Expansion of Tail Concept Using Web Tables

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Abstract

Human-curated knowledgebases like Freebase and DBPedia cover popular concepts such as persons, organizations and locations, but many more specific concepts fall into the long tail outside current knowledgebases, such as acidic fruits, HD video formats and renewable resources. These concepts are found in concept-entity pairs automatically extracted from text documents, but they cover a limited number of entities per concept due to insufficient mentions in text. In this paper, we propose to expand the coverage of entities for tail concepts using web tables. It is challenging to apply existing techniques because a tail concept often overlaps many other concepts. Our solution is based on the fact that many web tables contain a set of entities all belonging to a fine grained concept. We leverage the rich content signals and the structured entities in web tables to infer such exclusive tables. Our inference differs from previous label propagation methods via modeling a special table-entity relationship. It reduces semantic drift without using a reference ontology. Taking concept name and two seed entities as only input, it can augment thousands of popular tail concepts with 85 times recall boost on average, while maintaining over 90% precision.

1 Introduction

We study the following problem: *given the name of a concept as well as a few seed entities belonging to the concept, output all entities belonging to the concept.* This is referred to as the *concept expansion* problem. This problem has many applications:
• *Knowledgebase expansion*: Knowledgebases (also referred to as knowledge graphs) are used by web search engines for a variety of purposes: to answer search queries, understand short texts and annotate web tables [1, 36, 31, 32]. A knowledgebase contains concepts (e.g., country), entities belonging to those concepts (e.g., USA, China, India for the concept 'country') and attributes of those concepts (e.g., population, capital city for the concept 'country'). The state-of-the-art web scale knowledgebases like Freebase [7] and YAGO [28] have high coverage on head concepts, entities and attributes, but low coverage on tail ones [36, 37, 35]. That restricts the applications of

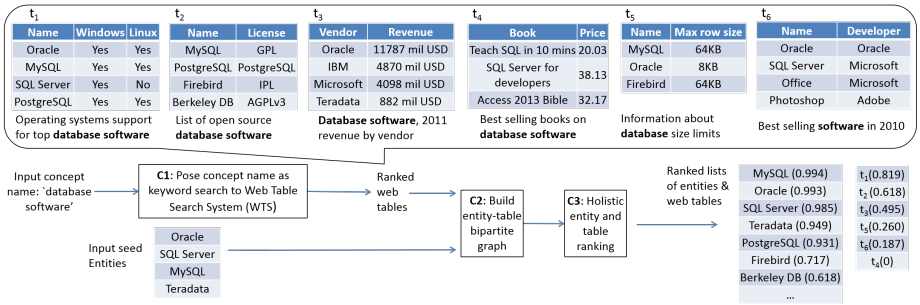


Figure 1: System architecture and running example. The tables returned by WTS for the concept name as keyword query is shown inside the rectangular callout. The text below the tables represent the caption/surrounding text/nearest headings

the knowledgebase, since web queries have a well-known long tail distribution. There is a growing interest to extend the knowledgebase to cover tail concepts, entities and attributes.

The problem we study can be applied to expanding the coverage of entities for tail concepts. While a small number of basic concepts (e.g., company, city, country) representing rough-grained types appear very frequently in user queries, web users do mention other fine-grained concepts, such as 'third world countries', 'emerging economies' and 'BRIC countries'. These tail concepts cannot be easily obtained by slicing their super concepts because the attributes in knowledgebases are also incomplete. The best coverage of these concepts can be found in automatically extracted concept-entity pairs from web documents, such as Microsoft's Probase [36] and Google's isA database [31]. They primarily use text patterns (specifically, Hearst patterns [20]), and the concept coverage is considerably higher than human-curated knowledgebases (2.7 million concepts in Probase v.s. 350K in YAGO, 25K in Freebase, and 685 in DBpedia). However, they have a limited number of entities per concept, due to the sparse coverage of high confidence textual patterns. For example, for the concept 'low-fertility country', Probase contains only 4 entities: Japan, Germany, Spain and Canada. In fact, none of them are among the top 20 lowest fertility countries in 2014, such as Singapore and South Korea. This is likely due to their rare mentions in Hearst patterns.

• *Ad-hoc list creation*: Users often create lists for concepts of interest (e.g., dog breeds, usa beach vacation spots) using a spreadsheet (Excel, Google Sheets) or a note-taking application (e.g., OneNote, Evernote). Manually creating such lists is labor-intensive; approaches that automatically populate such lists or at least suggest some lists can be immensely beneficial. Such auto-population is relatively easy for head concepts as knowledgebases already contain the necessary information; the challenge is to do so for *tail concepts*.

Since producing the exact set of entities belonging to a concept is hard, a realistic goal is to return a ranked list of entities instead. More likely an entity is to belong to the concept, higher should be its rank. This requires human effort to examine the returned entities and then populate the knowledgebase or user list. This is still significantly less burdensome than manual population. Better the ranking, lower the human effort.

Prior work and limitation. Though abundant work has been done for the general con-

cept expansion or set expansion problem, it is challenging to apply the existing settings and techniques to tail concepts. The difficulty arises because the space of 'competing concepts' now substantially increases. The assumption that different concepts have no common entities easily breaks when considering fine granular concepts. For example, Japan belongs to 2,459 different concepts in Probase, including 'populous area', 'island country', 'mountainous country'... We need to distinguish these concepts that have ad-hoc overlaps and do not form a tree-structured taxonomy.

We briefly review the prior work and their limitations. First of all, most set expansion approaches take a small set of "seed entities"[1] as input, to discover other entities belonging to the concept [19, 33, 34, 17, 27, 24]. When expanding fine grained concepts, this approach is subject to the ambiguity in the input: given the seed entities 'Canon', 'Sony' and 'Nikon', it is difficult to know which concept the user has in mind, 'camera brands' or 'Japanese companies' or something else. Also, existing techniques tend to mix entities belonging to different concepts as the set is expanded out to a certain degree. This is known as a 'semantic drift' issue [11]. Second, to prevent semantic drift, a common strategy is to populate negative examples and constraints using a reference ontology. This idea is used by Snowball [5], KnowItAll [16], and NELL [10] etc. A similar setting is hard to set up for ad-hoc tail concepts. There is no reference ontology to provide mutual-exclusiveness and constrain the expansion for most tail concepts. Finally, previous approaches are either designed for unstructured text data, or structured data like web tables[2] while ignoring the text information surrounding them. The former has exhibited poor recall for tail concepts, and the latter is bound to semantic drift when no constraint is available.

Our solution. We consider a different problem setting, taking both a concept name and a small set of seed entities as input, without negative examples or knowledge of other concepts; and we resort to both structured data in web tables and text data surrounding them. This setting has several unique benefits for expansion of tail concepts. First, the concept name helps delimit the relevant entity set[3]. In the meanwhile, the concept of a web table is often mentioned in the caption, surrounding text, nearest headings etc., providing opportunities for indexing and searching them with a web table search system (WTS) like Microsoft's Excel Power Query [4] or Google's Web Tables [2]. Second, the entities in each web table collectively concentrate to a common concept, and quite often the concept is fine grained.

Example 1 *Consider the concept 'database software'. Figure 1 shows 6 tables returned by the WTS (shown inside the rectangular callout). The WTS typically returns tables whose column names, captions, surrounding text in the page, etc. contain the query keywords; the matching keywords are shown in bold. The ranking order is* $t_1, t_2, t_3, t_4, t_5, t_6$*:* t_1, t_2, t_3 *and* t_4 *are ranked higher as they match both keywords while* t_5 *and* t_6 *are ranked lower as they match with only one keyword. The order is imperfect just like general search engine.*

[1] In our context, seed entities can be the entities already present in a knowledgebase or web-extracted concept-entity pairs, or provided by users

[2] When we refer to web tables, we also include web lists. Lists are simply single column tables

[3] An entity is *relevant* if it belongs to the concept and *irrelevant* otherwise

Each table in such a system has a subject column. This column contains the set of entities the table is about, while the other columns represent binary relationships or attributes of those entities; previous techniques can be used to accurately identify the subject column [31, 32]. In this case, it is the leftmost column in all the 6 tables.

The returned tables t_1, t_2 and t_5 exclusively contain names of database software in their subject column whereas t_3, t_4 and t_6 do not (they contain names of database vendors, books on database systems and all kinds of software respectively in their subject columns). We refer to the former tables as exclusive and the latter as non-exclusive.

Once we retrieve the web tables from a WTS, we have two kinds of information at hand: the seed entities are relevant, and the WTS returns a ranking of tables that *roughly* reflects their relevance to the concept query. A viable approach of utilizing this information is to build a bipartite graph of all retrieved tables and the entities in them, and then run a graph-based ranking method[4] similar to personalized Pagerank [14]. Such a method can utilize prior knowledge on both entity and table side, as well as the link structure. However, when using web tables to expand tail concepts, a traditional ranking method will fail due to the abundance of non-exclusive tables.

Example 2 *Consider the same concept and WTS results as in Example 1. A bipartite graph can be built as in Figure 2. There are 4 seed entities in bold, and the 6 tables are shown in their order in WTS. Using a reasonable entity prior and table prior (as we will discuss in Section 5.2), a generalized personalized Pagerank algorithm ranks entities in the following order: Oracle, MySQL, SQL Server, Teradata, PostgreSQL, Firebird, Microsoft, IBM, Photoshop, Office, Berkeley DB... and tables: $t_3, t_1, t_6, t_2, t_5, t_4$.*

This simple example well reflects reality: a WTS returns a large number of both exclusive and non-exclusive tables, since they cannot precisely isolate one tail concept from others (otherwise the task is easy). Large non-exclusive tables about overlapping concepts like enterprise software, high-revenue software etc. can accumulate high Pagerank score. Irrelevant entities that appear in many non-exclusive tables, such as Office in software and IBM in vendor, will get higher score than relevant but less popular entities, such as Berkeley DB. Unfortunately, the less popular missing relevant entities are often the target of our task, since popular entities have a high chance to exist in a knowledgebase already. This analysis applies to all propagation methods that linearly aggregate scores from all neighboring vertices.

Our insight to resolving this semantic drift issue, is to model the *exclusiveness* instead of *relevance* of tables. Using only exclusive tables to find relevant entities vastly boosts precision, without sacrifice in recall because: (i) it is common to retrieve from the WTS a large number of exclusive web tables for a tail concept such as t_1, t_2 and t_5 in Example 1; and (ii) it is rare for a relevant entity to *only* appear in non-exclusive tables. These observations do not generally hold for other settings, e.g., exclusive textual patterns with high recall are much harder to retrieve.

[4] This requires human effort to verify the top ranked entities/tables and admit the truly relevant ones into the knowledgebase. However, one exclusive table can help a human annotator simultaneously obtain many relevant entities, which saves tremendous effort of examining each single entity. Good ranking is critical to minimizing the amount of human effort

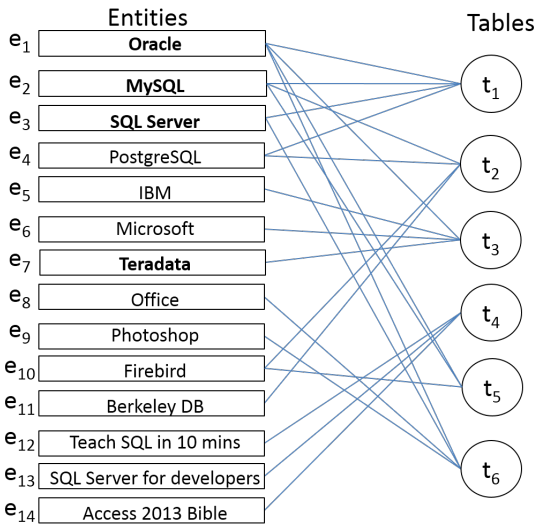


Figure 2: Bipartite graph of entities and tables. The seed entities are shown in bold

To infer exclusive tables and find relevant entities, our solution stems from the simple yet special entity-table relationship: *a table is exclusive iff all its subject entities are relevant, and an entity is relevant if it appears in at least one exclusive table.* Incorporating uncertainty, we propose a novel probabilistic model that holistically ranks the entities and tables. Our ranking method models the score of a table as 'how likely the entire table is exclusive' instead of 'the fraction of the table that is relevant,' and respects the asymmetric entity-table relationship: an exclusive table must contain only relevant entities while a relevant entity can appear in a non-exclusive table. The score from table to entity and entity to table is propagated in an asymmetric way, and aggregated nonlinearly to emulate taking 'all or none' from exclusive or non-exclusive tables. That is a key difference of our approach.

Our contributions can be summarized as follows:

• We address the challenges of tail concept expansion using a new approach, which leverages both structures and text information of web tables. Our approach can be triggered with an ad-hoc concept name and a few seed entities, without relying on negative examples or knowledge of other concepts (Section 2).

• We propose a novel holistic, probabilistic ranking model to rank entities based on their likelihood of belonging to the concept, and rank tables based on their likelihood of being exclusive to the concept. Specifically, we present properties that the score aggregation functions must satisfy in order to model the special table-entity relationship (Section 3); we develop a novel algorithm to perform inference, and prove the convergence for a broad class of aggregation functions (Section 4); and we present concrete choices of aggregation functions and prior knowledge (Section 5).

• We perform extensive experiments on expanding a large scale concept-entity database. Our experiments show that our method produces significantly better quality results compared with three existing algorithms: a competitive set expansion algorithm using web tables, a probabilistic graphical model that propagate table scores via column sim-

Table 1: Table identification using header matching

dutch city	asian country	european country
african country	american idol	american idol contestant
animated movie	indian movie	korean drama
palm tree	transition element	us airport
u.s. airport	vitamin b	world language

ilarities, and a generalized algorithm of personalized Pagerank that propagates entity and table scores via their links. Our technique can increase the number of entities per concept by one to two orders of magnitude with close to 100% precision (Section 6).

2 Problem Statement and System Architecture

2.1 System task

The end-to-end system task is: *given a concept name, seed entities and web tables, return a ranked list of entities belonging to the concept*. The ideal output is the exact set of entities belonging to the concept. We refer to them as relevant entities.

This task is challenging for an ad-hoc tail concept. A tail concept can be defined as concepts with web mention frequency below a cut point, which partitions the sum of concept frequencies roughly equally on its two sides. For example, the most frequent 350 concepts in Probase occupy 40% of the total frequency of all concepts. Any concept other than them is deemed tail concepts in this paper.

A realistic goal is to return a ranked list of entities based on their likelihood of belonging to the concept and allow the users to select the relevant ones.

Definition 1 (Concept Expansion with Web Tables) *Given a concept name C, a set of web tables $T = \{t_j\}_{j=1}^{m}$ and a set of entities $E = \{e_i\}_{i=1}^{n}$ appearing in these web tables, a seed entity set S, rank all entities with score $\{x_i\}_{i=1}^{n}$, according to whether they belong to concept C.*

We assume the seed entity set S is a subset of E; we ignore any seed entity not present in E.

2.2 System architecture

Figure 1 shows the architecture of the CONCEPTEXPAND system.

The CONCEPTEXPAND system has 3 main components, namely C1, C2 and C3, as shown in Figure 1:

(C1) Pose concept name to Web Table Search System: This component retrieves the set of web tables from which the relevant entities can be identified. Obviously, retrieving the entire corpus of web tables will introduce unnecessary work (as most web tables do not contain relevant entities) and increase the latency of the system.

A reasonable set of retrieved tables should comprise (i) most of the tables containing relevant entities and (ii) few of the ones that contain no relevant entities at all.

One option is to develop custom algorithms for this purpose. A plausible algorithm is to obtain the tables whose subject column name matches with the concept name. While this works well for broad concepts (e.g., 'city', 'country'), it misses most tables for specific concepts. For example, we tried this algorithm for the concepts shown in Table 1 (with both singular and plural variants). In a large fraction of the web snapshot, we found a total of only 32 tables altogether.

We resort to the rich content signals associated with web tables. For tables we aim to retrieve, the concept name typically appears in captions, nearest headings (h2, h3, h4), page titles, surrounding text, incoming anchor text and queries for which the page was clicked. These are typically the criteria used by a web table search system (WTS) (e.g., Microsoft's Excel Power Query [4], Google's Web Tables [2]) to return tables by keyword queries [31, 9]. Hence, we pose the ad-hoc concept name to a WTS and use the returned list of tables for further investigation. To obtain a reasonable amount of exclusive tables, we retrieve a large number of tables from WTS (such as 10,000). Since the WTS ranks the tables by relevance, these rank positions can be used as distant prior knowledge for better ranking. We assume that WTS outputs the identity of the subject column for each returned table. All WTSs internally identify it by certain means [31, 32]. We use Excel Power Query [4] as WTS in this paper. In the following, we use t_j to refer to the table ranked at position j by this WTS. For convenience, we also use t_j to refer to the set of entities mentioned in the table's subject column; the context disambiguates which meaning of t_j is used.

(C2) Build an entity-table bipartite graph: The inputs to this component are the set of seed entities and the tables returned by component C1. It identifies the set of distinct entities among the entity mentions in the subject columns of the input tables. It also identifies the seed entities among those distinct entities. In general, this is the entity resolution problem [6]. Since this is not the focus of the paper, we identify the distinct entities by simply grouping the entity mentions in the subject columns using a fuzzy string matching module [23]. We identify the seed entities amongst the distinct entities in the web tables using the same fuzzy string matching module. The output of this component is a bipartite graph. It comprises of the set of distinct entities on one side (with the seed entities identified) and the set of tables returned by WTS on the other side. An edge between an entity and a table indicates that the former is mentioned in the subject column of the latter. The bipartite graph for the example in Figure 1 is shown in Figure 2. Let $T(e_i) = \{t_j \ni e_i\}$ be the set of tables that are linked to e_i. $T(e_i)$ is referred to as *support table set*, and $|T(e_i)|$ as *support* of e_i. For example, $T(e_1) = \{t_1, t_3, t_5, t_6\}$.

(C3) Holistic entity and table ranking: The input to this component is the bipartite graph output by component C2, with seed entities and WTS table ranking included. The output is a ranked list of entities belonging to the concept as well as a ranked list of tables belonging to it. We perform ranking for both entities and tables because they are highly interdependent, as we will discuss in Section 3. The ranked list of tables can also complement the ranked list of entities and facilitate the investigation. Furthermore, the tables provide opportunities of adding relational attributes to the knowledgebase (e.g., the comparison shopper in Section 1), which is an ultimate goal of knowledgebase

expansion.

This component has a critical challenge and the rest of the paper focuses on it. We already use C to denote the user-provided concept name. For convenience, we also use C to denote the set of entities belonging to it; the context disambiguates which meaning of C is used.

Definition 2 (Holistic entity and table ranking) *Given a concept C, ordered web tables $T = \{t_j\}_{j=1}^{m}$ that cover entities $E = \{e_i\}_{i=1}^{n}$, and a seed entity set $S \subset E$, rank these entities with score $\{x_i\}_{i=1}^{n}$, and the tables with score $\{y_j\}_{j=1}^{m}$, according to whether they belong to concept C, i.e., $e_i \in C$ and $t_j \subset C$.*

3 Ranking Model

We first state the principles for entity and table ranking. We then propose a probabilistic model following the principles.

Finding relevant entities and exclusive tables are highly interdependent tasks and can mutually enhance each other. It is due to the following relationship between them:

Principle 1 *A table t_j belongs to a concept C if and only if all the entities $e_i \in t_j$ belong to C.*

Principle 2 *An entity e_i belongs to a concept C if it appears in at least one table t_j such that t_j belongs to C.*

Principle 2 is actually a straightforward corollary of Principle 1. We restate it in order to emphasize the assymetric relationship: an exclusive table must contain only relevant entities, but a relevant entity can appear in non-exclusive tables.

If we know either the complete set of relevant entities or the complete set of exclusive tables, we can leverage the two hard principles to obtain the other set. For example, if we know which entities belong to the concept C, we can deduce which tables belong to concept C using Principle 1. Conversely, we can deduce which entities belong to concept C using Principle 2 when the knowledge of tables is given. [5]

In reality, we do not have the complete knowledge on either side. The input provides partial prior information on both sides. If $e_i \in S$ is a seed entity, we have strong prior knowledge for e to belong to the concept C. If table t_j is ranked high (j is small) by WTS, we have weak prior knowledge for t_j to belong to concept C. The table prior is weak because the WTS does not rank tables according to their exclusiveness. We can only assume that the WTS ranking is overall positively correlated with the exclusiveness.

With the unavoidable uncertainty, we model the problem as a holistic entity and table ranking task that incorporates *soft counterparts* of the above principles.

[5]Note that in the latter case, false negatives are possible in theory, because some relevant entities may only appear in non-exclusive tables. Yet we assume this rare happens due to the large sample size of web tables and a reasonable performance of WTS. So the recall will be reasonably high

Probabilistic ranking model: Let $x_i = p(e_i \in C) \in (0, 1]$ denote the likelihood of entity e_i belonging to concept C, and $y_j = p(t_j \subset C) \in [0, 1]$ denote the likelihood of table t_j belonging to concept C. [6] We then model their relationship with soft counterparts of Principle 1 and 2. According to Principle 1, we model each y_j as an aggregation function $f_{E\to T}$ of $\{x_i, e_i \in t_j\}$. According to Principle 2, we model each x_i as an aggregation function $f_{T\to E}$ of $\{y_j, t_j \ni e_i\}$. Then, we solve the following equations to perform holistic entity and table ranking.

$$\begin{aligned} x_i &= f_{T\to E}(\{y_j, t_j \ni e_i\}) \\ y_j &= f_{E\to T}(\{x_i, e_i \in t_j\}) \end{aligned} \tag{1}$$

It is easy to incorporate the prior knowledge on entity and table side by adding pseudo tables and entities in the bipartite graph, which will be discussed in Section 5.2.

As we discussed in Section 1, symmetric, linear aggregation functions, like the random walk employed by Pagerank, Co-HITS, etc. fall with the semantic drift issue. The reason is that they do not suit the special relationship we are modeling between relevant entities and exclusive tables through Principle 1 and 2. We now discuss the design principle of the two aggregation functions $f_{E\to T}$ and $f_{T\to E}$, which both should produce values between 0 and 1.

3.1 Entity to table aggregation function

Given x_i for $e_i \in E$, we model $y_j = p(t_j \subset C)$ as an aggregation function $f_{E\to T}$ of $\{x_i | e_i \in t_j\}$. This is the soft counterpart of the relationship expressed in Principle 1.

Principle 1 suggests that as long as one entity $e_i \in t_j$ is not in concept C, the whole table t_j is not in concept C. To translate this to our probabilistic language, we would like $f_{E\to T}$ to reflect the likelihood that all the entities in t_j belong to C. It should produce a low value if any $x_i | e_i \in t_j$ is low. Also, it should well distinguish tables that have small difference. We abstract the following two axiomatic properties:

• Consider a table t_j. For any entity $e_i \in t_j$, its likelihood of belonging to C is an explanatory variable of the likelihood t_j belonging to C. When it is almost certain that the entity e_i does not belong to C, the table t_j is also almost certain to be non-exclusive. In contrast, if all the entities in t_j are certain to be relevant, the table t_j is also certain to be exclusive.

Property 1 (Asymptotic Principle 1)
$\forall e_i \in t_j$, $\lim_{x_i \to 0} y_j = 0$*; Let* $\mathbf{x} = [x_i | e_i \in t_j]$, $y_j = 1$ *iff* $\mathbf{x} = \mathbf{1}$.

• If two tables t_a and t_b are identical except two entities with equal support, the table containing the entity with a higher likelihood should have a higher likelihood of belonging to the concept (unless the likelihood for both is equal to zero).

Property 2 (Monotonicity) *If* $t_a = t \cup \{e_1\}, t_b = t \cup \{e_2\}$, $|T(e_1)| = |T(e_2)|$ *and* $x_1 < x_2$*, then* $0 \le y_a \le y_b \le 1$ *(*$y_a = y_b$ *happens only when* $y_b = 0$*).*

[6] We let $x_i > 0$ because we cannot assert an entity does not belong to concept C for sure, as we do not have negative evidence

As one example, the minimum value from $\{x_i|e_i \in t_j\}$, i.e.,

$$f_{E\to T}(\{x_i|e_i \in t_j\}) = \min_{e_i \in t_j} x_i \tag{2}$$

satisfies Property 1, but not Property 2. It is determined by a single element x^* in the set $\{x_i|e_i \in t_j\}$ and insensitive to other elements as long as they are not smaller than x^*.

Example 3 *Consider the two tables t_1 and t_3 in Figure 1. t_1 contains 4 entities $e_1 = Oracle$, $e_2 = MySQL$, $e_3 = SQL\ Server$ and $e_4 = PostgreSQL$ and t_3 contains 4 entities $e_1 = Oracle$, $e_5 = IBM$, $e_6 = Microsoft$ and $e_7 = Teradata$. Suppose $x_1 = x_2 = x_3 = 0.9, x_4 = x_5 = x_6 = x_7 = 0.1$. Then Equation (2) produces identical y_j value for these two tables. But t_1 should be deemed more likely to belong to C than t_3 as it has more relevant entities.*

As another example, the Pagerank aggregation function, i.e.,

$$f_{E\to T}(\{x_i|e_i \in t_j\}) = \sum_{e_i \in t_j} \frac{x_i}{|T(e_i)|} \tag{3}$$

violates Property 1.

3.2 Table to entity aggregation function

Given y_j for $t_j \in T$, we model $x_i = p(e_i \in C)$ as an aggregation function $f_{T\to E}$ of $\{y_j|t_j \ni e_i\}$. This is the soft counterpart of the relationship expressed in Principle 2.

Principle 2 suggests that if an entity appears in one exclusive table, it is relevant. To translate this in our probabilistic language, we would like $f_{T\to E}$ to reflect the likelihood that at least one table $t_j \ni e_i$ in e_i's support set belongs to C. It should produce a high value if any $y_j|t_j \ni e_i$ is high. Also, it should well distinguish entities that have slightly different support table sets. We abstract the following two axiomatic properties:

• Consider an entity e_i and its arbitrary support table t_j. When the table t_j is certain to belong to C, the entity e_i is also certain to belong to C.

Property 3 (Principle 2) $x_i = 1$ *if* $\exists t_j \ni e_i, y_j = 1$.

Note that Property 3 is unlike Property 1 in two aspects: (i) the limit ($\lim_{\mathbf{y}\to\mathbf{0}} x_i = 0$) is not true, because a relevant entity could occur in non-exclusive tables; and (ii) $x_i = 1$ if but not only if $\exists t_j \ni e_i, y_j = 1$, for the same reason.

• If the support table sets of two entities e_a and e_b are identical except two equal size tables, the entity contained in the table with a higher likelihood should have a higher likelihood of belonging to the concept (unless the likelihood for both is 1).

Property 4 (Monotonicity) *If* $T(e_a) = T_0 \cup \{t_1\}$, $T(e_b) = T_0 \cup \{t_2\}$, $|t_1| = |t_2|$ *and* $y_1 < y_2$, *then* $0 < x_a \leq x_b \leq 1$ *(*$x_a = x_b$ *happens only when* $x_a = 1$*).*

As one example, the maximal value from $\{y_j|t_j \ni e_i\}$, i.e.,

$$f_{E\to T}(\{y_j|t_j \ni e_i\}) = \max_{t_j \ni e_i} y_j \tag{4}$$

satisfies Property 3 but violates Property 4.

As another example, the Pagerank aggregation function, i.e.,

$$f_{T\to E}(\{y_j|t_j \ni e_i\}) = \sum_{t_j \ni e_i} \frac{y_j}{|t_j|} \tag{5}$$

violates Property 3.

The concrete design of the aggregation functions following these principles will be presented in Section 5.1.

4 Ranking Algorithm

Based on the model proposed in Section 3, we develop an algorithm to perform joint inference for entity likelihood x_i and table likelihood y_j. A simple idea is to find a solution that satisfies Equation (1). One could use an iterative algorithm shown in Algorithm 1 for this purpose.

Algorithm 1: A simple iterative algorithm

Input: Entity set E, table set T, seed entity set S
Output: entity score $\{x_i|e_i \in E\}$, table score $\{y_j|t_j \in T\}$

```
Initialize x_i scores to entity priors;
repeat
    Update y_j ← f_{E→T}({x_i, e_i ∈ t_j}) for t_j ∈ T;
    Update x_i ← f_{T→E}({y_j, t_j ∋ e_i}) for e_i ∈ E;
until x_i, y_j converge;
```

This simple algorithm may fail to rank the relevant entities and exclusive tables ahead of irrelevant and non-exclusive ones when the following are both true: i) there are a large number of tables in our reasoning set that belong to a different concept C'; and ii) these tables contain a similar set of entities. For example, in Figure 1, if there are many tables like t_6, the entities *Office* and *Photoshop* can amass high scores from these tables.

To address this issue, we develop an algorithm, called CONCEPTEXPAND (Section 4.1). We give a formal theorem about the convergence condition of our algorithm in Section 4.2.

4.1 CONCEPTEXPAND algorithm

The main idea is to perform restricted propagation on a subset of entities and tables, instead of propagating scores among all entities and tables. We consider a two-phrase algorithm. In the first phrase, we identify such a subset. We begin with the seed

entities which are most likely to be relevant. We then gradually expand the set by iteratively adding the most plausible tables based on current estimation. We stop adding tables when the remaining tables all have low estimated likelihood of belonging to C. We collect entities with enough support, and remove tables with few entities in this collection. In the second phrase, the iterative propagation will be performed within this set. It prevents adding too many irrelevant tables all at once and impairing score propagation. During the first phase, only those high-confidence tables contribute to entities' likelihood computation. And the second phase will have chance to refine the earlier estimation with incomplete information.

As the starting point of the probabilistic reasoning, the score for the seed entities can be set according to the prior knowledge (i.e., they are very likely to be in C). For all the other entities, x_i is unknown, and they will not be compuated until a table containing them is added to the reasoning set. To compute the table score with missing entity score, we use the table prior to replace the missing entities' score and feed to the aggregation function $f_{E\to T}$. The more knowledge we have of entities in a table, the less important the table prior is.

Algorithm 2: CONCEPTEXPAND

Input: Entity set E, table set T, seed entity set S, table likelihood threshold α
Output: entity score $\{x_i|e_i \in E\}$, table score $\{y_j|t_j \in T\}$

1 Initialize the support table set $T_0 \leftarrow \emptyset$;
2 Initialize the excluded entity set $U \leftarrow E \setminus S$;
3 Initialize seed entity score x_i using prior, for $e_i \in S$;
4 **repeat**
5 Update $y_j \leftarrow f_{E\to T}(\{x_i|e_i \in t_j\})$ for $t_j \in T$;
6 Choose the optimal $(y^*, t^*) = \max_{t_j \notin T_0, |t\setminus U|>0} y_j$;
7 $T_0 \leftarrow T_0 \cup \{t^*\}$;
8 Update $x_i \leftarrow f_{T\to E}(\{y_j|t_j \ni e_i, t_j \in T_0\})$ for $e_i \in t^*$;
9 $U \leftarrow U \setminus t^*$;
10 **until** $y^* < \alpha$ *or* $T_0 = T$;
11 **repeat**
12 $T_0 \leftarrow T_0 \setminus \{t \in T_0, |t \setminus U| < |t \cap U|\}$;
13 $U = U \cup \{e \in E \setminus U, |T(e) \cap T_0| \leq 1\}$;
14 **until** U *stops growing*;
15 **repeat**
16 Update $y_j \leftarrow f_{E\to T}(\{x_i|e_i \in t_j\})$ for $t_j \in T_0$;
17 Update $x_i \leftarrow f_{T\to E}(\{y_j|t_j \ni e_i\})$ for $e_i \in E \setminus U$;
18 **until** x_i*'s converge*;

We develop the CONCEPTEXPAND algorithm based on the above intuition. The pseudocode is shown in Algorithm 2. Lines 4–14 identify the table set and entity set for reasoning, by adding the most plausible table one by one, updating the estimation of both tables and entities, and removing the ones with low support. When adding a table, we require that the table contains some entity in the reasoning set. This reduces

the chance of adding a table simply because it has high prior. Lines 15–17 solves the equations within the reasoning set, using a fixed-point iteration.

The parameter α can be set according to the precision / recall requirement. Lower α leads to higher recall but lower precision in general. When $\alpha = 0$, all the tables will be added to the reasoning set. $\alpha = 1$ filters out all tables. In general, one can set α automatically according to table prior scores $\{\pi_j\}$ (e.g., the median of $\{\pi_j\}$). See Section 6.3 for a study of its effect.

The algorithm has a linear complexity with respect to the number of links in the table-entity bipartite graph.

4.2 Convergence of algorithm

Given that the CONCEPTEXPAND algorithm requires iterative computation of y_j and x_i, a desirable property of the computation is that it converges after a limited number of iterations. In the following, we provide a condition for aggregation functions $f_{E\to T}$ and $f_{T\to E}$ which guarantees convergence.

Property 5 (Diminishing Return) *Let x_i be the probability of any entity e_i, let $\mathbf{x} = [x_1, x_2, ..., x_n]$ be an n-dimensional vector with entity probability x_i as components. Let $g(\mathbf{x})$ be the entity probability after one iteration of updates using $f_{E\to T}$ and $f_{T\to E}$. The aggregation generates diminishing return if (i) there exists a compact set $\mathscr{C} \in [0,1]^n$ such that $g(\mathscr{C}) \subseteq \mathscr{C}$, and (ii) $\forall \mathbf{x} \in \mathscr{C}, \mathbf{y} \in \mathscr{C}, \max_{i\in[n]} |x_i - y_i| > \max_{i\in[n]} |g(\mathbf{x})_i - g(\mathbf{y})_i|$, unless $\mathbf{x} = \mathbf{y}$. Then $\mathscr{C}$ is the diminishing region of g.*

Discussions. The first part of Property 5 states that the aggregation has to produce proper probabilities in a compact region in $[0,1]^n$ if input are proper probabilities in the same region. The compact region can be $[0,1]^n$ itself, or a subset of it. This is a natural requirement since we want to output probabilities, and in some cases regularize them. For example, Pagerank requires the probabilities to be within a simplex $\sum_{i=1}^{n} x_i = 1$.

The second part of the property states that the maximum difference of probability for the same entity in $\mathbf{x}$ and $\mathbf{y}$ always diminishes after one iteration of $f_{E\to T}$ and $f_{T\to E}$. A special case of this is when we boost the belief of one entity by δ, then after one iteration the new belief will increase by strictly less than δ. Intuitively, this means that the initial boost will be "averaged out" by other entities and tables after iterative propagations. This requirement is also natural, since the change of inferred condidence should not surpass the change of original confidence.

We can in fact show that the condition holds in many common aggregation functions, when prior knowledge is incorporated as pseudo entities and pseudo tables. For example, if we use arithmetic mean as aggregation functions for both $f_{E\to T}$ and $f_{T\to E}$, and add a pseudo entity with likelihood π_j to table t_j as prior knowledge (e.g., based on the ranking position in WTS), then Property 5 holds.

Proposition 1 *Let $f_{E\to T}(\{x_i|e_i \in t_j\}) = \frac{\pi_j + \sum_{e_i\in t_j} x_i}{|t_j|+1}$, and $f_{T\to E}(\{y_j|t_j \ni e_i\}) = \frac{\sum_{t_j \ni e_i} y_j}{|T(e_i)|}$, i.e., both $f_{E\to T}$ and $f_{T\to E}$ are arithmetic mean, then the aggregation generates diminishing return in $[0,1]$.*

There are other combinations of common aggregation functions that also enjoy Property 5, e.g., the Pagerank aggregation functions as in Equations (3) and (5). We skip detailed proofs in the interest of space. ∎

Property 5 guarantees convergence.

Theorem 1 *If aggregation functions satisfy Property 5 with diminishing region $\mathscr{C}$, then Algorithm 2 converges to the unique solution to Equation* (1) *in $\mathscr{C}$, with initial $\mathbf{x} \in \mathscr{C}$.*

To prove Theorem 1, we can essentially view $g(\mathbf{x})$ defined by $f_{E \to T}$ and $f_{T \to E}$ as a function, and apply Banach's Fixed Point theorem [18] to ensure that a unique solution can be found for the system of equations $f_{E \to T}$ and $f_{T \to E}$ in Equation (1) using iterative computation. A proof of Theorem 1 can be found in the Appendix.

Theorem 1 requires fairly simply properties to guarantee the convergence of CONCEPTEXPAND algorithm. Proposition 1 implies that common aggregation functions, such as smoothed arithmetic mean, guarantees convergence. Therefore, our computational framework is generic – any reasonable aggregation functions satisfying the required properties can be plugged in Equation (1) to model a particular application, and Algorithm 2 will converge to the solution of it.

Although this theorem proves convergence, it does not give a Lipschitz constant to bound the rate of convergence. We observe that for the aggregation functions used in the paper, the algorithm converges fast, in most cases within 50 iterations.

5 Ranking Design

We now discuss concrete choices of aggregation functions and prior knowledge, which are functions that we plug into the generic framework outlined in Algorithm 2. We design these functions specifically for our problem.

5.1 Aggregation function

Entity to table aggregation. As discussed in Section 3.1, we need a function $f_{E \to T} : [0, 1]^n \to [0, 1]$ that satisfies the desirable Properties 1 and 2.

Property 2 (monotonicity) requires the function to be responsive to the change of every input element positively. Property 1 (asymptotic Principle 1) requires it to approach 0 when any input element approaches 0, and to approach 1 when all input elements approach 1. The three Pythagorean means, arithmetic mean, geometric mean, and harmonic mean satisfy the monotonicity, and the latter two satisfy Principle 1 asymptotically.

Between these two, we choose one that fits Principle 1 most closely. We reemphasize that the table ranking score reflects whether *all* entities in the subject column of a table are within the concept. We prefer the score to be low even when there are only a small number of non-relevant entities in the table. Since the harmonic mean of a list of numbers tends strongly toward the least elements of the list, it tends (compared with the arithmetic and geometric mean) to mitigate the impact of large outliers (relevant entities) and magnify the impact of small ones (non-relevant entities). As such, we

choose the harmonic mean as the aggregation function:

$$f_{E\to T}(\{x_i|e_i \in t_j\}) = \frac{|t_j|}{\sum_{e_i\in t_j}\frac{1}{x_i}} \tag{6}$$

Table to entity aggregation. As discussed in Section 3.2, we need a function $f_{T\to E} : [0, 1]^n \to [0, 1]$ that satisfies the desirable Properties 3 and 4.

Property 4 (monotonicity) requires the function to be responsive to the change of every input element positively. Property 3 (Principle 2) requires it to approach 1 when any input element approaches 1. The three Pythagorean means satisfy the monotonicity, but none of them satisfy Principle 2.

We derive a meaningful aggregation function from the probabilistic meaning of the score. If we assume the event '$t_j \subset C$' are independent for tables $t_j \ni e_i$ in the support set of e_i, we can use the 'noisy-or' model for table-to-entity score aggregation: $e_i \notin C$ is possible only if none of its support tables belong to C.

$$\begin{aligned} &f_{T\to E}(\{y_j|t_j \ni e_i\}) = p(\vee_{t_j\ni e_i} t_j \subset C) \\ =&1 - \prod_{t_j\ni e_i} p(t_j \not\subset C) = 1 - \prod_{t_j\ni e_i}(1 - y_j) \end{aligned} \tag{7}$$

The problem with this model is that it can accumulate weak evidences quickly to produce false positives, as illustrated by the following example.

Example 4 *Consider two entities Office and Berkeley DB. Berkeley DB appears in one table t_2, with $y_2 = 0.9$. Suppose there are 6 other tables identical to t_6 (say, $t_7, \ldots, t_{12}$) and they all contain Office. Suppose $y_6 = \cdots = y_{12} = 0.3$. This is realistic because tables about popular yet non-target concepts (e.g., general software in this case) often dominate the WTS results. Equation (7) produces higher likelihood for Office than for Berkeley DB (0.92 vs 0.9) which is undesirable. Note that there is no table that strongly supports that Office belongs to C; on the contrary, there is a table (t_2) that strongly supports Berkeley DB belongs to C.*

A similar issue is also discussed by Downey et al. [15], in a different scenario. They addressed the problem that when an entity is involved in a pattern for *multiple* times, the 'noisy-or' model will accumulate weak evidence. They proposed a *Urn* model for the repetitive sampling of entities that allows replacement. In our case, each entity appears once in each table, so this model does not apply to our problem.

We propose a new heuristic solution. Given the collection of $\{y_j|t_j \ni e_i\}$, a few large values in it should contribute more to the aggregated value x_i than many small values. Based on that intuition, we sort the y_j's in a descending order $y_{j_1} \geq y_{j_2} \geq \cdots$, and assign a decreasing series of weights $1 \geq w_1 > w_2 > \ldots$ to them.

$$f_{T\to E}(\{y_j|t_j \ni e_i\}) = 1 - \prod_{t_{j_u}\ni e_i, y_{j_u}\geq y_{j_{u+1}}} (1 - y_{j_u})^{w_u} \tag{8}$$

So, the small values in $\{y_j|t_j \in T(e_i)\}$ have relatively small contribution to x_i. In other words, the number of support tables of e has a diminishing marginal utility. The

more support tables we observe, the less important those small values are. When w_i's are all equal to 1, this function reduces to the 'noisy-or' model.

To determine w_i, we introduce a notion of *effective support*. For simplicity let us assume an entity appears in m tables with equal likelihood q. Then Equation (8) becomes: $f_{T\to E}(\{y_j|t_j \ni e_i\}) = 1-(1-q)^{\sum_{i=1}^{m} w_i}$. We call $\sum_{i=1}^{m} w_i$ the effective support of x_i. In the 'noisy-or' model, the effective support is equal to the actual support m. By assigning the decaying weight $1 \geq w_1 > w_2 > \ldots$, we desire the effective support to grow sublinearly with m. The question is how slowly the effective support should grow with respect to m. A fast growing example is $\Theta(m^{\frac{m-1}{m}})$, which is close to linear when m is large. A extremely slow growing example is $\Theta(\ln(m))$, which almost does not grow in our scale with thousands of tables. A medium example is $\Theta(\sqrt{m})$, where support 100 is converted to effective support 10. In general, we can set $w_i = \frac{1}{i^p}, 0 < p < 1$, to obtain a asymptotic growth rate $\Theta(m^{1-p})$ of effective support ($p = 0$ and $p = 1$ correspond to linear and logarithmic growth respectively). The sequence $\{w_i\}$ in this case is referred to as p-series.

In this paper, we use the $\frac{1}{2}$-series as the decaying weight w_i. It resolves the issue in Example 4 to a large extent: the undesirable accumulation is much slower, with a square root growth rate of effective support.

Proposition 2 *The rectified 'noisy-or' function with decaying weight, defined in Equation* (8)*, satisfies both Property 3 and 4.*

We omit the proof due to space of limit.

5.2 Prior knowledge

Now we discuss how to incorporate prior knowledge for the specific task of concept expansion by adding pseudo entities or tables.

Prior on entity side: For seed entities, we have strong prior knowledge that they belong to concept C. We add one pseudo table for each seed entity $e_i \in S$ and link the pseudo table to the corresponding entity. The table has a fixed confidence score $1-\epsilon_i$, where ϵ_i is a small error rate depending on the source of the entities. If the entities are provided by human curators, ϵ_i should reflect the error rate of the curators which is typically very low. If the entities come from a non-curated database such as web-extracted concept-entity pairs, ϵ_i should be set according to the precision of the database [36]. Furthermore, the different seed entities may have different confidence of belonging to C. For example, in Probase, an entity e_i has an integer support s_i about its occurrence in C. The larger s_i is, the more confident it is to be a correct seed entity for C. So we can set $\epsilon_i = \epsilon_C^{s_i}$, where ϵ_C is a small constant like 0.1.

Prior on table side: All WTSs return a ranked list of tables for a query. We assume the relevance of a table to the concept C degrades with their position in the ranked list returned by a WTS. Therefore, the prior estimation of the likelihood of a top ranked table belonging to C is higher than that of a lower ranked table. Since we retrieve a constant number of tables from WTS, we may retrieve tables that are partial matches to the concept name (like table $t6$ in Figure 1). To account for that, we penalize tables

that do not match all the tokens in the concept name. We define the table prior π_j as:

$$\pi_j = (\frac{1}{2})^{\text{\#missing tokens of } C \text{ in } t_j} \frac{1}{j+1} \tag{9}$$

Recall that j is the rank position of table t_j. When a table contains all tokens in C, its prior is $\frac{1}{j+1}$, which decays fast as the ranking position increases. Otherwise, its prior is penalized exponentially with respect to the number of missing tokens. We incorporate the prior by adding a pseudo entity with confidence π_j to link to each table t_j. In this way, the prior is just one value that participates in the aggregation function $f_{E \to T}$. The more knowledge of entities in a table we have, the less we rely on the table prior.

While it is possible to design more sophisticated prior score, we use this simple treatment that is general and easy to compute. The imperfect but reasonable prior score tests the ability of our reasoning framework of handling noises. Better prior score can be deigned in future work to exploit more features in web tables.

It can be verified that the chosen aggregation functions and prior score satisfy the convergence condition in Theorem 1. We leave detailed proofs to the full version of this paper.

6 Experimental Evaluation

We present an experimental evaluation of the proposed algorithm. The goals of the experimental study are:
• To compare the ranking quality of different approaches in terms of precision and recall.
• To understand the sensitivity of the proposed approach to different parameter settings.

6.1 Experimental Setup

6.1.1 Dataset

We use a production web table search engine (WTS) that indexes over 500M web tables extracted from a recent snapshot of the Microsoft Bing search engine. This is the same WTS that powers web table search in Excel PowerQuery [4]. We use the Probase [36] as the base for expansion. Probase contains 2.7 million concepts. We choose Probase instead of knowledgebases like YAGO [28] or Freebase [7] for the sake of better concept coverage, especially for tail concepts [36].

To prepare the set of concept queries, we acquired from Probase 9,926 tail concepts with sufficient popularity[7]. We retrieve 1,000 tables for each concept, ending up with a dataset of 10M web tables.

[7]In Probase, each concept-entity pair has a popularity value indicating the number of different domains it is found on the web. We chose concepts with total popularity above 150 in order to make sure the concept is not too niche and the web-extracted concept-entity pairs are relatively reliable

6.1.2 Compared methods

We compared the following methods:
• **Number of occurrences (# Occur).** In this baseline approach, we rank entities by their number of occurrences in the top ranked tables returned by WTS. Entities that occur more often in top tables are ranked higher.
• **Weighted number of occurrences (Weighted # Occur).** This approach enhances the previous one by weighting each occurrence of entity using the table prior. In addition, in order to utilize seed information, we only consider tables that contain 2 or more seeds. Entities are finally ranked by their aggregate weight across these tables.
• **SEISA [19].** Set expansion is a related problem in the literature where the goal is to automatically discover entities in the target concept using seed entities (but not concept names) as input. We implement the Dynamic Thresholding algorithm in the SEISA system [19], which is shown a competitive technique for set expansion using web lists.
• **Graphical Model [25].** We implement a graphical model-based table ranking method proposed in [25]. It takes column keywords as input and outputs a ranked list of relevant tables. The goal is similar with our table ranking when the input is a single concept name. We use the table prior as a feature for node potential and the column value overlap as edge potential in this graphical model.
• **Pagerank (Generalized Co-HITS [14]).** Personalized Pagerank and its variations have been adopted in set expansion systems like SEAL [33]. For our bi-partite graph with both entity prior and table prior, the most appropriate variation to use is a generalized Co-HITS algorithm [14]). We set high restart probability on entity prior and low on table prior.
• **CONCEPTEXPAND.** This is our proposed method Algorithm 2, using aggregation functions discussed in Section 5.1. The threshold α for table filtering is simply set to 0, without any tuning.
• **CONCEPTEXPAND_Pagerank.** For separation the value of aggregation functions, we include a method using the same expansion Algorithm 2, and Pagerank aggregation functions discussed in Section 3.

6.1.3 Evaluation

Ground truth preparation. Probase has an incomplete coverage of entities per concept, especially for tail concepts. We randomly checked 100 fine grained concepts and found that more than 90% of time the first relevant entity found in the web tables does not exist in Probase. We did a study for Yago's fine grained concepts and found similar results. So simply using the existing Probase entities as ground truth leads to rather incomplete judgment. To obtain a reliable set of ground truth, we first identify 90 concepts for which at least one top-10 table has at least 4 entities existing in Probase. Then we manually label 54 unambiguous concepts of them which are relatively easier to label by going through table URLs and subject columns. Finally, we merge our labels and Probase entities to form a ground truth set. The final ground truth for each concept may still be incomplete, but is largely augmented upon Probase entities. This set has 18,232 relevant entities in total, with an average number of 338 entities per concept. The number of Probase entities per concept ranges from 4 to 60, with a mean of 23.

Table 2: Example concepts and returned entities

asian country	third world country	trading partner
internet company	multiplayer game	national newspaper
adverse side effect	fitness class	flu-like symptom
amino acid	antifungal agent	cytotoxic agent
bacterial species	grape variety	mammal species
file system	memory card	programming language

Concept	Seed entities	Returned entities
adverse side effect	addiction, depression	headache, nausea, ...
grape variety	nebbiolo, barbera	ramisco, cornifesto, ...

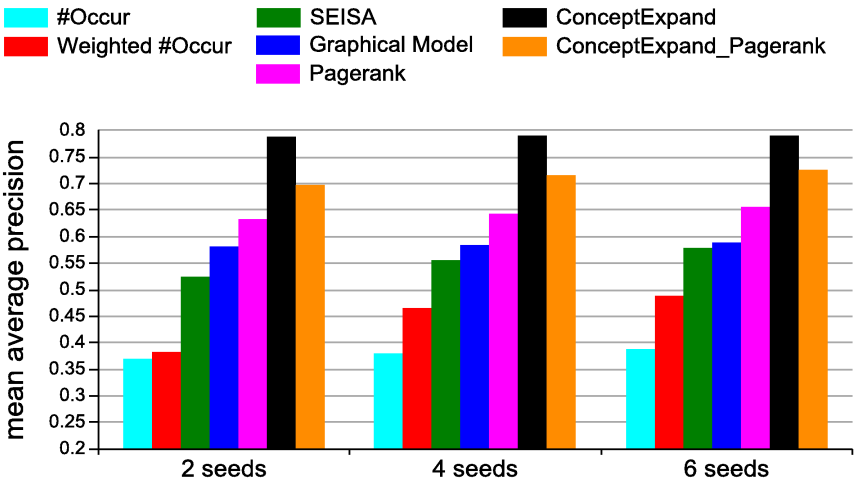
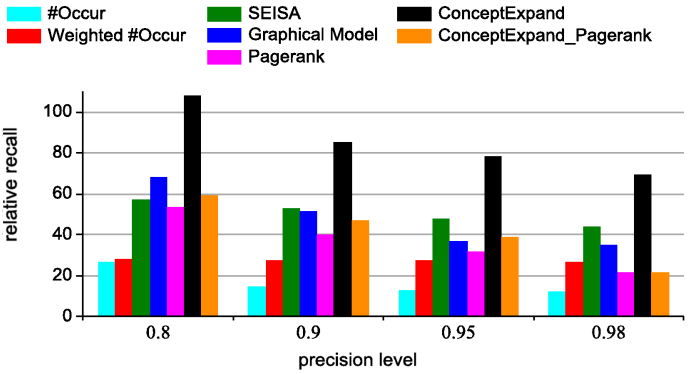
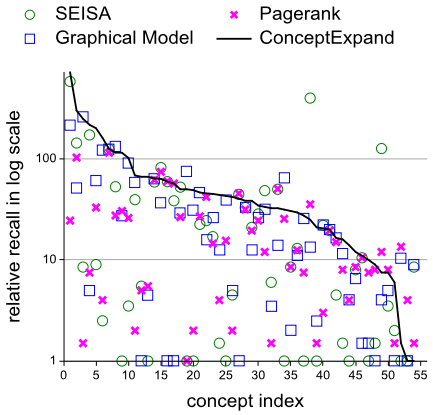


Figure 3: Mean average precision



(a) Mean relative recall at precision levels 0.8, 0.9, 0.95 and 0.98



(b) Scatter plot relative recall (p-level 0.98)

Figure 4: Relative recall at certain precision levels (two seeds)

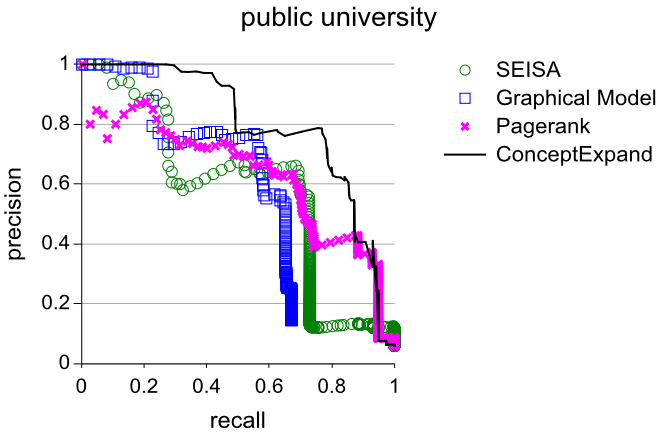


Figure 5: Precision-recall curve case study

The labeled concepts span across multiple domains, such as geography, economy, business, healthcare, education and technology. Sample concepts and output from the algorithm are listed in Table 2.

Metrics. We use two metrics for evaluation:

• Mean average precision (MAP). This is the standard information retrieval measure for overall ranking performance.

• Relative recall[8] at a certain precision level. This is a metric more concerned with the practical value of the concept expansion task. It reflects the best recall one algorithm can achieve before falling below a precision level. Typically, the requirement for the precision in a knowledgebase is very high. Although we do not expect the expansion algorithm to return 100% correct results to directly populate into a knowledgebase, a high precision level such as 0.9 is helpful for easing the job of human curators in noise filtering.

6.2 Results

In this section we compare the 7 methods. Figure 3 and Figure 4 plot the mean average precision and relative recall at different precision levels. In both figures, the methods are sorted according to the order they are introduced in Section 6.1.2.

The overall ranking performance measured by MAP is consistent when using different number of seeds (Figure 3). The first six methods can be roughly partitioned into three groups according to their MAP: (i) baseline algorithms, # Occur and Weighted # Occur; (ii) existing methods adapted to this task, SEISA, Graphical Model and Pagerank; and (iii) our proposed method CONCEPTEXPAND. The gap is large across groups.

[8]Since we do not have the complete ground truth in most cases, we use relative recall to measure the coverage improvement relative to the number of seed entities. Formally, $r = \frac{\#\text{ returned relevant entities}}{\#\text{ seed entities}}$

CONCEPTEXPAND outperforms existing algorithms by 20-50%. Note that the filtering parameter α for CONCEPTEXPAND has not been tuned in this experiment.

The last method CONCEPTEXPAND_Pagerank is about halfway between CONCEPTEXPAND and Pagerank. It shows that both the inference algorithm and the aggregation functions contribute to the superior performance of CONCEPTEXPAND.

CONCEPTEXPAND is not sensitive to the number of seeds. Without parameter tuning, it achieves a mean average precision of close to 80% with only two seeds per concept.

Regarding the relative recall at high precision levels, there is an even larger gap between CONCEPTEXPAND and competing algorithms. Though all methods can increase the entity coverage before the precision falls below a tolerable threshold, the degree of increase differs across the methods. For example, at precision level 0.98, Pagerank increases the coverage by 20 times, SEISA does a better job and achieves 44 times expansion, none of which is comparable to the 70 times gain of CONCEPTEXPAND (Figure 4a). Figure 4b further visualizes the individual performance for these 54 concepts. With a few outliers, CONCEPTEXPAND dominates in the relative recall. When the requirement to precision gradually lowers down, CONCEPTEXPAND achieves even higher recall (108 times at precision level 0.8). Again, without parameter tuning, CONCEPTEXPAND shows strong superiority in its practical value.

When connecting the overall ranking performance (Figure 3) to the performance at high precision (Figure 4), we have two interesting observations.

First, CONCEPTEXPAND_Pagerank improves the overall performance of Pagerank algorithm by removing low confidence entities and tables, but the improvement is not much on the high precision end. In Figure 4a, CONCEPTEXPAND_Pagerank's recall is as one third to one half as CONCEPTEXPAND's. Therefore, the high recall at high precision of CONCEPTEXPAND is mainly attributed to its asymmetric, non-linear score propagation following the special entity-table relationship, rather than the filtering.

Second, there is no clear winner among the three existing algorithms SEISA, Graphical Model and Pagerank. Though Pagerank has a better MAP than the other two, it pooly performs at high precision levels (lower than baseline at p-level 0.98). In contrast, SEISA does a good job at precisionl levels above 0.9, but underperforms Graphical Model at p-level 0.8, and eventually has a lowest MAP among the three. This observation reflects the limitations of existing algorithms. We take the concept 'public university' as an example to illustrate. The precision-recall curve is shown in Figure 5. Set expansion techniques like SEISA find most similar entities in the beginning, yet they are subject to semantic drift (e.g., from public university to other universities) without constraining the expansion. Concept-name based table ranking like Graphical Model does not utilize seed entities, and suffers from imperfect table ranking. For example, several tables about public university cost, programs, salaries, faculty numbers are ranked among top 20. Pagerank takes advantage of both concept names and seed information, employs linear score aggregations, but it tends to select popular entities from different tables and mix them. Popular irrelevant entities (e.g., New York University) are ranked high and inserted between relevant ones, thus it cannot produce contiguous high precision results.

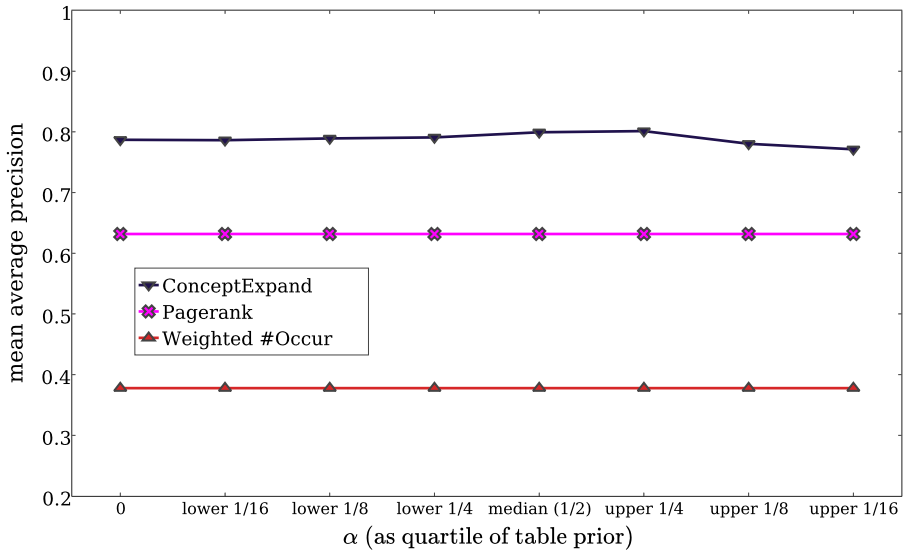


Figure 6: MAP, vary filtering threshold α

6.3 Parameter study

In this section we study how the algorithm performs in response to changing parameters values.

Our algorithm has only one parameter, the stopping criteria α. Recall that this parameter controls the precision/recall trade-off, as it determines when the core table set stops to expand. We used $\alpha = 0$ for all previous experiments, which means all tables will be added to the table set T. As we increase α, fewer tables will be added, which helps eliminating irrelevant tables. When α is equal or larger than 1, only one table will be added, presumably leading to poor results.

In our experiments, we sort all table prior scores in descending order and set α to the score at certain positions of the ranked scores. For example, we use the lower quartile (denoted as lower 1/4), median (1/2), upper quartile (upper 1/4) and so on. Figure 6 and 6 show the mean average precision and relative recall at different precision levels. It turns out that CONCEPTEXPAND is works robustly well in a wide range of α. In fact, the MAP has very small change when α is varied from 0 to upper 1/16 quantile of table prior. The most sensitive metric is recall at precision level 0.8. It reaches the peak around 110 at median and declines when α is further increased, but still above 100 when α is equal to upper quartile of table prior, where other three curves reach a high point. In the worst case in our test (α = upper 1/16 quantile), the recall at precision 0.98 is still way higher than Pagerank's recall at precision 0.8. These results indicate a stop criterion ranging from median to upper quartile of table prior is a good choice, depending on the goal of precision. For higher precision a slight higher α is preferred. As long as α is not too large so that very few tables are left, stable performance can be expected thanks to the strong reasoning power of our method.

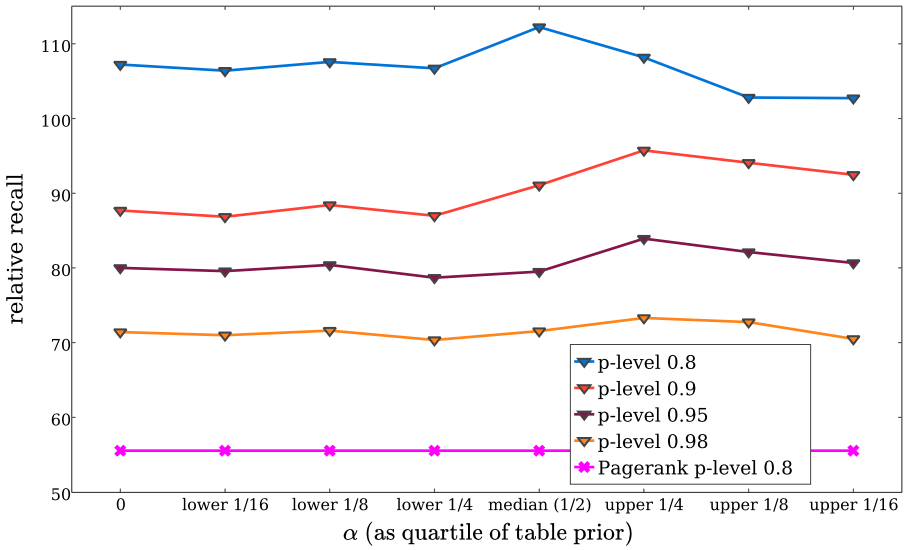


Figure 7: Relative recall, vary filtering threshold α

7 Related Work

Google Sets was an early set expansion system, and now only available as a feature in Google Sheets. Recently, IBM releases a Concept Expansion API [3] that provides similar functions as our system. The technique is not disclosed and its documentation suggests that it works with certain domain text data (medical transcriptions and social media).

The problem of knowledgebase expansion or completion has attracted a bulk of interest due to its practical value. In general, the goal is to automate the process of adding new knowledge to an existing knowledge base, by leveraging web information sources that contain the knowledge as well as noises. The related work can be divided according to different criteria.

In terms of the target missing knowledge to augment, there are mainly two categories: (a) expanding the concepts (a.k.a. types or classes) and entities (a.k.a. instances) belonging to each concept; and (b) expanding the attributes (a.k.a. facts or relations) of entities. Category (a) includes set expansion [19, 27, 33, 34, 24, 17] and multi-concept expansion [16, 10, 29]. The former takes a set of seed entities as input to expand a single unknown concept, and the latter takes entities in two or more mutually exclusive concepts together and classify other entities. The best known methods for set expansion are SEISA [19] and SEAL [33], based on iterative similarity aggregation and Pagerank respectively. None of these methods are designed for tail concept expansion. Category (b) is introduced as an annual competition in 2008 to the Text Analysis Conference. One can refer to Ji and Grishman [21] for an overview of the approaches. Recent work by West *et al.* [35] and Yahya *et al.* [37] in this category specifically addresses the completion of tail entity attributes. Our work belongs to Category (a), with

a special focus on tail concept expansion.

To differentiate the working mode, West *et al.* [35] discusses the 'pull' model and the 'push' mode for attribute completion (Category b). The 'push' model refers to extracting values for specific entities and attributes, while the 'push' mode refers to processing a large number of documents in batch and populates whatever facts it can find. The similar categorization applies to concept expansion (Category a). Set expansion works in 'pull' mode and mult-concept expansion works in 'push' mode. 'Pull' mode is found to better suit tail domains and tail entities. Our approach works in 'pull' mode. Similar to West *et al.* [35] who leverages a web-search based question-answering system, we leverage a web table search system.

With regard to information source from which to harvest knowledge, the most popular sources are unstructured text [16, 24, 37, 35, 21] and semi-structured web wrappers, lists and tables [29, 19, 33]. Typically, textual patterns have good coverage for head entities, and the context helps identifying the concept. Semi-structured lists and tables contain both head entities and tail ones. A good strategy is to leverage both the semantics in text and the co-occurrence information in lists. For example, NELL [10] is a system for multi-concept expansion that combines a variety of sources for bootstrapping. However, textual signals and structure signals are utilized separatedly from different sources. This work provides a new approach of utilizing web tables, by simultaneously utilizing text and structure from one source.

Our work is related to the holistic table ranking approach proposed by Pimplikar and Sarawagi [25]. It takes concept keywords (column names) as input and returns relevant web tables. Though our method can rank tables as well, the ranking criteria is exclusiveness instead of relevance. Other closely related work involving web tables include table column annotation [13, 22, 26, 31], and entity attribute discovery [8, 38, 39].

Recently, researchers have proposed crowdsourcing as a way to gather data and answer top-k queries [30, 12]. For example, Davidson et. al. studied the problem of evaluating top-k queries using the crowd to answer specific types of questions (e.g., type and value questions). These techniques can be applied to identify the relevant entities among all the entities in the bipartite graph. These techniques are complementary to the approach proposed in this paper.

8 Conclusion and Future Work

In this paper, we studied the problem of finding entities belonging to a tail concept, given an ad-hoc concept name and a few seed entities. Compared with head concept expansion, the semantic drift is a bigger challenge, and useful negative examples are harder to acquire. We resort to exclusive web tables and leverage both text signals and structure information. We formulate the task as a holistic ranking problem and develop a novel solution for probabilistic reasoning. It is the first one tailored for tail concept expansion, and experiments demonstrate its superiority to state-of-the-art approaches.

This work can be extended in multiple directions. There is much more information in the knowledgebase and web tables that can be leveraged for concept expansion as well as attribute expansion. First, one can utilize the relational attributes in web tables;

tables belonging to the same concept often have similar attributes, and the missing attributes in knowledgebases can be potentially populated from them. Second, we distinguish exclusive tables and non-exclusive tables in this work since the latter is more risky to use for expansion. In future work, one can study how to select relevant portions in non-exclusive tables, e.g., via the attributes. Third, our solution is designed for data collectors and curators to more efficiently find missing entities. How to use crowdsourcing techniques to perform the above task with least cost is also an open challenge.

A Appendix: Proof of Theorem 1

First, notice that Lines 1-14 of Algorithm 2 is guaranteed to stop, since T_0 and U are bounded by T and E respectively. What we need to show is that Lines 15-17 will converge given a set of tables T_0 and the corresponding entity set $E \setminus U$, if Property 5 holds for the aggregation functions used.

We prove convergence of Lines 11-14 using Banach's Fixed Point Theorem [18]. Recall that Banach's Theorem states that given a metric space (X, d), and a contraction mapping $f : X \to X$, then there is a unique fixed point with $f(x^*) = x^*$. Furthermore, x^* can be found by repeatedly applying f, namely, $\lim_{k\to\infty} f^k(x) = x^*$, where $f^k = \underbrace{f \circ f \circ ... \circ f}_{k}$. Similarly, a weak version of the theorem states that if the metric space X is compact, and the mapping $f : X \to X$ is sub-contraction, namely, $d(x, y) > d(f(x), f(y))$ unless $x = y$, then there is also a unique fixed point.

Consider the two table-to-entity and entity-to-table probability propagation $f_{E\to T}$ and $f_{T\to E}$. Let $x_i, i \in [n]$, be some arbitrary initial belief that entity e_i belongs to concept C, or $P(e_i \in C)$, and x'_i be the updated belief after one iteration of computation. Furthermore, let $\mathbf{x} = [x_1, x_2, ..., x_n]$ be an n dimensional vector with entity probability x_i as components, and $\mathbf{z}$ be another n-dimensional vector defined similarly. Treating $\mathbf{x}$ as a variable, the computation defined in the system of equations can be seen as a function $g : [0, 1]^n \to [0, 1]^n$, with $\mathbf{x}' = g(\mathbf{x})$ and $\mathbf{z}' = g(\mathbf{z})$, where $\mathbf{x}' = [x'_1, x'_2, ..., x'_n]$ and $\mathbf{z}'$ defined similarly. Our goal here is to show that g is a sub-contraction mapping over a compact space, using some metric distance d.

First, notice that the first half of Property 5 guarantees the projection of g in a compact set $\mathscr{C}$ has an image within $\mathscr{C}$.

Next we need to show that the projection of g in $\mathscr{C}$ is a sub-contraction mapping, that is, $d(\mathbf{x}', \mathbf{z}') < d(\mathbf{x}, \mathbf{z})$, unless $\mathbf{x} = \mathbf{z}$. Choosing infinity-norm distance as d and $\mathbf{x}, \mathbf{z}$ as points in n dimensional subspace $\mathscr{C}$, we need to show the following

$$\max_{i\in[n]} |x'_i - z'_i| < \max_{i\in[n]} |x_i - z_i|, \forall \mathbf{x} \neq \mathbf{z} \tag{10}$$

Notice that this is exactly what is guaranteed by the second half of Property 5, thus proving that g is sub-contractive.

Combining, the projection of g in $\mathscr{C}$ is a sub-contractive mapping from compact space $\mathscr{C}$ to $\mathscr{C}$. Under the weak version of Banach's Theorem, the described probability propagation model converges to the unique fixed point in $\mathscr{C}$, which is also the unique solution defined by the system of equations $f_{E\to T}$ and $f_{T\to E}$.

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