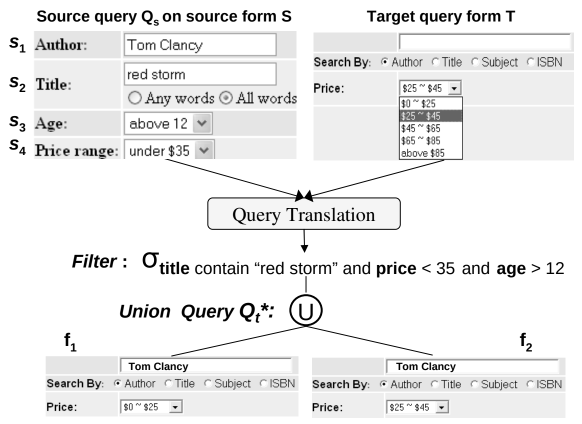


Figure 1: Form assistant: A translation example.

As the applications mandate, such a query translator should have two properties: First, *source-generality*: We require the built-in translation techniques can generally cope with new or "unseen" sources. Second, *domain-portability*: We require the translator can be easily customized with domain-specific knowledge and thus deployed for new domains. As a realization of such a query translator, we develop a *light-weight domain-based form assistant*. It is domain-based because it can generally handle alternative sources in the same domain with a manageable size of domain-specific knowledge. It is light-weight because customizing to a new domain only needs limited efforts to encode domain-specific knowledge. To better understand new challenges we are facing in building this form assistant, let us look at a translation example.

Example 1: Assume we want to build a form assistant for Books domain, which can translate queries between any two book sources. In particular, consider a translation from a source query Q_s (issued on a source form S) to a target form T in Figure 1. Q_s is a conjunctive query over four predicates s_1 : [author; *contain*; Tom Clancy], s_2 : [title; *contain*; red storm], s_3 : [age; $>$; 12], and s_4 : [price; $\leq$; 35], *i.e.*, $Q_s = s_1 \wedge s_2 \wedge s_3 \wedge s_4$. The target form T supports predicate templates on author, title, subject, ISBN one at a time with an optional predicate template on price. Figure 1 shows one of the possible translations. ■

To translate Q_s from S to T in the above example, we need to reconcile three levels of *query heterogeneities*:

Attribute level: Two sources may not support querying the same concept or may query the same concept using different attribute names. For instance, S supports querying the concept of reader's age, while T does not. Also, S denotes book price using price range, while T using price.

Predicate level: Two sources may use different predicates for the same concept. For instance, price predicate in T has a different set of value ranges from S. As a result, in the predicate level, we can only translate a predicate as "close" as possible. In particular, we set our closeness goal as *minimal subsumption*, *i.e.*, to subsume the source query Q_s with fewest extra answers.

Query level: Two sources may have different capabilities on querying valid combinations of predicates. In our example, form T only supports queries on one of the attributes author, title, subject and ISBN at a time with an optional attribute price. Therefore, T cannot query author and title together, while S can.

To realize the source query, we need to reconcile the heterogeneities at the three levels and generate a query plan expressed upon the target form T. Such a plan, as Figure 1 shows, in general, consists of two parts: a *union query* Q_t^* which is a union of queries upon the target form to retrieve relevant answers from the target database, and a *filter* σ which is a selection to filter out false positives. (Further optimization is possible by logic transformation of the query plan, but this transformation does not change the semantics of the plan.) To minimize the cost of post processing, *i.e.*, filtering, we want the union query Q_t^* to be as "close" to the source query Q_s as possible so that it retrieves fewest extra answers. Q_t^* in Figure 1 is such a query. We will discuss its construction throughout the paper.

Building such a form assistant brings us two new challenges: predicate mapping and system architecture design. First, we need to develop a general predicate mapping mechanism that can be easily adopted to new sources and domains. While extensive studies have been done to the attribute level, known as *schema matching*, and the query level, known as *capability-based query rewriting*, little has been done to reconciling the heterogeneity at predicate level, which we name as *predicate mapping*. Existing work on predicate mapping [2] relies on *per-source* based rules to encode the mapping knowledge, which cannot achieve our goal of source-generality and domain-portability. Our approach is inspired by an intriguing insight that matching predicates often form *localities*, which are consistent with the notion of *data types*. This observation enables us to encode a more general mapping knowledge based on the types and thus motivates a type-based search-driven approach for mapping predicates.

Second, guided by the application requirements, we need to carefully design the system architecture of the form assistant. In particular, to realize source-generality, each component of the system should incorporate general techniques to cope with heterogeneities for new sources. To realize domain-portability, the system should require minimal amount of human involvement to customize the form assistant for new domains.

Tackling these challenges, we develop a *light-weight domain-based form assistant*. We realize this form assistant in a complete application– form assistant toolkit, which starts from extracting the query capabilities of query forms and finally generates suggested queries as output. We evaluate the entire system over real Web query forms in 8 domains and the experimental results show the promise of both our system design and predicate mapping techniques. In summary, the contributions of this paper are:

- *Framework:* To realize the dynamic query translator, we develop a *light-weight domain-based form assistant*, which can generally handle alternative sources in the same domain and is easily customizable to new domains.

- *Techniques:* At the core of the form assistant, we propose a *type-based search-driven* approach for predicate mapping by leveraging the mapping localities.

The rest of the paper is organized as follows: Section 2 formalizes the query translation problem. Section 3 presents the system architecture of the form assistant. Section 4 motivates the type-based search-driven predicate mapping machinery and Section 5 discusses concrete techniques for realizing it. Section 6 presents our development of other components in building the form assistant. Section 7 reports our experimental results. Section 8 discusses related works and Section 9 concludes the paper.

2 The Query Translation Problem

In this section, we formalize the query translation problem. As Figure 1 illustrates, the input to the query translator is a *source query* Q_s on a *source form* S and a *target form* T. The output of translator is an expression with a filtering σ applied upon a union query Q_t^*. The union query is built upon a set of *form queries*, f_1, ..., f_n, where each form query is a valid way of filling the form T.

Such a translation, as Example 1 shows, needs to meet two goals: First, the union query must be a valid query. That is, it must be built upon only valid form queries f_1, ..., f_n of the target form. Second, the union query must be "close" to the source query to minimize the selection as the post processing. As we can see, these two objectives are placed on the union query without considering the actual selection σ. The reason is that we can always apply the source query Q_s as the tightest filter to remove false positives. We notice that some other works, *e.g.*, [2], also studied the "optimality" of the filters, *i.e.*, to choose a filter with fewest number of predicates. We do not consider this issue in our paper since it is straightforward to get an optimal filter for a union query.

We thus define the query translation problem as: *Given a source query Q_s and a target form T, among all the valid union queries of T, we choose the one semantically closest to Q_s as the best translation.* Next, we need to formally define *valid union query* and *semantic closeness*.

Query Model

The query model of a source describes templates of acceptable queries. Many specification languages, *e.g.*, [19], have been proposed for describing general data sources, often in the form of datalog or context-free grammar. However, since developed for general purposes, those languages, although sufficiently powerful, are not very intuitive for expressing query forms. Therefore, we adopt a simple query model to describe source capabilities, which we will discuss below. This query model can be automatically recognized by our previous work on form extraction [22]. Further, as Section 6 will discuss, when necessary, this model can be transformed into other specification languages and thus we can apply existing query rewriting techniques.

The query model of a form consists of *vocabulary* Σ and *syntax* $\mathcal{F}$. Vocabulary Σ specifies a set of usable *predicate templates* on the query form. A predicate template is a three-tuple [attribute; *operator*; value], with one or more variables as "placeholder" to be instantiated by concrete values. For instance, Figure 2(a) shows the vocabulary of the target form T in Figure 1, which contains five predicate templates $\{P_1, \ldots, P_5\}$ on attributes author, title, subject, isbn and price respectively. In particular, P_1 =[author; *contain*; $au] queries on attribute author with a default operator *contain* applied to a value parameter $au.

Further, upon the vocabulary of predicate templates, the syntax $\mathcal{F}$ specifies all the valid combinations of these templates with respect to the form. Like many other specification languages, *e.g.*, [19], our syntax focuses on conjunctive queries, because it is sufficient to capture the capabilities of most deep Web sources. We name a valid combination of predicate templates a *conjunctive form*.

We observe that deep Web sources often have two types of *constraints* on how predicate templates can be queried together. First, some predicate templates may only be queried "exclusively." For instance, form T allows only an exclusive selection among attributes author, title, subject and ISBN; P_1, P_2, P_3 and P_4 can thus only appear one at a time (with an optional P_5). Second, a form may have "binding" constraints, which require certain predicate templates be filled as mandatory. For instance, form T may require price not be queried alone and thus each form query must bind a predicate template from $P_1, \ldots, P_4$. In our modeling, we thus define $\mathcal{F}$ as all valid conjunctive forms that satisfy these two constraints. For instance, form T requires one template from $P_1, \ldots, P_4$ with an optional P_5, and thus its syntax contains eight conjunctive forms $\mathcal{F} = \{F_1, \ldots, F_8\}$, as Figure 2(a) shows. (In section 6, we will discuss the construction of such a model for a query form, especially how to deal with the binding patterns which are usually not explicitly indicated in the form.)

Based on the above modeling, we can define what a valid union query is, given the target form. To begin with, we define a *predicate* p_i as an instantiation of a predicate template P_i, *i.e.*, assigning concrete values for the parameters in P_i. For instance, p_1 in Figure 2(b) is an instantiation of P_1. Further, a *form query* f_j is an instantiation of a conjunctive form F_j, *e.g.*, f_1 in Figure 2(b) is an instantiation of F_1. Overall, a *valid union query* on the target form is thus $f_1 \vee \ldots \vee f_n$, where f_i is a form query. In particular, Figure 2(b) shows a valid union query Q_t on form T.

We limit our focus on union only translations, as many other works [18, 19] do, because of two reasons. First, the union operation is "non-blocking," which allows results to be incrementally constructed, while intersection is "blocking." Second, an intersection (*e.g.*, $A \cap B$) usually can be more efficiently realized by a selection (*e.g.*, $\sigma_B A$) without retrieving input from one of the operands (*e.g.*, B).

Semantic Closeness

To capture the closeness between a valid query and the source query, we need to define a closeness metric. In par-

Σ	P_1 = [author; *contain*; \$au] P_2 = [title; *contain*; \$ti] P_3 = [subject; *contain*; \$su] P_4 = [ISBN; *contain*; \$isbn] P_5 = [price; *between*; \$s,\$e]
$\mathcal{F}$	$F_1 = P_1 \wedge P_5$ $F_2 = P_2 \wedge P_5$ $F_3 = P_3 \wedge P_5$ $F_4 = P_4 \wedge P_5$ $F_5 = P_1$ $F_6 = P_2$ $F_7 = P_3$ $F_8 = P_4$

(a). Query model M of form T.

Predicate	p_1 = [author; *contain*; Tom Clancy] p_2 = [title; *contain*; red storm] p_5^1 = [price; *between*; 0-25] p_5^2 = [price; *between*; 25-45]
Form query	$f_1 = p_1 \wedge p_5^1$ $f_2 = p_1 \wedge p_5^2$
Union query	$Q_t = f_1 \vee f_2$

(b). Example instantiations of query model for form T.

Figure 2: Query model and exampl

ticular, we adopt the *minimal subsuming* metric $\mathcal{C}_{min}$, *i.e.*,

Definition 1: Given a source query Q_s and a target query form T, a query Q_t^* is a minimal subsuming translation *w.r.t.* T if:

1. Q_t^* is a valid query *w.r.t.* T;
2. Q_t^* subsumes Q_s, *i.e.*, for any database instance D_i, $Q_s(D_i) \subseteq Q_t^*(D_i)$;
3. Q_t^* is minimal, *i.e.*, there is no query Q_t such that Q_t satisfies (1) and (2) and Q_t^* subsumes Q_t. ■

We choose $\mathcal{C}_{min}$ as many other query rewriting works [16, 2] do, because it has several advantages: First, a $\mathcal{C}_{min}$ translation does not miss any correct answer and contains fewest incorrect answers. Consequently, the overhead of filtering out "false positives" (in the selection operation) is minimal. Second, the $\mathcal{C}_{min}$ metric is database content independent, as the above definition indicates. Since human users usually are not aware of the content before querying a source, such content independent translation is consistent with users' behavior. Also, in Section 5, we will apply this property to generate a complete database for subsumption testing. Third, it enables the separation of predicate mapping from query rewriting, as Section 3 will discuss.

The following example demonstrates a translation using the $\mathcal{C}_{min}$ metric.

Example 2: Consider the source query Q_s in Example 1 and three valid queries Q_{t_1}, Q_{t_2} and Q_{t_3} as below, wherein predicate p_1, p_2, p_5^1 and p_5^2 were introduced in Figure 2.

Q_{t_1}	$(f_1 : p_1 \wedge p_5^1) \vee (f_2 : p_1 \wedge p_5^2)$
Q_{t_2}	$f_2 : p_1 \wedge p_5^2$
Q_{t_3}	$f_3 : p_1$

We can see that Q_{t_1} and Q_{t_3} subsume Q_s, while Q_{t_2} does not, because it misses the price range between 0 to 25 and thus cannot be the best translation. Further, between Q_{t_1} and Q_{t_3}, we can prune Q_{t_3} because it subsumes Q_{t_1} and thus cannot be the $\mathcal{C}_{min}$ translation. In fact, we can show that Q_{t_1} is the $\mathcal{C}_{min}$ translation. ■

3 System Architecture

To realize the query translation as defined in Section 2, conceptually we need to search among all valid queries for the minimal subsuming one. This is certainly inefficient. To avoid exhaustive "search," we want to "construct" the best translation. In particular, since translation essentially is to reconcile the heterogeneities at the three levels, it is thus desirable to address them separately, and then construct the translation by putting them together. That is, we first find the matching predicates, then map each pair of matching

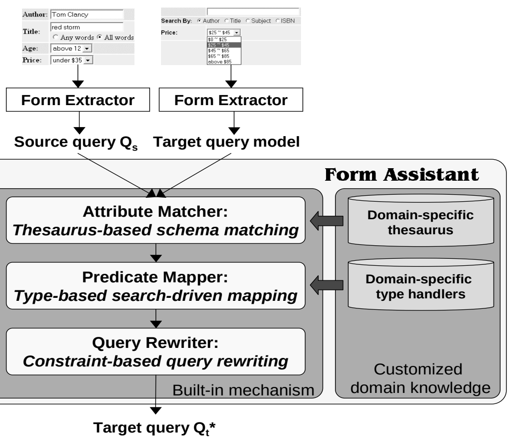

Author: Tom Clancy
Title: red storm
Any words All words
Age: above 12
Price: under $35
Search By: Author Title Subject ISBN
Price: $25 ~ $45
$0 ~ $25
$25 ~ $45
$45 ~ $65
$65 ~ $85
above $85
Form Extractor
Form Extractor
Source query Q_s
Target query model
Form Assistant
Attribute Matcher: Thesaurus-based schema matching
Predicate Mapper: Type-based search-driven mapping
Query Rewriter: Constraint-based query rewriting
Built-in mechanism
Domain-specific thesaurus
Domain-specific type handlers
Customized domain knowledge
Target query Q_t*

Figure 3: System architecture of the form assistant.

predicates individually by the $\mathcal{C}_{min}$ metric, which composes a *mapped query*, and finally find the $\mathcal{C}_{min}$ rewriting of the mapped query on the target form.

Is such separation possible? While the separation of predicate mapping from attribute matching is obvious, how about the separation of query rewriting from predicate mapping? To guarantee the correctness of such separation, we require that *the mapped query, generated by mapping predicate individually, must be rewritable to a minimal subsuming translation*. This requirement has two implications: First, the mapped query must be rewritable to a valid translation (if a valid translation of the source query exists at all); second, the rewriting of the mapped query must be an overall minimal subsuming translation. In our extended report [23], we show that under the $\mathcal{C}_{min}$ translation metric, the mapped query meet these two requirements and thus predicate mapping and query rewriting can be separated.

The separation thus enables a modular design for the form assistant, which consists of three components: *attribute matcher*, *predicate mapper* and *query rewriter*, as Figure 3 shows. First, attribute matcher discovers semantically corresponding attributes. Then, for each pair of matching predicates, predicate mapper maps the source predicate to the target one with the $\mathcal{C}_{min}$ metric. After matching attributes and mapping each individual predicate, we get a *mapped query*. Finally, query rewriter rewrites the mapped query to a valid query in terms of the capability of the target form. Example 3 illustrates the functionality of each component with a concrete example.

Example 3: Consider the translation example in Example 1, where source query $Q_s = s_1 \wedge s_2 \wedge s_3 \wedge s_4$. First, attribute matcher will find that s_1, s_2 and s_4 have matching attributes in T, while s_3 does not. Then, predicate mapper will map each pair of matching predicates with the $\mathcal{C}_{min}$

metric. In particular, for s_1, the mapped predicate is p_1 = s_1; for s_2, the mapped predicate is p_2 = s_2; for s_4, the mapped predicate is $p_5^1 \vee p_5^2$, where p_5^1 = [price; *between*; 0-25] and p_5^2 = [price; *between*; 25-45]. After matching and mapping, the mapped query is thus $Q_s^{'} = p_1 \wedge p_2 \wedge (p_5^1 \vee p_5^2)$. Finally, applying the query rewriting, we can rewrite $Q_s^{'}$ into $\sigma_{p_2}(f_1 \cup f_2)$, where $f_1 = p_1 \wedge p_5^1$ and $f_2 = p_1 \wedge p_5^2$. The union query $f_1 \cup f_2$ is thus (one of) the best translation Q_t^* for source query Q_s, and the selection σ_{p_2} is a part of the final filter, which we omit here. ■

Such modularization on one hand reduces the complexity of translation– Each component only focuses on a subproblem to solve. On the other hand, it allows us to plug in, for each component, corresponding techniques suitable for specific application needs. In particular, attribute matching and query rewriting have been extensively studied. Our form assistant can thus take advantage of the existing techniques by taking them as building blocks of the system.

To prepare the input for the form assistant, we explore the form extractor we developed in [22] to automatically extract query capabilities of sources. Next, we need to design each component of the form assistant to satisfy the application requirements, *i.e.*, source-generality and domain-portability. The key is to identify, for each component, what knowledge can be built-in as generic techniques and what should be customized as domain-specific knowledge. Further, we want the customized knowledge to be per-domain based instead of per-source, and we want to keep such knowledge within human-manageable scale.

Attribute Matcher: To match attributes is essentially to identify synonym attributes. This problem, known as schema matching, has been an important problem and thus extensively studied in data integration. Depending on the application scenarios of the form assistant, we can employ either automatically discovered or manually encoded synonym thesaurus, based on which we can explore a general thesaurus-based matching approach. For instance, for the MetaQuerier system (discussed in Section 1), since sources are on-the-fly selected and thus form dynamic domains, the thesaurus has to be automatically discovered by exploring existing automatic matching techniques, *e.g.*, [11, 12]. While for domain portals and form assistant toolkit, since sources are in pre-configured domains, the thesaurus can be manually customized with more reliable domain-specific knowledge. Our survey [4] on query forms shows that, for each domain, there only exist a small number of frequently used attributes, which makes the manual encoding of such a domain-specific thesaurus feasible in practice.

Predicate Mapper: To map predicates, we need to know, for each pair of matching predicates, how to choose the operators and fill in the values. To achieve the requirement of easy deployment for new domains, we thus ask whether there exists domain-generic mapping mechanism which addresses most if not all mappings in various domains. We observed that, as an enabling insight, predicates with the same data type often share similar mapping patterns. Motivated by this observation, we develop a *type-based search driven* mapping approach with several built-in type handlers to handle the majority cases of general "built-in" types. For those domain-specific mappings (*e.g.*, airport code to city name in airfares domain), we can customize the required mapping knowledge by adding new type handlers if needed.

r_1	[author; *contain*; $t] → *emit:* [author; *contain*; $t]
r_2	[title; *contain*; $t] → *emit:* [title; *contain*; $t]
r_3	[price; *under*; $t] → **if** $t ≤ 25, *emit:* [price; *between*; 0,25]
	elif $t ≤ 45, *emit:* [price; *between*; 0,25] ∨ [price; *between*; 25,45]
	...

Figure 4: Example mapping rules of source S and target T.

Query Rewriter: To tackle the query-level heterogeneity is essentially to rewrite the query to satisfy the syntax constraints of the target form. Such a task, has been studied as capability-based query rewriting [18, 20, 15], is not specific to any source or domain. Hence, as Figure 3 shows, the query rewriter component can be entirely built-in into the system. Section 6 will discuss our development of this component by exploiting existing rewriting techniques.

4 Predicate Mapping: The Motivation

With extensive existing study on schema matching and query rewriting, together with our modular separation of predicate mapping from query rewriting, the essential challenge of translation boils down to predicate mapping. As Section 3 motivated, the requirement of easy-customization calls for domain-generic mapping knowledge. Does there exist such generic mapping knowledge applicable to sources across different domains? How to encode such knowledge? Those are the critical questions we need to address in predicate mapping.

Existing solutions on predicate mapping usually assume a static small-scale setting. In such scenarios, it is common, *e.g.*, as [2] studies, to use a source-based pairwise-rule driven mapping machinery to map predicates. Figure 4 gives some example rules to encode the mapping knowledge required for translation in Example 1.

However, such a mapping machinery, characterized by a "per-source" knowledge *scope* and "pairwise" rule encoding *mechanism*, is not suitable for our light-weight domain-based form assistant, since it lacks both *generality* and *extensibility*. To begin with, the source-based scope can only handle mappings between sources whose mapping knowledge has been specified. It cannot generally deal with mappings involving "unseen" sources. Also, the pairwise-rule mechanism to encode the knowledge is not extensible because writing rules for each pair of predicate templates is hard to scale when mapping are required among a large set of sources. Further, as sources are autonomously developed, their query capabilities may change, which makes maintenance of rules labor intensive.

4.1 A Motivating Survey

To understand the feasibility of developing a more general and extensible mapping machinery, we thus ask: Are there generic scopes orthogonal to domains wherein the mapping happens? If such scopes exist, we thus can leverage them to encode our domain generic mapping knowledge.

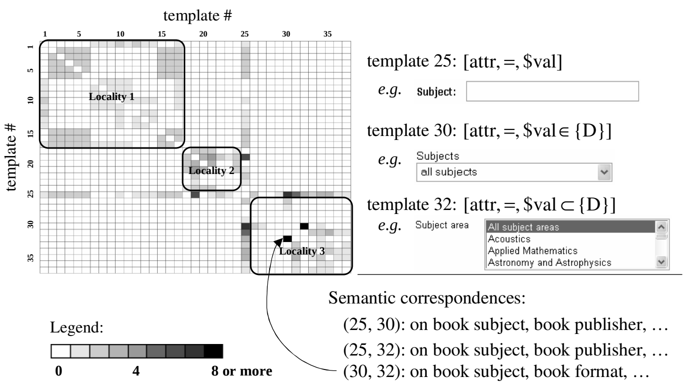


Figure 5: The correspondence matrix.

To answer this question, we conduct a survey to examine the *mapping correspondence* between predicate templates. Such mapping correspondence hints the required translation scope: only templates with mapping correspondence need to be translated. In particular, we examined 150 query forms in three domains, *i.e.*, Books, Airfares and Automobiles, in the TEL-8 dataset of the UIUC Web Integration Repository [5]. This TEL-8 dataset contains around 440 manually collected deep Web sources with their query forms. We totally find 37 template patterns in 150 sources. For instance, as two popular patterns, [attr; *default*; $val] uses a default operator and accepts arbitrary values from the user input (*e.g.*, template P_1 in T belongs to this pattern), and pattern [attr; *default*; $val∈{D}] accepts a value from a set of given options (*e.g.*, P_5 in T belongs to this pattern). In the rest of the section, we will use template to generally refer to template pattern for simplicity.

We notice that two predicate templates have mapping correspondence only if there exists a concept expressed with these two templates in different sources. For example, to support querying book subject, a source may use [subject; *default*; $val] and another [category; *default*; $val∈{D}]. Since subject and category are matching attributes, templates [attr; *default*; $val] and [attr; *default*; $val∈{D}] need to be translated and thus have mapping correspondence. We record such mapping correspondence between any two predicate templates P_i and P_j in a *correspondence matrix* CM. In particular, $CM(i, j)$ denotes the number of concepts that are expressed using both templates P_i and P_j. Figure 5 shows our survey result (*i.e.*, the correspondence matrix), where the value of $CM(i, j)$ is illustrated as the degree of grayness.

As Figure 5 indicates, mappings happen mostly only within certain clusters of templates. In the figure, we order the templates in a way to clearly observe such localities: In particular, we observe three localities of templates among which mapping happens. Such mapping localities thus formulate the scope of mappings.

We further ask: *What templates can share a locality?* Are there something common among templates in the same locality? Not surprising, we found there is indeed an underlying explanation for the phenomenon. While the predicate templates in a locality are used by various concepts in different domains, those concepts often share the same "data type." In particular, the first locality in Figure 5 corresponds to templates usually used by concepts of `datetime` type, the second one `numeric` type and the third one `text` type. The only outlier is the template [attr; *default*; $val], as shown in Figure 5. Concepts with different data types can all use this template to express their query predicates and this template thus has mapping correspondence to most other templates.

4.2 Type-based Search-driven Predicate Mapping

Our observations above clearly reveal that mapping between predicate templates are not arbitrary– Their associations not only suggest "locality," but also are clearly "aligned" with their underlying data types. Such observation motivates a *type-based search-driven* predicate mapping machinery.

First, our observation shows the promise of pursuing a *type-based* knowledge scope. Since mappings are only worthy inside localities of types, we can express the mapping knowledge in the scope of types. Such a type-based mapping scope is more general than the source-based or domain-based scope, since data types are widely reused across different sources and domains, and we are able to translate queries to unseen sources or adapt the knowledge to new domains as long as they reuse those data types.

Second, we find that data type gives us a "platform" to compare semantics (*i.e.*, the subsuming relationship) of different mappings and thus enables an extensible *search-driven* mechanism. Instead of writing rules to hard code the mapping for every pair of predicate templates, we can encode our mapping knowledge as an evaluator for each template. This evaluator "materializes" the semantics of a query against a type specific platform, as Section 5.1 will discuss. By doing so, semantic comparison can thus be performed on the materialized results. For instance, to realize rule r_3 in Figure 4, we can project the source predicate as well as all target predicates onto an axis of real numbers, and thus compare their semantics based on their coverage. Finding the closest mapping thus naturally becomes a search problem - to search for the ranges expressible in the target form that minimally cover the source. Such a search-driven approach achieves extensibility by exploring evaluators rather than static pairwise rules. With a data type of n templates, we only need n evaluators instead of n^2 rules; when adding a new pattern, only one evaluator needs to be added instead of n rules.

5 Predicate Mapping: The Solution

In this section, we discuss our development of predicate mapper, which realizes the type-based search-driven mapping machinery. According to our system design (Section 3), predicate mapper takes a source predicate s and a matched target predicate template P as input, and outputs the closest target translation t^* for s. In particular, predicate mapper consists of two components: *type recognizer* and *type handler*, as Figure 6 shows. Type recognizer recognizes the data type of the predicates and then dispatches

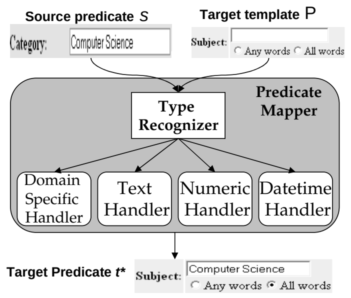


Figure 6: Framework of predicate mapper.

to a corresponding type handler. A type handler maps predicates of a specific type with a search approach.

Since our focus in this section is type handler, we only briefly discuss the development of type recognizer. In particular, since the data type of a predicate can often be hinted by its syntactic features, we explore those syntactic clues to implement the type recognizer. For instance, we can exploit distinctive operators (*e.g.*, *all*, *any* for `text` type), the value filled in the source predicate (*e.g.*, s_3 in Example 1 contains value 35) and the value domain in the target template (*e.g.*, a selection list of P_5 in Example 1) to infer type information. We have developed a type recognizer in our previous work for schema matching [12], wherein the type information is used to help matching. Due to space limitation, please refer to [12] for more details.

5.1 Overview of Type Handler

At core of the predicate mapping, each type handler realizes the search-driven mechanism for its responsible type. Like any other search-based algorithms, a type handler needs to have three key components: search space, closeness estimation, and search strategy.

Example 4: Consider a predicate mapping problem. The source predicate is s = [category; *contain*; "computer science"] and the target predicate template is P = [subject; *\$op*; \$val], where the operator *\$op* is from { "any words", "all words" } (simply as "any", "all"). ■

Defining Search Space

Defining a reasonable search space is essential to any search process, because it impacts the complexity of search significantly. Given a predicate template P, we define *instance space* of P, denoted by $I(P)$, as all possible instantiations (*i.e.*, predicate) of P. Due to the predicate-level heterogeneity, we often need to map a source predicate into multiple target predicates (*e.g.*, the price predicate in Example 1). We thus define the *search space* of P, denoted by $\Omega(P)$, as any disjunction of predicates in $I(P)$. Each item in $\Omega(P)$ thus corresponds to a possible mapping.

As $I(P)$ often can be infinite, we take a "close-world" assumption to shrink the search space. Specifically, while operators are clearly limited by P (*e.g.*, two operators *any*, *all* in Example 4), the values can often be infinite– for a predicate template without pre-defined domain of values (*e.g.*, an attribute name with a text input box), any value can be filled in, which thus results in an infinite instance space. To define a reasonable space of $I(P)$, we make a

instance space $I(P)$:
p_1 : [subject; *any*; "computer"]
p_2 : [subject; *all*; "computer"]
p_3 : [subject; *any*; "science"]
p_4 : [subject; *all*; "science"]
p_5 : [subject; *any*; "computer science"]
p_6 : [subject; *all*; "computer science"]

search space $\Omega(P)$:
$t_1 = \{p_1\}$, $t_2 = \{p_2\}$, $t_3 = \{p_3\}$, $t_4 = \{p_4\}$, $t_5 = \{p_5\}$, $t_6 = \{p_6\}$
$t_7 = \{p_1, p_2\}$, $t_8 = \{p_1, p_3\}$, $t_9 = \{p_1, p_4\}$
$t_{10} = \{p_1, p_5\}$, $t_{11} = \{p_1, p_6\}$

Figure 7: The instance space and search space of P.

"closed-world" assumption: We denote the values filled in the source predicate s as W_s. For a target template without pre-defined domain of values, we assume the values of the target predicate can only choose from W_s. Therefore, we define the instance space $I(P)$ as all possible instantiations of P using values either in a pre-defined domain if it is available or composed from W_s otherwise. For instance, in Example 4, the target template P is thus restricted to the words used in the source predicate, *i.e.*, W_s = {"computer", "science"}. Figure 7 shows the instance space and part of the search space of P. In particular, with the close-world assumption, the instance space of P contains 6 possible instantiations.

Such a close-world assumption is reasonable, because without domain-specific knowledge, it is difficult to invent new values. In fact, the search space can be enriched (*e.g.*, by expanding queries words with their synonyms) if more domain knowledge is available (*e.g.*, by providing synonym thesaurus), as we will discuss in Section 5.3.

Closeness Estimation

Given the search space $\Omega(P)$ covering all possible mappings, finding a $\mathcal{C}_{min}$ mapping boils down to inferring subsumption relationship between a mapping and the source predicate, and between two mappings. This inference is specific to data types– For some types, it is straightforward, while others, it is not. In particular, for numeric type, since a predicate with numeric type can be projected to an axis of real numbers, evaluating subsumption relationship upon the numeric axis becomes an easy task. Datetime type can be processed in similar way as numeric type and thus we discuss their handlers together in Section 5.2. However, for text type, the inference of subsumption relationship is not trivial since it essentially needs logical reasoning. To avoid convoluted logical inference, we develop an equivalent "evaluation-by-materialization" approach. Section 5.2 will discuss this approach in details.

Search Algorithm

With the subsuming testing, we can find the $\mathcal{C}_{min}$ mapping using the following simple algorithm, where s, P are the source predicate and target template, H records all subsuming mappings and R records $\mathcal{C}_{min}$ mappings and x is the returned mapping:

```
1. $H = \emptyset$, $R = \emptyset$
2. for $\forall t \in \Omega(P)$:
3.     if subsume$(t, s)$: add $t$ to $H$
4. for $\forall t \in H$:
```

```
5.   if $\nexists t' \in H$ and $t' \neq t$ such that subsume$(t, t')$
6.       add $t$ to $R$
7. choose an $x \in R$ with minimal number of predicates
```

This algorithm, generally used by all type handlers, basically exhausts the entire search space $\Omega(P)$ to find all $\mathcal{C}_{min}$ mappings, and then chooses the one with minimal number of predicates to minimize the number of form queries issued on the target form. To improve its efficiency, we may refer to an approximate algorithm. In particular, we can take a greedy approach in practice: We find the mapping iteratively and in each iteration, we look for a (not-selected) instantiation from $I(P)$ that maximally covers the uncovered part of the source predicate s until we can entirely cover s. If there are multiple candidates which have the same coverage over the uncovered in an iteration, we choose the one with minimal overall coverage to minimize false positives.

5.2 Built-in Handlers

Text Type Handler: Text is the most commonly used type in query forms for querying string-based fields (*e.g.*, subject in Example 4). We will use the mapping task in this example to illustrate how the search proceeds towards finding the best mapping of the target template P. In Figure 7, we have illustrated the instance space and search space of P. Next, we need to develop an approach to evaluate the subsumption relationship of text type.

While it may be possible to logically reason the subsumption relationship, such an approach can be very convoluted. On one hand, we have to encode for each operator, its logic relation with all other operators, *e.g.*, in a form of pairwise rules or operator subsumption lattice [3]. On the other hand, it is also non-trivial to apply those rules to reason between queries involving complex boolean expressions. Further, it is not extensible, since adding a new operator (*e.g.*, *start with*) requires encoding its relationship with every existing operators (*e.g.*, *any*, *all*, *exact*).

To circumvent such reasoning, we employ an "evaluation-by-materialization" approach. The idea is that, instead of semantically reasoning the subsumption relationship between two queries Q_1 and Q_2, we can "materialize" them against a database instance D and compare the query results $Q_1(D)$ and $Q_2(D)$. The question is which database instance can be used to reliably test the subsumption relationship? It is obvious that we cannot arbitrarily choose a database instance D_i. We observe that a "complete" database D, which conceptually is the union of all possible database instances D_i, satisfies our requirement.

Property 1: Given two queries Q_1 and Q_2, and a complete database $D = \bigcup D_i$, Q_1 semantically subsumes Q_2 if and only if $Q_1(D) \subseteq Q_2(D)$. ■

The "only if" direction obviously holds, and we only show the "if" direction informally. Let us suppose that $Q_1(D) \subseteq Q_2(D)$ but Q_1 does not semantically subsume Q_2. Then there exists a database instance D_i such that $Q_1(D_i) \nsubseteq Q_2(D_i)$, *i.e.*, $\exists x \in Q_1(D_i)$ and $x \notin Q_2(D_i)$.

Complete Database D: C, S, D, CS, CD, SC, SD, DC, DS, CSD, CDS, DSC, DCS, SCD, SDC

Source Predicate	Materialization
c : [category; *contain*; CS]	CS, SC, CSD, CDS, DSC, DCS, SCD, SDC

Mapping	Materialization
t_1 : [subject; *any*; C]	C, CS, CD, SC, DC, CSD, CDS, DSC, DCS, SCD, SDC
t_2 : [subject; *all*; C]	*same as above*
t_3 : [subject; *any*; S]	S, CS, SD, SC, DS, CSD, CDS, DSC, DCS, SCD, SDC
t_4 : [subject; *all*; S]	*same as above*
t_5 : [subject; *all*; CS]	CS, SC, CSD, CDS, DSC, DCS, SCD, SDC

Figure 8: Example of database and evaluation results.

This means that $Q_2(x)$ is false and thus for any database instance D_j, $Q_2(D_j)$ cannot contain x. Therefore, $Q_2(D)$ cannot contain x, and $Q_1(D) \nsubseteq Q_2(D)$. This is contradictory to our assumption and thus the property holds.

Next, the question becomes how to construct such a complete database? Conceptually, a complete database is a complete enumeration of all possible phrases composed from English words (assuming we only handle English). This is simply too huge to construct and we thus need to look for a practical solution.

We observe that the "completeness" of a database depends on the "logical properties" to be tested by operators. For instance, operators *contain* and *any* concern only membership of words in a string field without caring their ordering, while operators *start* and *exact* concern both membership and sequence. In practice, we observe that membership and sequence can almost cover all the operators for text type. Therefore, we construct the database using words from W_s plus some additional random words. The database is composed of all possible combinations of the words (for testing the membership) with all possible orders (for testing the sequence). Since the exact set of additional words used in the test database does not matter, we thus can use a small number of random words to generally represent all words outside W_s. In our implementation, to avoid constructing a database for every mapping, we use a set of five fixed words to construct a static database. At runtime, we dynamically designate each word to represent a particular constant in W_s. If the size of W_s is greater than 5, we will dynamically construct a test database.

To test subsumption between a mapping and the source predicate, we build a database D with alphabet $D = \{\text{computer, science, dummy}\}$, as Figure 8 shows the content. For simplicity, we use only initials for corresponding words. Figure 8 shows, for source predicate c and each mapping t_i in the search space, the result set against the complete database. As we can see all the listed mappings are subsuming mapping. Among them, t_5 is $\mathcal{C}_{min}$ mappings as it subsumes no other mappings. Alternatively, the greedy approach searches over all predicates in $I(P)$ can also find the right mapping t_5, but it is much more efficient.

Numeric & DateTime Handler: Numeric and datetime have very similar nature in that they all form a linear space, and have similar operators, such as $\leq$ *vs. before*, *between vs. during* and so on. In fact, datetime is internally presented as an integer in many programming languages. Therefore, the mapping techniques for the two types are generally the same. In this section, we will thus focus on numeric type and the general discussion applies to datetime type too.

We use an example to run through the mapping process. Consider mapping between the price predicates in Example 1. Since the target predicate has a pre-defined domain of values, each representing a range, our search space is restricted to disjunctions of those ranges. To estimate the closeness, we project the source predicate c :[price; $\leq$; 35] and the target predicate, *e.g.*, p_5^1 :[price; *between*; 0,25] into ranges in numeric line. By projecting c and p_5^1 to the numeric line, their false positive range (empty) and false negatives $(25, 35)$ can be straightforwardly evaluated as their coverage on the line. Using the greed search approach, we will choose the one that maximally covers the uncovered range. Therefore, we choose range $(0, 25)$ and $(25, 45)$ in turn, which forms our mapping [price; *between*; 0,25] $\vee$[price; *between*; 25,45].

5.3 Domain Specific Type Handler

While the type handlers discussed above handle domain-generic types, there are situations where domain specific knowledge is required, such as handling m:n mappings (*e.g.*, from lastname, firstname to author) or mappings that need domain-specific ontology (*e.g.*, from [subject; *equal*; computer science] to [subject; *equal*; computer architecture]). Since the focus of the paper is built-in type handlers, we refer readers to the extended version [23] for discussions on implementation of domain specific type handlers.

6 Implementation: Form Assistant Toolkit

With form assistant as a core component to many applications, in this section, we study an example application– building a form assistant toolkit, to concretely evaluate the effectiveness of our approach. Form assistant toolkit is a browser based toolbar, which gives users suggested translations across sources in the same domain. In particular, users can register a query of her interest, *e.g.*, a query on amazon.com, and when she browses other sources in the same domain, *e.g.*, barnesandnoble.com, she can ask for suggested translation. This toolbar is pre-configured with a set of supported domains, and users need to specify the domain of interaction when registering a query.

When activated, the assistant will automatically translate the source query to the target form. To prepare the input to translation, the assistant has a *form extractor* module to automatically extract the query capability of the target form. With predicate mapping addresses the predicate heterogeneity, in this section, we briefly discuss the remaining three components - *form extractor*, *attribute matcher* and *query rewriter* to complete the framework.

Form Extractor: Form extractor automatically constructs the query capability of a form to prepare the input for form assistant. We have studied the problem of form extraction in [22], which extracts the set of predicate templates as vocabulary from a query form, by applying a parsing approach with a hypothetical grammar. In particular, the grammar captures the common template patterns, for which we encode their semantics, and the parser generates a parse tree that decomposes the query form into such template patterns. As the parsing result, a set of predicate templates is output in the format of [attr; *op*; val].

To further construct the syntax of query capability, as Section 2 discussed, we identify the exclusively queried attribute and the required fields in query forms. The exclusive predicates are usually presented in a pattern, where a set of attributes is enumerated in radio-button or selection list, with a textbox accepting input. Therefore, by incorporating this pattern in the grammar, the same form extractor automatically recognizes such exclusive attributes. The set of common attributes is preconfigured as domain knowledge, which is used in attribute matching as well. Identifying required fields is a challenging task because there usually is no standard way of indicating those fields. However, most existing rewriting techniques can accommodate this problem by pushing as many predicates as possible to each form query. We will discuss this issue in query rewriter module.

Attribute Matcher: Attribute matcher identifies the semantical corresponding attributes. Our attribute matcher is customized with a domain thesaurus, which indexes synonyms for commonly used concepts. At runtime, attribute matcher fuzzily matches the input attributes with those synonyms to check whether they express the same concept. In particular, the attribute matcher consists of two steps:

Preprocess: Given two predicates, the *preprocess* step performs some standard normalization, including, stemming, normalizing irregular nouns and verbs (e.g., "children" to "child," "colour" to "color") and removing stop words.

Synonym check: After preprocessing, *synonym check* checks whether the two predicates match. We view input predicates as matched if their types match and their attributes are synonyms. The reason for checking on types is that some attributes, *e.g.*, departure, arrival in airfares, must be accompanied by their type to reflect its semantics (*e.g.*, departure city or departure date). To do so, we recognize the types of the predicate using the same type recognizer used in predicate mapping of Section 5. If their types match, we further check whether they are synonyms. In particular, for each input attribute, we first search for its "representative," which is an indexed attribute in the thesaurus with the highest similarity score above a predefined threshold. If the system successfully finds the representatives for both attributes and both representatives correspond to the same concept, we return them as matching attributes.

Query Rewriter: Query rewriter takes a mapped query and constructs a minimal subsuming query as the best translation. The core of this translation is a well-studied problem known as capability-based rewriting. Many existing solutions, *e.g.*, [19, 16, 15], can be applied here by transforming our query model into their specification languages. In particular, our rewriter builds upon the techniques developed in [18], which generates a minimal subsuming rewriting of a query. Essentially, this approach pushes as many predicates as possible to each form query so that it maximizes the use of source query capability.

Finally, we discuss the issue of incomplete modeling of required fields in form extraction. We find that, for a required field of a target form, as long as the source query fills in the corresponding matched predicate, the query rewriter is able to find a valid rewriting even without explicitly modeling of this required field. Let us use an example to informally illustrate this point. Consider the target query form T. If we fail to identify that at least one of the four predicates on author, title, subject, ISBN is required, we may enlarge the search space by including "false" translations which fill in none of these four fields. In this example, queries with only price predicate, *e.g.*, [price; *between*; 0,25] are (falsely) regarded valid. However, the query rewriter will not choose such a translation because it is not minimal subsuming– more predicates, *e.g.*, p_1, can be pushed to the form query to make it more specific. Therefore, as long as the source query specifies those fields required by the target form, our translation will not abuse those "false" instances even if we do not explicitly capture those required fields. (If the source query does not specify those required field, we cannot have any valid translation at all.)

7 Experiment

Experimental Data: To evaluate the complexity of deploying the form assistant and the accuracy of the translation, we collected 120 query forms from 8 domains of the TEL-8 dataset [5]. In particular, we separate the forms into two datasets - Basic dataset and New dataset. The Basic dataset contains 60 query forms with 20 from each of the three domains we surveyed (Section 4.1). The purpose is to evaluate the complexity of domain knowledge needed for translation and the performance over sources from which the types and their patterns are derived. The New dataset contains 60 query forms, which we sampled from 5 domains (*i.e.*, CarRentals, Jobs, Hotels, Movies and MusicRecords) in the TEL-8 dataset. The purpose is to test how well the type handlers can apply to new domains.

Experiment Setting: The experiment evaluates the translation accuracy between two randomly picked forms in the same domain. In particular, suppose a domain has n forms as $[Q_1, \ldots, Q_n]$. We random shuffle those forms to get a permutation $[Q_{i_1}, \ldots, Q_{i_n}]$, and translate queries between $(Q_1, Q_{i_1}), \ldots, (Q_n, Q_{i_n})$. With 120 forms in total, we thus evaluate 120 translations.

We manually prepare the commonly used concepts and synonyms, as the domain-specific thesaurus, for each domain. In particular, for each of the Airfares, Books and Automobiles domains, those concepts and synonyms are prepared based on 20 forms randomly sampled from the forms used in the survey of Section 4.1. We store only concepts appearing in more than one source. We apply those knowledge to new forms to understand the feasibility of manually preparing matching knowledge and the impact of mismatching to translation accuracy.

To avoid biased queries against different sources, we randomly generate queries. Given a source form Q_i, we instantiate its query templates by randomly choosing a value for each variable. In particular, if the domain of the variable is finite with a set of pre-defined options, we randomly choose one from these options. Otherwise, we randomly generate a value with the corresponding type. The query generated in the experiment is thus "maximal," *i.e.*, it instantiates all predicate templates in the source form. As we will see in the following discussion, as one of our performance metric measures the percentage of queries that are perfectly translated, using a maximal query thus measures the worst-case performance.

Performance Measurement: In the experiment, we measure two aspects of the system performance: the translation accuracy and the complexity of customization.

Translation Accuracy: For the translation accuracy, we measure how many mappings in the suggested translation are correct, which indicates the amount of efforts the form assistant saves for users. In particular, we adopt a *form-based* metric: For a source query Q_s and a target form T, let $P(Q_s, T)$ denote the number of predicates in the target query, and $R(Q_s, T)$ denote the number of predicate templates correctly filled by the form assistant. The form-based metric is defined as the percentage of correctly filled predicate templates and is thus $R(Q_s, T)$ over $P(Q_s, T)$.

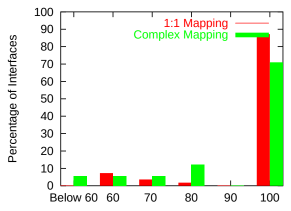
To validate the impact of 1:1 mapping assumption, for each set of experiments, we measure the performance with and without this assumption. Measurement with 1:1 mapping counts, among all 1-1 mappings, how many predicates are correctly filled. For complex mapping (*e.g.*, last-name+firstname→author), as the form assistant does not handle such mappings, those predicates - to be filled by complex mapping - are taken as a negative count in measurement with complex mapping.

To understand the impact of other components to predicate mapping, we further separately report the errors caused by form extraction and attribute matching from those caused by predicate mapping.

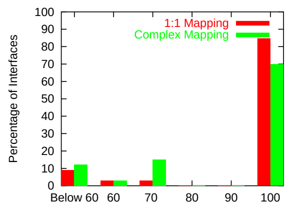
Complexity of customization: For each domain, we only customize the domain-specific thesaurus for attribute matcher. To evaluate how well the domain generic translation can achieve, we do not add any domain specific type hander. That is, the form assistant handles only three domain generic types, as described in Section 5. To measure the complexity of such customization, we report the number of commonly queried concepts and the corresponding synonyms for each concept.

Experimental Result

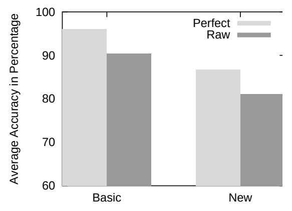
Form-based Measurement: Figure 9 (a) and (b) report the performance without counting the errors caused by form extraction and attribute matching. In particular, they show the frequency distribution over form-based metric for the



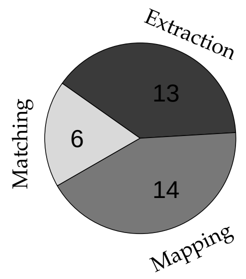
(a) Accuracy distribution for Basic dataset.



(b) Accuracy distribution for New dataset.



(c) Average accuracy.



(d) Error Distribution.

Figure 9: Translation accuracy and error distribution.

two datasets respectively. As we can see, for 1:1 mappings, the system achieves very good results for both Basic and New datasets - 87% of the forms achieve perfect accuracy for the Basic dataset and 85% for New dataset. Further, as Figure 9(a) and (b) show, the system perform reasonably well even counting complex mappings– 76% of the forms achieves accuracy above 80% for the Basic dataset, and 70% for New dataset.

Figure 9(c) shows the performance impact of form extraction to the system (under 1:1 assumption). In particular, it shows average accuracy of translation with and without perfect input from form extraction. To generate perfect input, we manually corrected the errors caused by form extraction. As we can see, in average, we achieve 90.4% for Basic dataset with raw input from form extraction, and by correcting the errors of raw input, we achieve 96.1% accuracy. For the New dataset, we achieve 81.1% with raw input and 86.7% with perfect input.

We observe that error propagation from form extraction to predicate mapping is quite insignificant. One of the reasons is that the attribute matching step helps to resolve some ambiguities of form extraction. For instance, in parsing *delta.com*, the form extractor generates two conflicting predicates with the same value component but different attribute names "departure date" and "One-way & multi-city reservations" (a link to alternative reservation). However, during matching, *e.g.*, to *aa.com*, the former is matched to the source predicate, while the later is not. Therefore, this error caused by form extraction does not propagate. On the other hand, error propagation from attribute matcher to predicate mapping is more significant since a mismatching will finally lead to an error translation.

Figure 9(d) further reports, among all the mappings, the number of errors caused by each component. As we can see, the impact of attribute matching is smallest– it causes only 6 errors out of 33 in total; form extractor causes 13 errors and predicate mapping causes 14 errors. The majority errors in predicate mapping are caused by the lack of domain specific mapping knowledge. For instance, to map between subject "computer science" to subject "programming language," we need a domain ontology; to map between zipcode to city, we need a domain dictionary. Therefore, adding domain specific type handlers will be helpful to improve the mapping performance.

Domain	*#. of Concepts*	*#. of Synonyms*
Airfares	13	34
Automobiles	14	17
Books	17	24

Figure 10: Size of domain thesaurus.

Complexity of domain knowledge: Figure 10 shows the number of concepts and synonyms we prepared for each domain. Note that the number of synonyms shown in the figure also counts in those "singleton" concepts without synonyms, each of which thus contributes one to the total count. As we can see, the number of concepts and synonyms needed for translation is reasonably small. For example, the Books domain contains 17 concepts with 7 more synonyms. More importantly, those knowledge is collected on only 20 sources per domain, and the accuracy of matching based on the prepared knowledge is very high. As Figure 9(d) shows, only 6 errors are caused by the mismatching of attributes, which is very acceptable. We thus believe that high quality domain knowledge can be obtained at very affordable efforts.

8 Related Work

Query translation has been actively studied in information integration systems in the literature. In particular, we observe that the existing techniques can be classified into four categories, to address data source heterogeneity at four levels. This paper, while is closely related to those works, clearly has its own focus: First, we focus on a specific subproblem of dynamic predicate mapping, which is largely unexplored in the literature. Second, we focus on the design and development of a complete query translator, which satisfies our requirements for a light-weight domain-based form assistant. In this section, we connect and compare our work with those existing solutions.

Attribute Heterogeneity: Schema matching [8, 11, 17, 14, 12, 8] focuses on mediating the heterogeneity at attribute level. Those works are concrete building blocks for form assistant. Different approaches of schema matching suit for different application settings. Some approaches, *e.g.*, [11, 12, 21] require a collection of sources to mine the matchings, which are suitable for applications such as MetaQuerier. Others, *e.g.*, [8, 14], perform matching across pairwise sources, which are suitable for applications such as a domain portal.

Data Heterogeneity: Schema mapping [13, 7] focuses on addressing the heterogeneity of data format across different sources. Its main objective is to convert a set of data records from a source schema to a target one and thus it does not need to cope with constraints on predicates (*i.e.*, available operators and values). Unlike schema mapping, which focuses on equivalence conversion, predicate mapping must deal with more complicated semantics (*e.g.*, *any*, *exact* in text type and *less than* in numeric type).

Predicate Heterogeneity: Predicate mapping focuses on addressing the heterogeneity of the predicates across different source capabilities. Existing solutions, *e.g.*, [2] usually assume a static system setting, where sources are preconfigured with source-specific translation rules. In contrast, our approach dynamically maps predicates across unseen sources without prepared source knowledge. Further, the mapping in [2] depends on static rules to describe how to choose operators and fill in the values, while we propose a general search-driven approach to dynamically search for the best mapping.

Query Heterogeneity: Capability-based query rewriting focuses on mediating the heterogeneity of query syntax across different sources. Current query mediation works [10, 9, 20, 18, 15, 19, 16] studied the problem of how to mediate a "global" query (from the mediator) into "local" subqueries (for individual sources) based on capabilities described in source descriptions. Such rewriting is essentially transformation of Boolean expressions upon predicates, and does not consider the heterogeneity inside predicates. Therefore, predicate mapping and query rewriting are two complementary aspects of query translation. In particular, reference [18] focuses on $\mathcal{C}_{min}$ query rewriting at query level, and is thus a concrete building block of our form assistant to achieve the overall $\mathcal{C}_{min}$ translation.

9 Conclusion

In this work, we developed a light-weight domain-based form assistant, which is a core component in many integration applications. For building such a system, we proposed an architecture that satisfies the requirements of source-generality and domain-portability. In particular, we studied the dynamic predicate mapping problem, which, together with existing solutions for other components, complete the form assistant.

While the entire framework shows promise, human efforts are inevitable to encode knowledge needed for translation. To begin with, for built-in type handlers, considerable engineering efforts are involved to encode the domain independent knowledge, including understanding of predicate templates in form extraction and their evaluation against a database in type handlers. However, such knowledge is engineered once-for-all, and it works really promising for sources across different domains. Further, for handling complex situations, such as m:n mappings and domain specific mappings, our system needs customized type handlers provided by domain experts. However, as our experiment shows, the three basic type handlers well handle most important and pervasive cases in the real world. In a nutshell, the form assistant with built-in type handlers provides a good starting point for developing more sophisticated translation tools with moderate human efforts.

References

[1] BrightPlanet.com. The deep web: Surfacing hidden value. Accessible at `http://brightplanet.com`, July 2000.

[2] K. C.-C. Chang and H. García-Molina. Approximate query mapping: Accounting for translation closeness. *VLDB Journal 2001.*

[3] K. C.-C. Chang, H. García-Molina, and A. Paepcke. Boolean Query Mapping Across Heterogeneous Information Sources. *IEEE Transactions on Knowledge and Data Engineering 1996.*

[4] K. C.-C. Chang, B. He, C. Li, M. Patel, and Z. Zhang. Structured databases on the web: Observations and implications. *SIGMOD Record*, 33(3):61–70, 2004.

[5] K. C.-C. Chang, B. He, C. Li, and Z. Zhang. The UIUC web integration repository. http://metaquerier.cs.uiuc.edu/repository.

[6] K. C.-C. Chang, B. He, and Z. Zhang. Toward large scale integration: Building a metaquerier over databases on the web. In *CIDR Conference*, 2005.

[7] S. Cluet, C. Delobel, J. Siméon, and K. Smaga. Your mediators need data conversion! *SIGMOD Conference*, 1998.

[8] A. Doan, P. Domingos, and A. Y. Halevy. Reconciling schemas of disparate data sources: A machine-learning approach. *SIGMOD Conference*, 2001.

[9] M. R. Genesereth, A. M. Keller, and O. M. Duschka. Infomaster: an information integration system. 1997.

[10] A. Y. Halevy. Answering queries using views: A survey. *The VLDB Journal*, 10(4):270–294, 2001.

[11] B. He and K. C.-C. Chang. Statistical schema matching across web query interfaces. *SIGMOD Conference*, 2003.

[12] B. He, K. C.-C. Chang, and J. Han. Discovering complex matchings across web query interfaces: A correlation mining approach. In *SIGKDD Conference*, 2004.

[13] M. A. Hernández, R. J. Miller, and L. M. Haas. Clio: a semi-automatic tool for schema mapping. *SIGMOD Conference*, 2001.

[14] J. Kang and J. F. Naughton:. On schema matching with opaque column names and data values. *SIGMOD Conference 2003.*

[15] A. Y. Levy, A. Rajaraman, and J. J. Ordille. Querying heterogeneous information sources using source descriptions. In *VLDB Conference*, 1996.

[16] C. Li, R. Yerneni, V. Vassalos, H. Garcia-Molina, Y. Papakonstantinou, J. Ullman, and M. Valiveti. Capability based mediation in TSIMMIS. *SIGMOD Conference*, 1998.

[17] J. Madhavan, P. A. Bernstein, and E. Rahm. Generic schema matching with cupid. In *VLDB 2001.*

[18] Y. Papakonstantinou, A. Gupta, H. Garcia-Molina, and J. D. Ullman. A query translation scheme for rapid implementation of wrappers. In *International Conference on Deductive and Object-Oriented Databases*, 1995.

[19] Y. Papakonstantinou, A. Gupta, and L. Haas. Capabilities-based query rewriting in mediator systems. In *International Conference on Parallel and Distributed Information Systems*, 1996.

[20] A. Rajaraman, Y. Sagiv, and J. D. Ullman. Answering queries using templates with binding patterns. In *PODS Conference 1995.*

[21] W. Wu, C. T. Yu, A. Doan, and W. Meng. An interactive clustering-based approach to integrating source query interfaces on the deep web. *SIGMOD Conference*, 2004.

[22] Z. Zhang, B. He, and K. C.-C. Chang. Understanding web query interfaces: Best-effort parsing with hidden syntax. *SIGMOD Conference*, 2004.

[23] Z. Zhang, B. He, and K. C.-C. Chang. Light-weight domain-based form assistant: Querying Web Databases On the Fly, technical report, department of computer science. http://metaquerier.cs.uiuc.edu, 2005.