Searching with Numbers

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Abstract

A large fraction of the useful web comprises of specification documents that largely consist of ⟨attribute name, numeric value⟩ pairs embedded in text. Examples include product information, classified advertisements, resumes, etc. The approach taken in the past to search these documents by first establishing correspondences between values and their names has achieved limited success because of the difficulty of extracting this information from free text. We propose a new approach that does not require this correspondence to be accurately established. Provided the data has "low reflectivity", we can do effective search even if the values in the data have not been assigned attribute names and the user has omitted attribute names in the query. We give algorithms and indexing structures for implementing the search. We also show how hints (i.e., imprecise, partial correspondences) from automatic data extraction techniques can be incorporated into our approach for better accuracy on high reflectivity datasets. Finally, we validate our approach by showing that we get high precision in our answers on real datasets from a variety of domains.

1 Introduction

'o dear ophelia, I am ill at these numbers; *Hamlet: II, ii*

Numbers play a central role in modern life. Yet the current search engines treat numbers as strings, ignoring their numeric values. For example, as of this writing, the search for 6798.32 on Google yielded two pages that correctly associate this number with the lunar nutation cycle [18]. However, the search for 6798.320 on Google found no page. The search for 6798.320 on AltaVista, AOL, HotBot, Lycos, MSN, Netscape, Overture, and Yahoo! also did not find any page about the lunar nutation cycle.

[1] *A preliminary version of this paper appeared in the Proceedings of the 2002 World Wide Web Conference, Honolulu, Hawaii, May 2002.*

- CMOS for optimum speed/power
- High speed
  - 18 ns address set-up
  - 12 ns clock to output
- Low power
  - 495 mW (commercial)
  - 660 mW (military)

Figure 1: Specifications for Cypress CY7C225A PROM (www.cypress.com/cypress/prodgate/prom/cy7c225a.html)

A large fraction of the useful web comprises of what can be called *specification documents*. They largely consist of attribute-value pairs surrounded with text. Examples of such documents include product information, classified advertisements, resumes, etc. For instance, Figure 1 shows a partial extract of the data sheet for the Cypress CY7C225A PROM. A design engineer should be able to ask a query that looks something like this:

> address set-up speed 20 ns power 500 mW CMOS PROM

and get the CY7C225A data sheet. None of the search engines could find this datasheet using the above query (or its variations). We were able to get the data sheet when we provided the exact numeric values for the speed and power attributes because the search engines could then match the string. It is unreasonable to expect that the user will provide exact numeric values when doing such searches. In fact, users typically search for items whose specifications roughly match the values provided in the query.

The approach taken in the past to retrieve the specification documents has been to extract the attribute-value pairs contained in a document and store them in a database. Queries can now be answered using nearest neighbor techniques [1] [15] [21]. There has been some research on automating the task of data extraction (see surveys in [7] [19]). However, the automatic extraction of attribute-value pairs has a spotty record of success. It is a hard problem, exacerbated by the fact that it is often difficult to identify attribute names and establish correspondence between an attribute name and its value. Very often, different documents refer to the same attribute by different names. We experienced first-hand this problem in building an experimental portal for electronic components, called Pangea. For semiconductor components alone, we obtained more than 200,000 datasheets from nearly 1000 manufacturers. Our effort to extract parametric information from these datasheets met with only limited success. It is noteworthy that the major content companies in electronics industry employ a large number of people who manually extract the parametric information.

This paper proposes a new approach to retrieving specification documents. In essence, we are suggesting that it is not necessary to establish exact correspondences between attribute names and numeric values in the data. A user query can instead choose to provide only values, without specifying corresponding attribute names. For this approach to work, data must have what we call *low reflectivity*. This property, introduced in this paper, is exhibited by many real world datasets and the extent to which a dataset satisfies this property can be computed a priori. For a simple example of a non-reflective dataset, assume that the documents contain only two attributes: 'memory' and 'disk-size'. Further assume that the range of values for memory is 64 to 512 and that for disk-size is 10 to 40. Given a query $\{20, 128\}$, the system can correctly retrieve documents that have disk-size and memory values close to 20 and 128 respectively. In this example, the attributes have non-overlapping domains. However, low reflectivity is not limited to data having such non-overlapping attributes. If memory and disk-size overlapped, but were correlated such that high memory configurations had high disk-size, the data would still have low reflectivity.

The target repositories for our techniques are document collections on focused topics. Classification and clustering techniques can often be applied to partition a general repository into a set of topic-specific repositories. Our techniques can also be applied in other applications where providing attribute names in a query is difficult or inconvenient. For example, in a federated database system, the same attribute might be called with different names in different constituent databases [8] [16] [17].

The techniques we propose complement current search technology. One can envision a system in which the ranked results produced using our techniques are combined with the results obtained using words and links in the pages [2] [3] [9] [22]. Techniques such as [10] can be used for combining the results.

The rest of the paper is organized as follows. Section 2 provides the data and query models. We discuss reflectivity in Section 3. We present algorithms for finding matching documents without hints in Sections 4, and with hints in 5. Section 6 gives experimental results showing the accuracy and performance characteristics of our techniques. We conclude with a summary and directions for future work in Section 7.

2 Model

We assume that a document is preprocessed to extract numbers appearing in it. For each number, the potential attribute names are optionally extracted by examining the text surrounding the number.[2] This extraction need not be precise. One may associate zero or multiple attribute names with a number depending on the confidence on the quality of extraction.

To simplify exposition, we will initially ignore units normally associated with numeric values. In Section 5.2, we discuss the handling of units within our framework.

At the time of querying, the user may simply provide numbers, or optionally specify attribute names with numbers. The attribute names provided in a query may not always correspond to the names present in the data since the same attribute may be called with multiple names, e.g., salary, income, pay, etc. We consider nearest neighbor queries where the user is interested in retrieving the top t documents containing values close to the query terms.

2.1 Database and Queries

Let $\mathcal{N}$ be the universe of numbers and $\mathcal{A}$ the universe of attribute names. The database $\mathcal{D}$ consists of a set of documents. A document $D \in \mathcal{D}$ is defined to be

$$D = \{\langle n_i, H_i \rangle \,|\, n_i \in \mathcal{N}, H_i \subseteq \mathcal{A}, 1 \leq i \leq m\} \tag{1}$$

where H_i is the set of attribute names (hints) associated with the number n_i and m is the number of unique $\langle$number, attribute names$\rangle$ pairs present in D. Note that it is possible to have $n_i = n_j$ but $H_i \neq H_j$, since more than one attribute name can have the same numeric value. Duplicates ($n_i = n_j$ and $H_i = H_j$) may optionally be admitted by treating D as a multi-set. However, we assume that a document does not contain multiple different values for an attribute, i.e., if $H_i = H_j$, then $n_i = n_j$.

[2] The specific extraction techniques used are not of concern in this paper. One could, for example, use a regular expression based extractor [5].

If the document does not have hints associated with numbers, D is simply a multi-set:

$$D = \{n_i \,|\, n_i \in \mathcal{N}, 1 \leq i \leq m\} \tag{2}$$

A search query Q consists of

$$Q = \{\langle q_i, A_i \rangle \,|\, q_i \in \mathcal{N}, A_i \subseteq \mathcal{A}, 1 \leq i \leq k\} \tag{3}$$

Here each $\langle$number, attribute names$\rangle$ pair represents a query term and k is the number of query terms present in Q. A_i is the set of attribute names associated with the number q_i. We allow the user to associate a set of attribute names with a number since there may be synonyms. There is an implied conjunction between the query terms. It is possible to have $q_i = q_j$ but $A_i \neq A_j$, i.e., a query may contain more than one occurrence of the same number.

If the query does not have hints associated with the numbers, Q is simply a multi-set:

$$Q = \{q_i \,|\, q_i \in \mathcal{N}, 1 \leq i \leq k\} \tag{4}$$

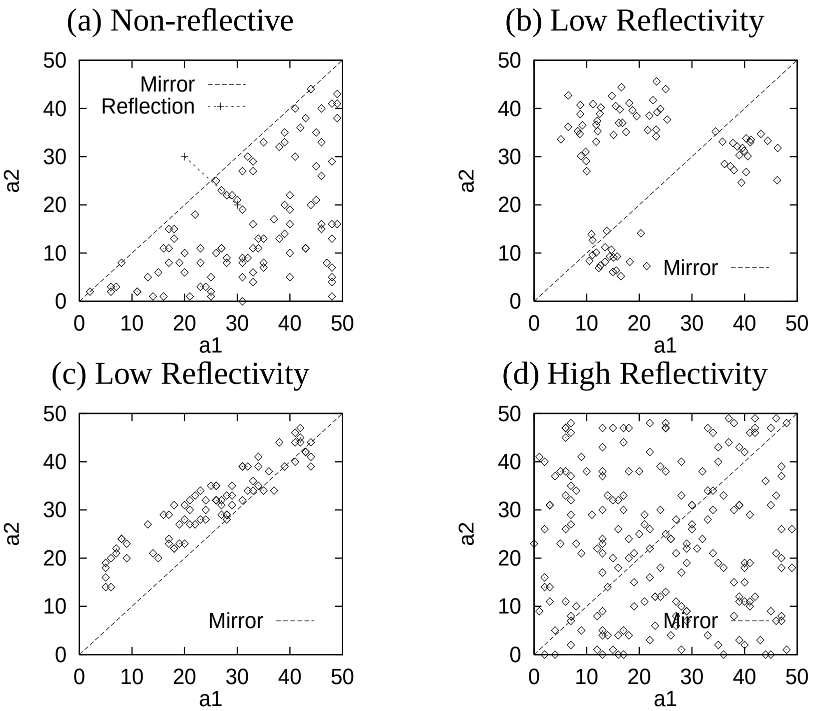
2.2 Matching Without Attribute Names

The goal for any search is to return documents that are most similar to the query, ordered by their similarity score. The real problem lies in defining similarity. The generally accepted approach is to use some L_p norm as the measure of distance and take similarity to be inverse of this distance.

Consider a query system where the attribute names are not available in both the data and in the query. For a query $Q = \{q_1, \ldots, q_k\}$, there must be a true attribute that the user has in mind corresponding to each number q_i in Q. Similarly, for a document $D = \{n_1, \ldots, n_m\}$, each number n_i in D has a corresponding true attribute.

We call a document D a *true close match* to a query Q if D contains a set of k numbers $D' = \{n_{j_1}, \ldots, n_{j_k}\}$ such that the distance between Q and D' is small (i.e., less than some constant r) and both q_i and n_{j_i} are the values of the same true attribute. We have treated both Q and D as ordered sets in this definition.

We call a document D a *nameless close match* to a query Q if D contains a set of k numbers $D' = \{n_{j_1}, \ldots, n_{j_k}\}$ such that the distance between Q and D' is small. Unlike the case of a true close match, the true attributes corresponding to n_{i_j} and q_i need not be the same. Notice that by


(a) Non-reflective

(b) Low Reflectivity

(c) Low Reflectivity

(d) High Reflectivity

Figure 2: Examples of non-reflective and reflective data

requiring a set of k numbers in D, we impose the desired constraint that a number instance in the document should not match multiple query terms.

Conjecture 1 (Realistic Query) *For most queries asked by users, there exists a document $D \in \mathcal{D}$ that is a true close match to the query.*

Conjecture 2 (Implicit Name Match) *In domains where the Realistic Query conjecture holds, if a document D is a nameless close match to a query Q, it is likely that that D is also a true close match to Q.*

Informally, if we get a good match on the numbers between a document and query, then it is likely that we will have correctly matched the attributes as well. Thus for datasets where this conjecture holds, we can match using only the numbers, and still get good accuracy compared to the benchmark where we know the true attributes in both the documents and the query.

In Section 3, we define a property called *reflectivity* that allows us to quantify the extent to which this conjecture holds in a given dataset. In fact, if the query distribution for some set of true attributes is the same as the data distribution projected onto that subspace, the likelihood in the above conjecture is the same as the value of non-reflectivity.

3 Reflectivity

Consider the data shown in Figure 2(a) for two attributes a_1 and a_2. The diamonds indicate the points actually present in the data. This data is completely non-reflective: for any point $\langle a_1 = n_i, a_2 = n_j \rangle$ present in the data, its reflection $\langle a_1 = n_j, a_2 = n_i \rangle$ does not exist. Figure 2(b) gives an example of clustered data that is almost completely non-reflective. The correlated data in Figure 2(c) is also largely non-reflective. However, the data in Figure 2(d) is highly reflective.

The implication of reflectivity is that the queries against a low reflectivity data can be answered accurately without knowing the attribute names, provided the realistic query conjecture is true. Hence, although there is complete overlap between the range of values of the two attributes in Figures 2(a)-(c), we will get high accuracy on any 2-dimensional query. For example, consider the query $\langle 20, 30 \rangle$ on the data in Figure 2(a). This query can only map to $\langle a_1 = 30, a_2 = 20 \rangle$ since there are no points in the region around $\langle a_1 = 20, a_2 = 30 \rangle$.

Queries will often span a subset of the dimensions in the dataset, and reflectivity will depend on the exact set of dimensions being considered. Consider the query $\langle 20 \rangle$ on the data in Figure 2(a). This query can map to either $\langle a_1 = 20 \rangle$ or $\langle a_2 = 20 \rangle$, and the answer to this query will consist of points for which either a_1 or a_2 is close to 20. Thus precision on this query will be around 50%, in contrast to the close to 100% precision that we can get on the query $\langle 20, 30 \rangle$ for the same dataset. Similar behavior is exhibited by data in Figures 2(b)-(c): they are highly non-reflective in 2 dimensions, but quite reflective in either of the 1-dimensional projections.

Before formally defining reflectivity, we make the following observations.

- Above, we took a given query Q and checked whether or not the reflections of Q coincided with other data points. However, for similarity queries, we care not only about the exact query values, but points close to the query values. Hence we should look at the number of points within distance r of each reflection of Q.
- Rather than taking a query and considering whether there are points close to the reflections of the query, we take a dual viewpoint. For a given query Q, we consider how many reflections of other points are within distance r of Q and compare this number with the number of points that are truly within distance r of Q.

3.1 Definition

We first define reflectivity under the assumption that there are no duplicates, i.e., a document contains the value of an attribute only once. We extend the definition to handle duplicates in Section 3.5.

Let $\mathcal{D}$ be a set of m-dimensional points of cardinality $|\mathcal{D}|$. Let $\vec{n_i}$ denote the co-ordinates of point x_i. We first define reflectivity over the full m-dimensional space, and then give a more general definition for subspaces.

We define the *reflections* of the point x_i to be the set of co-ordinates obtained by permuting $\vec{n_i}$ (including $\vec{n_i}$). For example, if x_i were $\langle 1, 2\rangle$, the reflections of x_i would be $\{\langle 1, 2\rangle$,$\langle 2, 1\rangle\}$.

Let $\theta(\vec{n_i})$ denote the number of points within distance r of $\vec{n_i}$ (in m-dimensional space). The value of r is so chosen that the average value of $\theta(\vec{n_i})$ (over all $x_i \in \mathcal{D}$) is close to the number of top answers that users will be interested in. Let $\rho(\vec{n_i})$ denote the number of points in $\mathcal{D}$ that have at least one reflection within distance r of $\vec{n_i}$. The reflectivity of $\mathcal{D}$ in m-dimensional space is then defined to be:

$$\text{Reflectivity}(m, r) \;=\; 1 - \frac{1}{|\mathcal{D}|}\sum_{x_i \in \mathcal{D}} \frac{\theta(\vec{n_i})}{\rho(\vec{n_i})} \tag{5}$$

Now consider a k-dimensional subspace S of the space of $\mathcal{D}$. We define the k-reflections of a point x_i in $\mathcal{D}$ to be the set of co-ordinates obtained by considering the k! permutations of ${}^{m}C_k$ combinations of k co-ordinates chosen from $\vec{n_i}$. For example, the 2-reflections of a 3-dimensional point $\langle 1, 2, 3\rangle$ will be the set $\{\langle 1, 2\rangle$, $\langle 2, 1\rangle$, $\langle 2, 3\rangle$, $\langle 3, 2\rangle$, $\langle 1, 3\rangle$, $\langle 3, 1\rangle\}$.

Let $\vec{n_i^s}$ represent the co-ordinates of point x_i projected onto this subspace. Let $\theta(S, \vec{n_i^s})$ denote the number of points in $\mathcal{D}$ whose projections onto the subspace S are within distance r of the co-ordinates $\vec{n_i^s}$ (in the k-dimensional space). As before, the value of r is so chosen that the average value of $\theta(S, \vec{n_i^s})$ (over all $x_i \in \mathcal{D}$) is close to the number of desired top answers. Let $\rho(S, \vec{n_i^s})$ denote the number of points in $\mathcal{D}$ that have at least one k-reflection within distance r of the co-ordinates $\vec{n_i^s}$ (in the k-dimensional space). The reflectivity of the subspace S is defined to be:

$$\text{Reflectivity}(S, r) \;=\; 1 - \frac{1}{|\mathcal{D}|}\sum_{x_i \in \mathcal{D}} \frac{\theta(S, \vec{n_i^s})}{\rho(S, \vec{n_i^s})} \tag{6}$$

Finally, let $\widehat{\mathcal{S}}_k$ represent the set of k-dimensional subspaces of $\mathcal{D}$. Let $|\widehat{\mathcal{S}}_k| = {}^{m}C_k$ denote the number of k-dimensional subspaces Then, the reflectivity of $\mathcal{D}$ over k-dimensional subspaces is

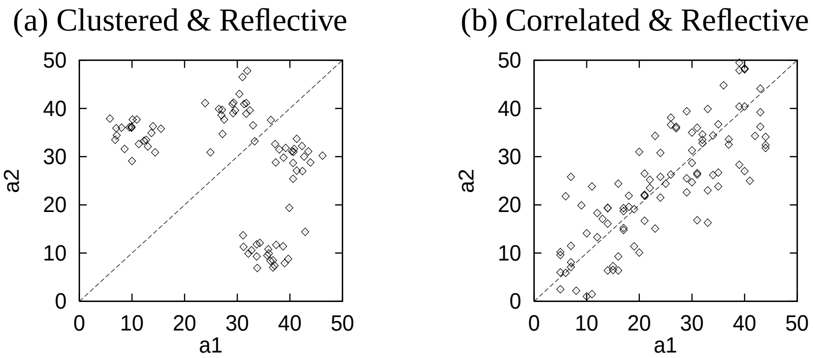


Figure 3: Counter-examples showing clustered and correlated datasets that are reflective.

defined to be the average of the reflectivity in each subspace:

$$\text{Reflectivity}(k, r) \; = \; \frac{1}{|\widehat{\mathcal{S}}_k|} \sum_{S \in \widehat{\mathcal{S}}_k} \text{Reflectivity}(S, r) \tag{7}$$

Note that:

$$\text{Non-reflectivity} \; = \; 1 - \text{Reflectivity} \tag{8}$$

3.2 Implicit Name Match Conjecture Revisited

Let S be the subspace corresponding to the attribute in a query $Q = \{q_1, \ldots, q_k\}$. Let $\vec{Q}$ denote the co-ordinates corresponding to $\{q_1, \ldots, q_k\}$. Then there are $\theta(S, \vec{Q})$ documents that are true close matches to Q, and $\rho(S, \vec{Q})$ documents that are nameless close matches to Q. Hence for this query, the probability that a document that is a nameless close match will also be a true close match is simply $\theta(S, \vec{Q})/\rho(S, \vec{Q})$.

Let us represent a query distribution for a subspace S by a random sample of queries $\mathcal{Q} = \{Q_1, \ldots, Q_N\}$ drawn from that distribution. Then for a query belonging to this distribution, the probability that a document that is a nameless close match will also be a true close match is

$$\frac{1}{|\mathcal{Q}|} \sum_{Q_i \in \mathcal{Q}} \frac{\theta(S, \vec{Q}_i)}{\rho(S, \vec{Q}_i)}$$

Finally, if the query distribution for a subspace S is close to the distribution of documents projected onto S, we can treat the set of points as a sample of the query distribution, and the probability that a document that is a nameless close match will also be a true close match is simply non-reflectivity(S, r). Thus reflectivity can serve as a close proxy for expected accuracy.

3.3 Remarks

1. *Non-overlapping Attributes:* If the attributes of a dataset do not overlap, such data is necessarily non-reflective for queries of any length.

2. *Clustering and Correlation:* For a fixed amount of overlap between attributes, clustered and/or correlated datasets are likely to have lower reflectivity than datasets where the attributes are independent. Figures 2(b) and (c) support this intuition. In Section 6.4, we study this effect for nine real-world datasets by computing reflectivity both for the original dataset and for a modified dataset where we destroy any correlation or clustering while keeping the actual values of each attribute fixed. Destroying correlation and clustering increases reflectivity in all nine datasets, often dramatically. Of course, it is easy to come up with counter-examples of correlated or clustered datasets that are quite reflective, as shown in Figure 3.

3.4 Computing Reflectivity

If the database knows the correct attribute names corresponding to data values, we can use Eq. 7 to compute reflectivity. Null values in the data can be handled as follows. Suppose the values of some of the co-ordinates of an m-dimensional point x_i are null (unknown). We ignore this point in the computation of reflectivity in Eq. 5. When computing the reflectivity of a subspace S in Eq. 6, the term $\theta(S, \vec{n_i^s})/\rho(S, \vec{n_i^s})$ for point x_i is excluded from the summation if a null value is present in the set of co-ordinates projected onto S. However, x_i may still contribute to the denominator of the above term for some other point x_j if a k-reflection of x_i does not have any null co-ordinate values and this reflection is within distance r of $\vec{n_j^s}$.

The cost of computing reflectivity can be reduced by doing the summation in Eq. 6 for a sample of data points. Similarly, we can do summation over a sample of subspaces in Eq. 7.

Consider now the scenario where attribute names have not been assigned to most of the values in the documents. If we can get hints for the attribute name, we can treat the highest-ranked hint for each number as the attribute name and compute reflectivity. We empirically evaluate this idea in Section 6.7. Our results show that this idea tends to be useful if the accuracy of hints is relatively high.

Finally, consider the situation in which we do not even have good hints. The proposed techniques may still work well; we just will not be able to estimate accuracy a priori. If the answers displayed to the user show sufficient summary information that the user's selections are a reliable indicator of the accuracy of the answer, we can use the precision of the answers as a rough estimate of reflectivity.

3.5 Duplicates

In longer documents such as product specifications, the value of an attribute may be repeated, e.g., in a summary as well as in the main body of the document. We now extend our definition of reflectivity to handle such duplicates. In the presence of duplicates, we might not be able distinguish whether two identical values in a document belong to the same attribute or to two different attributes. Thus reflections of a point now include not just permutations of co-ordinates, but also additional reflections arising out of a duplicate value appearing in multiple co-ordinate positions.

As before, let $\mathcal{D}$ be a set of m-dimensional points, and let $\vec{n_i}$ denote the co-ordinates of point x_i. Let $\Delta(x_i)$ denote the multi-set constructed as follows: if the jth value in x_i occurs p times in the document corresponding to x_i, then we add p instances of the jth value to $\Delta(x_i)$. For example, if $x_i = \langle 1, 2, 3 \rangle$, and the first two co-ordinates occur twice in the document corresponding to x_i, $\Delta(x_i) = \{1, 1, 2, 2, 3\}$.

Consider a k-dimensional subspace S of the space of $\mathcal{D}$. We now define the k-reflections of a point x_i in $\mathcal{D}$ to be the set of co-ordinates obtained by considering the k! permutations of ${}^{|\Delta(x_i)|}C_k$ combinations of k values chosen from $\Delta(x_i)$. For example, if $\Delta(x_i) = \{1, 1, 2, 2, 3\}$, the 2-reflections of x_i would be the set $\{\langle 1, 2 \rangle$, $\langle 2, 1 \rangle$, $\langle 2, 3 \rangle$, $\langle 3, 2 \rangle$, $\langle 1, 3 \rangle$, $\langle 3, 1 \rangle$, $\langle 1, 1 \rangle$, $\langle 2, 2 \rangle\}$. In this example, the last two reflections are the additional reflections due to the presence of duplicates.

As before, let $\vec{n_i^s}$ represent the co-ordinates of point x_i projected onto this subspace. Let $\theta(S, \vec{n_i^s})$ denote the number of points in $\mathcal{D}$ whose projections onto the subspace S are within distance r of the co-ordinates $\vec{n_i^s}$ (in the k-dimensional space). Let $\rho(S, \vec{n_i^s})$ denote the number of points in $\mathcal{D}$ that have at least one k-reflection within distance r of the co-ordinates $\vec{n_i^s}$ (in the

k-dimensional space). The reflectivity of the subspace S is defined to be:

$$\text{Reflectivity}(S, r) \;=\; 1 - \frac{1}{|\mathcal{D}|} \sum_{x_i \in \mathcal{D}} \frac{\theta(S, \vec{n_i^s})}{\rho(S, \vec{n_i^s})} \tag{9}$$

The other definitions follow directly from the above equation. For instance,

$$\text{Reflectivity}(k, r) \;=\; \frac{1}{|\hat{\mathcal{S}}_k|} \sum_{S \in \hat{\mathcal{S}}_k} \text{Reflectivity}(S, r) \tag{10}$$

When computing reflectivity, the only difference is that we use the modified definition of reflections that incorporates duplicates.

The algorithms we describe in the next section work as such on documents with duplicate values.

4 Algorithms

We now give algorithms for finding documents in response to a user query. These algorithms assume that the database as well as queries have no attribute names associated with the numbers. Section 5 discusses how to take advantage of this extra information.

Recall that a document D consists of $D = \{n_i \,|\, n_i \in \mathcal{N}, 1 \le i \le m\}$ (Eq. 2). A search query Q consists of $Q = \{q_i \,|\, q_i \in \mathcal{N}, 1 \le i \le k\}$ (Eq. 4). Note that both D and Q are multi-sets. Each value corresponds to an unspecified attribute name.

In computing the distance of query Q from a document D, each q value is matched with exactly one n value. Given a set of query numbers $q_1, \ldots, q_k$ and a set of matching document numbers $n_{j_1}, \ldots, n_{j_k}$, the distance function F with the L_p norm ($1 \le p \le \infty$) is defined as

$$F(Q, D) = \left(\sum_{i=1}^{k} w(q_i, n_{j_i})^p \right)^{1/p} \tag{11}$$

where $w(q_i, n_{j_i})$ is the distance between q_i and n_{j_i}. We expect that F will typically use relative distance, since otherwise some of query terms will get disproportionate importance and other query terms will be ignored. For example, $w(q_i, n_j)$ may be defined as $|q_i - n_j|/|q_i + \epsilon|$.

Maximizing similarity is equivalent to minimizing distance.

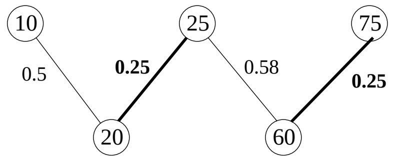


Figure 4: Bipartite graph

4.1 Matching a Document to a Query

Given a set $Q = \{q_1, \ldots, q_k\}$ of k numbers, and a set $D = \{n_1, \ldots, n_m\}$ of m document numbers, we want to select the numbers in D that will lead to the minimum distance. Each number in D is allowed to match with a single number in Q, and vice versa.

Construct a weighted bipartite graph G as follows:

- Create k source vertices labeled $q_1, \ldots, q_k$ corresponding to k numbers in Q.
- Create m target vertices labeled $n_1, \ldots, n_m$ corresponding to m numbers in D. If $m < k$, add $k - m$ target vertices with value ∞.
- From each source vertex q_i, create an edge to the k closest target vertices in $\{n_1, \ldots, n_m\}$.[3] Assign weight $w(q_i, n_j)^p$ to the edge (q_i, n_j).

Figure 4 shows the weighted bipartite graph for Q={20,60} and D={10,25,75}, assuming the distance function to be L_1 and $w(q_i, n_j) = |q_i - n_j|/|q_i + \epsilon|$.

Lemma The optimum solution to the minimum weight bipartite graph matching problem for the graph G matches each number in Q with a distinct number in D such that we get the lowest value for the distance score $F(Q, D)$.

We have marked in bold the edges comprising the optimum solution for the graph in Figure 4. Thus, 20 in Q is matched with 25 in D and 60 with 75 for a total distance score of 0.5.

We can now refer to the rich weighted bipartite graph matching literature (see survey in [4]) to find the best matching between the numbers in a query and the numbers in a document. We also obtain the distance score at the same time, which is used for ranking the documents. By repeating this process for every document in the database, we have a solution to our problem. In Section 4.2, we present techniques that avoid examining every document.

[3] For a given source vertex, we only need to create edges to the k closest targets, since the other $k - 1$ source vertices can match at most $k - 1$ targets.

The best known algorithm for the weighted bipartite matching problem is due to Feder and Motwani [13] and its time complexity is $O(e\sqrt{(k+m)}\log((k+m)^2/e)/\log(k+m))$, where e is the number of edges in the graph. Since $e = k^2$, the complexity is $O(k^2\sqrt{(k+m)}\log((k+m)/k)/\log(k+m))$.

4.2 Limiting the Set of Documents that are Matched

We now address the question of how to limit the number of documents for which we have to compute the distance. This problem turns out to be similar to that of retrieving the top t objects that have highest combined score on k attributes, introduced in [11]. We first describe the score aggregation problem and the threshold algorithm for solving this problem [12] [14] [20].

Score Aggregation Problem Assume that each object in a database has k scores, one for each of k attributes. For each attribute, there is a sorted list, which lists each object and its score for that attribute, sorted by score (highest score first). There is some monotone aggregation function f for combining the individual scores to obtain an overall score for an object. The problem is to efficiently find the top t objects that have the best overall score.

Threshold Algorithm (TA) There are two modes of access to data. Sorted access obtains the score of an object in one of the sorted lists by proceeding through the list sequentially from the top. Random access obtains the score of an object in a list in one access. The threshold algorithm works as follows [12].

1. Do sorted access in parallel to each of the k sorted lists L_i. In other words, access the top member of each of the lists under sorted access, then the second member, and so on. As an object D is seen in some list, do random access to other lists to find score s_i of object D in every list L_i. Then compute the overall score $f(D) = f(s_1, \dots, s_k)$ of object D. If this score is one of the t highest we have seen, then remember D and its score $f(D)$.
2. For each list L_i, let $\underline{s}_i$ be the score of the last object seen under sorted access. Define the threshold value τ to be $f(\underline{s}_1, \dots, \underline{s}_k)$. Halt when t objects have been seen whose overall score is at least equal to τ.
3. Let Y be a set containing the t objects that have been seen with the highest scores. The result is the graded set $\{\langle D, f(D)\rangle \mid D \in Y\}$.

Proposed Adaptation We now discuss how our problem is similar to the score aggregation problem. We then show how the threshold algorithm can be adapted to our problem.

Assume that the documents have been pre-processed to create data structures to support the following types of accesses.

- *Database Access:* Given a document id, return the multi-set of numbers present in the document.
- *Index Access:* Given a number, return the set of documents in which this number is present. Only numbers that appear in at least one document are included in this index. Numbers are kept sorted so that it is easy to determine the nearest left neighbor (smaller number) and nearest right neighbor (larger number) of a number. We can use B-tree [6] for this purpose if the index is too large to fit in memory.

Here is the algorithm, stated in the TA framework. While reading the algorithm, keep in mind that a document with a lower distance score is closer to the query, and hence better in our setting.

1. Form k conceptual lists, one for each query term q_i as follows. For every q_i, create an ordered list of numbers $n_i^1, n_i^2, \ldots$ such that $w(q_i, n_i^j) \leq w(q_i, n_i^{j+1})$. (Recall that $w(q_i, n_i^j)$ is the distance between q_i and n_i^j.) Associate the score $s_i^j = w(q_i, n_i^j)$ with every document returned by index access on n_i^j. The list L_i for q_i is now defined to consist of documents obtained from index look up on terms $n_i^1, n_i^2, \ldots$ sorted in ascending value of score (lowest score first). Note that these lists are not physically materialized, but the next() operation on these lists is well-defined and can be efficiently implemented using the index access described above.
2. Do a round-robin access to each of the k sorted lists L_i. As a document D is seen in some list, do a database access for this document and match it with the query using the algorithm from Section 4.1. The distance score returned by the matching algorithm gives the overall score of the document.
3. Let n_i' be the number in the index that we last looked at for query term q_i. Define the threshold value τ to be the distance $(\sum_{i=1}^{k} w(q_i, n_i')^p)^{1/p}$ from Eq. 11. Halt when t documents have been seen whose distance from Q is less than or equal to τ.

At this point, for any document that has not been seen in the index, the closest number to each query term q_i must be at least as far from q_i as n_i', and hence the distance between the document and the query must be at least as high as τ.

Note that unlike the original threshold algorithm, the s_i scores in the adaptation are lower bounds on the distance, not necessarily the actual distance. In other words, when we match a document D to a query, the number that ends up being matched with q_i may be further away from q_i than indicated by the score for D in the sorted list for q_i. The reason is that during matching, a number in D can only match one query term, but we do not track this constraint during index access (to avoid the bookkeeping overhead). Thus if a single number in D is the closest number to two different query terms, one of the two scores for D will be a lower bound for the actual distance. This does not affect the correctness of the halting criteria in step 3, since the threshold value τ is a lower bound on the distance of a document that we have not yet seen, and we stop when we have seen t documents whose distance is lower than τ.

5 Using Attribute Names and Units

5.1 Attribute Names

We now describe how to use hints about attribute names to aid matching. Let H_i denote the set of attribute names associated with the number n_i in a document. As before, let A_i denote the set of attribute names associated with q_i in a query. We extend the distance function from Eq. 11 to incorporate hints as follows:

$$F(Q, D) = \left(\sum_{i=1}^{k} (w(q_i, n_{j_i})^p + B \times v(A_i, H_{j_i})^p) \right)^{1/p} \tag{12}$$

The parameter B balances the importance between the match on the numbers and the match on the hints. In general, the higher the accuracy of the hints and the higher the reflectivity of the data, the higher should be the value of B.

Recall that the function $w(q_i, n_j)$ determines the distance between a query number and a document number. Analogously, $v(A_i, H_j)$ is a function that determines the distance between the set of attribute names associated with a query number and the set of attribute names associated with a document number. We use the following distance function v in our experiments:

$$v(A_i, H_j) = \begin{cases} 0 & \text{if } A_i \cap H_j \neq \phi \\ 0 & \text{if } A_i = \phi \\ 1 & \text{otherwise} \end{cases} \tag{13}$$

This function penalizes a match only if q_i and n_j are likely to belong to different attributes. Hence if any of the attribute names in the query matches any of the hints, or if there is no attribute name specified in the query, the distance is zero. Otherwise, the distance is 1.

Our techniques are independent of the specific form of the function v. A more sophisticated function form tuned to the specific data extractor being used (e.g., by incorporating belief values generated by the data extractor) may yield better results. However, as we will see, our experiments indicate that even this simple function can be quite effective.

Determining the weight B A good value for B is important for successfully using hints. Suppose the website provides enough summary with each answer that the user is likely to click on relevant answers. By tracking user clicks, we can get a set of queries for which we know the true answers with high probability. Treat this set as a tune set and evaluate the performance of the matching algorithm for different values of B. Then pick the value that gives the highest accuracy. If a set of values give similar accuracy, pick the median value in the set. Note that the best value of B is likely to be different for different query sizes, and hence we will need a tune set per query size.

Constructing the Bipartite Graph As before, we map the matching problem to weighted bipartite graph matching. The only difference is that we now assign $w(q_i, n_j)^p + B \times v(A_i, H_j)^p$ as the weight of the edge (q_i, n_j).

Limiting the Set of Matches The algorithm proposed in Section 4.2 can be used as is, since we only need the s_i^j score to be a lower bound on the true distance. That is, we can use $s_i^j = w(q_i, n_i^j)$ to create the sorted list L_i for q_i, ignoring the match on attribute names.

However, the algorithm will be considerably more efficient if we modify it as follows. First, create an index to support an additional type of access, *hint index access:* given a number n_i together with an attribute name a_i, return the set of documents in which n_i is present and the set of hints for n_i includes a_i. The original index can be (conceptually) treated as a special case of this index, where the attribute name $a_i = \phi$.

Now, in Step 1, for each query term q_i, create an ordered list $\langle n_i^1, a_i^1\rangle, \langle n_i^2, a_i^2\rangle, \ldots$ and associate the score $s_i^j = w(q_i, n_i^j)^p + B \times v(A_i, \{a_i^j\})^p$ with the entry $\langle n_i^j, a_i^j\rangle$, such that $s_i^j \leq s_i^{j+1}$. We can do this efficiently by using hint index access for each attribute name in the set of hints A_i associated with the query term q_i, and also for the empty attribute name ϕ. Step 2 does not change. In Step 3, the only change is that we now define the threshold value τ to be $(\sum_{i=1}^{k}(w(q_i, n_i')^p + B \times v(A_i, \{a_i'\})^p))^{1/p}$ from Eq 12, where $\langle n_i', a_i'\rangle$ is the entry in the index that we last looked at for query term q_i.

5.2 Units

If the unit names are available in addition to attribute names, we extend the distance function from Eq. 12 by adding a term $B^u \times u(A_i^u, H_{j_i}^u)^p$ for whether the units match:

$$F(Q, D) = \left(\sum_{i=1}^{k}(w(q_i, n_{j_i})^p + B \times v(A_i, H_{j_i})^p + B^u \times u(A_i^u, H_{j_i}^u)^p)\right)^{1/p} \tag{14}$$

A_i^u denotes the set of unit names for q_i, H_j^u is the set of unit names for n_j, and $u(A_i^u, H_j^u)$ is the distance function between the two sets of unit names. The function $u(A_i^u, H_j^u)$ is defined in a manner similar to $v(A_i, H_j)$. The parameter B^u is analogous to B and can be similarly computed.

An additional complication arises due to different units (e.g., MHz and GHz) being assigned to the values of the same attribute. In some cases, this problem can be approached by converting the corresponding quantities into a “standard” form.

6 Experiments

In this section, we report the results of experiments we performed to study the accuracy and performance characteristics of the proposed techniques. We used synthetic as well as real datasets in this study. Synthetic datasets are amenable to controlled experiments, while real datasets are used to check that the results are indeed applicable in the real world.

6.1 Accuracy Metric

Given a database $\mathcal{D}$ in which the correct correspondences between the numbers and the attribute names are known, a query Q consisting of numbers and full information about the attribute names corresponding to those numbers, we could generate the "perfect" answer of top t matching documents $M_P(t) = \{D_{p_1}, \ldots, D_{p_t}\}$ for a given distance function F. If the information about the attribute name is not available or only partially available in the form of hints, we would generate a different set of top t matching documents $M(t) = \{D_1, \ldots, D_t\}$.

Precision(t) is defined to be the the percentage of documents in $M_P(t)$ that are also present in $M(t)$:

$$\text{Precision}(t) = \frac{|M_P(t) \cap M(t)|}{|M(t)|} \times 100 \tag{15}$$

We set t to 10 in our experiments, corresponding to the number of hits typically displayed on the first page by search engines, and refer to Precision(10) as simply Precision.

6.2 Datasets

6.2.1 Synthetic Data

A document is modeled as a set of m numbers, corresponding to m known attributes. We generated three types of synthetic data:

1. *Independent*: Each attribute is independent of the other attributes.
2. *Correlated*: Attribute a_{i+1} is correlated with attribute a_i.
3. *Clustered*: Data is clustered around a few cluster centers.

We expect Independent to be more reflective, and Clustered and Correlated to be less reflective. Therefore, we should get higher precision on Clustered and Correlated, and lower precision on Independent.

Figure 5 shows the pseudocode for generating the three types of synthetic data. We use $s[\,]$ to control the amount of reflectivity. The value of $s[j]$ is initially set to $R \times j$, where R is a parameter that controls to the amount of overlap between the range of values of various attributes, which in turn influences reflectivity. If we wanted to generate a dataset with almost no overlap between any of the attributes, R would be set to a high value, e.g., 10. On the other hand, if we wanted very high overlap between the attributes, R would be set to 0. In our experiments, we manually tuned R such that the 1-dimensional non-reflectivity is roughly 80% for each of the three datasets (with the default number of attributes). The values in $s[\,]$ are then randomly permuted, so that for the correlated dataset there is no connection between which attributes are correlated and which attributes are adjacent in terms of values.

Figure 6 shows the settings used in the synthetic data experiments. The Range column gives the range of values used in various experiments. The Default column provides the default value of the corresponding parameter. Query size refers to the number of terms in the query.

To generate a query of size k, we first pick a document at random. Next, for Independent and Clustered, we randomly pick k attributes from the document, and for Correlated, we randomly pick a set of k consecutive attributes. We then remove this document from the dataset, and compute the precision. (If we kept the document in the dataset, our scores would be artificially boosted.) We average the results over 1000 queries for each combination of parameters and query size. We use L_1 to compute distance between a query and a document in all our experiments.

6.2.2 Real Data

Figure 7 gives information about the nine real datasets used in our experiments. The first four datasets came from the Pangea data on electronic components for different categories of electronic parts. The last five datasets are from the University of California–Irvine Repository of Machine Learning. A record here corresponds to a document.

The query generation procedure used with the real data is identical to the procedure we described for the Independent and Clustered data. All results are the average of 1000 queries.

6.3 Relationship of Precision to Reflectivity

Figure 8(a) shows the precision on the three synthetic datasets as the query size is increased. We compute answers to the same query under two settings: (i) attribute names are known for both data and query, and (ii) attribute names are ignored in data as well as query. We then use Eq. 15 to compute precision. Figure 8(b) plots non-reflectivity versus subspace dimensionality. Non-reflectivity is computed assuming attribute names are known in the data. Both precision and non-reflectivity have been plotted as a percentage. These figures show that precision at a given

```
// $N$: number of documents
// $m$: number of attributes
// $D_i$: $i^{\text{th}}$ document
// $D_i(j)$: value of the attribute $j$ in document $D_i$
// $R$: controls the amount of overlap
// $s[\,]$: $s[j]$ set to $R \times j$ and then $s[\,]$ is permuted
// Gauss(): Gaussian with $\mu = 0$ and $\sigma = 1$

Independent:
for $i$ := 1 to $N$
    for $j$ := 1 to $m$
        $D_i(j)$ := Gauss() + s[$j$]

Correlated:
for $i$ := 1 to $N$
    $D_i(1)$ := Gauss()
    for $j$ := 2 to $m$
        $D_i(j)$ := ($D_i(j-1)$ + Gauss()) $\times$ 0.7
    for $j$ := 1 to $m$ begin
        $D_i(j)$ := $D_i(j)$ + s[$j$]

Clustered:
// $C$: number of clusters
for $i$ := 1 to $C$
    for $j$ := 1 to $m$
        $D_i(j)$ := Gauss() + s[$j$]
for $i$ := $C + 1$ to $N$
    cid := ($i$ mod $C$) + 1
    for $j$ := 1 to $m$
        $D_i(j)$ := $D_{\text{cid}}(j)$ + 0.2 $\times$ Gauss()
```

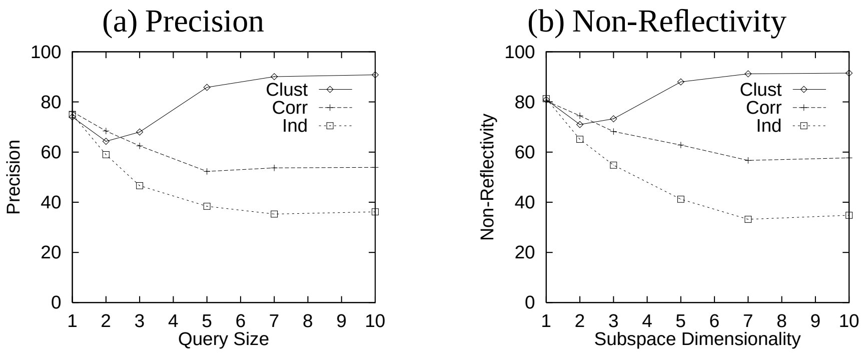
Figure 5: Synthetic data generation

Parameter	Default	Range
Number of Attributes (m)	20	5 to 50
Number of Documents (N)	10K	1K to 800K
Query Size (k)	5	1 to 10
1-dim. non-reflectivity	80%	100% to 10%
Data Type		Ind., Corr., Clust.

Figure 6: Parameters for synthetic data experiments

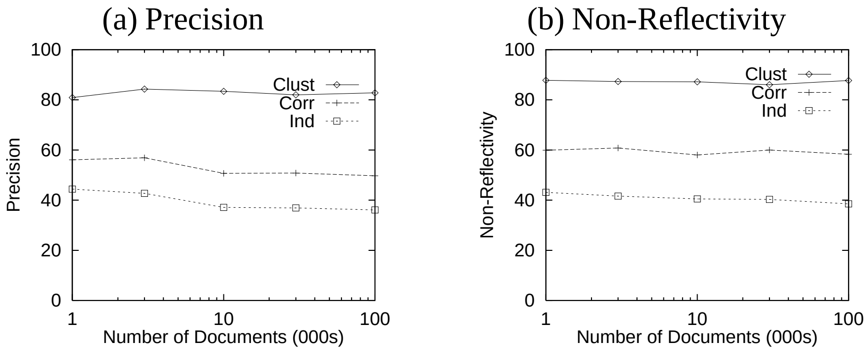
Source	Dataset	Number of Records	Maximum Number of Attributes	Average Number of Attributes
Pangea	DRAM	3,866	10	6.8
	LCD	1,733	12	9.4
	Microprocessor	1,133	12	5.3
	Transistor	22,273	24	13.3
UCI	Automobile	205	16	15.7
	Housing	506	14	14
	Glass	214	10	10
	Wine	179	14	14
	Credit	666	6	6

Figure 7: Real datasets


(a) Precision

(b) Non-Reflectivity

Figure 8: Precision and non-reflectivity vs. query size (#documents = 10K, #attributes = 20)


(a) Precision

(b) Non-Reflectivity

Figure 9: Precision and non-reflectivity vs. number of documents (Query Size = 5, #attributes = 20)

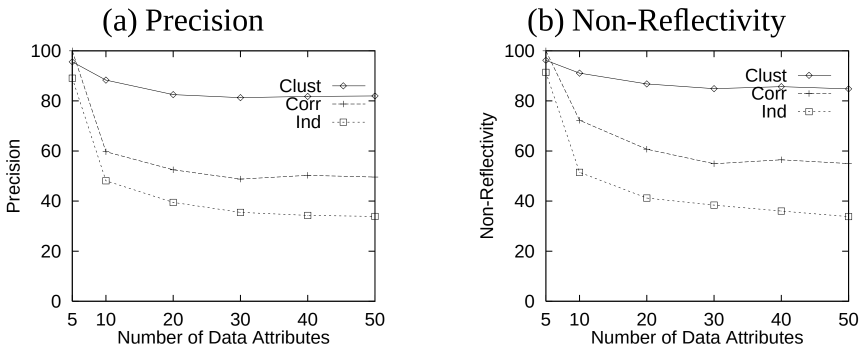


Figure 10: Precision and non-reflectivity vs. number of attributes (Query Size = 5, #documents = 10K)

query size closely tracks non-reflectivity for the corresponding subspace dimensionality.

As anticipated, both Clustered and Correlated gave higher precision than Independent. Clustered gave higher precision than Correlated for higher query dimensions. To understand the behavior of Clustered with increasing subspace dimensionality, recall our example from Figure 2(b). This dataset has very low reflectivity in 2 dimensions, but high reflectivity in one dimension. Similarly, in our synthetic data, the clusters gradually merge as we drop dimensions, leading to an increase in reflectivity for lower dimensions. By the time we reach 2 dimensions, the clusters have completely disappeared and Clustered starts behaving like Correlated and Independent.

Figure 9(a) shows the precision as a function of the number of documents. Figure 10(a) shows the precision as a function of the number of data attributes. We again note from corresponding (b) figures that the precision closely tracks non-reflectivity.

6.4 Precision on Real Data

Figure 11 shows the precision and non-reflectivity as a percentage in the same graph for the nine real datasets. The x-axis for precision and non-reflectivity is query size and subspace dimensionality respectively. We again see that non-reflectivity can provide a good estimate of the expected precision. We also see that real datasets can be quite non-reflective and hence our techniques can be effectively used on them.

Effect of Clustering and Correlation In Section 3, we stated our intuition that clustering and correlation would typically increase non-reflectivity. To verify this conjecture, we study the effect of destroying any clustering or correlation effects in a dataset by randomly permuting the values

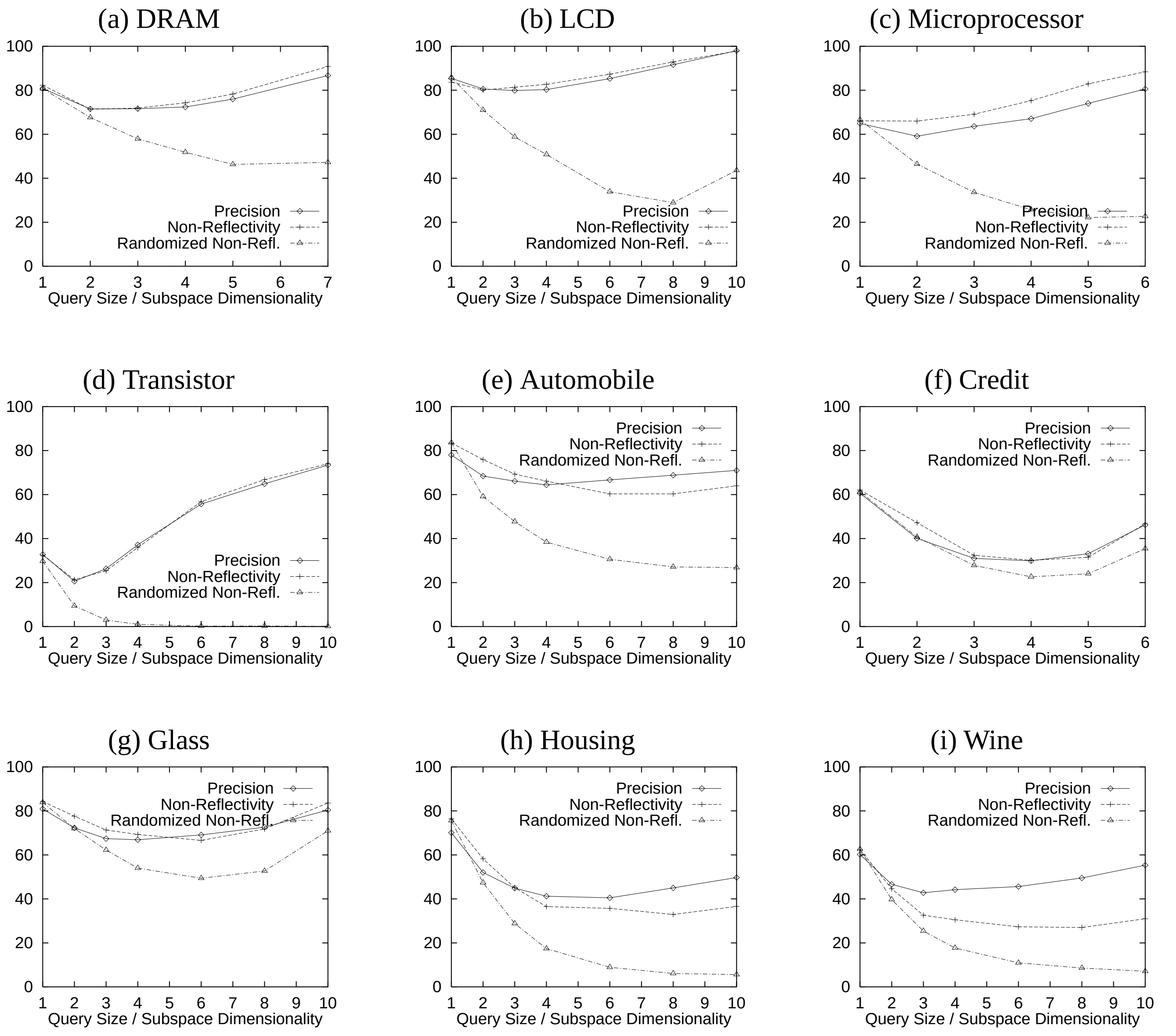


Figure 11: Precision on real datasets

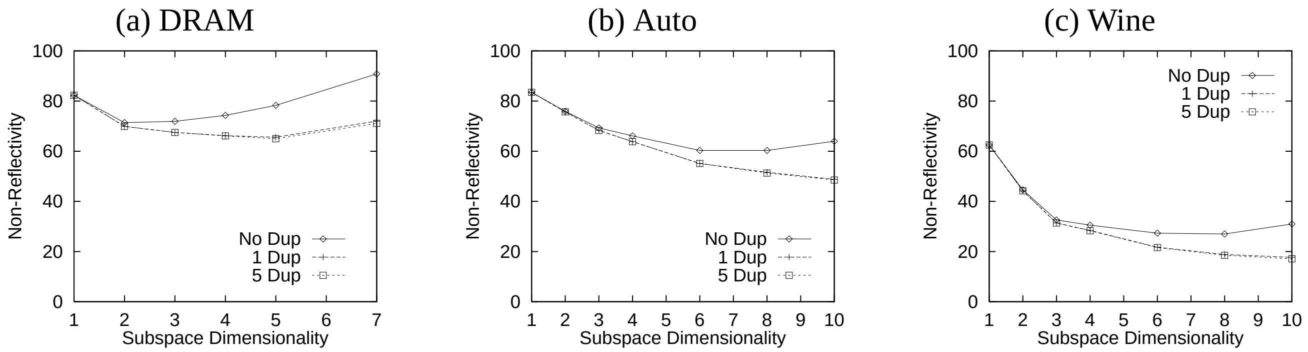


Figure 12: Effect of duplicates on reflectivity

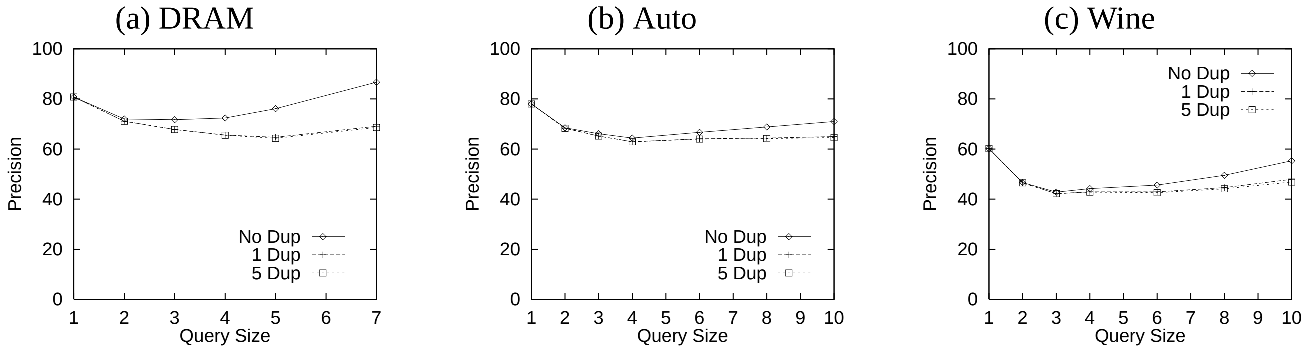


Figure 13: Effect of duplicates on precision

for every attribute. (We permute the values of an attribute across documents, not across different attributes.) If the attributes were originally independent, this permutation will not affect reflectivity, since permutation does not affect the distribution of values for each attribute. Hence the difference in non-reflectivity between the original data and the randomized data can be attributed to clustering and correlation. The line “Randomized Non-Refl.” (in Figure 11) shows the non-reflectivity on the randomized datasets. For all but the Credit dataset, randomized non-reflectivity is substantially lower than non-reflectivity.

6.5 Duplicates

We explore the effect of duplicates on reflectivity (Section 3.5) by creating two new versions of each real dataset. The “1 Dup” version has each value in a document repeated once. The “5 Dup” version has each value repeated 5 times. We show results for three datasets: DRAM, Auto and Wine. DRAM and Auto have high non-reflectivity, and Wine has lower non-reflectivity.

Figures 12 and 13 show the effect of duplicates on non-reflectivity and precision respectively.

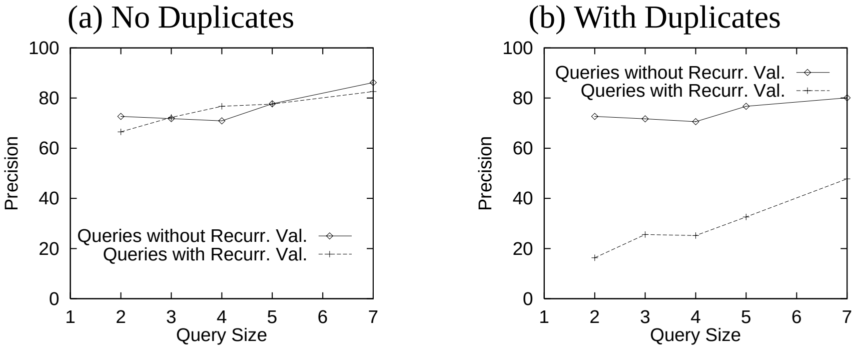


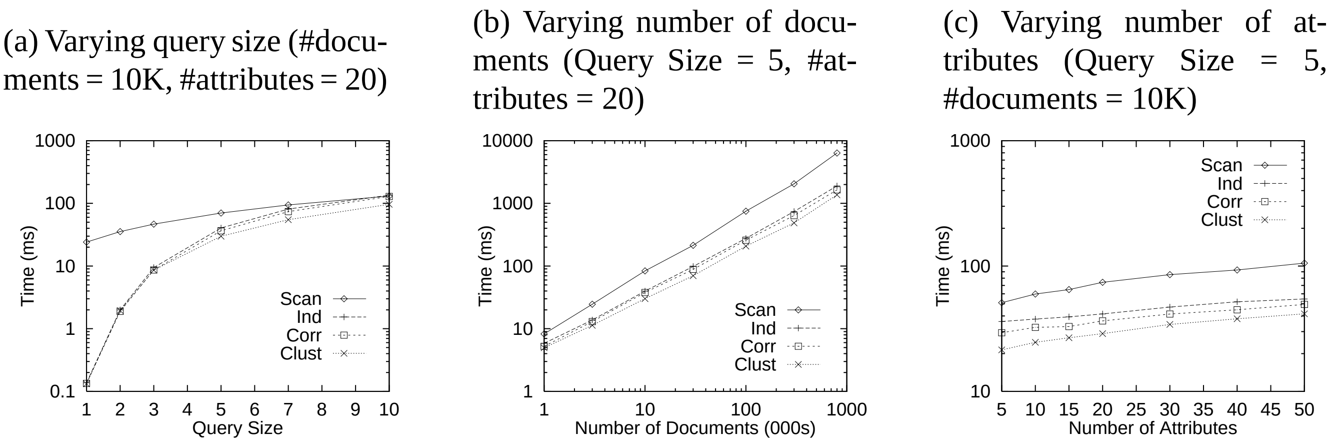
Figure 14: Analysis of effect of duplicates on DRAM

The precision again follows the non-reflectivity. When the subspace dimensionality (or equivalently, query size) is small, duplicates have almost no impact on non-reflectivity. Even for larger subspace dimensionalities of 5 to 10, the impact is still quite moderate.

To understand why duplicates have so little impact, we partitioned the queries into two types: (i) those in which all the query values are unique, and (ii) those in which the same value occurs multiple times (corresponding to different attributes).[4] Figure 14(a) shows that when the DRAM data does not have duplicates, these two query types give almost the same precision. However, in the version of DRAM with duplicates, the queries in which a value does not recur maintain almost the same precision, while those with recurring values show a large drop in precision, as shown in Figure 14(b). Thus most of the loss in precision comes from those queries that have recurring values (or more generally, that have two or more values close to each other). The reason is that the additional reflections created by the presence of duplicates have the property that they have two or more identical co-ordinates (recall the example in Section 3.5). These reflections will often match queries with recurring values causing loss in precision, but rarely match queries that do not have two close values.

It is worth noting in Figure 14(b) that for queries with recurring values the precision increased with increasing query size. It is because the amount of information in the remaining query values makes it more likely that the correct document will be matched. One might now wonder as to why we get a larger drop in precision for larger query sizes in Figure 13(a). The reason is that in the query mix, the fraction of queries with recurring values goes up with an increase in query size. For

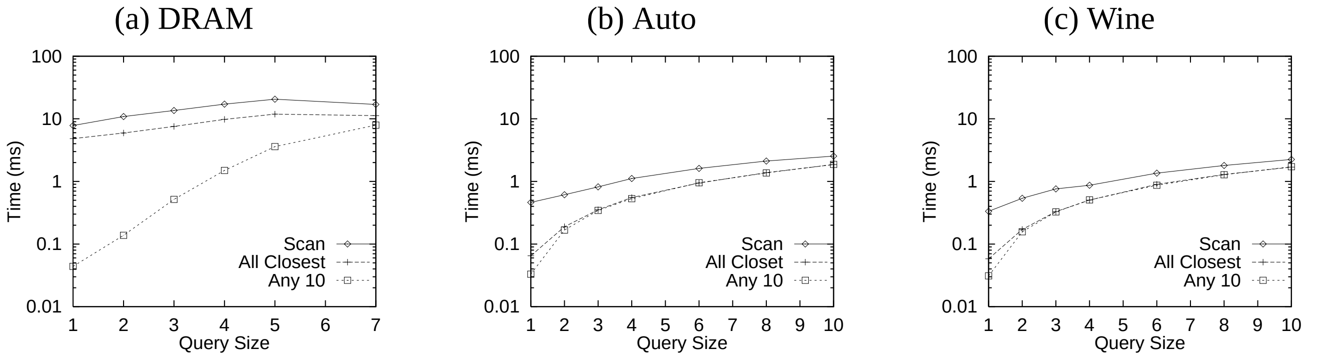
[4] We can also do this analysis in terms of reflectivity, and partition points based on whether different co-ordinate values are equal (after projecting to the subspace). We have given the analysis in terms of queries since the latter is easier to explain.


(a) Varying query size (#documents = 10K, #attributes = 20)

(b) Varying number of documents (Query Size = 5, #attributes = 20)

(c) Varying number of attributes (Query Size = 5, #documents = 10K)

Figure 15: Effectiveness of indexing: synthetic data


(a) DRAM

(b) Auto

(c) Wine

Figure 16: Effectiveness of indexing: real data

DRAM, the fraction increased from around 3% at query size 2 to around 40% at query size 10. Thus, although individual queries are making less error, there are more queries incurring errors as the query size is increased. Hence, the overall loss in precision is quite small for the smaller query sizes, but increases for larger query sizes.

6.6 Effectiveness of Indexing

We now study the effectiveness of indexing in limiting the set of documents for which we have to compute the distance for a query. All our experiments were run on a 933 MHz Pentium III with 512 MB of memory. The code was written in Java and run with Sun JDK 1.3 Hotspot Server. The execution times will be faster with C++, but the relative impact of various factors is likely to be the same. Both index and documents were kept completely in memory, limiting us to around 800,000 documents.

Figure 15 shows the execution times with and without indexing for the Independent, Correlated and Clustered synthetic datasets. The time without indexing was almost identical for the three datasets, and hence we only plot one curve, “Scan” for the no indexing case.

Figure 15(a) shows the execution time results for different query sizes for the three synthetic datasets. The index is quite effective for smaller query sizes, which we expect to be the norm. For larger query sizes, the dimensionality curse begins to catch up and using the index only does a little better than a full scan.

Scalability Figure 15(b) shows the scalability of the indexing as we increase the number of documents from 1000 to almost 1 million. At query size 5, the number of documents matched goes up by a factor of about 250 times as we increase the number of documents by 800 times, and the number of index entries scanned goes up around 200 times. Hence while the fraction of the index scanned and the percentage of documents checked both decrease slightly, the absolute time goes up almost linearly with the number of documents. At 800,000 documents, we take slightly more than 1 second for query size 5 and around 0.03 seconds for query size 2.

Figure 15(c) shows that the execution time remains flat as we increase the number of attributes. In our synthetic datasets, adding new attributes does not change the average amount of overlap between attributes. Hence the number of documents matched or index entries scanned is not affected by adding more attributes. However, matching takes a little longer, and hence the overall time goes up slightly.

Real Datasets Figure 16 shows results on three of the real datasets. For DRAM, there were often a large number of documents at a distance of zero from the query Q for smaller query sizes. Hence whether we stop as soon as we get 10 documents with zero distance, or whether we get all documents at zero distance (and then present a random sample), makes a dramatic difference in the running time. The “All Closest” line shows the former case, and the “Any 10” line the latter. For the other two datasets, this is not a significant issue, and hence these two lines are very close to each other. Again, we can conclude that indexing is quite effective for smaller query sizes.

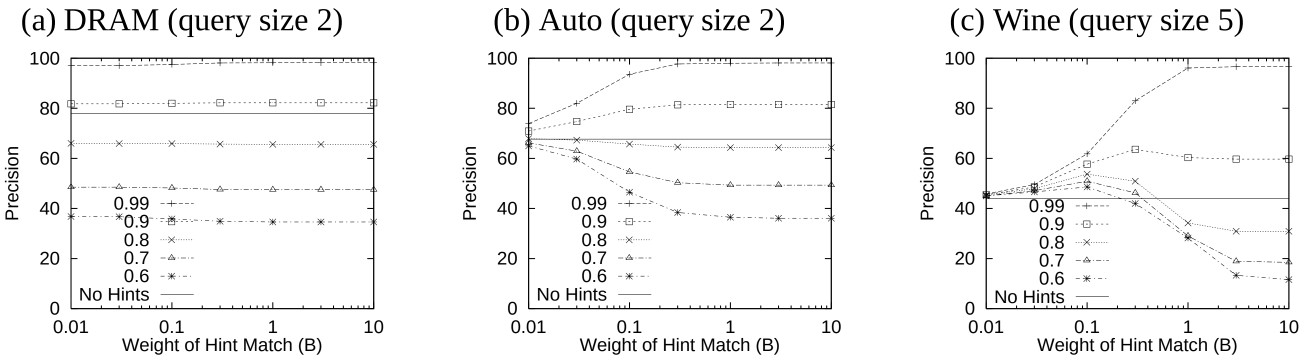
6.7 Using Attribute Names as Hints

We generated data for this set of experiments by starting with the real datasets and then augmenting them with hints. Our procedure for generating hints takes two parameters: AvgNumHints and

```
// ProbTrue: Prob. of true attribute name being in the set of hints
// Rand(0,1): Uniform Random number between 0 and 1

$n$ := 1 + Poisson(AvgNumHints-1)
$\mathcal{A}_f$ := $\mathcal{A}$ $-$ true attribute name
if (Rand(0,1) $\leq$ ProbTrue)
    Output true attribute name and $n-1$ names randomly
            selected from $\mathcal{A}_f$
else
    Output $n$ attribute names randomly selected from $\mathcal{A}_f$
```

Figure 17: Generating hints


(a) DRAM (query size 2)

(b) Auto (query size 2)

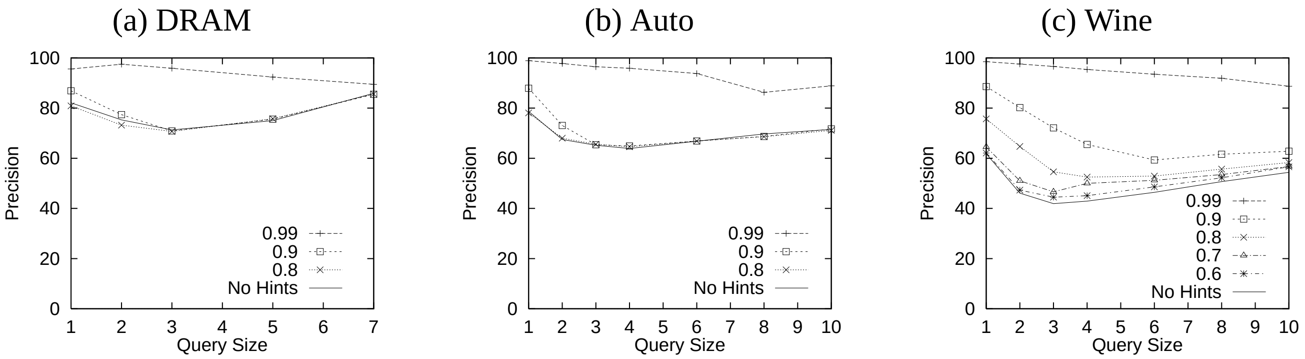
(c) Wine (query size 5)

Figure 18: Effect of balance between number match and hint match

ProbTrue. AvgNumHints is the average number of hints per data value. Each data value is assigned at least one hint, hence the minimum value of AvgNumHints is 1. If AvgNumHints is greater than 1, then the number of hints for a specific data value is determined using a Poisson distribution. ProbTrue is the probability that the set of hints for a data value includes the true attribute name. Figure 17 gives the pseudocode for generating hints for a given data value. In general, increasing AvgNumHints should result in increasing ProbTrue. However, since the exact relationship is data and data extractor dependent, in any given experiment, we fix one of the values and vary the other. The query consists of numbers together with the corresponding true attribute name.

We synthesized nine datasets from the real datasets described earlier, and experimented with all of them. However, we show the graphs for only three representative datasets: DRAM, Auto and Wine. DRAM and Auto have high non-reflectivity, and Wine lower non-reflectivity.

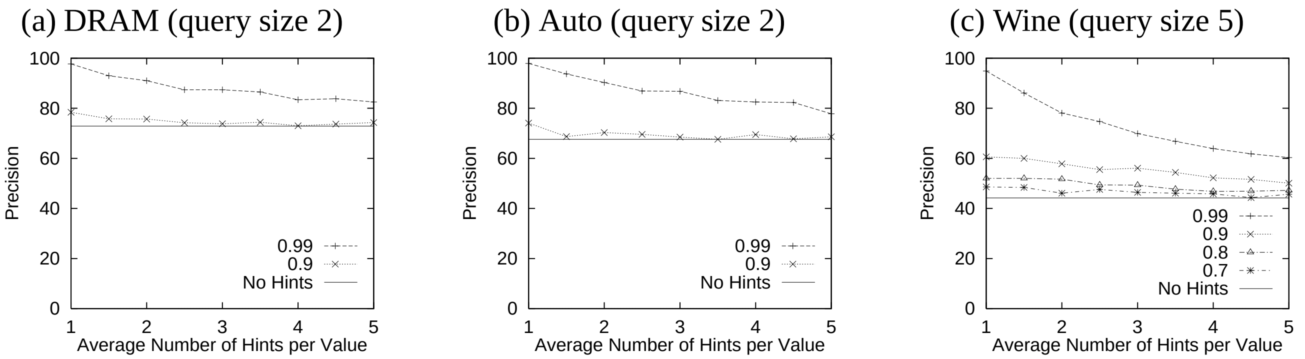
Weighting the Match on Hints Figure 18 shows the effect of changing the weight given to the match on the attribute names (the parameter B in Eq. 12). AvgNumHints was set to 1, so


(a) DRAM

(b) Auto

(c) Wine

Figure 19: Effectiveness of hints


(a) DRAM (query size 2)

(b) Auto (query size 2)

(c) Wine (query size 5)

Figure 20: Number of hints

that every data value had exactly one hint assigned to it. The different curves show precision for different values of ProbTrue. If the hints are accurate (high value of ProbTrue), then precision rapidly goes up with increasing B. For DRAM, the precision goes up for values of B much smaller than 0.01, and hence Figure 18(a) does not show this increase. For queries on DRAM, there are often different attributes with the same numeric value as the query value, and even a small value of B is sufficient to pick between them. If the hints are not very accurate, precision goes down with increasing B. One should not conclude that B should be ∞ if hints are accurate and 0 otherwise. For example, in the case of wine with ProbTrue between 0.6 and 0.8, the precision initially goes up with B and then drops back down. Therefore it is important to choose a good value of B.

In the rest of the experiments, we assume we have a tune set of 100 queries (per query size) for which we know the best match. We compute Precision over this tune set for different values of B (specifically, we used $\{$ 0.01, 0.03, 0.1, 0.3, 1, 3, 10 $\}$). We then choose the value that gives the highest precision. As we mentioned in Section 5, this method can be used as long as the website provides enough summary with each answer so that the user is likely to click on relevant answers.

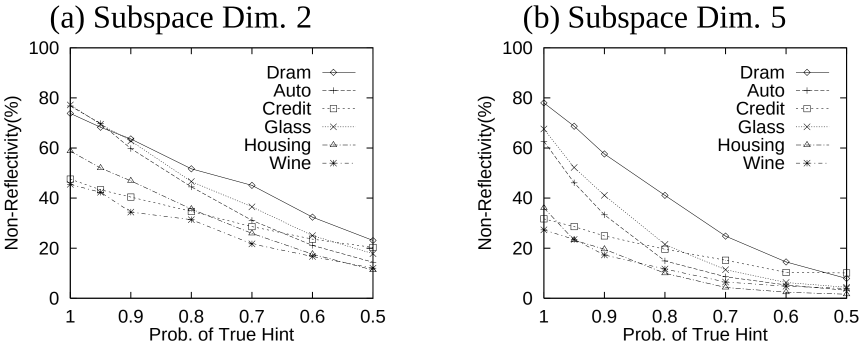


Figure 21: Estimating reflectivity using hints

Effectiveness of Hints Figure 19 shows the gains in precision for different values of ProbTrue when AvgNumHints is set to 1. Notice that for datasets with high non-reflectivity (DRAM and Auto), the hints have to be extremely accurate (ProbTrue $>$ 0.9) to add significant value. However, for datasets with low non-reflectivity (Wine), even hints with lower levels of accuracy can increase precision.

Number of Hints In the previous set of experiments, we found that ProbTrue (the probability that the set of hints will include the true attribute name) had to be quite high to increase precision. In many domains, such high values of ProbTrue may not be achievable without having multiple hints per attribute, where only one of the hints is correct. Figure 20 shows precision for different values of the average number of hints (AvgNumHints). For each line, we have fixed the value of ProbTrue.

As expected, for a fixed value of ProbTrue, precision decreases as the number of hints increases. However, we expect ProbTrue to increase with the number of hints. Consider Figure 20(c), and assume we have a data extractor that gives ProbTrue of 0.7 when AvgNumHints = 1, ProbTrue of 0.9 when AvgNumHints = 1.5, and ProbTrue of 0.99 when AvgNumHints $\geq$ 3. In this scenario, choosing AvgNumHints = 3 will result in the highest precision. Thus, having multiple hints can improve precision if there is an accompanying increase in ProbTrue.

Estimating Reflectivity using Hints Finally, we explore how well we can estimate non-reflectivity when we do not know true attributes but only have hints about them. We generate data with AvgNumHints = 1 and different values of ProbTrue, treat each hint as if it were the true attribute name, and compute reflectivity. Figure 21 shows the results. The values on the y-axis, with Prob-True = 1, are the true values of non-reflectivity. The non-reflectivity estimates are lower with hints than with true attribute names. However, for small subspace dimensions, the drop-off is sufficiently gradual that the estimate is still useful when the hints are reasonably accurate. For larger subspace dimensions, the drop-off is sometimes quite steep. Hence if the estimate for non-reflectivity has a low value, we cannot be sure that the true value of non-reflectivity is indeed low or whether it is an artifact of the inaccuracy of hints. But if we get a high value, we can be confident that the true value of non-reflectivity is also high.

7 Conclusions

Many web text repositories consist of documents in which it is difficult to establish exact correspondences between attribute names and their numeric values. To enable nearest-neighbor queries over such repositories, we explored a rather audacious approach of using only sets of numbers in the search, ignoring any attribute names. We showed that matching a document with a query in this setting corresponds to the weighted bipartite graph matching problem. We also showed how to limit the number of documents that we have to match with a given query.

We identified a data property, called reflectivity, that can tell a priori how well our approach will work against a dataset. High non-reflectivity in data assures that our techniques will have high precision. Our experiments showed that real datasets can exhibit high non-reflectivity and our techniques yielded high precision against these datasets. Using synthetic data, we also showed the scalability and resilience of our techniques in terms of the number of documents, number of attributes in the data, size of queries, and types of data.

We also showed how we can use imprecise attribute names as hints to improve precision. Hints are particularly helpful when the data has low non-reflectivity. However, for datasets with high non-reflectivity, hints have to be extremely accurate to improve precision beyond what we get by matching numbers.

In the future, we plan to extend this work in three directions. First, we would like to handle queries in which value ranges are provided. Second, some extraction procedures associate confidence values with the attribute names assigned to a number. We wish to explore how to take advantage of this additional information. Finally, we would like to better understand the interaction between correlated and clustered data and reflectivity.

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References

[1] S. Berchtold, C. Bohm, D. A. Keim, F. Krebs, and H.-P. Kriegel. On optimizing nearest neighbor queries in high-dimensional data spaces. In *Proc. of the 8th Int'l Conf. on Database Theory*, London, January 2001.

[2] A. Broder and M. Henzinger. Information retrieval on the web: Tools and algorithmic issues. In *Foundations of Computer Science*, Invited Tutorial, 1998.

[3] S. Chakrabarti. Data mining for hypertext: A tutorial survey. *SIGKDD Explorations*, 1, 2000.

[4] B. Cherkassky, A. Goldberg, P. Martin, J. Setubal, and J. Stolfi. Augment or push? A computational study of bipartite matching and unit capacity flow algorithms. Technical Report 97-127, NEC Research Institute, 1997.

[5] J. Cho and S. Rajagopalan. A fast regular expression indexing engine. In *Proc. of the Int'l Conference on Data Engineering*, San Jose, California, Feb. 2002.

[6] D. Comer. The ubiquitous B-tree. *ACM Computing Surveys*, 11(2):121–138, June 1979.

[7] A. Crespo, J. Jannink, E. Neuhold, M. Rys, and R. Studer. A survey of semi-automatic extraction and transformation. http://www-db.stanford.edu/ crespo/publications/.

[8] U. Dayal and H.-Y. Hwang. View definition and generalization for database integration in a multidatabase system. *IEEE Trans. Software Eng.*, 10(6):628–645, 1984.

[9] S. Deerwester, S. Dumais, G. Furnas, T. Landauer, and R. Harshman. Indexing by latent semantic analysis. *Journal of the American Society for Information Science*, 41(6):391–407, 1990.

[10] C. Dwork, M. Naor, R. Kumar, and D. Sivakumar. Rank aggregation methods for the web. In *Proc. of the 10th Int'l World Wide Web Conference*, Hong Kong, May 2001.

[11] R. Fagin. Combining fuzzy information from multiple systems (extended abstract). In *Symposium on Principles of Database Systems*, 1996.

[12] R. Fagin, A. Lotem, and M. Naor. Optimal aggregation algorithms for middleware. In *Symposium on Principles of Database Systems*, 2001.

[13] T. Feder and R. Motwani. Clique partitions, graph compression and speeding-up algorithms. *Journal of Computer and System Sciences*, 51:261–272, 1995.

[14] U. Guntzer, W.-T. Balke, and W. Kiessling. Optimizing multi-feature queries for image databases. In *Proc. of the 26th Int'l Conf. on Very Large Databases*, Cairo, 2000.

[15] P. Indyk and R. Motwani. Approximate nearest neighbors: Towards removing the curse of dimensionality. In *ACM Symposium on Theory of Computing*, pages 604–613, 1998.

[16] V. Kashyap and A. P. Sheth. Semantic and schematic similarities between database objects: A context-based approach. *VLDB Journal*, 5(4):276–304, 1996.

[17] W. Kim and J. Seo. Classifying schematic and data heterogeneity in multidatabase systems. *IEEE Computer*, 24(12):12–18, 1991.

[18] Z. Kopal, editor. *Physics and Astronomy of the Moon*. Academic Press, 1962.

[19] I. Muslea. Extraction patterns for information extraction tasks: A survey. In *The AAAI-99 Workshop on Machine Learning for Information Extraction*, 1999.

[20] S. Nepal and M. V. Ramakrishna. Query processing issues in image (multimedia) databases. In *Proc. of the 15th Int'l Conf. on Data Engineering*, 1999.

[21] N. Roussopoulos, S. Kelley, and F. Vincent. Nearest neighbor queries. In *Proc. of the 1995 ACM SIGMOD Int'l Conf. on Management of Data*, pages 71–79, 1995.

[22] G. Salton. *Automatic Text Processing: The Transformation, Analysis, and Retrieval of Information by Computer*. Addison-Wesley, New York, 1989.