Towards Rich Query Interpretation: Back and Forth on Mining Query Templates

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ABSTRACT

In this paper, we propose to mine templates from search engine query logs, with the goal of rich structured query interpretation. To begin with, we formalize the notion of templates as a sequence of keywords and domain attributes, instantiating many queries based on the instances of these domain attributes. We identify the key challenge in template discovery as the limited seed knowledge. Our solution bootstraps from small seed input to discover relevant query templates, by harnessing the wealth of information available in search logs. We model this information in a tri-partite inference network of queries, sites and templates—together forming the "QueST" network. We propose iterative probabilistic inferencing framework based on dual metrics of precision and recall. We have deployed and tested our algorithm over a real-world large-scale search log of 15 Million queries from the MSN search engine. We find the accuracy of our algorithm to be as much as 90% (on F measure), with very little seed input knowledge and even incomplete domain schema.

1. INTRODUCTION

The wide spread of the Internet and the emergence of search engines have rendered *keyword queries* as the dominating lingua franca of information access. Meanwhile, as the nature of the Web evolves, information search over the Web has become increasingly diverse and thus complicated. The proliferation of semistructured or structured data, such as those from online databases, or the so called "deep Web," provides abundant information in various "domains" of interest. Consequently, today, users are looking for all kinds of information online—with simple keyword queries.

The prevalence of simple keyword queries coupled with the proliferation of diverse information online clearly challenges search systems for effective data retrieval. As the key barrier, how to "interpret" a query for the wide variety of target domains it may aim at? This issue of *query interpretation* is central in every aspect of search: What contents to match? What vertical search services to invoke (*e.g.*, in "universal search" or in vertical search routing)? What advertisements to show? With the simplicity of keyword queries and the complexity of information they target, query interpretation has become more demanding in two ways:

First, as its traditional focus, query interpretation aims to recognize the *intent*, or the *domain* of interest—the diversity of the Web has mandated such recognition to be specific and fine grained. While much work has focused on classifying queries to predict their intents (*e.g.*, [1, 2]), the challenge is ever increasing. To effective match queries to contents, vertical services, and ads, the recognition has evolved from high-level types (such as *navigation*, *transaction*, *information*), topics (*travel*, *health*) to finer-grained categories, such as *hotel*, *flight*, *job*, each of which represents certain information objects (hotels or flights to book, and job to apply).

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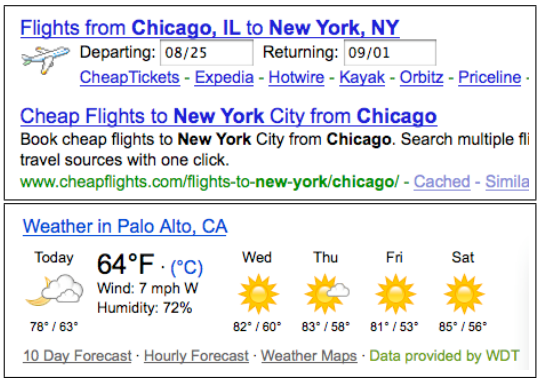


Figure 1: "chicago new york"(Google); "palo alto weather"(Bing).

Second, as a new issue, for each specific domain, query interpretation now also faces the challenge of recognizing the *attributes*, or the various "aspects," that are inherently associated with a given intent. When users look for a particular domain of data objects (*e.g.*, *job*), they naturally specify the attributes (*e.g.*, *location* of jobs like "jobs in chicago"; or *type* of jobs like "accounting jobs").

This paper aims to enable rich query interpretation, which recognizes intents for not only a specific domain but also its associated attributes. Such rich interpretation is essential for search response tailored for specific intents, in ranking contents, invoking verticals, or matching ads. *E.g.*, Figure 1 shows Q_1: "chicago new york" from Google and Q_2: "palo alto weather" from Bing. Observe that, *first*, the responses tailor to the specific domains: While Q_1 does not mention "flight", Google lists verticals like flight Expedia. Similarly, Bing directs Q_2 to a weather vertical. Second, the responses tailor to the attributes. For Q_1, Google recognizes "chicago" as attribute *from* and "new york" as *to*. For Q_2, Bing recognizes "palo alto" as attribute *location* of the desired weather forecast.

While rich query interpretation is essential, how can we achieve such intent recognition of both domains and attributes? To date, this problem has not been systematically addressed, although current search engines have shown sporadic usages for certain scenarios (such as for *flight* and *weather* as in Figure 1).

As our *first* contribution, while the notion of query templates has been implicitly exploited (in search engines and in other mining tasks; Sec. 2), this paper is the first to survey its prevalence and formulate the new concept with formal quality metrics.

We begin by surveying, as Sec. 3 will report, a large scale search log [3], with a sample of 28,000 queries, which indicated that a high frequency of queries follow structured patterns– *e.g.*, 90+% for *real*

estate and *hotel*, 80+% for *automobile* and *rental car*. Users naturally refer to different aspects of their search needs, *e.g.*, when looking for jobs, users may mention the "location" (*e.g.*, chicago, boston), or the "company" (*e.g.*, microsoft, boeing, *etc.*) offering the job. Thus, across many users with same *domain* of interest, we would observe that, although each of them talk about the specific *instances* of different aspects, the overall *template* is similar, *i.e.*, all these user queries may share the same template, differing only in the specific instances. *E.g.*, in job domain, we may see many users queries sharing similar template, *e.g.*, "jobs in boston", "jobs in seattle", "jobs in chicago", all of which are specific *instantiations* of the common query template—"jobs in #location", where #location represents the location aspect in job domain.

The concept of structured query patterns as "templates" is useful in two ways: First, it serves as a query intent *classifier*. Given a query, such as "accounting jobs in chicago", by matching to a "job" template, say ⟨#category jobs in #location⟩, we can interpret the query as intending for the Job domain. Second, it is also a query *parser*. The matching will also reveal that the query is looking for a job with #location="chicago" and #category="accounting". Such structured interpretation will help us in better handling or dispatching the query, as discussed above.

As our *second* contribution, this paper proposes the problem of query template discovery, and develops a principled probabilistic inference framework as the solution. We define the metrics for distinguishing good templates—in terms of *precision* and *recall* with respect to the domain of queries interested. We then develop the QueST framework, a graphical model of inference upon the network of instantiation (between queries and templates) and click-through (between queries and sites), which will infer the "probabilities" of precision and recall.

The resulting dual frameworks, QuestP for precision-based ranking and QuestR for recall-based ranking, show interesting duality: We show that, in the view of inferencing as *random walks*, they are simply walks of opposite directions—walking backward for precision, and forward for recall. We also identify how the dual frameworks have close ties to several random walk-based inference models, which thus help us to directly address the formal computation properties of our QueST algorithm through these known vehicles. While random walk has been widely applied, to date, it is unclear the exact difference between forward and backward walks, with only empirical comparison [4]. To our knowledge, our work is the first to establish the *duality* of precision and recall and its *connection* to the directions of random-walk propagation.

As our *third* contribution, we realized our solution and evaluated it over a large-scale search log of 15 million queries [3]. The experiments showed that QueST significantly outperforms the baseline "classify then match" to derive query templates. We tested our discovered templates in the actual application scenarios of predicting query intents across seven domains of 28,000 manually labeled queries. Overall, the system is effective in finding structured query patterns that accurately predict query intents—achieving $70-90\%$ on F-measure, with as little as just four example sites as input, and the performance is robust to different types and sizes of inputs, as well as incomplete schema of attributes and instances.

2. RELATED WORK

1. In terms of problem, our work attempts to find patterns from query log, which is an instance of the general problem of knowledge discovery from query logs [5], an active area of research, with variety of applications such as implicit relevance feedback [6, 7], result caching [8], query suggestion [9, 10], query classification [1], and name-entity mining [11, 12, 13]. Ours is the first work that identifies the prevalence of query patterns, and formally addresses this new problem of query template mining.

The notion of query templates has been explored in other contexts, albeit implicitly; (1) in search engines for specialized handling of certain queries (*e.g.*, examples in Fig. 1); (2) in name-entity mining literature, as intermediate bridges, by using hand crafted patterns [11], or by learning a few top templates [12, 13], *e.g.*, ⟨#movie-name trailer⟩ to discover new instances of movie names. In contrast, this paper formalizes the explicit concept of query templates, and defines the metrics of precision and recall of templates.

2. In terms of techniques, we compare our solution with two-staged Classify&Match method as baseline, which first uses existing classification technique [1], and then, matches templates against the classification results to predict their precision/recall. Our experiments show this approach is ineffective in mining templates.

Our solution is based on integrated inferencing upon a tripartite QueST graph of **Que**ries, **S**ites, and **T**emplates. In contrast, several related techniques have used bipartite Q-S graphs [1, 14]. Our extension to include templates in an integrated inferencing framework is necessary, as we discuss in Section 5. Query logs are known to be sparse and noisy; the integrated inferencing helps in regulating propagation by accounting for all signals, as is demonstrated by the superior performance of our solution compared to the two staged baseline.

We develop random walk based solution to solve our precision and recall based equations. Our first inference method–QuestP–solves the precision based modeling using backward random walk. We formally show (in Sec. 6) that precision based modeling is equivalent to harmonic energy minimization [15]. Our second inference method–QuestR–solves recall based modeling using forward random walk, which has been used in the PageRank family of inferencing frameworks [16].

While both the forward as well as backward propagation have been used in many contexts [17, 18, 19], with some empirically comparing their performances [4], our work is the first to establish the correspondence of the random walk in forward and backward direction, respectively, to the recall and precision based modeling.

3. In terms of related research areas, since our solution needs domain schema as input, which may not be readily available, for practical deployment, we need to extend our framework to incorporate automatic Named-Entity Mining (NEM) techniques that can learn domain schema (*i.e.*, discovering new attribute classes and their instances). Several techniques exist, *e.g.*, learning from Web corpus [20, 21], and more recently, from query logs, *e.g.*, using hand-crafted query patterns [11], learning query patterns using seed knowledge [12], and probabilistic framework using click-through logs [13]. Our study in Section 7.3 demonstrates that our iterative $S \rightleftharpoons Q \rightleftharpoons T$ framework can be effectively extended to incorporate existing NEM techniques by adding another step of $T \rightarrow D$.

3. PROPOSAL: QUERY TEMPLATE

3.1 Motivating Survey: Structured Patterns

While structured patterns are useful for interpreting queries–do such patterns exist? That is, for similar search purpose, do users formulate keyword queries of similar structures? As this question must be answered from actual query behaviors, we surveyed a search log of 15 million queries from Microsoft's MSN search engine [3].

In the survey, we checked if the sampled queries followed some patterns. As Section 3.2 defines formally, a pattern is an abstract structure that can be instantiated into *multiple* query instances. For a query $s1$, to see *whether* it follows some pattern, we identify *if*

id	Query	Structured Pattern	Domain
s_1	280zx scissor doors	⟨#model scissor doors⟩	*automobile*
s_2	dreams about tornadoes what does it mean	none	n/a
s_3	fractionated stereotactic radiosurgery california	⟨#surgery #location⟩	*hospital*
s_4	j william montgomery minnesota	⟨#name #location⟩	*people*
s_5	locate mercedes inventory	⟨locate #make inventory⟩	*automobile*
s_6	morgan milzow	⟨#realtorcompany⟩	*real estate*
s_7	play nintendo online	⟨play #videogame online⟩	*video game*
s_8	psychology of severus snape	⟨psychology of #character⟩	*literature*
s_9	sport bike portland or	⟨#model bike #location⟩	*motorcycle*
s_{10}	uhaul in colorado	⟨#rentalcompany in #location⟩	*car rental*

Figure 2: Structured patterns: *Any* queries.

Domain	Schema	Queries	Pattern%
airfare	#airline, #airport, #apcode, #location	428	73.60%
automobile	#make, #model, #year, #location	1656	85.87%
hotel	#hotel, #location	1378	91.36%
job	#location, #category, #company	921	74.38%
real estate	#location	1471	91.71%
car reantal	#company, #cartype, #location	99	84.85%
movie	#title, #actor, #director	723	37.62%

Figure 3: Structured patterns: 7 domains among 28K queries.

$s1$ mentions an instance of some attributes and *if* we could find another query $s2$ that shares everything *but* the instances of the attributes. *E.g.*, consider $q1$ = "280zx scissor doors" in Fig. 2. By manual checking, we recognized that "280zx" is a car model, which we denoted attribute #model. Looking in the query log, we found another query "300zx scissor doors", where "300zx" is a different #model instance. Thus, these queries share the pattern ⟨#model scissor doors⟩, and we name their similar interests as domain *automobile*.

Survey 1: *How likely does* any *random query follow some pattern with* any *attributes we could recognize?* We sampled 100 queries and, by manual checking, found that 90 of them—or a 90% "pattern ratio"— follow certain patterns (shared with at least one other query) that we could recognize. Figure 2 shows 10 example queries, including one ($s2$) that does not follow a pattern and others that do. For each patterned query, we also identify the pattern in Fig. 2 and name the domain as we recognized. For instance, in addition to $s1$ just mentioned, $s4$ shares pattern ⟨#name #location⟩ (*e.g.*, with another query "john tabor georgia") and $s10$ pattern ⟨#rentalcompany in #location⟩ (*e.g.*, with query "hertz in chicago"). Overall, we believe query patterns are prevalent.

Survey 2: *How likely do queries in a* particular *domain follow patterns with respect to some* specified *attributes?* We asked this question because, often, we are only interested in a certain domain (*e.g.*, *hotel*) to tailor search for, and for each domain we would expect some particular attributes, which we informally call "domain schema" (*e.g.*, #hotel, #location). We performed this survey for seven domains; Fig. 3 shows each domain and its schema as we determined. As dataset, we sampled 28K queries, with random sampling that was biased for these domains of interest so that we could get more queries in these domains. For each query, we manually labeled if it is relevant to one of the domains. If so, we further checked if it followed some pattern *w.r.t.* the attributes in the pre-specified schema, using some pre-collected "vocabularies" of these attributes (*e.g.*, actual hotel names for #hotel). *E.g.*, as Fig. 3 summarizes, we found 1378 of the 28K queries were in *real estate*, of

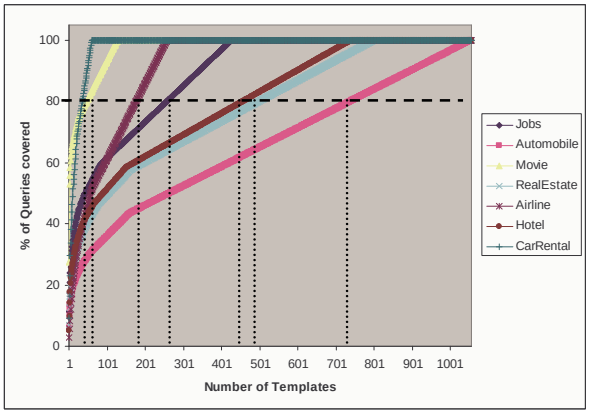


Figure 4: Cumulative coverage of query templates.

which 1259 or 91.36% were "patterned." In 6 out of 7 domains, we saw the pattern ratio were greater than 70%, which revealed the prevalence of patterns *w.r.t.* naturally specified schemas.

We note that the survey inevitably *underestimated* pattern ratios—due to our incomplete vocabularies we were not able to recognize all attribute instances and thus query patterns. In particular, the low ratio in *movie* domain (37.62%) resulted from our incomplete movie #title and #actor names. We would miss, say, "bolt showtimes" for pattern ⟨#title showtimes⟩ if we do not include "bolt" as a #title.

Survey 3: *How popular are each pattern? How many patterns are there?* Since we resort to structured patterns for rich query interpretation, as Section 1 motivated, we wonder how many patterns do we need to "cover" a domain of interest, say, *hotel*? That is, for each pattern, we ask how likely it will cover a query for the domain? We thus measured the *coverage* of a pattern t as the ratio of queries in a domain that are instances of t. Figure 4 shows the cumulative distribution of the coverage ratios in each domain, with color-coded curves. We order the templates of each domain, on the x-axis, by their coverage of the domain queries. For example, for *automobile*, the top template is ⟨#make #model #year⟩, which covered 95 out of 1580 automobile queries as its instances (*e.g.*, "toyota corolla 2004"). For each rank position, we show on the y-axis the cumulative coverage over the domain queries. We observe that, for all domains, while the coverage increases rapidly in the beginning, it then slows down and overall requires a large number of patterns to cover most queries. *E.g.*, to reach 80% coverage, the *hotel* (brown-colored curve) and *real estate* (light blue) both need about 450 templates, and *job* (blue) about 250 templates. How these templates in a domain is thus our problem to solve.

3.2 Query Templates

We now propose the notion of query templates. As our objective is to find structured query patterns for query interpretation, for intents of both domains and attributes, we will focus on templates for a domain of interest. Each domain, as mentioned earlier, we will assume a given *schema* as a set of *attributes* that define various aspects of the domain and their *instance vocabularies*.

Definition 1 (Domain Schema): The *domain schema* $\mathcal{D} = (A, I)$, for a given a domain of interest, consists of:

1. $A = \{a_1, \ldots, a_n\}$, where each a_i is an *attribute*.
2. $I = \{I(a_1), \ldots, I(a_n)\}$, where $I(a_i)$ is the *vocabulary* of possible *instances* of a_i. ■

Example 1 (Domain Schema): For *job*, we may specify schema $\mathcal{D}_{job}$ = (A, I): A contains attributes for job listings, say, A =

{#location, #category, #company}. Each attribute has a vocabulary, which is conceptually a "dictionary" of instances, *e.g.*, I(#location) = {'new york', 'chicago', ... }, I(#category) = {'accounting', 'software', ... }, I(#company) = {'microsoft', 'boeing', ... }. ■

For simplicity of explanation of our technique, this paper assumes that the complete domain schema is available. However, it is important to note that this is not a limitation of our framework. In practical deployment, our method will be coupled with widely studied named-entity mining (NEM) techniques (*e.g.*, from Web corpus [20, 21], or from query log [11, 12, 13]). Our experiments in Sec. 7.3 empirically demonstrate that our framework can effectively incorporate existing NEM techniques, to provide robust results even under the scenario of incomplete domain schema. Without loss of generality, for rest of the development, we will assume domain schema is available.

With respect to a schema, we now define templates for the domain. As eluded so far, in general, a *query template* is an abstract query pattern that specifies certain structure characteristics– which can be instantiated into multiple (concrete) query instances that preserve the characteristics. *E.g.*, our discussion used templates like t_j = ⟨jobs in #location⟩. Here, template t_j specifies the characters that "jobs" and "in," in that order must appear as the first two words and that some #location instance must follow them.

To concretely define template, we must decide the types of characteristics we wish to use. For simplicity, while our framework can handle any patterns (when the computational requirement of "template generation" is met; see 4.1), we assume a template as simply a sequence of literal keywords or abstract attributes. *E.g.*, template t_j is a sequence of keyword jobs, in, and then attribute #location.

Definition 2 (Query Template): With respect to domain schema $\mathcal{D} = (A,\ I)$ and W as the universe of all keywords, a *query template* t is a sequence of terms $\langle v_1 \dots v_n \rangle$, where each $v_i \in \Omega$, for the *vocabulary* $\Omega = W \cup A$, such that at least one of the terms is an attribute, *i.e.*, $\exists\ j \in [1, n]$ for which $v_j \in A$. ■

Such a template, by definition, can be instantiated into different queries; *i.e.*, it represents a class of queries, where the sequence and the keywords are preserved, while the attributes become instances. *E.g.*, template t_j can be instantiated into queries like $q1$: "jobs in chicago" and $q2$: "jobs in new york" or, generally, "jobs in p", where p is a phrase (one or multiple words) in I(#location). A template is thus also a parametrized query, which can be "materialized" into various queries, by filling in instance values at the attribute slots; thus, in this view, $q2 = t_j$("new york").

Definition 3 (Template Instantiation): Given a query template t = $\langle v_1 \dots v_n \rangle$ and query q = "$u_1 \dots u_m$", with respect to domain schema $\mathcal{D}$= (A, I), we say that t is *instantiated* into q, or q *instantiates* t, which is denoted by $q \in I(t)$, if $m = n$ and $\forall i$: $u_i \in I(v_i)$ when $v_i \in A$, or $u_i = v_i$ otherwise. ■

For our motivation, a template is useful for "interpreting" queries that instantiate it. Given a template for a domain D, for a query q that instantiates the template, we can interpret q with the structure and meaning of t. *E.g.*, given t_j for *job*, since $q1$ instantiates t_j, we know that $q1$ has an intent of the *job* domain (*i.e.*, finding job listings) and that "chicago" refers to the place of desired jobs.

4. PROBLEM: TEMPLATE DISCOVERY

4.1 Problem: Mining Templates

Our objective in this paper is to discover *good* templates for query interpretation for a given domain D. Let $L(D)$ denote all the possible queries in D—for now, assume it is ideally given, say, by identifying them by some oracle from a search log. Our desired templates are those that can match (*i.e.*, be instantiated into) and thus interpret those domain queries $L(D)$.

Template Universe T: For template discovery, we need to first identify the set of possible templates as our closed universe to consider. We are only interested in "relevant" templates—ones that can be instantiated into some queries q in $L(D)$.

To form such a universe, instead of looking at each possible form of templates (*e.g.*, arbitrary combinations of any keywords and any attributes in any lengths), we assume the ability to enumerate relevant templates. That is, given query q and domain schema $\mathcal{D}$, we assume function $\mathcal{U}(q)$, which can "unify" q with respect to $\mathcal{D}$ into its relevant templates—by abstracting keywords as the attributes in $\mathcal{D}$; *i.e.*, $\mathcal{U}(q)$ = { $t \mid q \in I(t)$ *w.r.t.* $\mathcal{D}$}.

Note that, while a template t can be instantiated into multiple queries, which is $I(t)$, a query q can also instantiate multiple templates, which is $\mathcal{U}(q)$. We stress that this "template enumeration" into a closed relevant universe is the *only* assumption in our template modeling—our framework can support *any* template model as long as this assumption is valid. For our simple model (Definition 2), to generate $\mathcal{U}(q)$, we need only check if any subsequence of q matches an attribute—and substitute it with the attribute if so.

Example 2 (Template Generation): From Example 1, consider q: "accounting jobs in new york". Matching keywords to $\mathcal{D}_{job}$, we find 'accounting' $\in I$(#category) and 'new york' $\in I$(#location). We then enumerate templates by these attributes: $x1$:⟨#category jobs in chicago⟩, $x2$:⟨accounting jobs in #location⟩, and $x3$:⟨#category jobs in #location⟩. Thus, $\mathcal{U}(q)$ = {$x1$, $x2$, $x3$}. ■

By generating relevant templates, our problem becomes to discover good templates from the template universe generated by all domain queries, *i.e.*, T = {$t \mid t \in \mathcal{U}(q), \forall q \in L(D)$}.

Quality Metrics: As the target metrics, how do we measure the "quality" of a template t? Naturally, we measure the quality of t by how it can interpret $L(D)$; *i.e.*, how the queries that t can be instantiated into, $I(t)$, match those of $L(D)$.

First, t should broadly capture as much coverage over $L(D)$ as possible. We thus ask: What faction of $L(q)$ queries are instantiations of t? Some templates are more "popular" than others; they match more queries in the domain, which means users are more likely to formulate instances of such templates as their queries. Our Survey 3 measured in Figure 4 such coverage, where we saw that a few templates (*e.g.*, ⟨#make #model #year⟩ for *automobile*) are more popular than others. Given $L(D)$ as the "target" set and $I(t)$ as the "matched" set, such coverage is the standard metric of *recall*:

$$R(t) = |L(D) \cap I(t)/|L(D)| \tag{1}$$

Second, t should precisely capture only $L(D)$ to make accurate prediction of intent. We thus ask: What fraction of $I(t)$ actually fall in $L(D)$? Due to the inherent ambiguity of keyword queries, a template may make wrong predictions. *E.g.*, the simple template ⟨#company⟩—say, for query "microsoft"—may mean to find *job* at a company, but it may also mean to find something else about the company, say, *product*. In contrast, template ⟨jobs at #company⟩ ("jobs at microsoft") seems more reliable, although not perfect: Query "jobs at apple" may intend for "Steve Jobs" and not an employment. Such accuracy is the standard metric of *precision*:

$$P(t) = |L(D) \cap I(t)|/|I(t)| \tag{2}$$

Note that precision and recall are well known to be "competing." A broad template, such as ⟨#company⟩, may have good recall by

- **Input:** $(Q, S, \mathcal{C})$, $\mathcal{D} = (A, I)$, Q_0, threshold θ.
- **Output:** Templates t, ranked by $score(t)$.

1: **classify** Q to $L(D)$ from Q_0, thresholded by θ.
2: $T = \{t \mid t \in \mathcal{U}(q), \forall q \in L(D)\}$ *//candidates.*
3: **for** (each template t in T) **do**
4: $X = L(D) \cap I(T)$ *//queries in $D \wedge$ match t.*
5: **compute** $score(t)$ *//by $P(t)$, $R(t)$, or $F(t)$.*
6: **end for**
7: **return** T sorted by $score(t)$

Figure 5: Baseline algorithm: Classify&Match.

matching many queries but poor precision due to its also matching non-domain queries. A strict template like ⟨jobs at #company⟩ may have good precision but poor recall. The trade off depends on applications; we may also adopt the combined F-measure $F(t)$.

We can now state our problem quite simply as finding good templates by precision, recall, or F-measure, from a search log L, with respect to domain schema $\mathcal{D}$ and labeled example queries Q_0.

Problem: ***Query Template Mining from Search Log***

Input: • Search log: (queries Q, sites S, click-through $\mathcal{C}$).
• Schema $\mathcal{D} = (A, I)$ for domain D.
• Seed queries Q_0 labeled as in domain D.

Output: Ranked list of templates t, sorted by $score(t)$, for $score(t) \equiv P(t)$, $R(t)$, or $F(t)$.

The *input* consists of the following: 1) For our purpose, a *query log* gives a set of *queries* Q, a set of URLs or *sites* S, and how queries clicked-through to sites. We denote the *click-through queries* of site $s \in S$ by $\mathcal{C}(s) = \{q | q \in Q$, and q clicks to $s\}$. 2) The domain schema specifies attributes A and instance vocabularies I. 3) We also need "seed knowledge" about domain relevance, *i.e.*, example queries that are in the domain. While seed knowledge is necessary, we should require only "minimal" supervision. For simplicity, here we assume a few *seed queries* $q \in Q_0$. Our framework will work generally for seed *sites* or *templates*, and we will will experiment with all settings (Sec. 7).

The *output* returns a ranked list of templates, sorted by their usefulness. For scoring, we must be *able* to adopt different measures: precision, recall, or F, *depending* on application requirements.

4.2 Baseline Approach

To motivate our solutions, we start with a natural baseline algorithm. Since our goal is to find templates that match domain queries, if we were able to separate $L(D)$ from all queries Q in the log, we can simply count in $L(D)$, for each template, how it performs in terms of precision and recall.

A natural baseline is thus Classify&Match (Fig. 5), with *two stages*. The first stage classifies log Q to find domain queries $L(D)$, applying some threshold θ on the results. The second stage matches each t in the template universe T to this "estimated" $L(D)$, to *estimate* $P(t)$, $R(t)$, or $F(t)$ as $score(t)$.

The two-staged baseline, while intuitive, suffers two major issues inherent from the separation of the two stages. Our experiments show the poor performance of this approach, using a state of the art classifier [1] for query log as the stage 1. These deficiencies motivated our development of a robust, principled probabilistic inference framework.

First, it lacks **probabilistic modeling**. In order to straightforwardly connect the two stages, we have to decide a threshold for the classifier to divide Q as $L(D)$ and $\neg L(D)$. As we explained,

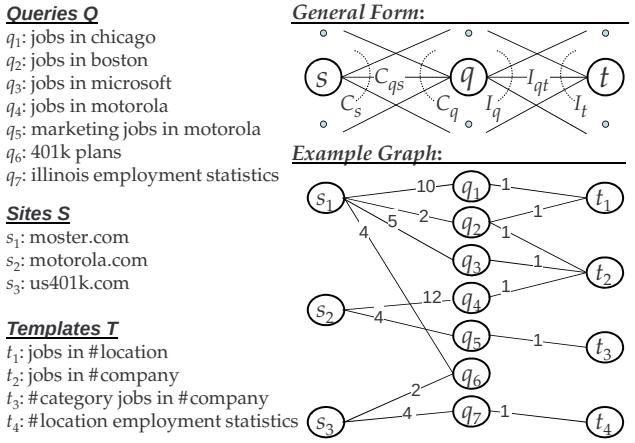


Figure 6: Example: a toy search log and the graph.

queries are ambiguous, and such hard division is crude—in our experiments, we tried several choices of threshold (in the range of [0.80, 0.95] and none worked well. What we need is more robust probabilistic modeling that captures the fuzzy nature of semantic relevance and, in turn, that of recall and precision.

Second, it lacks **integrated inference**. Search logs, while valuable for learning query interpretation, are also known to be noisy and sparse. They are *noisy*: A click-through does not always mean semantic relevance—it might be a trial or a mistake. They are also *sparse*: Users only click on a few sites for each query. By separating template induction (stage 2) from query classification (stage 1), the baseline is critically missing semantic connections through templates during query classification, which will lead to suboptimal results. With templates integrated in the loop of inference, the "global inference" will *regulate* noises, since irrelevant queries are less likely to share templates. They will also *enrich* sparsity, by connecting queries through sharing the same templates.

5. MODELING: QueST FRAMEWORK

We now develop our overall framework, Algorithm QueST, as Fig. 7 summarizes, for discovering templates with recall and precision as the quality metrics. As just motivated, we will model the quality measures in the probabilistic sense, upon which we will then cast the discovery as a semi-supervised learning problem.

5.1 Probabilistic Modeling

As the foundation, we develop the probabilistic sense of recall and precision, for all constructs—templates, queries, and sites.

First, we generalize P and R for templates to the probabilistic sense. Eq. 1 and 2 and define them in the standard set-semantics intersections, where $L(D)$ and $I(t)$ are both "crisply" defined. However, a random query q, with the inherent ambiguity of keywords, may be only *likely* to be in domain D; *e.g.*, as explained earlier, query "microsoft" might be in *job* or *product*.

Thus, we need the probabilistic notion of *semantic relevance*—a probability of how things are intended to *match*. To simplify notations, we will "generically" denote $\text{match}(A, B)$ for the event that A and B are semantically matching (for some A and B pertinent in discussion). In particular, how is a query q relevant to domain D? *E.g.*, is "jobs in chicago" matching domain *job*? This statement is, in terms of the set notation above: How likely is $q \in L(D)$? We write $\text{match}(q, D)$ for the event that q is relevant to D, and $p(\text{match}(q, D))$ is their probability of relevance. Similarly, we write $\text{match}(q, t)$ for that q is semantically matching t, among the multiple templates (as discussed earlier) that q can be instantiated from. We will denote $\text{match}(q, s)$ for query q relevant to a site s

(among the multiple sites that q clicks to). Together, we note that such probabilistic "matching" is necessary—not only that keyword queries are ambiguous, but click-throughs are also noisy in nature.

Now, we can view Eq. 1 is a statistical way: Since the numerator is the count of $(L(D) \cap I(t))$, it is proportional to the probability that, when we draw a random query q, $p(q \in L(D) \wedge q \in I(t))$ or, in our "match" notation, $p(\text{match}(q, D), \text{match}(q, t))$. Similarly, the denominator becomes $p(\text{match}(q, D))$. Substituting them into Eq. 1, we get the probabilistic recall as the conditional probability below. Similarly, we can rewrite Eq. 2 statistically.

$$R(t) = p(\text{match}(q, t)|\text{match}(q, D)) \quad (3)$$

$$P(t) = p(\text{match}(q, D)|\text{match}(q, t)) \quad (4)$$

Second, we extend precision and recall to each query q and site s. By this extension, we will be able to "interrelate" P and R between these related events, and thus achieving inference across them.

For site s, we can model its precision similar to that of a template t. As Eq. 3 states the recall $R(t)$ for template t, we can analogously capture the precision of a site s, $R(s)$, as the probability of how a query q may match D, if it matches s.

$$R(s) = p(\text{match}(q, s)|\text{match}(q, D)) \quad (5)$$

$$P(s) = p(\text{match}(q, D)|\text{match}(q, s)) \quad (6)$$

For query q, we can also model its precision and recall, by capturing the semantic relevance to domain D. The recall of q is the "fraction" of domain queries that are actually q,*i.e.*, the probability that $x = q$ among queries x matching D. The precision, on the other hand, is simply the probability that q matches D.

$$R(q) = p(x = q|\text{match}(x, D)) \quad (7)$$

$$P(q) = p(\text{match}(q, D)) \quad (8)$$

5.2 Inference Framework

Our framework, in order to discover templates by their probabilistic recall and precision, will resort to integrated inference (unlike the partitioned phases in baseline Classify&Match) between all related constructs–queries Q, sites S, and templates T. To capture their potential semantic relevance, we build a *tripartite* graph, QST-graph. Figure 6 shows the graph for a toy example. In the QST-graph $G = (V, E)$, the nodes are $V = Q \cup S \cup T$, and the weighted edges E are as follows:

- $\forall q \in Q, \forall t \in T$: if $q \in I(t)$, or q instantiates t, there is an edge in between, with weight $I_{qt} = 1$.
- $\forall q \in Q, \forall s \in S$: if $q \in \mathcal{C}(s)$, or q clicks to s, there is an edge in between, with weight C_{qs} as the click-through frequency.

Our problem is to discover good templates from seed queries, which now translates to inferring the quality metrics—probabilistic recall and precision—of each template through the semantic connections as the graph captures. Upon the QST-graph as a graphical network, we will develop the inference mechanism in Section 6.

As a semi-supervised learning problem, initially, we are given a few seed queries Q_0, where each query x is labeled with precision $P_0(x)$. Note that, while users can label seed precision as how likely x indicates the domain of interest, it is infeasible for users to provide "seed recall," which depends on *all* relevant queries. As an estimate, we initialize the seed recall as precision normalized among all the given queries. Our initial condition is thus the given precisions (which are ground truth) and estimated recalls (which will be re-estimated through the inference process), as follows.

$$\forall x \in Q_0\text{: } P(x) = P_0(x); \quad R(x) = R_0(x) \equiv \frac{P_0(x)}{\sum_{x \in Q_0} P_0(x)} \quad (9)$$

- **Input:** $(Q, S, \mathcal{C})$, $\mathcal{D} = (A, I)$, Q_0 with P_0 (and P_0; Eq. 9)
- **Output:** Templates t, ranked by $score(t)$.

1: $T = \{t \mid t \in \mathcal{U}(q), \forall q \in Q\}$ //*or, materialize t on demand.*
2: **construct** QST-Graph G by Q, S, T, $\mathcal{C}$, I.
3: **inference** recall by QuestR on G with R_0
4: **update** R **till convergence** by $R1$, $R2$, $R3$
5: **inference** precision by QuestP on G with P_0
6: **update** P **till convergence** by $P1$, $P2$, $P3$
7: **return** T sorted by $score(t) = P(t)$, $R(t)$, or $F(t)$

Figure 7: Algorithm QueST: Mining query templates.

Our goal of inference is to estimate $R(t)$ and $P(t)$, $\forall\ t \in T$, that satisfy the probabilistic dependencies captured in the graph; as necessary intermediaries, the inference will also estimate $R(q)$ and $P(q)$, $\forall\ q \in Q$ as well as $R(s)$ and $P(s)$, $\forall\ s \in S$.

Overall, we develop Algorithm QueST, for template discovery. As Fig. 7 shows, it starts by generating template candidates and constructing the QST-graph. We note that the construction is only conceptual; we can "materialize" the graph during inference only as needed. On this graph, starting from Q_0 with given P_0 (and estimated R_0), QueST will infer R and P for each node. It infers recall by QuestR and precision by QuestP, as we will develop next in Sec. 6. Finally, QueST will rank templates by P, R, or the combined F-measure (depending on application requirements).

6. INFERENCE: QuestR AND QuestP

To complete the QueST framework, we develop inferencing equations that propagate the precision and recall across the QST-graph. Specifically, we will derive probability estimation of a node in terms of its neighbors, through the semantic relevance across their edges. As Fig. 8 summarizes, we will study the inference equations for both recall and precision, deriving QuestR and QuestP—which reveals surprising duality.

As the result of our modeling, the QueST framework is a Markov random field over the tripartite QST-graph. The probability (of precision or recall) of a node depends on only its direct neighbors (through instantiation or click-through). The desired semantics–precision or recall– result in different dependency equations as we will derive in Fig. 8. These inference equations, together, constrain the most *probable* configuration over the random field.

We will study the intuitive interpretations of the inferencing mechanisms, which turn out to be random walk of opposite directions for recall and precision—To our knowledge, this paper is the first to identify this interesting duality. To understand the solutions of such inferencing, we will formally connect to existing learning frameworks for their computational properties.

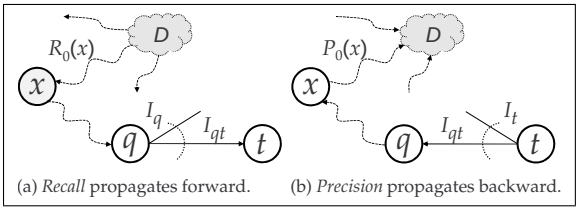
6.1 Recall: Quest Forward

We now establish the inference of probabilistic recall, deriving equations $R1$, $R2$, and $R3$ as Fig. 8 summarizes. To begin with, as input, the system is given initial recall estimates $R_0(x)$ for a small number of seed queries $x \in Q_0$, as calculated from their given precisions (Eq. 9). The inference is to determine, from the seed knowledge, the recall measures of every node (including updating the seed nodes). We thus must "interconnect" the nodes by their dependencies– *i.e.*, how to estimate the probability $P(x_i)$, for each $x_i \in V$, given all the neighbor nodes, which it depends on. As the graph is tripartite of the form S–Q–T (Fig. 6), we must specify inference of $Q \rightarrow T$, $S \leftarrow Q$, as well as $Q \leftarrow T$ and $S \rightarrow Q$.

We will derive Equation $R1$, for $Q \rightarrow T$, inferencing the recall of template t from those of its neighboring q, by rewriting $R(t)$ from definition as given to an expression in terms of $R(q)$. Step 1 starts

1) **QuestR:** *Quest Forward for Recall Inference*	2) **QuestP:** *Quest Backward for Precision Inference*
R1: $R(t) = \sum_{q \in I_{(t)}} I_{qt}/I_q \cdot R(q)$, where $I_q = \sum_{\forall t:q \in I_{(t)}} I_{qt}$	***P1***: $P(t) = \sum_{q \in I_{(t)}} P(q) \cdot I_{qt}/I_t$, where $I_t = \sum_{\forall q:q \in I_{(t)}} I_{qt}$
R2: $R(s) = \sum_{q \in \mathcal{C}(s)} C_{qs}/C_q \cdot R(q)$, where $C_q = \sum_{\forall s:q \in \mathcal{C}(s)} C_{qs}$	***P2***: $P(s) = \sum_{q \in \mathcal{C}(s)} P(q) \cdot C_{qs}/C_s$, where $C_s = \sum_{\forall q:q \in \mathcal{C}(s)} C_{qs}$
R3: $R(q) = \begin{cases} \beta_1 R_0(q) + \beta_2 \cdot \sum_{\forall t:q \in I_{(t)}} I_{qt}/I_t \cdot R(t) \\ +(1-\beta_1-\beta_2) \cdot \sum_{\forall s:q \in \mathcal{C}(s)} C_{qs}/C_s \cdot R(s) \end{cases}$	***P3***: $P(q) = \begin{cases} P_0(q) & \text{if } q \in Q_0; \\ \alpha \cdot \sum_{\forall t:q \in I_{(t)}} P(t) \cdot I_{qt}/I_q & \\ +(1-\alpha) \cdot \sum_{\forall s:q \in \mathcal{C}(s)} P(s) \cdot C_{qs}/C_q & \text{otherwise.} \end{cases}$

Figure 8: The QueST dual inferencing framework: QuestP and QuestR.



(a) *Recall* propagates forward. (b) *Precision* propagates backward.

Figure 9: Inferencing recall and precision.

with the definition of $R(t)$ (Eq. 3). In step 2, to bring in queries, we expand it to the joint distributions with every $q_i \in Q$. Step 3 restricts q_i to only those instantiated by t, or $q_i \in I(t)$, which are the neighbors of t, so that $\text{match}(q_i, t)$ can have a non-zero probability. By the Bayes' theorem, step 4 rewrites using $p(AB|C) = p(A|BC)\ p(B|C)$. In step 5, since $\text{match}(q, t)$ depends only on what q is– *i.e.*, it is conditionally independent of $\text{match}(q, D)$, *given* $q = q_i$– we can remove $\text{match}(q, D)$. As the first term equals $I_{q_i t}/I_t$ (where I_t is a shorthand given in Fig. 8) and the second term $R(q_i)$ (Eq. 7), step 6 completes the rewriting.

$$
\begin{aligned}
R(t) &\equiv^1 p(\text{match}(q,t)|\text{match}(q,D)) \\
&=^2 \sum_{q_i \in Q} p(\text{match}(q,t), q = q_i|\text{match}(q,D)) \\
&=^3 \sum_{q_i \in I_{(t)}} p(\text{match}(q,t), q = q_i|\text{match}(q,D)) \\
&=^4 \sum_{q_i \in I_{(t)}} p(\text{match}(q,t)|q = q_i, \text{match}(q,D)) \\
&\qquad \cdot p(q = q_i|\text{match}(q,D)) \\
&=^5 \sum_{q_i \in I_{(t)}} p(\text{match}(q,t)|q = q_i) \cdot p(q = q_i|\text{match}(q,D)) \\
&=^6 \sum_{q_i \in I_{(t)}} I_{q_i t}/I_{q_i} \cdot R(q_i) \qquad (10)
\end{aligned}
$$

We can similarly derive the other two inference equations, which we omit due to space limit. As Fig. 8 shows, Equation $R2$ is in a form parallel to $R1$, since $S \leftarrow Q$ is symmetric to $Q \rightarrow T$ at the two sides of the tripartite graph. At the center, $R(q)$ for query $q \in Q$ depends on the initial estimate $R_0(q)$ and the recalls from the two sides, $R(t)$ and $R(s)$, thus the mixture of the dependence sources combined by parameters β_1 and β_2.

Interpretation. We observe that the result is simple yet interesting. Consider $R1$: The recall of t, $R(t)$, is the sum of the neighboring recalls, $R(q)$, each of which is distributed proportionally among its outgoing edges towards t—or, t *receives* recall proportionally from its neighboring query nodes.

While several interpretations are possible, it is intuitive to view the inferencing as random walk. As Fig. 9 illustrates, we think of $R(t)$ as the probability of arriving at t, in a random walk starting from some hidden origin—the hidden domain D. The hidden domain is only specified through its probability $R_0(x)$ to reach seed nodes x. This random walk interpretation of $R(t)$, in hindsight, is consistent with what probabilistic recall, in Eq. 3, shall capture: the proportion of queries from D that will reach t. Equation $R1$ thus means—the probability of arriving at t sums up the probabilities of arriving at its neighbors and then one last hop to t.

In sum, as we generalized recall from the standard deterministic sense (Eq. 1) to a probabilistic measure (Eq. 3), upon the semantic relevance graph, we observe that the inference mechanism (as $R1$, $R2$, and $R3$ captures) lends itself naturally to the random walk interpretation. We identify the walk in the *forward* direction, from *given* seeds x (indicating the hidden domain as the origin) to *unknown* nodes t.

Connections: The recall inference, as a forward walk model, connects to the PageRank [22] family of models. In particular, with "seed nodes" assignments, QuestR connects directly to topic-sensitive or personalized PageRank ([23, 16]). (We can rewrite Eq. $R1$, $R2$, and $R3$ to matrix forms that directly parallel the personalized PageRank formulation.) The connection thus allows us to understand that (subject to making the graph irreducible) iterative matrix computation would converge to the solutions.

6.2 Precision: Quest Backward

We next establish the inference of probabilistic precision—in which, we witness the interesting duality of recall and precision on the graph—The derivation of precision inference follows an exactly symmetric process to recall inference just discussed. Fig. 8 also summarizes the precision Equations $P1$ (for $Q \rightarrow T$), $P2$ (for $S \leftarrow Q$), and $P3$ ($Q \leftarrow T$ and $S \rightarrow Q$). We omit the symmetric process due to space limit. As the only difference, here, for seed queries q, as their $P_0(q)$ are specified in labeling (Eq. 9; unlike $R_0(q)$ which is only estimated), $R(q)$ will take this "ground truth" and will not change throughout inferencing.

Interpretation. With the symmetry between precision and recall in the derivations of their inference, we also observe interesting duality in their interpretations. Consider $P1$: The precision of t, $P(t)$, is the sum of the neighboring precisions, $P(q)$, each of which is weighted by how t can reach q. As Fig. 9 illustrates, we think of $P(t)$ as the probability of reaching D, the domain as a hidden destination, in a random walk starting from t. The hidden domain is specified through $P_0(x)$, *i.e.*, how seed queries x can reach D.

This random walk interpretation of $P(t)$ is, again, consistent with what probabilistic precision, in Eq. 4, shall capture: the proportion of queries from t that will reach D. Equation $P1$ thus means—the probability of t reaching D sums up the probabilities of one hop to its neighbors and then going from there.

While we identified recall inference as forward random walk, we now recognize that the inference of probabilistic precision turns out to be the opposite—backward random walk, from *unknown* nodes t to *given* seeds x (indicating the hidden domain as the destination).

Connections: The backward random walk interpretation connects QuestP to a relatively recent semi-supervised learning framework, *harmonic energy minimization* [15], over a graph with labeled and unlabeled nodes. As the result of our formulation, we obtained inference equations $P1$, $P2$, and $P3$, which are *harmonic—i.e.*, the value $P(u)$ of a node u is the (weighted) average of its neighbors. The harmonic update functions will lead to the assignment of P values over graph G in a way that will minimize the quadratic energy function below: That is, the closer nodes u and v are, *i.e.*, the larger their edge weight w_{uv} is, the closer their P values shall be. Thus, on the QST-graph, nodes that are close with edges (of instantiation or click-through) will have similar precision.

Type	Size: *small*	Size: *median*	Size: *large*
site	2 sites	4 sites	8 sites
query	5 queries	20 queries	50 queries
template	2 templates	5 templates	10 templates

Figure 10: Seed input configurations.

Domain	*f-Quest*	*b-Quest*
Job	#location jobs jobs in #location	#companyname #location job fairs #location #industry positions
Airfare	cheap flights to #location #airline airlines	#airline #location reservations #location #airport airport
Automobile	#year #make #model #make #model	#location #make used cars #year #make #location for sale
Car Rental	#carrentalcompany rental car #carrentalcompany rental	#carrentalcompany rental car #location #cartype rent a car
Hotel	#hotelname #location #location hotels	#hotelname #location hotels #hotelname at #location
Movie	#movietitle #actorname	#actorname new movie #movietitle characters
Real Estate	#location real estate #location homes for sale	#location area homes for sale #location commerical real estate

Figure 11: Top 2 templates derived by QuestRand QuestP.

$$E(P) = \frac{1}{2} \sum_{u,v \in G} w_{uv}(P(u) - P(v))^2 \quad (11)$$

As essentially an instance of the harmonic energy minimization framework [15], the solution of QuestP is unique, and can be evaluated by iterative matrix computation till convergence.

7. EXPERIMENTS

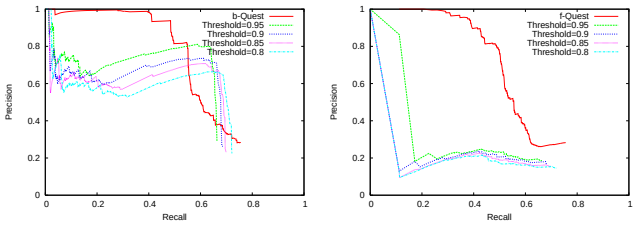
We report our evaluation of QueST for template discovery over a large scale real query log across a range of query domains. Overall, the experiments demonstrate that QueST is accurate for finding templates for predicting query intents, outperforming the baseline of Classify&Match significantly, and is robust over a wide range of seed input types and sizes. Further, we extend QueST to handle incomplete schema, which shows the robustness for discovering not only new instances of attributes, but also new attributes.

7.1 Experiment Setting

Query Log: We used a real world query log from the MSN search engine [3] with 15 million queries and 12.25 million click-through (query, site) pairs. We preprocessed this query log: (i) As we were only interested in the clicked site, we truncated the clicked URL to its top-level domain name, *e.g.*, *monster.com*, rather than the complete URL. (ii) We remove *navigational queries* [24] (*e.g.*, "ebay"), whose target is a particular site (*ebay.com*). The preprocessing resulted in 2.8 million unique queries. We used 80% of these queries as the "query log" for mining templates from, and used the rest 20% for testing the discovered templates.

Target Domains: We experimented widely over seven domains—*airfare*, *automobile*, *hotel*, *job*, *real estate*, *car rental*, *movie*—as our survey (Sec. 3) also studied. For the overall performance, we will report all the domains (Fig. 15). Due to space limit, for fine grained studies, we report only for *job* domain, as the results are similar in all the domains.

Application Scenarios: We evaluated the usefulness of query templates, as QueST aims to discover, directly in their applications—for predicting query intents (by matching user queries). As the ground truth to test against, we sampled 28,000 unseen queries (see next)—the same set of queries that we manually labeled and surveyed, as Sec. 3 reported. In particular, as Fig. 3 summarizes, among the 28K, 921 queries are for *job*, of which 74.38% (*i.e.*, 685) have patterns. We thus used these 685 queries (which have patterns) as ground truth that our discovered templates should ideally match—and we used such matching to calculate the precision and recall of intent prediction in every experiment for *job* domain.



(a) Scoring by precision (b) Scoring by recall

Figure 12: Comparison of QueST with Classify&Match.

Test Set: Our test set included 28K unique queries—20K sampled *randomly* and 7K sampled with *domain-focus* (from queries clicking on manually enumerated sites relevant for our 7 domains). To facilitate the task of labeling, we created a labeling interface which showed results for each query from google.com—the search results for a given query helped our labelers to understand the intents. At peak speed, our labelers (undergraduate students in Psychology) could label 600 queries per hour.

Evaluation Metrics: Our algorithms (Figure 7) as well as the baseline method (Figure 5) produce a ranked list of templates. For each template, we compute its precision, recall, and F-measure by counting the number of matches to positively labeled *vs.* negatively labeled queries in the test set of 28K queries (the application scenarios for intent prediction as just discussed).

Seed Input Configuration: Our QueST algorithm can take any types of seeds (site, query, template) as input, and requires only a modest size of input. We studied all the three types of input, *w.r.t.* three different sizes, as Fig. 10 summarizes. For each configuration, we manually compiled the specified number of input seeds (*e.g.*, 5 queries for the *query-small* configuration).

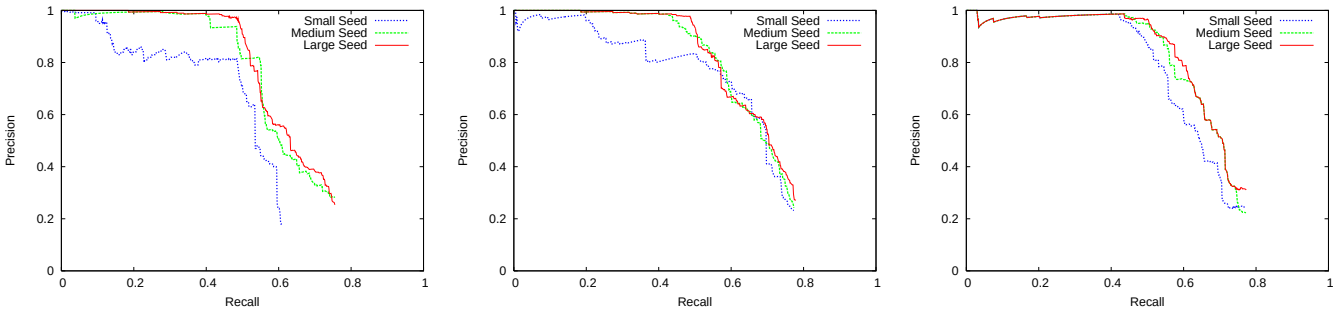
Parameter Setting: We experimented with different settings α, β_1 and β_2 referred to in Fig. 8. Here, we report the results for $\alpha = 0.5$, $\beta_1 = 0.1$, and $\beta_2 = 0.45$.

7.2 Results

Illustrative Results: As shown in Fig. 11, the top-2 templates produced by QuestR and QuestP algorithms illustrate that the two methods very well match the desired objectives of ranking templates based on recall and precision, respectively. These illustrative results are for input configuration of medium size input sites. *E.g.*, for *job*, top-2 templates produced by QuestR algorithm are ⟨#location jobs⟩ and ⟨jobs in #location⟩, indicating QuestR method ranks "popular" templates first. Likewise, for QuestP we see that the top-2 templates, *i.e.*, ⟨#companyname #location job fairs⟩ and ⟨#location #industry positions⟩, are "surely" for *job* domain.

Baseline: Classify&Match As our first experiment, we compare the performance of our algorithms to the two-staged baseline method of Classify&Match method, as described in Section 4.2. We implemented Algorithm 1 of [1] for query classification, and ran it for 20 iterations. We report results for *job* domain, with input configuration of type as sites and size as medium.

As Fig. 12 (a) shows, QuestR (red color) consistently outperforms baseline method with recall based scoring (other colors), for all values of threshold.



(a) Input sites (b) Input queries (c) Input templates

Figure 13: Performance under different seed input configurations

Likewise, Fig. 12 (b) shows QuestP (red color) outperforms baseline method with precision based scoring (other colors). Our QuestP method provides quite reliable ranking of templates—precision stays high for lower recall values, and gradually drops as recall increases. On the other hand, baseline method with precision based scoring ranks several non-relevant templates in top ranked positions, which results in poor precision even at low recall values.

Thus, we validate a key hypothesis of this paper, that—in order to mine templates, iterative bootstrapping must be interleaved and regulated via templates, as in our QueST network.

Robustness to Seed Input Configurations: Next, we study the performance of QueST framework under different input configurations. We report results for QuestP algorithm; the behavior for QuestR algorithm is similar. Also, we present results only for *job* domain, while we observed similar robustness in other domains. We can see from the P-R curve in Fig. 13 that our framework provides similar performance for all types of inputs. For variation in input size, we tend to get better results as the input size increases; however, the increase in performance is more significant from small (blue color) to medium (green color) than from medium (green color) to large (red color).

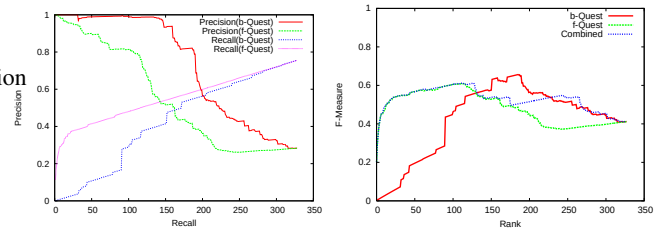
We also tested the performance under hybrid input configuration, by providing a combination of medium size of sites, queries and templates together as input. Our framework tends to provide similar performance for this hybrid input configuration as well, with optimal F-measure of 0.87 in *job* domain.

We note that for all configurations, our algorithm converges in 4-5 iterations.

Duality of Forward vs. Backward QueST: We study the duality of recall-based (QuestR), *i.e.*, forward propagation, *vs.* precision-based (QuestP), *i.e.*, backward propagation on the QueST network. We report results for *job* domain for medium sized input.

We first compare the cumulative precision and recall at each ranked position for the two methods in Fig. 14 (a). As expected, QuestR finds out higher recall templates earlier. For example, the top 75 templates give a recall of 0.41 for QuestR (pink color) compared to 0.16 for QuestP(blue color). However, on precision metric, QuestP (red color) performs better than QuestR(green color). Thus, the two algorithms QuestR and QuestP optimize for recall and precision, respectively.

Next, we combine the two rankings to get an overall better performance. In particular, we studied F-measure scheme; for each template, we obtained combined score as harmonic mean of the predicted recall (by QuestR) and predicted precision (by QuestP). As shown in Fig. 14 (b), combined ranking (blue color) performs better on F-measure metric than each of the two methods (other colors). At top ranked positions, QuestR (green color) performs better; while at later ranked positions, QuestP (pink color) performs better. The performance of combined method, interestingly, follows the performance of the better of the two methods.



(a) QuestR vs. QuestP (b) Combined Ranking

Figure 14: The duality of Forward and Backward QueST

Domain	Input Site	Conf Intvl	Input Query	Conf Intvl	Input Template	Conf Intvl
Job	.82	.82 ± .05	.75	.77 ± .06	.83	.83 ± .05
Airfare	.79	.78 ± .05	.73	.75 ± .05	.77	.78 ± .06
Automobile	.81	.80 ± .04	.81	.81 ± .03	.86	.85 ± .04
CarRental	.91	.89 ± .11	.89	.88 ± .10	.91	.89 ± .11
Hotel	.76	.77 ± .04	.77	.78 ± .05	.78	.78 ± .05
Movie	.76	.75 ± .06	.72	.73 ± .06	.75	.76 ± .06
RealEstate	.76	.76 ± .04	.70	.70 ± .04	.75	.76 ± .04

Figure 15: Optimal F-measure over all domains.

In summary, QuestR is better in finding popular templates whereas QuestP ranks more precise templates higher. Furthermore, better F-measure can be obtained by combining the two scores.

Overall Performance in All Domains: We present the optimal F-measure for QuestP algorithm for each of the 7 domains, in Fig. 15. While both the methods have their merit, we observed that QuestP achieves higher optimal F-measure compared to QuestR. We used medium size input configuration for this experiment.

We observed that for all types of input, and for all 7 domains, our method can achieve F-measure of 70-90%. Averaged over all domains, our method can achieve F-measure of 0.80, 0.81 and 0.76 using sites, templates and queries, respectively.

Confidence Interval: We also report 95% confidence interval for overall performance by partitioning the test set into 5 parts and evaluating each partition independently. Confidence interval is calculated as $Mean \pm (z - score * StandardError)$, where z-score =1.96 for 95% confidence interval and Standard Error is calculated as $(StandardDeviation/\ NumberofTrials)$. We can see the confidence intervals for the experiments in Fig. 15, which shows that our algorithm gives a stable performance.

7.3 Extensions: Incomplete Domain Schema

Our framework can be easily extended to application domains where domain schema is not fully available, *i.e.*, the list of attributes, or vocabulary instances are incomplete. Recent research on *named-entity mining* (NEM) using search engine query logs has shown the usefulness of templates in discovering new attribute classes as well as instances of existing attribute classes, *e.g.*, using hand-crafted query patterns [11], learning query patterns using seed attribute classes and instances [12], and probabilistic framework using click-through logs [13].

All of these techniques start with generating candidate terms using templates, and then grouping them into homogeneous clusters. In our iterative $S \rightleftharpoons Q \rightleftharpoons T$ framework, we can add another step of $T \rightarrow D$, to infer domain schema from templates. Suppose, for example, in job listing domain, only 2 instances of #location were known, *e.g.*, $I(()\#\text{location}) = \{\text{chicago, seattle}\}$.

First, we use "inferencing" query templates to obtain the list of candidate terms for inclusion in existing attributes, or for forming new attribute classes. We replace the attributes of existing template, *e.g.*, ⟨jobs in #location⟩ to formulate inferencing template, *e.g.*, ⟨jobs in $\star$⟩, where $\star$ can match any term. This inferencing template will match many more queries such as jobs in boston, jobs in microsoft, jobs in houston, jobs in yahoo, *etc.* Collecting the terms matching $\star$ position, we get the candidate list of terms for schema extension, *i.e.*, {boston, microsoft, houston, yahoo}.

Second, we cluster the candidate terms for schema extension based on their contextual similarity, *i.e.*, by comparing the overlap of the terms in query log that co-occur with each candidate term. In our implementation, we use Jensen-Shannon divergence (JSD), which is a smoothed and symmetric version of Kullback-Liebler divergence, as was also used in [12]. In this step, we will then be able to group the candidate terms into two separate groups: {boston, houston}, whose context is similar to existing instances of #location, and {microsoft, yahoo}, which will formulate the new attribute class of #company.

We evaluated our extension in two domains: *job* and *automobile*. For *job*, we provided only one attribute, #location, without giving (#category. For *automobile*, we only specified #make and #year, without giving #model. For each of the attributes, we provided only 10 instances, compared to our full vocabulary in earlier experiments. We used QuestP algorithm for these experiments, using medium-size seed input, and sites as input type.

Inferring Domain Schema: For both the domains, not only our algorithm could discover all the missing attributes, it also discovered new attributes. In *job* domain, we discovered the missing attribute #category, and also a new attribute (not included in our original experiments) #company. Likewise, in Automobile domain, we discovered #model, and also a new attribute #location. We should mention that in Automobile domain, we observed four clusters of new attributes, of which one was #model, and the other three represented #country, #state and #city. Thus, the algorithm can also discover attribute classes at different levels of granularity.

Impact on Quality of Templates: With incomplete domain schema, the performance of basic QueST framework was 0.27 and 0.16 for Job and Automobile domain, respectively, as measured on F-measure metric. With our extension to infer domain schema, we could improve the corresponding performance to 0.75 and 0.73. While this is still lower than the performance when complete domain schema was available (0.82 and 0.73), it is significantly better than the performance with no extension.

8. CONCLUSION

As keyword queries have become the standard query language for searching over the Web, we believe rich query interpretation—understanding not only the intent but also the structures of keyword queries—is crucial for better search. In this paper, we formally define the concept of *query templates* and propose the problem of template discovery from search logs. We develop QueST, an inferencing framework over the graph of queries, sites, and templates to discover good templates. We define the quality measures of templates based on the dual metrics of precision and recall– and propose iterative inferencing using backward and forward random walks, respectively. We evaluated the system over a query log of 15 million queries from MSN search, and the results indicated high accuracy for query intent prediction. We look forward to extending the techniques for more complex and expressive query patterns.

9. REFERENCES

[1] Xiao Li, Ye-Yi Wang, and Alex Acero. Learning query intent from regularized click graphs. In *Proceedings of the 31st annual international ACM SIGIR conference on Research and development in information retrieval*, Singapore, 2008. ACM.

[2] Steven M. Beitzel, Eric C. Jensen, Ophir Frieder, David D. Lewis, Abdur Chowdhury, and Aleksander Kolcz. Improving automatic query classification via semi-supervised learning. In *ICDE*, 2005.

[3] Microsoft Research. Microsoft live labs: Accelerating search in academic research 2006 rfp awards. *Research Grant*, 2006.

[4] Nick Craswell and Martin Szummer. Random walks on the click graph. In *SIGIR '07: Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval*. ACM Press, 2007.

[5] Ricardo Baeza-Yates. Applications of web query mining. *ECIR*, 2005.

[6] T. Joachims. Optimizing search engines using clickthrough data. In *KDD*, 2002.

[7] E. Agichtein, E. Brill, and S. Dumais. Improving web search ranking by incorporating user behavior information. In *SIGIR*, 2006.

[8] Charles Ling, Jianfeng Gao, Huajie Zhang, Weining Qian, and Hongjiang Zhang. Improving encarta search engine performance by mining user logs. *Journal of Pattern Recognition and Artificial Intelligence*, 2002.

[9] Ricardo Baeza-Yates, Carlos Hurtado, and Marcelo Mendoza. Query recommendation using query logs in search engines. *EDBT*, 2004.

[10] H. Cao, D. Jiang, J. Pei, Q. He, Z. Liao, E. Chen, and H. Li. Context-aware query suggestion by mining click-through and session data. In *SIGKDD*, 2008.

[11] Marius Pasca and B. Van Durme. What you seek is what you get: Extraction of class attributes from query logs. In *IJCAI*, 2007.

[12] Marius Pasca. Organizing and searching the world wide web of facts - step two: Harnessing the wisdom of the crowds. In *WWW*, pages 101–110, 2007.

[13] Gu Xu, Shuang-Hong Yang, and Hang Li. Named entity mining from click-through data using weakly supervised latent dirichlet allocation. In *KDD*, 2009.

[14] Ariel Fuxman, Panayiotis Tsaparas, Kannan Achan, and Rakesh Agrawal. Using the wisdom of the crowds for keyword generation. In *WWW*. ACM, 2008.

[15] Xiaojin Zhu, Zoubin Ghahramani, and John Lafferty. Semi-supervised learning using gaussian fields and harmonic functions. *In ICML*, 2003.

[16] Taher Haveliwala. Topic-sensitive PageRank. In *Proceedings of the Eleventh International World Wide Web Conference*, 2002.

[17] Dengyong Zhou, Olivier Bousquet, Thomas Navin Lal, Jason Weston, and Bernhard Sch Olkopf. Learning with local and global consistency. *Advances in Neural Information Processing Systems 16*, 16, 2004.

[18] M. Szummer and T. Jaakkola. Partially labeled classification with markov random walks. *Advances in Neural Information Processing Systems*, 2001.

[19] Jason K. Johnson, Dmitry M. Malioutov, and Alan S. Willsky. Walk-Sum interpretation and analysis of gaussian belief propagation. In *Advances in Neural Information Processing Systems 18*. MIT Press, 2006.

[20] Sergey Brin. Extracting patterns and relations from the web. *WebDB*, 1998.

[21] Oren Etzioni, Michael Cafarella, Doug Downey, Ana-Maria Popescu, Tal Shaked, Stephen Soderland, Daniel S. Weld, and Alexander Yates. Unsupervised named-entity extraction from the web: An experimental study. *Artificial Intelligence*, 165(1):91–134, 2005.

[22] Lawrence Page, Sergey Brin, Rajeev Motwani, and Terry Winograd. The pagerank citation ranking: Bringing order to the web. Technical report, Stanford Digital Library Technologies Project, 1998.

[23] Glen Jeh and Jennifer Widom. Scaling personalized web search. In *In Proc. of 12th WWW*, 2003.

[24] Uichin Lee, Zhenyu Liu, and Junghoo Cho. Automatic identification of user goals in web search. In *WWW*, pages 391–400, 2005.