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Understanding, Estimating, and Incorporating Output Quality Into Join Algorithms For Information Extraction

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Abstract

Information extraction (IE) systems are trained to extract specific relations from text databases. Real-world applications often require that the output of multiple IE systems be joined to produce the data of interest. To optimize the execution of a join of multiple extracted relations, it is not sufficient to consider only execution time. In fact, the quality of the join output is of critical importance: unlike in the relational world, different join execution plans can produce join results of widely different quality whenever IE systems are involved. In this paper, we develop a principled approach to understand, estimate, and incorporate output quality into the join optimization process over extracted relations. We argue that the output quality is affected by (a) the configuration of the IE systems used to process the documents, (b) the document retrieval strategies used to retrieve documents, and (c) the actual join algorithm used. Our analysis considers a variety of join algorithms from relational query optimization, and predicts the output quality –and, of course, the execution time– of the alternate execution plans. We establish the accuracy of our analytical models, as well as study the effectiveness of a quality-aware join optimizer, with a large-scale experimental evaluation over real-world text collections and state-of-the-art IE systems.

1 Introduction

Many unstructured text documents contain valuable data that can be represented in structured form. Information extraction (IE) systems automatically extract and build structured relations from text documents, enabling the efficient use of such data in relational database systems. Real-world IE systems and architectures, such as DBLife[1], Avatar[2], and UIMA [13], view IE systems as blackboxes and "stitch" together the output from multiple such blackboxes to produce the data of interest. A common operation that lies at the heart of these multi-blackbox systems is thus *joining* the output from the IE systems. Accordingly, recent work [13, 20, 24] has started to study this important problem of *processing joins over multiple IE systems.*

Just as in traditional relational join optimization, efficiency is, of course, important when joining the output of multiple IE systems. Existing work [13, 24] has thus focused on this aspect of the problem, which is critical because IE can be time-consuming (e.g., it often involves expensive text processing operations such as part-of-speech and named-entity tagging). Unlike in the relational world, however, the *join output quality* is of critical importance, because different join execution plans might differ drastically in the quality of their output. Several factors influence the output quality, as we discuss below. The following example highlights one such factor, namely, how errors by individual IE systems impact the join output quality.

Example 1.1 Consider two text databases, the blog entries from SeekingAlpha (SA), a highly visible blog that discusses financial topics, and the archive of The Wall Street Journal (WSJ) newspaper. These databases embed information that can be used to answer a financial analyst's query (e.g., expressed in SQL) asking for all companies that recently merged, including information regarding their CEOs (see Figure 1). To answer such a query, we can use IE systems to extract a Mergers⟨Company, MergedWith⟩ relation from SA and an Executives⟨Company, CEO⟩ relation from WSJ. For Mergers, we extract tuples such as ⟨Microsoft, Softricity⟩, indicating that Microsoft merged with Softricity; for Executives, we extract tuples such as ⟨Microsoft, Steve Ballmer⟩, indicating that Steve Ballmer has been a CEO of Microsoft. After joining all the extracted tuples, we can construct the information sought by the analyst. Unfortunately, the join result is far from perfect. As shown in Figure 1, the IE system for Mergers incorrectly extracted tuple ⟨Microsoft, Symantec⟩,

[1]`http://dblife.cs.wisc.edu/`
[2]`http://www.almaden.ibm.com/cs/projects/avatar/`

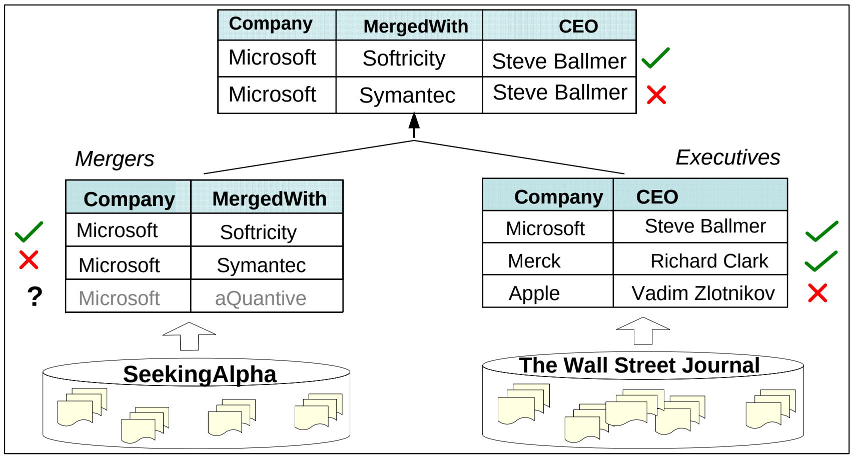


Figure 1: Joining information derived from multiple extraction systems.

and failed to extract tuple ⟨Microsoft, aQuantive⟩. Missing or erroneous tuples, in turn, hurt the quality of join results. For example, the erroneous tuple ⟨Microsoft, Symantec⟩ is joined with the correct tuple ⟨Microsoft, Steve Ballmer⟩ from the Executives relation to produce an erroneous join tuple ⟨Microsoft, Symantec, Steve Ballmer⟩. □

A key observation that we make in this paper is that different join execution plans for extracted relations can *differ vastly in their output quality*. Therefore, considering the expected output quality of each candidate plan is of critical importance, and is at the core of this paper. As we will see, the output quality of a join execution plan depends on (a) the configuration and characteristics of the IE systems used by the plan to process the text documents, and (b) the document retrieval strategies used by the plan to retrieve the documents for extraction. Previous work has recognized the importance of output quality for single-relation extraction [17, 18, 15]. Recent work [20] has also considered these two factors for choosing a join execution plan over multiple extracted relations.

Unfortunately, the earlier work has failed to consider a third, important factor, namely, (c) the *choice of join algorithm*. Our analysis reveals that the choice of join algorithm plays a crucial role in determining the overall output quality of a join execution plan over extracted relations, just as this choice crucially affects execution time in a relational model setting. In fact, different join algorithms for extracted relations might sometimes produce join results of drastically different quality.

To the best of our knowledge, this paper presents the first holistic, in-depth study—incorporating all the above factors, including the choice of join algorithms—of how to understand, estimate, and incorporate output quality into the processing of joins for information extraction. Our analysis reveals that even a simple two-way join has a vast execution plan space, where each execution plan might exhibit unique output quality—and, of course, execution efficiency—characteristics. This highlights the need for estimation techniques for the output quality of each candidate join execution plan, to guide the join optimization process in a quality-aware manner.

Our goal in this paper is to develop a principled approach to understand, estimate, and incorporate output quality into the join optimization process. We examine several important questions: How should we configure the underlying IE systems? What is the correct balance between precision and recall for the IE systems? Should we retrieve and process all the database documents, or should we selectively retrieve and process only a small subset? What join execution algorithm should we use, and what is the impact of this choice on the output quality?

A substantial challenge that we address is defining and extracting appropriate, comprehensive database statistics to guide the join optimization process in a quality-aware manner. As a key contribution of this paper, we show how to build rigorous statistical inference techniques to estimate the parameters necessary for our analytical models of output quality; furthermore, our parameter estimation happens efficiently, *on-the-fly* during the join execution. As another key contribution, we develop an end-to-end, quality-aware join optimizer that adaptively changes join execution strategies if the available statistics suggest that a change is desirable.

In summary, the main contributions of this paper are:

- We introduce a principled approach to estimate the output quality and incorporate it into the join optimization process over multiple extracted relations.

- We present an end-to-end, quality-aware join optimization approach based on our analytical models, as well as effective methods to estimate all necessary model parameters.

- We establish the accuracy of our output quality models and the effectiveness of our join optimization approach through an extensive experimental evaluation over real-life text collections and state-of-the-art IE systems.

The rest of this paper is organized as follows. In Section 2, we discuss background on joining extracted relations, to understand the various factors that impact join quality. Then, in Section 3, we discuss three join algorithms for extracted relations. In Section 4, we present our core results and introduce analytical models for the output quality of these join algorithms. In Section 6, we introduce an approach for incorporating output quality into the join optimization process. We then present our experimental results in Sections 7 and 8. Finally, we review related work in Section 9 and conclude our paper in Section 10.

2 Understanding Join Quality

In this section, we provide background on the problem of joining relations extracted from text databases via IE systems. We discuss important aspects of the problem that affect the overall *quality* of the join results. We define the family of join execution plans that we consider, as well as user-specified quality preferences.

2.1 Tuning Extraction Systems: Impact on Extraction Quality

Extraction is a noisy process, and the extracted relations may contain erroneous tuples or miss valid tuples. An extracted relation can be regarded as consisting of *good* tuples, which are the correctly extracted tuples, and *bad* tuples, which are the erroneous tuples. For instance, in Figure 1, *Mergers* consists of one good tuple, ⟨*Microsoft, Softricity*⟩, and one bad tuple, ⟨*Microsoft, Symantec*⟩. To control the quality of such extracted relations, IE systems often expose multiple tunable "knobs" that affect the proportion of *good* and *bad* tuples in the IE output. These knobs may be decision thresholds, such as the minimum confidence required before generating a tuple from text. We denote a particular configuration of such IE-specific knobs by θ [21].

Given a knob configuration θ for an IE system, we can robustly characterize the effect of such knob settings for the IE system over a database D using two values [21]: (a) the *true positive rate* $tp(\theta)$ is the fraction of good tuples that appear in the IE output over all the good tuples that could be extracted from database D with the IE system across all possible knob configurations, while (b) the *false positive rate* $fp(\theta)$ is the fraction of bad tuples that appear in the IE output over all the bad tuples that could be extracted from database D with the IE system across all possible knob configurations. In practice, we estimate the $tp(\theta)$ and $fp(\theta)$ values using a "development set" of documents and a set of "ground truth" tuples [21].

After computing the $\langle tp(\theta), fp(\theta)\rangle$ values for an IE system and for all possible configurations θ, we can keep only the Pareto optimal configurations, that is, each configuration θ that has a $\langle tp(\theta), fp(\theta)\rangle$ value that is not dominated by other configurations. The resulting configurations correspond to the optimal quality tradeoffs that we can make when materializing the underlying relation with the IE system in question: we can either pick high values of $tp(\theta)$ and high values of $fp(\theta)$, which result in a high-recall, low-precision relation, or vice versa, or anything in between.

2.2 Choosing Document Retrieval Strategies: Impact on Extraction Quality

Analogous to the above classification of the tuples extracted by an IE system from a database of E, we can classify each document in database D with respect to IE system E as a *good* document, if E can extract at least one good tuple from the document, as a *bad* document, if E can extract only bad tuples from the document, or as an *empty* document, if E cannot extract any tuples—good or bad—from the document. Ideally, when processing a text database with an IE system, we should focus on *good* documents and process as few *empty* documents as possible, for efficiency reasons; we should also process as few *bad* documents as possible, for both efficiency and output quality reasons. To this end, several document retrieval strategies have been introduced [17, 18, 19], including the following ones, which we consider in this paper.

Scan (SC) sequentially retrieves and processes each document in a database. While this strategy is guaranteed to process all *good* documents, it also processes all the *empty* and *bad* ones, and may then introduce many bad tuples.

Filtered Scan (FS) is another scan-based strategy; instead of processing all available documents, FS uses a document classifier to decide whether a document is *good* or not. By avoiding bad documents, *Filtered Scan* is more efficient than *Scan*, and tends to have fewer bad tuples in the output. However, since the classifier may also erroneously reject *good* documents, *Filtered Scan* also suffers from false negatives, and might not include all the good tuples in the output.

Automatic Query Generation (AQG) is a query-based strategy that attempts to retrieve *good* documents from the database. *Automatic Query Generation* sends (automatically generated [2]) queries to a database; these queries are expected to retrieve *good* documents. This strategy tends to retrieve and process only a small subset of the database documents, and might have a relatively large number of false negatives.

We now show that we can leverage these document retrieval strategies, which focus on a single relation, and develop *join* execution plans that involve multiple extracted relations and, in turn, multiple IE systems.

2.3 Choosing Join Execution Plans: User Preferences and Impact on Extraction Quality

In this paper, we focus on *binary natural joins*, involving two extracted relations; we leave higher order joins as future work. As discussed above, and unlike in the relational world, different join execution plans in our text-based scenario can differ radically in the quality of the join results that they produce. The output quality is affected by (a) the configuration of the IE systems used to process the database documents, as argued in Section 2.1, and (b) the document retrieval strategies used to select the documents for processing, as argued in Section 2.2. Interestingly, (c) the choice of join algorithms also has an impact on output quality, as we will see. We thus define a *join execution plan* as follows:

Definition 2.1 [Join Execution Plan] Consider two databases D_1 and D_2, as well as two IE systems E_1 and E_2. Assume E_i is trained to extract relation R_i from D_i ($i = 1, 2$). A *join execution plan* for computing $R_1 \bowtie R_2$ is a tuple $\langle E_1\langle\theta_1\rangle, E_2\langle\theta_2\rangle, X_1, X_2, JN\rangle$, where θ_i specifies the knob configuration of E_i (see Section 2.1) and X_i specifies the document retrieval strategy for E_i over D_i (see Section 2.2), for $i = 1, 2$, while JN is the choice of join algorithm for the execution, as we will discuss below.$\Box$

Given a join execution plan S over databases D_1 and D_2, the *execution time* $Time(S, D_1, D_2)$ is the total time required for S to generate the join results from D_1 and D_2. We identify the important components of execution time for different join execution plans in Section 4, where we will also analyze the output quality associated with each plan.

We now introduce some additional notation that will be needed in our output-quality analysis in the remainder of the paper. Recall from Section 2.1 that the tuples that an IE system extracts for a relation can be classified as *good* tuples or *bad* tuples. Analogously, we can also classify the *attribute value occurrences* in an extracted relation according to the tuples where these values occur. Specifically, consider an attribute value a and a tuple t in which a appears. We say that the occurrence of a in t is a *good attribute value occurrence* if t is a good tuple; otherwise, this is a *bad attribute value occurrence*. Note that an attribute value might have *both* good and bad occurrences. For instance, in Figure 1 the value "*Microsoft*" has both a good occurrence in (good) tuple ⟨*Microsoft, Softricity*⟩ and a bad occurrence in (bad) tuple ⟨*Microsoft, Symantec*⟩. We denote the set of good attribute value occurrences for an extracted relation R_i by Ag_i and the set of bad attribute value occurrences by Ab_i.

Consider now a join $R_1 \bowtie R_2$ over two extracted relations R_1 and R_2. Just as in the single-relation case, the join $T_{R_1 \bowtie R_2}$ contains *good* and *bad* tuples, denoted as $\mathbf{Tgood}_{\bowtie}$ and $\mathbf{Tbad}_{\bowtie}$, respectively. The tuples in $\mathbf{Tgood}_{\bowtie}$ are the result of joining only good tuples from the base relations; all other combinations result in bad tuples. Figure 2 illustrates this point using example relations R_1 and R_2, with 2 good and 3 bad tuples each. In this figure, we have $Ag_1 = \{a, c\}$ and $Ab_1 = \{b, d, e\}$ for relation R_1, and $Ag_2 = \{a, b\}$ and $Ab_2 = \{x, c, e\}$ for relation R_2. The composition of the join tuples yields $|\mathbf{Tgood}_{\bowtie}| = 1$ and $|\mathbf{Tbad}_{\bowtie}| = 3$.

User Preferences: In our extraction-based scenario, there is a natural trade-off between output quality and execution efficiency. Some join execution plans might produce "quick-and-dirty" results, while other plans might result in high-quality results that require a long time to produce. Ultimately, the right balance between quality and efficiency is user-specific, so our query model includes such user preferences as an important feature. One approach for handling these user preferences, which we follow in this paper, is for users to specify the desired output quality in terms of the minimum number τ_g of good tuples that they request, together with the maximum number τ_b of bad tuples that they can tolerate, so that $|\mathbf{Tgood}_{\bowtie}| \geq \tau_g$ and $|\mathbf{Tbad}_{\bowtie}| \leq \tau_b$. Other cost functions can be designed on top of this "lower level" model: examples include minimum "precision" at top-k results, minimum "recall" at the end of execution, or even a goal to maximize a weighted combination of precision and recall within a pre-specified execution time budget. Fundamentally, such alternate quality constraints can be mapped to the (somewhat lower level) model that we study in this paper. Therefore, for conciseness and clarity, in our work the user quality requirements are expressed in terms of τ_g and τ_b, as discussed above.

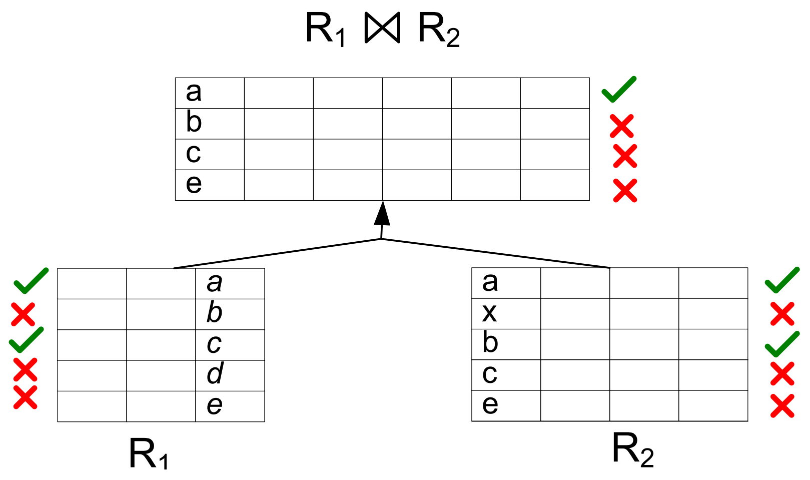


Figure 2: Composition of $R_1 \bowtie R_2$ from extracted relations R_1 and R_2.

3 Join Algorithms for Extracted Relations

As argued above, the choice of join algorithm is one of the key factors affecting the result quality. (Other factors, which we have already discussed, are the tuning of the IE systems and the choice of document retrieval strategies; see Sections 2.1 and 2.2.) We now briefly discuss three alternate join algorithms, which we later analyze in terms of their output quality and execution efficiency. Following Section 2.3, each join algorithm will attempt to meet the user-specified quality requirements as efficiently as possible. This goal is then related to that of *ripple joins* [16] for online aggregation, which minimize the time to reach user-specified performance requirements. Our discussion of the alternate join algorithms builds on the ripple join principles.

As we will see, the join algorithms base their stopping conditions on the user-specified quality requirements, given as τ_g and τ_b bounds on the number of good and bad tuples in the join output. Needless to say, the join algorithms do not have any a-priori knowledge of the correctness of the extracted tuples, so the algorithms will rely on estimates to decide when the quality requirements have been met (see Section 4). On a related note, the join algorithms might estimate that the quality requirements cannot be met, in which case the join optimizer may build on the current execution with a different join execution plan or, alternatively, discard any produced results and start a new execution plan from scratch (see Section 6).

3.1 Independent Join

The Independent Join algorithm (IDJN) [19] computes a two-way join by extracting the two relations *independently* and then joining them to produce the final output. To extract each relation, IDJN retrieves the database documents by choosing from the document retrieval strategies in Section 2.1, namely, *Scan*, *Filtered Scan*, and *Automatic Query Generation*.

Figure 3 describes the IDJN algorithm for the settings of Definition 2.1 and for the case where the document retrieval strategy is *Scan*. IDJN receives as input the user-specified output quality requirements τ_g and τ_b (see Section 2), and the relevant extraction systems $E_1\langle\theta_1\rangle$ and $E_2\langle\theta_2\rangle$. IDJN sequentially retrieves documents for both relations, runs the extraction systems over them, and joins the newly extracted tuples with all the tuples from previously seen documents. Conceptually, the join algorithm can be viewed as "traversing" the Cartesian product $D_1 \times D_2$ of the database documents, as illustrated in Figure 4: the horizontal axis represents the documents in D_1, the vertical axis represents the documents in D_2, and each element in the grid represents a document pair in $D_1 \times D_2$, with a dark circle indicating an already visited element. (The documents are displayed in the order of retrieval.) Figure 4 shows a "square" version of IDJN, which retrieves documents from D_1 and D_2 at the same rate; we can generalize this algorithm to a "rectangle" version that retrieves documents from the databases at different rates.

The number of documents to explore will depend on the user-specified values for τ_g and τ_b, and also on the choice of the retrieval strategies for each relation. When using *Filtered Scan*, we may filter out a retrieved document from a database and, as a result, some portion of $D_1 \times D_2$ will remain unexplored. Similarly, when using *Automatic Query Generation*, the maximum number of documents retrieved from a database may be limited, resulting in a similar effect.

```
Input: number of good tuples $\tau_g$, number of bad tuples $\tau_b$, $E_1\langle\theta_1\rangle$, $E_2\langle\theta_2\rangle$
Output: $R_1 \bowtie R_2$
$\mathbf{R}_j = \emptyset$ /* tuples produced for $R_1 \bowtie R_2$ */
$Tr_1 = \emptyset$, $Tr_2 = \emptyset$ /* tuples extracted for $R_1$ and $R_2$ */
$Dr_1 = \emptyset$, $Dr_2 = \emptyset$ /* set of documents retrieved from $D_1$ and $D_2$ */
while {estimated # good tuples in $\mathbf{R}_j < \tau_g$} && {estimated # bad tuples in $\mathbf{R}_j \leq \tau_b$} do
    if $|Dr_1| < |D_1|$ then
        Retrieve an unseen document $d$ from $D_1$ and add to $Dr_1$
        Process $d$ using $E_1$ at $\theta_1$ to generate tuples $t_1$
    end
    if $|Dr_2| < |D_2|$ then
        Retrieve an unseen document $d$ from $D_2$ and add to $Dr_2$
        Process $d$ using $E_2$ at $\theta_2$ to generate tuples $t_2$
    end
    $T_{join} = (t_1 \bowtie t_2) \cup (Tr_1 \bowtie t_2) \cup (t_1 \bowtie Tr_2)$
    $Tr_1 = Tr_1 \cup t_1$
    $Tr_2 = Tr_2 \cup t_2$
    $\mathbf{R}_j = \mathbf{R}_j \cup T_{join}$
    if {$|Dr_1| = |D_1|$} && { $|Dr_2| = |D_2|$} then
        return $\mathbf{R}_j$
    end
end
return $\mathbf{R}_j$
```

Figure 3: The IDJN algorithm using *Scan*.

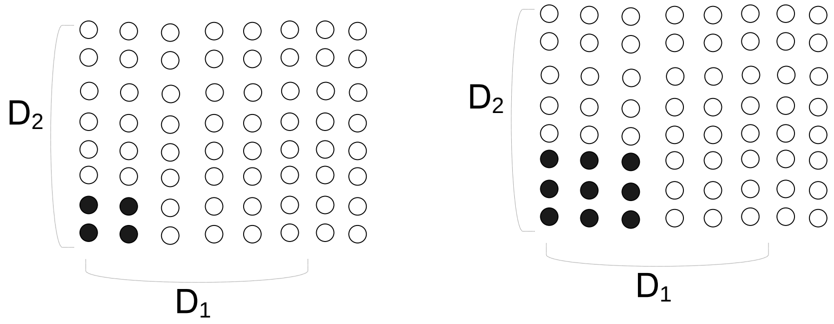


Figure 4: Exploring $D_1 \times D_2$ with IDJN using *Scan*.

3.2 Outer/Inner Join

The IDJN algorithm does not effectively utilize any existing keyword-based indexes on the text databases. Existing indexes can be used to guide the join execution towards processing documents likely to contain a joining tuple. The next join algorithm, Outer/Inner Join (OIJN), shown in Figure 5, corresponds to a nested-loops join algorithm in the relational world. OIJN thus picks one of the relations as the "outer" relation and the other as the "inner" relation. (Our analysis in Section 4 can be used to identify which relation should serve as the outer relation in a join execution.) OIJN retrieves documents for the outer relation using one of the document retrieval strategies (i.e., *Scan*, *Filtered Scan*, or *Automatic Query Generation*) and processes them using an appropriate extraction system. OIJN then generates keyword queries using the values for the joining attributes in the extracted outer relation. Using these queries, OIJN retrieves and processes documents for the inner relation that are likely to contain the "counterpart" for the already seen outer-relation tuples.

Figure 6(a) illustrates the traversal through $D_1 \times D_2$ for the OIJN algorithm: each querying step corresponds to a *complete* probe of the inner relation's database, which sweeps out an entire row of $D_1 \times D_2$. Thus, OIJN effectively traverses the space, biasing towards documents likely to contain joining tuples from the inner relation, which may result in an efficient refinement over IDJN. However, the maximum number of documents that can be retrieved via a query may be limited by the search interface, which, in turn, limits the maximum number of tuples retrieved using OIJN. The impact of this limit on the number of matching documents is denoted in Figure 6(a) as gray circles that depict some unexplored area in the $D_1 \times D_2$ space.

3.3 Zig-Zag Join

The Zig-Zag Join (ZGJN) algorithm generalizes the idea of using keyword queries from OIJN, so that we can now query for *both* relations and interleave the extraction of the two relations; see Figure 7. Starting with one tuple extracted for one relation, ZGJN retrieves documents—via keyword querying on the join attribute values—for extracting the second

```
Input: number of good tuples $\tau_g$, number of bad tuples $\tau_b$, $E_1\langle\theta_1\rangle$, $E_2\langle\theta_2\rangle$
Output: $R_1 \bowtie R_2$
$\mathbf{R}_j = \emptyset$ /* tuples produced for $R_1 \bowtie R_2$ */
/* $R_1$ is the outer relation and $R_2$ is the inner relation */
$Tr_1 = \emptyset$, $Tr_2 = \emptyset$ /* tuples extracted for $R_1$ and $R_2$ */
$Dr_1 = \emptyset$, $Dr_2 = \emptyset$ /* sets of documents retrieved from $D_1$ and $D_2$ */
while {estimated # good tuples in $\mathbf{R}_j < \tau_g$} && {estimated # bad tuples in $\mathbf{R}_j \leq \tau_b$} do
    $Q_s = \emptyset$ /* queries for the inner relation */
    Retrieve an unseen document $d$ from $D_1$ and add to $Dr_1$
    Process $d$ using $E_1$ at $\theta_1$ to generate tuples $t_1$
    Generate keyword queries from $t_1$ and add to $Q_s$
    $Tr_1 = Tr_1 \cup t_1$
    $\mathbf{R}_j = \mathbf{R}_j \cup (t_1 \bowtie Tr_2)$
    foreach query $q \in Q_s$ do
        Issue $q$ to $D_2$ to retrieve unseen matching documents and add them to $Dr_2$
        Process all unprocessed documents in $Dr_2$ using $E_2$ at $\theta_2$ to generate tuples $t_2$
        $Tr_2 = Tr_2 \cup t_2$
        $\mathbf{R}_j = \mathbf{R}_j \cup (Tr_1 \bowtie t_2)$
    end
    if $|Dr_1| = |D_1|$ then
        return $\mathbf{R_j}$
    end
end
return $\mathbf{R_j}$
```

Figure 5: The OIJN algorithm using *Scan* for the outer relation.

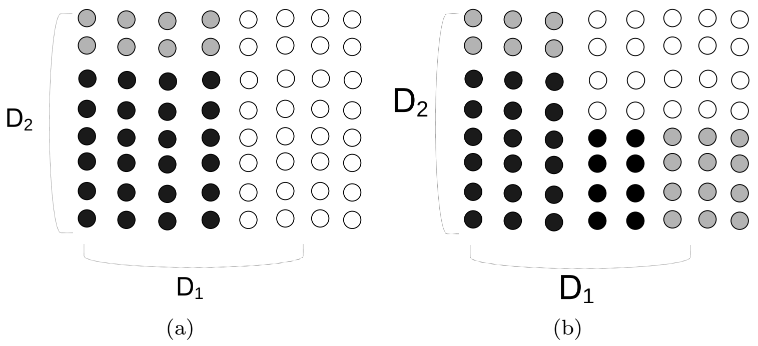


Figure 6: Exploring $D_1 \times D_2$ with (a) OIJN and (b) ZGJN.

relation. In turn, the tuples from the second relation are used to build keyword queries to retrieve documents for the first relation, and the process iterates, effectively alternating the role of the "outer" relation of a nested loops execution over the two relations. Conceptually, each step corresponds to a sweep of an entire row or column of $D_1 \times D_2$, as shown in Figure 6(b). Similarly to OIJN, ZGJN can efficiently traverse the $D_1 \times D_2$ space; however, just as for OIJN, the space covered by ZGJN is limited by the maximum number of documents returned by the underlying search interface.

4 Estimating Join Quality

Each join execution plan (Definition 2.1) produces join results whose quality depends on the choice of IE system—and their tuning parameters (see Section 2.1)—, document retrieval strategies (see Section 2.2), and join algorithms (see Section 3). We now turn to the core of this paper, where we present *analytical models for the output quality* of the join execution plans. Specifically, for each execution plan we derive formulas for the number $|\mathbf{Tgood}_{\bowtie}|$ of good tuples and the number $|\mathbf{Tbad}_{\bowtie}|$ of bad tuples in $R_1 \bowtie R_2$ that the plan produces, as a function of the number of documents retrieved and processed by the IE systems.

4.1 Notation

In the rest of the discussion, we consider two text databases, D_2 and D_2, with two IE systems E_1 and E_2, where extraction system E_i extracts relation R_i from D_i ($i = 1, 2$). Table 1 summarizes our notation for the good, bad, and empty database documents, for the good and bad tuples and attribute values, as well as for their frequency in the

```
Input: number of good tuples $\tau_g$, number of bad tuples $\tau_b$, $E_1\langle\theta_1\rangle$, $E_2\langle\theta_2\rangle$, $Q_{seed}$
Output: $R_1 \bowtie R_2$
$\mathbf{R}_j = \emptyset$ /* tuples produced for $R_1 \bowtie R_2$ */
$Tr_1 = \emptyset$, $Tr_2 = \emptyset$ /* tuples extracted from $R_1$ and $R_2$ */
$Dr_1 = \emptyset$, $Dr_2 = \emptyset$ /* sets of documents retrieved from $D_1$ and $D_2$*/
$Q_1 = Q_{seed}$, $Q_2 = \emptyset$ /* set of queries issued to $D_1$ and $D_2$ */
foreach query $q_1 \in Q_1$ do
    Issue $q_1$ to $D_1$ to retrieve unseen matching documents and add them to $Dr_1$
    Process all unprocessed documents in $Dr_1$ using $E_1$ at $\theta_1$ to generate tuples $t_1$
    Generate keyword queries from $t_1$ and append to $Q_2$
    $Tr_1 = Tr_1 \cup t_1$
    $\mathbf{R}_j = \mathbf{R}_j \cup (t_1 \bowtie Tr_2)$
    foreach query $q_2 \in Q_2$ do
        Issue $q_2$ to $D_2$ to retrieve unseen matching documents and add them to $Dr_2$
        Process all unprocessed documents in $Dr_2$ using $E_2$ at $\theta_2$ to generate tuples $t_2$
        Generate keyword queries from $t_2$ and append to $Q_1$
        $Tr_2 = Tr_2 \cup t_2$
        $\mathbf{R}_j = \mathbf{R}_j \cup (Tr_1 \bowtie t_2)$
        if {estimated # good tuples in $\mathbf{R}_j \geq \tau_g$} && {estimated # bad tuples in $\mathbf{R}_j \leq \tau_b$} then
            return $\mathbf{R}_j$
        end
    end
end
```

Figure 7: The ZGJN algorithm.

extracted relations (see Section 2.3). Additionally, for a natural join attribute A[3], we denote the attribute values common to both extracted relations R_1 and R_2 as follows: $Agg = Ag_1 \cap Ag_2$, $Agb = Ag_1 \cap Ab_2$, $Abg = Ab_1 \cap Ag_2$, and $Abb = Ab_1 \cap Ab_2$. In Figure 2, for example, these sets are $Agg = \{a\}$, $Agb = \{c\}$, $Abg = \{b\}$, and $Abb = \{e\}$.

Symbol	**Description**
R_i	Extracted relations ($\mathbf{i = 1, 2}$)
E_i	Extraction system for R_i
X_i	Document retrieval strategy for E_i
D_i	Database for extracting R_i
Dg_i	Set of good documents in D_i
Db_i	Set of bad documents in D_i
De_i	Set of empty documents in D_i
Dr_i	Set of documents retrieved from D_i
Ag_i	Good attribute values in R_i
Ab_i	Bad attribute values in R_i
$g_i(a)$	Frequency of a in Dg_i
$b_i(a)$	Frequency of a in Db_i
$O_i(a)$	Frequency of a in Dr_i

Table 1: Notation summary.

4.2 Analyzing Join Execution Plans: General Scheme

We begin our analysis by sketching a general scheme to study the output of an execution plan in terms of its number of good tuples $|\mathbf{Tgood}_{\bowtie}|$ and the number of bad tuples $|\mathbf{Tbad}_{\bowtie}|$. In later sections, we will instantiate this general scheme for the various join execution plans that we study.

Consider relations R_1 and R_2, to be extracted and joined over a single common attribute A, and let a be a value of join attribute A with $g_1(a)$ *good* occurrences in D_1[4] and $g_2(a)$ *good* occurrences in D_2. Suppose that a join execution retrieves documents Dr_1 from D_1 and documents Dr_2 from D_2, and we observe $gr_1(a)$ *good* occurrences of a in Dr_1 and $gr_2(a)$ *good* occurrences of a in Dr_2. Then, the number of good *join* tuples with $A = a$ is $gr_1(a) \cdot gr_2(a)$ (see Section 2.3). Generalizing this analysis to *all* good attribute occurrences common to both relations (i.e., to the values in Agg) the total number $|\mathbf{Tgood}_{\bowtie}|$ of good tuples extracted for $R_1 \bowtie R_2$ is:

$$|\mathbf{Tgood}_{\bowtie}| = \sum_{a \in Agg} gr_1(a) \cdot gr_2(a) \quad (1)$$

[3]Without loss of generality, we assume that we have a single join attribute A. When we have multiple join attributes, we treat their union as a "conceptual" single attribute.

[4]Conceptually, $g(a)$ can be defined in terms of the number of good tuples that contain attribute value a. For simplicity, we assume that each attribute value appears only once in each document. This simplification significantly reduces the complexity of the statistical model, without losing much of its accuracy, since most of the attributes indeed appear only once in each document. (We verified the latter experimentally.)

where Agg is the set of join attribute values with good occurrences in both relations (see Section 4.1). Among other factors, the values of $gr_1(a)$ and $gr_2(a)$ depend on the frequencies $g_1(a)$ and $g_2(a)$ of a in the complete databases D_1 and D_2. As we will see in the next sections, we can estimate the conditional expected frequency $E[gr_i(a)|g_i(a)]$ for each attribute value given the configuration of the IE systems, the choice of document retrieval strategy, and the choice of join algorithm. Assuming, for now, that we know the conditional expectations, we have:

$$E[|\mathbf{Tgood}_{\bowtie}|] = \sum_{a \in Agg} E[gr_1(a)|g_1(a)] \cdot E[gr_2(a)|g_2(a)]$$

In practice, we do not know the exact frequencies $g_1(a)$ and $g_2(a)$ for each attribute value. However, we can typically estimate the probability $Pr\{g_i\}$ that an attribute value occurs g_i times in an extracted relation, using parametric or nonparametric approaches (e.g., often the frequency distribution of attribute values follows a power-law [3, 17]). So,

$$E[|\mathbf{Tgood}_{\bowtie}|] = |Agg| \cdot \sum_{g_1=1}^{|Dg_1|} \sum_{g_2=1}^{|Dg_2|} E[gr_1|g_1] \cdot E[gr_2|g_2] \cdot Pr\{g_1, g_2\}$$

The factor $Pr\{g_1, g_2\}$ is the probability that an attribute value has g_1 good occurrences in D_1 and g_2 good occurrences in D_2. We make a simplifying independence assumption so that $Pr\{g_1, g_2\} = Pr\{g_1\} \cdot Pr\{g_2\}$. Alternatively, we can use the fact that frequent attribute values in one relation are commonly frequent in the other relation as well, and vice versa. In this scenario, we would have: $Pr\{g_1\} \approx Pr\{g_2\}$ and $Pr\{g_1, g_2\} \approx Pr\{g_1\} \approx Pr\{g_2\}$.

To compute the number $|\mathbf{Tbad}_{\bowtie}|$ of bad tuples in $R_1 \bowtie R_2$ we proceed in the same fashion, with two main differences: we need to consider three different classes of attributes, namely, Agb, Abg, and Abb, and we need to compute the expected number of *bad* attribute occurrences in an extracted relation. Specifically,

$$|\mathbf{Tbad}_{\bowtie}| = J_{gb} + J_{bg} + J_{bb}$$

where $J_{gb} = |Agb| \cdot \sum_{g_1=1}^{|Dg_1|} \sum_{b_2=1}^{|Db_2|} E[gr_1|g_1] \cdot E[br_2|b_2] \cdot Pr\{g_1, b_2\}$. We can compute values for J_{bg} and J_{bb} using $|Abg|$ and $|Abb|$, respectively, along with appropriate tuple cardinality values.

Using this generic analysis along with the expected frequencies for the attribute occurrences, we can derive the exact composition of the join $R_1 \bowtie R_2$. We now complete and instantiate this analysis to the alternate join algorithms of Section 3.

4.3 Independent Join

Our goal is to derive the expected frequency $E[gr_i]$ for good attribute occurrences and $E[br_i]$ for bad attribute occurrences in R_i after we have retrieved Dr_i documents from D_i, given the frequencies of occurrence in D_i $(i = 1, 2)$. As IDJN independently generates each base relation, the analysis for $E[gr_1]$ is the same as that for $E[gr_2]$, and depends on the choice of document retrieval strategy and extraction system configuration; similarly, the analysis for $E[br_1]$ is the same as that for $E[br_2]$. Hence, we ignore the relation subindex in the discussion.

We start by computing $E[gr]$ for an attribute value a with $g(a) = g$ good occurrences. We focus only on the good documents Dg in D, as good occurrences only appear in the good documents. We model a document retrieval strategy as *sampling processes over the good documents* Dg [17, 18]. After retrieving Dgr good documents, the probability of observing k times the good attribute occurrence a in the retrieved documents follows a hypergeometric distribution, $Hyper(|Dg|, |Dgr|, g, k)$, where $Hyper(D, S, g, k) = \binom{g}{k} \cdot \binom{D-g}{S-k} / \binom{D}{S}$.

We process the retrieved documents Dgr using an extraction system E. As E is not perfect, even if we retrieve k documents that contain the good attribute occurrences, E examines each of the k documents independently and with probability $tp(\theta)$ for each document, outputs the occurrence. So, we will see good occurrences in the extracted tuples only $l \leq k$ times, and l is a random variable following the binomial distribution. Thus, the expected frequency of a good attribute occurrence in an extracted relation, after processing j good documents, is:

$$E[gr \big| |Dgr| = j] = \sum_{k=0}^{g} Hyper(|Dg|, j, g, k) \cdot \sum_{l=0}^{k} l \cdot Bnm(k, l, tp(\theta))$$

where $Bnm(n, k, p) = \binom{n}{k} \cdot p^k \cdot (1-p)^{n-k}$ is the binomial distribution and g is the frequency of good attribute occurrences in D. The derivation for bad attribute occurrences $E[br]$ is analogous to that for $E[gr]$, but now a bad attribute occurrence can be extracted from *both* good and bad documents in the database.

So far, the analysis implicitly assumed that we know the exact proportion of the good and bad documents retrieved, i.e., $|Dgr|$ and $|Dbr|$. In reality, though, this proportion depends on the choice of document retrieval strategy. The effect of a document retrieval strategy was analyzed in [21]. We now discuss this analysis in the context of our setting.

Scan sequentially retrieves documents for E from database D, in no specific order. Therefore, when *Scan* retrieves $|Dr|$ documents, E processes $|Dgr|$ *good* documents, where $|Dgr|$ is a random variable that follows the hypergeometric distribution. Specifically, the probability of processing exactly j good documents is:

$$Pr(|Dgr| = j) = Hyper(|D|, |Dr|, |Dg|, j)$$

where $Hyper(D, S, g, k) = \binom{g}{k} \cdot \binom{D-g}{S-k} / \binom{D}{S}$ is the hypergeometric distribution. We compute the probability of processing j bad documents analogously.

Filtered Scan is similar to *Scan*, except that a document classifier filters out documents that are not good candidates for containing good tuples. Thus, only documents that *survive* the classification step will be processed. Document classifiers are not perfect either, and they are usually characterized by their *true positive rate* C_{tp} and *false positive rate* C_{fp}. Intuitively, for a classifier C, the true positive rate C_{tp} is the fraction of documents in Dg classified as good, and the false positive rate C_{fp} is the fraction of documents in Db incorrectly classified as good. Therefore, the main difference from *Scan* is that now the probability of processing j *good* documents after retrieving $|Dr|$ documents from the database is:

$$Pr(|Dgr| = j) = \sum_{n=0}^{|Dr|} Hyper(|D|, |Dr|, |Dg|, n) \cdot Bnm(n, j, C_{tp})$$

We compute the probability of processing j bad documents in a similar way using C_{fp}.

Automatic Query Generation retrieves documents from D by issuing queries designed to retrieve mainly good documents. Consider the case where AQG has sent Q queries to the database. If a query q retrieves $g(q)$ documents and has precision $P(q)$, where $P(q)$ is the fraction of documents retrieved by q that are good, then the probability that a good document is retrieved by q is $\frac{P(q) \cdot g(q)}{|Dg|}$. Assuming that the queries sent by AQG are only biased towards documents in Dg, the queries are conditionally independent within Dg. In this case, the probability that a *good* document d is retrieved by at least one of the Q queries is:

$$Pr_g(d) = 1 - \prod_{i=1}^{Q} \left(1 - \frac{p(q_i) \cdot g(q_i)}{|Dg|}\right) \tag{2}$$

Since each document is retrieved independently of each other, the number of good documents retrieved (and processed) follows a binomial distribution, with $|Dg|$ trials and $Pr_g(d)$ probability of success in each trial.

$$Pr(|Dgr| = j) \quad = \quad Bnm(|Dg|, j, Pr_g(d))$$

The analysis is analogous for the bad documents.

The execution time for an IDJN execution strategy follows from the general discussion above. Consider the case when we retrieve $|Dr_1|$ documents from D_1 and $|Dr_2|$ documents from D_2 using *Scan* for both relations. In this case IDJN does not filter or query for any documents, so the execution time is:

$$Time(S, D_1, D_2) = \sum_{i=1}^{2} |Dr_i| \cdot \left(t_R^i + t_E^i\right)$$

where t_R^i is the time to retrieve a document from D_i and t_E^i is the time required to process the document using the E_i IE system. For execution strategies that use *Filtered Scan* or *Automatic Query Generation*, we compute the execution time by considering the time t_F^i to filter a document, or the time t_Q^i (together with the number of queries issued $|Qs^i|$) to send and retrieve the results of a query[5].

4.4 Outer/Inner Join

For OIJN, the analysis for the outer relation is the same as that for an individual relation in IDJN: the expected frequency of (good or bad) occurrences of an attribute value depends solely on the document retrieval strategy and the extraction system for the outer relation. On the other hand, the expected frequency of the attribute occurrences for

[5]We make a number of simplifying assumptions here, assuming that the time to retrieve a document, to process it using an extraction system, and so on is constant across documents. Even though this is rarely true in practice, the approximation is good enough for our purposes, given the difficulty of knowing such values for each document.

the inner relation depends on the number of queries issued using attribute values from the outer relation, as well as on the extraction system used to process the matching documents. Our analysis focuses on the inner relation; again, we omit the relation subindex, for simplicity.

Consider again an attribute value a with $g(a)$ good occurrences in the database, and a query q generated from a which has $H(q)$ document matches and precision $P(q)$, where $P(q)$ is the fraction of documents matching q that are good. Thus, the set of good documents that can match q is $H_g(q)$ with $|H_g(q)| = |H(q)| \cdot P(q)$. When we issue q, the subset of $H_g(q)$ documents returned is limited by the search interface. Specifically, if the search interface returns only the top-k documents for a query, for a fixed value of k, we expect to see $k \cdot P(q)$ good documents. An important observation is that the documents that match q but are not returned in the top-k results can also be retrieved by queries other than q. Thus, when we issue Qs queries and retrieve Dgr good documents, we can observe a from two disjoint sets: $k \cdot P(q)$, the good documents in the top-k answers for q, and the rest, $Dgr_{rest} = Dgr - k \cdot P(q)$.

If $Pr_q\{gr_q|g(a), q\}$ is the probability that we will observe attribute value a a total of gr_q times in the top results for q, and $Pr_r\{gr_{rest}|g(a), Dgr_{rest}\}$ is the probability that we will observe attribute value a a total of gr_{rest} times in the remainder documents, we have:

$$E[gr(a)] = \sum_{l=0}^{g(a)} l \cdot (Pr_q\{l|g(a), q\} + Pr_r\{l|g(a), Dgr_{rest}\})$$

For $Pr_q\{gr_q|g(a), q\}$, we model querying as sampling over $H_g(q)$ while drawing $k \cdot P(q)$ samples, and derive:

$$Pr_q\{gr_q|g(a), q\} = \sum_{i=0}^{g(a)} Hyper\big(|H_g(q)|, k \cdot P(q), g(a), i\big) \cdot B_g(i, gr_q)$$

where $B_g(k, l) = Bnm(k, l, tp(\theta))$.

For $Pr_r\{gr_{rest}|g(a), Dgr_{rest}\}$, we observe that the total number $g(a)$ of documents in Dgr_{rest} is the number of documents containing a minus the good documents that matched the query. Specifically, among documents not retrieved via the query q, an attribute value can occur $g'(a)$ times where $g'(a) = g(a) \cdot \frac{|H_g(q)| - k \cdot P(q)}{|H_g(q)|}$. We model the process of retrieving documents for a, using queries other than q, as sampling over Dg while drawing samples Dgr_{rest}, and derive:

$$Pr_r\{l|g(a), |Dgr_{rest}| = j\} = \sum_{i=0}^{g(a)} H_g\left(g'(a), i\right) \cdot B_g(i, l)$$

where $H_g(k, i) = Hyper(|Dg|, j, k, i)$. For $E[br(a)]$, i.e., a bad attribute value, we proceed similarly.

Regarding execution time, if we retrieve Dr_o documents using *Scan* for the outer relation and send Qs queries for the inner relation, in turn retrieving Dr_i documents, the execution time is:

$$Time(S, D_1, D_2) = |Dr_o| \cdot (t_R^o + t_E^o) + |Dr_i| \cdot \big(t_R^i + t_E^i\big) + |Qs| \cdot t_Q^i$$

where t_R^o and t_E^o are the times to retrieve and process, respectively, a document for the outer relation, t_R^i and t_E^i are the times to retrieve and process, respectively, a document for the inner relation, and t_Q^i is the time to issue a query to the inner relation's database. The value for $|Dr_o|$ is determined so that the resulting join execution meets the user requirements.

4.5 Zig-Zag Join

To analyze the ZGJN algorithm, we define a *zig-zag* graph consisting of two classes of nodes: *attribute* nodes ("a"nodes) and *document* nodes ("d" nodes), and two classes of edges: *hit* edges and *generates* edges. A *hit* edge $A \rightarrow D$ connects an a node to a d node, and denotes that a generated a *hit* on d, that is, d matches the query generated using a. A *generates* edge $d \rightarrow a$ connects a d node to an a node and denotes that processing d generated a.

As an example, consider the *zig-zag* graph in Figure 8 for joining *Mergers* and *Executives* from Example 1.1 on the *Company* attribute. We begin with a *seed* query ["Microsoft"] for *Mergers* and issue it to the D_2 database. This query hits a document d_{21}. Processing d_{21} generates tuples for *Executives*, which contain values Microsoft and AOL for *Company*. At this stage, the total number of attributes generated for *Executives* is determined by the number of documents that matched the query ["Microsoft"]. Next, we issue the query ["AOL"] to D_1, which retrieves documents d_{11} and d_{12}. The total number of documents retrieved from D_1 is determined by the number of attribute values generated for *Executives* in the previous step. Processing d_{11} for *Mergers* generates a new attribute value, AOL, which is used to generate new queries for D_2, and the process continues.

The above example shows that the characteristics of a ZGJN execution are determined by the total number of attribute values and documents that could be *reached* following the edges on the *zig-zag* graph. Thus, the structure of

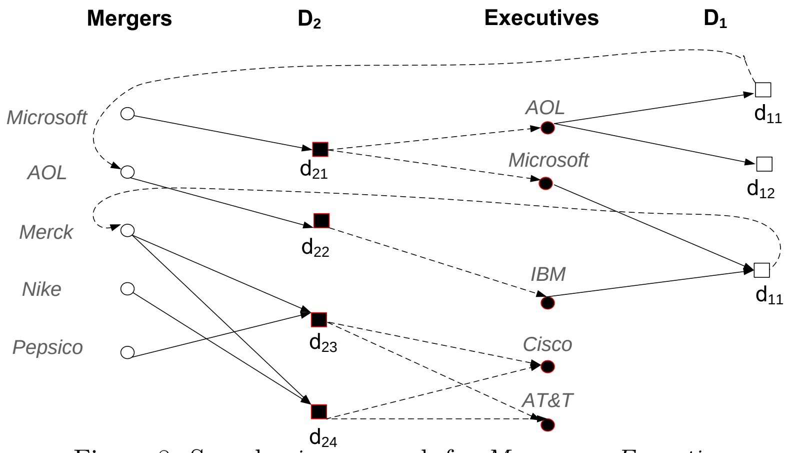


Figure 8: Sample *zig-zag* graph for *Mergers* ⋈ *Executives.*

the graph defines the execution time and the output quality for ZGJN. We study the interesting properties of a *zig-zag* graph using the theory of random graphs [23]. Specifically, we extend the approach in [17, 18] and use generating functions to describe the properties of a *zig-zag* graph. We begin by defining two generating functions, $h_0(x)$, which describes the number of hits for a *randomly chosen* attribute value, and $ga_0(x)$, which describes the number of attributes generated from a *randomly chosen* document.

$$h_0(x) = \sum_k pa_k \cdot x^k, \qquad ga_0(x) = \sum_k pd_k \cdot x^k$$

where pa_k is the probability that a randomly chosen attribute a matches k documents, and pd_k is the probability that a randomly chosen document generates k attributes. To keep the model parameters manageable, we approximate the distribution for pa_k with the attribute frequency distribution used by our general analysis (Section 4.2), as the two distributions tend to be similar. Specifically, we derive the probability that an attribute a matches k documents using the probability that a is extracted from k documents.

Our goal, however, is to study the frequency distribution of an attribute or a document chosen by *following a random edge*. For this, we use the method in [23, 17] and define functions $H(x)$ and $Ga(x)$ that, respectively, describe the attribute and the document frequency chosen by following a random edge on the *zig-zag* graph.

$$H(x) = x\frac{h_0{}'(x)}{h_0{}'(1)}, \quad Ga(x) = x\frac{ga_0{}'(x)}{ga_0{}'(1)}$$

where $h_0{}'(x)$ is the first derivative of $h_0(x)$ and $ga_0{}'(x)$ is the first derivative of $ga_0(x)$. To distinguish between the relations, we denote the functions using subindices: $H_i(x)$ and $Ga_i(x)$, respectively, describe the attribute and the document frequency distributions for R_i $(i = 1, 2)$.

We will now derive equations for the number of documents $E[|Dr_1|]$ and $E[|Dr_2|]$ retrieved from D_1 and D_2, respectively, and the number of attribute values $E[|Ar_1|]$ and $E[|Ar_2|]$ generated for relation R_1 and R_2, respectively. For our analysis, we exploit three useful properties, *Moments*, *Power*, and *Composition* of generating functions (see [23, 17]). The distribution of the total number $|Dr_2|$ of documents retrieved from D_2 using attributes from R_1 can be described by the function:

$$Dr_2(x) = H_1(x)$$

Further, the distribution of the attribute values generated from a D_2 document picked by following a random edge is given by $Ga_2(x)$. Using the *Composition* property, the distribution of the total number of attribute values generated from $|Dr_2|$ is given by the function:

$$Ar_2(x) = H_1(Ga_2(x))$$

The total number $|Ar_2|$ of R_2 attribute values that will be used to derive the D_2 documents is a random variable with its distribution described by $Ar_2(x)$. Furthermore, the distribution of the documents retrieved by an R_2 attribute value picked by following a random edge is described by $H_2(x)$. Once again, using the *Composition* property, we describe the distribution of the total number of D_2 documents retrieved using Ar_2 attribute values using the generating function:

$$Dr_1(x) = Ar_2(H_2(x)) = H_1(Ga_2(H_2(x)))$$

To describe the total number $|Ar_1|$ of R_1 attribute values derived by processing a Dr_1 document, we compose $Dr_1(x)$ and $Ga_1(x)$, and define:

$$Ar_1(x) = Dr_1(Ga_1(x)) = H_1(Ga_2(H_2(Ga_1(x))))$$

Next, we generalize the above functions for Q_1 queries sent from R_1 attribute values and using the *Power* property:

$$Dr_2(x) = [H_1(x)]^{|Q_1|}, \qquad Ar_2(x) = [H_1(Ga_2(x))]^{|Q_1|}$$

Finally, we compute the expected values $E[|Dr_2|]$ after we have issued Q_1 queries using R_1 attribute values. For this, we resort to the *Moments* property.

$$\begin{aligned} E[|Dr_2|] &= \left[\frac{d}{dx}\,[H_1(x)]^{|Q_1|}\right]_{x=1} \\ E[|Ar_2|] &= \left[\frac{d}{dx}\,[H_1(Ga_2(x))]^{|Q_1|}\right]_{x=1} \end{aligned}$$

We derive values for $E[|Dr_1|]$ and $E[|Ar_1|]$ in a similar manner.

We derived the total number of attributes $E[|Ar_1|]$ and $E[|Ar_2|]$ for the individual relations, but we are interested in the total number of good and bad attribute occurrences generated for each relation. For this, we split the number of attributes in a relation, using the fraction of good or bad attribute occurrences in a relation. For instance,

$$E[|gr_1|] = E[|Ar_1|] \cdot \frac{|Ag_1|}{|Ag_1| + |Ab_1|}$$

Given the analysis above, we compute the execution time of a zig-zag join that satisfies the user-specified quality requirements: if we issue $|Qs^i|$ queries and retrieve $|Dr_i|$ documents for relation R_i, $i = 1, 2$, the execution time is:

$$Time(S, D_1, D_2) = \sum_{i=1}^{2} |Dr_i| \cdot \left(t_R^i + \cdot t_E^i\right) + |Qs^i| \cdot t_Q^i$$

The values for $|Qs^1|$ and $|Qs^2|$ are the minimum values required for the output quality to meet the user-specified quality requirements.

To summarize, in this section we rigorously analyzed each join algorithm for the various choices of document retrieval strategies and extraction system configurations. Our analysis resulted in formulas for the join quality composition in terms of the number of documents retrieved for each relation or the number of keyword queries issued to a database. Conversely, this analysis can be used to determine these input values for a given output quality.

5 Estimating Model Parameters

To estimate the output quality, our analysis in Section 4 relies on three classes of parameters, namely, the retrieval-specific parameters, the single-relation-specific parameters, and the join-specific parameters. The retrieval-specific parameters involve parameters such as $E[p_g(q)], E[p_b(q)]$, and $E[g(q)]$ for the AQG queries, or the classifier properties C_{tp} and C_{fp} for *FS*, or $E[|H(q)|]$ and $E[P(q)]$ for OIJN. The single-relation-specific parameters on which our analysis relies are, $|Dg_i|$, $|Db_i|$, $|De_i|$, for each extracted relation R_i, as well as the frequency distribution of the good and bad attributes in the database and the document degree distribution (see Section 4.5). Finally, the join-specific parameters are $|Agg|, |Agb|, |Abg|$, and $|Abb|$. Of these three classes of parameters, , the retrieval-specific parameters can be easily estimated in a pre-execution, offline step [17, 21]. On the other hand, estimating the other family of parameters is a more challenging task, which we discuss next.

Our parameter estimation method builds on the MLE-based estimation methods presented in [21]. Specifically, we begin with estimating the parameters for each individual relation, namely, $|Dg|$, $|Db|$, $|De|$, along with the attribute frequency distribution and document degree distribution. For this, we follow the *PT-Iter-MLE* estimation method from [21]; the following discussion can be easily extended for other estimation methods from [21].

One of the fundamental parameters required by our analysis is the frequency of each attribute occurrence in the database (e.g., $g(a)$ and $b(a)$ for an attribute a) and the document degree for each document in the database (i.e., number of attributes generated, denoted as $a(d)$ from a document d). Following our estimation approach for a single relation, we rely on the fact that the attribute frequencies for both category of attributes (good and bad) as well as the document degree tend to follow a power law distribution, as we will see later in Section 7. Therefore, for the random variable $g(a)$, which represents the good attribute occurrence frequency, and the random variable $g(a) + b(a)$, which represents the bad attribute occurrence frequency, we have:

$$Pr\{g(a) = i\} \quad = \frac{i^{\beta_{ga}}}{\zeta(\beta_{ga})} \tag{3}$$

$$Pr\{g(a) + b(a) = i\} \quad = \frac{i^{\beta_{ba}}}{\zeta(\beta_{ba})} \tag{4}$$

where β_{ga} and β_{ba} are the exponents of the power law distributions for the frequencies of good and bad attribute occurrences, respectively. Similarly, for the random variable $a(d)$ which represents the attributes generated from a document, the probability mass function is given as:

$$Pr\{a(d) = i\} = \frac{i^{\beta_d}}{\zeta(\beta_d)} \tag{5}$$

where β_d is the exponent of the power law for the document degree distribution. Knowing the distribution of the frequencies of good and bad attribute occurrences can greatly facilitate the estimation task: our goal now is to derive values for β_{ga}, β_{ba}, and β_d.

Given a relation that can be extracted from database D, we begin with retrieving and processing documents from D. After processing the retrieved documents Dr, we observe some tuples and their frequencies in the retrieved documents. Following the *PT-Iter-MLE* method, we partition these observed tuples [21] into good and bad tuples, and based on this classification we numerically derive the values for $|Dg|$, $|Db|$, and $|D_e|$.

Estimating β_{ga}, β_{ba}, and β_d: To estimate values for β_{ga}, we focus on the good attribute occurrences derived from processing Dr, i.e., on the attribute values that are associated with the good tuples observed in Dr. To this end, we use a maximum-likelihood-based estimation approach similar to *PT-Iter-MLE* [21], but with attribute occurrences instead of tuples. Consider a good attribute occurrence a, and assume that the number of documents in Dr that generate a is $gs(a)$. We need to identify for a, its frequency in the *entire database* (i.e., $g(a)$), since there may be other database documents not yet processed that can generate a. For this, we rely on the analysis from Section 4. Specifically, given a good attribute occurrence a, the most likely frequency $g(a)$ for a in the entire database is the one that maximizes the following probability:

$$Pr\{g(a) \big| gs(a)\} = \frac{Pr\{gs(a) \big| g(a)\} \cdot Pr\{g(a)\}}{Pr\{gs(a)\}} \tag{6}$$

Since $Pr\{gs(a)\}$ is constant across all values for $g(a)$ in the above equation, we can ignore it for the maximization task. To derive the factor, $Pr\{gs(a)\big|g(a)\}$, which is the probability that we observe a good attribute occurrence $gs(a)$ times when it occurs $g(a)$ times in the database, we use Equation 4.3 from our analysis. Finally, we estimate $Pr\{g(a)\}$ using Equation 3. Applying these factors to Equation 6, we iterate over the two steps of the *PT-Iter-MLE* approach until we converge on a final value for β_{ga} [21].

For bad attribute occurrences, we derive β_{ba} in a similar fashion. Given a bad attribute occurrence a that was observed $bs(a)$ times we estimate the *most likely* frequency that maximizes the probability of observing $bs(a)$, and iteratively identify β_{ba}.

The task of estimating the distribution parameter β_d for the document degree is relatively simple. Following the estimation approach discussed [21], as we retrieve database documents and process them using the maximum-sensitivity setting of the associated extraction system. Thus, for each document in Dr, we know exactly the total number of attributes in that document and, thus, we can directly fit a power law to the observed document degrees. Specifically, given documents d_1, d_2, $\cdots$, $d_{|Dr|}$ in Dr, from which the number of attributes we derived are $a(d_1)$, $a(d_2), \cdots, a(d_{|Dr|})$, respectively, we identify the value of a power law distribution parameter β_d that maximizes the probability of observing the number of attributes per document, $a(d_i)$, using the likelihood function:

$$l\{\beta_d \big| a(d_i)\} = \prod_{i=1}^{|Dr|} \frac{a(d_i)^{-\beta_d}}{\zeta(\beta_d)}$$

We numerically derive β_d using the derivative of the log-likelihood function [21].

Estimating $|Agg|, |Agb|, |Agb|$, and $|Abb|$: The final step in our parameter estimation process is to derive the join-specific parameters, namely $|Agg|, |Agb|, |Abg|$, and $|Abb|$. For this, we numerically solve the equations from Section 4 for deriving the expected number of good or bad tuples after processing documents Dr. Specifically, in Equation 4.2, we showed how we can estimate $E[|\mathbf{Tgood}_{\bowtie}|]$ given $|Agg|$ and other parameters discussed above. Conversely, for the estimation task, we observe the value for $E[|\mathbf{Tgood}_{\bowtie}|]$ and numerically solve Equation 4.2 to derive $|Agg|$. To derive the other values, namely, $|Agb|, |Agb|$, and $|Abb|$, we proceed analogously.

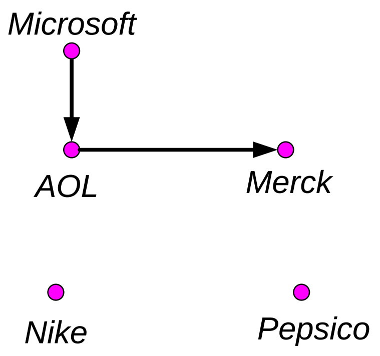


Figure 9: Sample *reachability* graph for *Executives* based on the *zig-zag* graph in Figure 8

6 Incorporating Output Quality into Join Optimization

In Section 3, we discussed three join algorithms and rigorously analyzed each algorithm in Section 4. Our analysis predicts the execution time and the output quality of each join execution strategy and thus, allows us to generate quality curves [21] for join execution strategies. Then, in Section 5, we showed how we can estimate the necessary parameters for our analysis.

Using our analytical models along with the estimation techniques, we can build a *quality-aware* optimizer to process join queries for a given user-specified quality requirement. Specifically, our optimization approach takes as input the user-provided minimum number of good tuples τ_g and the maximum number of bad tuples τ_b, and selects an execution strategy to efficiently meet the desired quality level. The optimizer begins with an initial choice of execution strategy. As the initial strategy progresses, the optimizer derives the necessary parameters and determines a desirable execution strategy for τ_g and τ_b, while checking for robustness of its decision using cross-validation.

A fundamental task in the optimization process is to identify the Cartesian space to explore for a given quality requirement. Exhaustively "plugging in," for each database, D in our output quality model of Section 4 all possible values for $|Dr|$ $(0, \ldots, |D|)$ or $|Qs|$ $(0, \ldots, |Ag| + |Ab|)$ is inefficient, so instead we resort to a simple heuristic to minimize the sum of documents retrieved and processed (and hence the total execution time), conditioned on the product of the number of occurrences of good attribute values in each relation. Specifically, we aim to reduce the difference between the number of documents retrieved for each relation, since intuitively we are minimizing the sum of two numbers, conditioned on their product. Thus, we select the number of documents for each database to be as close as possible. Conceptually, this heuristic follows a "square" traversal of the Cartesian space $D_1 \times D_2$ (see Section 3).

6.1 Reachability of ZGJN algorithm

A peculiarity of ZGJN is that it solely depends on documents retrieved and processed for a relation to "generate" new queries to retrieve documents *for the other relation.* These retrieved documents, in turn, govern the extent to which we discover new attributes for the first relation. Essentially, the success of the ZGJN algorithm depends on whether this query-based join execution "reaches" all (or most of) the documents (and thus attributes) in each database. In this section, we will examine the *reachability* of ZGJN in order to understand whether our proposed algorithm can successfully "reach" all the documents in each database. Our study builds upon the query-based reachability model proposed by Agichtein et al. [3] for the case of single relations.

In Section 4.5, we introduced the *zig-zag* graph which describes the process of querying and retrieving documents for each relation. However, when studying the reachability of a database, our goal is to examine the extent to which new attributes from *each individual relations* are reached. For this, we define a *reachability graph* for each database involved in the join. Interestingly, the reachability graph can be derived by "folding" the *zig-zag* graph.

Definition 6.1 [Reachability Graph] We define the *reachability graph* RG(T, E) of a database with respect to the ZGJN as a graph consisting of attributes from a single relation as nodes with edges such that a directed edge $a_i \rightarrow t_j$ means that the attribute value a_j occurs in a document that can be retrieved using the attribute value a_i. $\square$

Figure 9 shows the reachability graph for the database associated with the *Mergers* relation using the zig-zag graph in Figure 8. As shown in Figure 9, *RG* contains five nodes, one for each attribute value, with an edge originating from the node associated with the attribute value, Microsoft, to the node associated with the attribute value, AOL.

This edge was placed because using Microsoft as a query on the database for *Executives* relation, we could retrieve documents that, in turn, generated queries for the *Merges* relation that retrieved documents containing the attribute AOL. Similarly, there is a directed edge between the nodes associated with AOL and Merck. The figure also shows two nodes with no incoming or outgoing edges as the documents associated with these attributes cannot be reached via querying.

Earlier, Agichtein et al. [3] formalized the components of a reachability graph using the "bowtie" structure in [5]. Specifically, the directed reachability graph consists of (a) the strongly connected component, *Core*, (b) the nodes not in *Core* from which we can reach the nodes in *Core* via a directed path, *In*, and (c) the nodes not in *Core* or *In* which can be reached from the *Core* via a directed path, *Out*. Given this general shape of the reachability graph, we are interested in studying the size of the connected components in the graph. For this, we rely on the knowledge that the reachability graph of a text database belongs to the general family of power law graphs. For power law graphs, the biggest strongly connected component is denoted as the *giant component*, and it is well-known that if the giant component emerges then the remaining connected components are expected to be small with the distribution of their sizes following a power law. (We will show this later in our experiments.) Knowing the distribution of the vertex degrees of the reachability graph, allows us to directly apply existing results. Specifically, Aiello et al. [4] showed how we can predict the size of the giant component using only the average degree of the vertices in a graph, for a class of power law graphs. The size of the giant component is an interesting property as it gives us an idea on the attributes that can be reached by a ZGJN execution: intuitively, an execution that involves at least one attribute that belongs to the *Core*, can reach all the other attributes in the *Core* and the *Out* components. We quantify the reachability for a text database using the *reachability metric* introduced by Agichtein et al. [3]. Specifically, we define *reachability* as the fraction of the nodes A that belong to the *Core* and *Out* components of the giant component C_{RG} of a graph RG:

$$reachability = \frac{|Core(C_{RG})| + Out(C_{RG})}{|A|} \tag{7}$$

As discussed above, given a power law graph if a giant component emerges the rest of the components are expected to be small. Therefore, we use a reachability metric based on the giant component, and now we are interested in estimating the size of the giant component of a reachability graph. Chung and Lu [7] showed that for the class of power law graphs with their exponent β as $\beta < 3.475$, we can derive the size of the giant component using the average degree d of the vertices in a graph G. Following [3], we compute the relative size of the giant component as:

$$\frac{|C_G|}{|A|} \geq \begin{cases} 1/d \cdot \left(1 - \frac{2}{\sqrt{de}}\right) & \text{if } d \geq e \\ 1/d \cdot \left(1 - \frac{1+\log d}{d}\right) & \text{if } 1 < d < e \\ 0 & \text{if } 0 < d \leq 1 \end{cases} \tag{8}$$

As noted in [3], these equations can be applied for the case of directed graphs where d is the average outdegree of RG. Furthermore, the value derived using the above equations may overestimate the reachability as it focuses on the *complete* giant component as opposed to only focusing on the size of the *Core* and the *Out* components as defined in Equation 7.

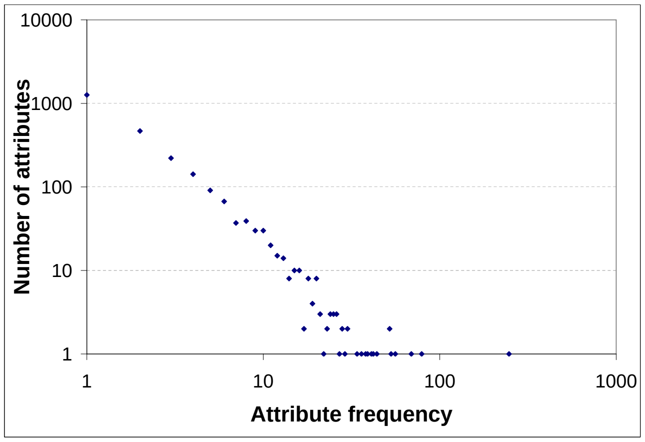
Next, our experimental evaluation show that the analytical models build for the various components of a join execution strategies in this chapter accurately predict the output quality of each execution strategy, which, in turn, allows us to build an effective *quality-aware* join optimization approach.

7 Experimental Settings

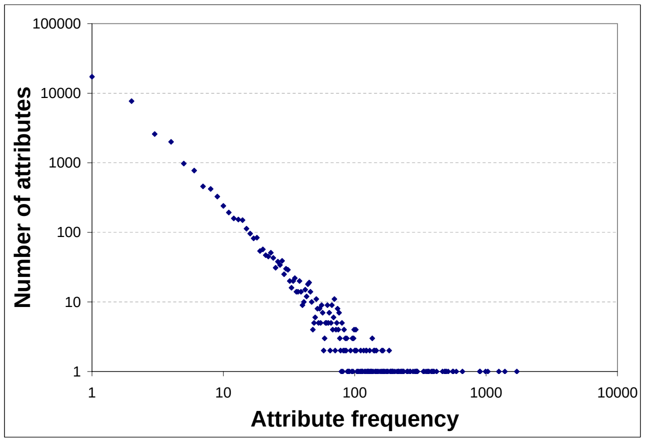
We now describe the settings for the experiments in Section 8, focusing on the IE systems, text collections, and the retrieval strategies used.

IE Systems: We trained Snowball [1] for three relations: *Executives*$\langle$*Company*, *CEO*$\rangle$, *Headquarters* $\langle$*Company*, *Location*$\rangle$, and *Mergers(Company, MergedWith)*. We refer to these relations as *EX*, *HQ*, and *MG*, respectively. For θ (Section 2.1), we picked *minSim*, a tuning parameter exposed by Snowball, which is the similarity threshold for extraction patterns and the terms in the context of a candidate tuple.

Data Set: We used a collection of newspaper articles from The New York Times from 1995 (NYT95) and 1996 (NYT96), and from The Wall Street Journal (WSJ). The NYT96 database contains 135,438 documents and we used it to train the extraction systems and the retrieval strategies. To evaluate the effectiveness of our approach, we used a subset of 49,527 documents from NYT96, 50,269 documents from NYT95, and 98,732 documents from WSJ. For each

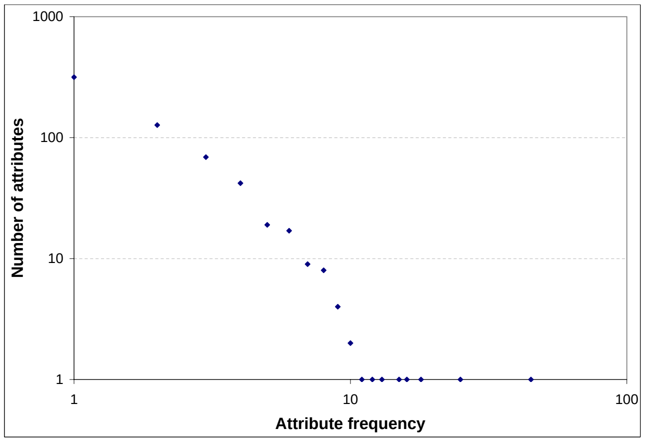


(a)

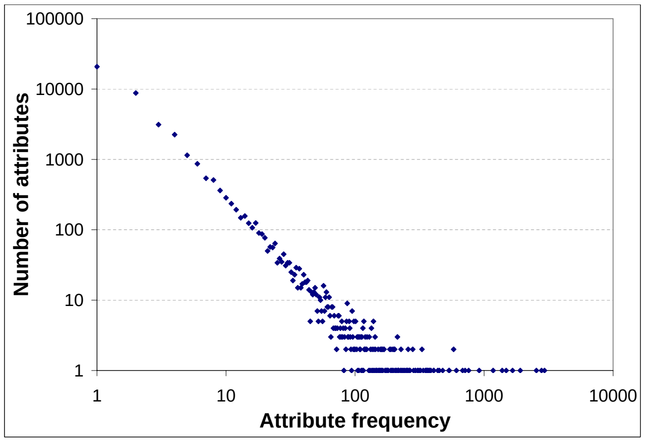


(b)

Figure 10: Good (a) and bad (b) attribute frequency distribution for *HQ*.



(a)



(b)

Figure 11: Good (a) and bad (b) attribute frequency distribution for *EX*.

relation and data set, we verified that the attribute and document frequency distributions tend to be power law for both good and bad tuples. Figures 10 shows the tuple frequency distributions of both good (Figure 10(a)) and bad tuples (Figure 10(b)) for *HQ*. Similarly, Figure 11 shows the attribute frequency distribution for *EX*.

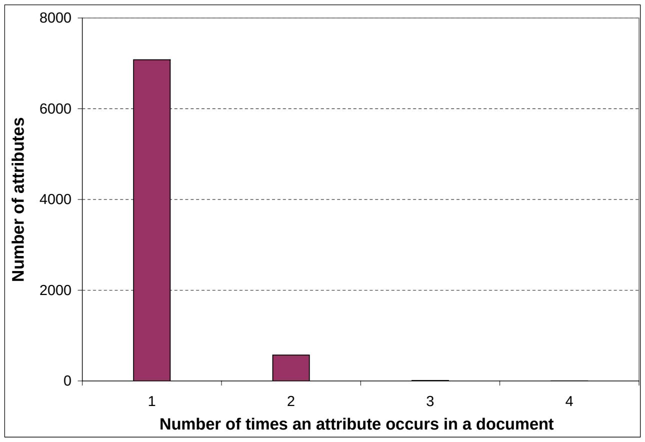
Retrieval Strategies: For *FS*, we used a rule-based classifier created using Ripper [9]. For *AQG*, we used QXtract [2], which relies on machine learning techniques to automatically learn queries that match documents with at least one tuple. In our case, we train QXtract to only match *good* documents, avoiding the *bad* and *empty* ones.

Tuple Verification: To verify whether a tuple is good or bad, we follow the template-based approach described in [20]. Additionally, we also use a web-based "gold" set from `www.thompson.com`.

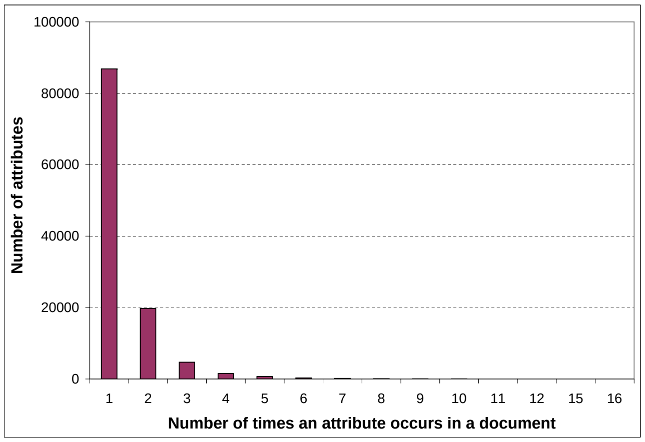
Join Task: We defined a variety of join tasks involving combinations of the three relations and the three databases. For our discussion, we will focus on the task of computing the join $HQ \bowtie EX$, with NYT96 and NYT95 as the hosting databases for *HQ* and *EX*, respectively.

Join Execution Strategies: To generate the join execution strategies for a task, we explore various candidates for individual relations and combine them using the three join algorithms of Section 3. For each relation, we generate single-relation strategies by using two values for *minSim* (i.e., 0.4 and 0.8) and combining each such configuration with the three document retrieval strategies.

Metrics: To compare the execution time of an execution plan chosen by our optimizer against a candidate plan, we measure the *relative difference in time* by normalizing the execution time of the candidate plan by that for the chosen



(a)



(b)

Figure 12: Distribution of the number of times an attribute value is generated from a document for (a) good and (b) bad attributes.

plan. Specifically, we note the relative difference as $\frac{t_c}{t_o}$, where t_c is the execution time for a candidate plan and t_o is the execution time for the plan picked by the optimizer.

8 Experimental Results

We now discuss our experimental results. We begin with establishing the accuracy of our analytical models for estimating the output quality for join execution plans. We then evaluate the effectiveness of our optimization approach.

Accuracy of the Analytical Models:

In our analysis, we define the frequency of an attribute occurrence (e.g., $g(a)$ for a good attribute occurrence a) in terms of the number of good tuples that contain an attribute value. For this, we assumed that each attribute occurs only once in a document, which significantly reduced the complexity of the statistical models. First, we verify this assumption for our relations: Figure 12 shows the distribution of the number of times that each good attribute value is extracted from each document (Figure 12(a)). This figure validates our simplifying assumption: most attribute occurrences are extracted just once from each document. (Figure 12(b)) shows the corresponding figure for bad attribute occurrences.)

We now turn to verifying the accuracy of our Section 4 analysis. For this, we assumed perfect knowledge of the various database-specific parameters: we used the actual frequency distributions for each attribute along with the values for $|Dg|$, $|Db|$, and $|D_e|$ for each database. Given a join execution strategy, we first estimate the output quality of the join, i.e., $E[|\mathbf{Tgood}_{\bowtie}|]$ and $E[|\mathbf{Tbad}_{\bowtie}|]$, using the appropriate analysis from Section 4, while varying values for the number of retrieved documents from the database, i.e., $|Dr_1|$ and $|Dr_2|$. For each $|Dr_1|$ and $|Dr_2|$ value, we measure the *actual* output quality for an execution strategy. Figure 13 shows the actual and the estimated values for the good (Figure 13(a)) and the bad (Figure 13(b)) join tuples generated using IDJN, *Scan* for both relations, and $minSim = 0.4$. Similarly, Figure 14 shows the same results for OIJN when using *Scan* as the retrieval strategy for the outer relation and $minSim = 0.4$ for both relations. Then, Figure 15 compares the estimated and the actual values for ZGJN, for $minSim = 0.4$. We performed similar experiments for all other execution strategies. Additionally, we also examined the accuracy of the estimated number of documents for query-based join algorithms, i.e., for OIJN and ZGJN. Figure 16 shows the expected and the actual number of documents retrieved for varying number of queries issued to each database, for ZGJN.

Overall, our estimates are either close to the actual values or follow similar trends as the actual values, thus confirming the accuracy of our analysis. Of these observations, we discuss the case for bad tuples for OIJN (Figure 14(b)) and ZGJN (Figure 15(b)), where our model overestimates the number of bad tuples. This overestimation can be traced to a few outlier cases. To gain insight into this, we compared the expected and the actual number of bad attribute occurrences. We observed four main cases where our estimated values were more than two orders of magnitude greater than the actual values. These attribute values frequently appeared in the database but were not extracted by the extraction system at the *minSim* setting used in our experiments. For instance, one such bad attribute occurrence,

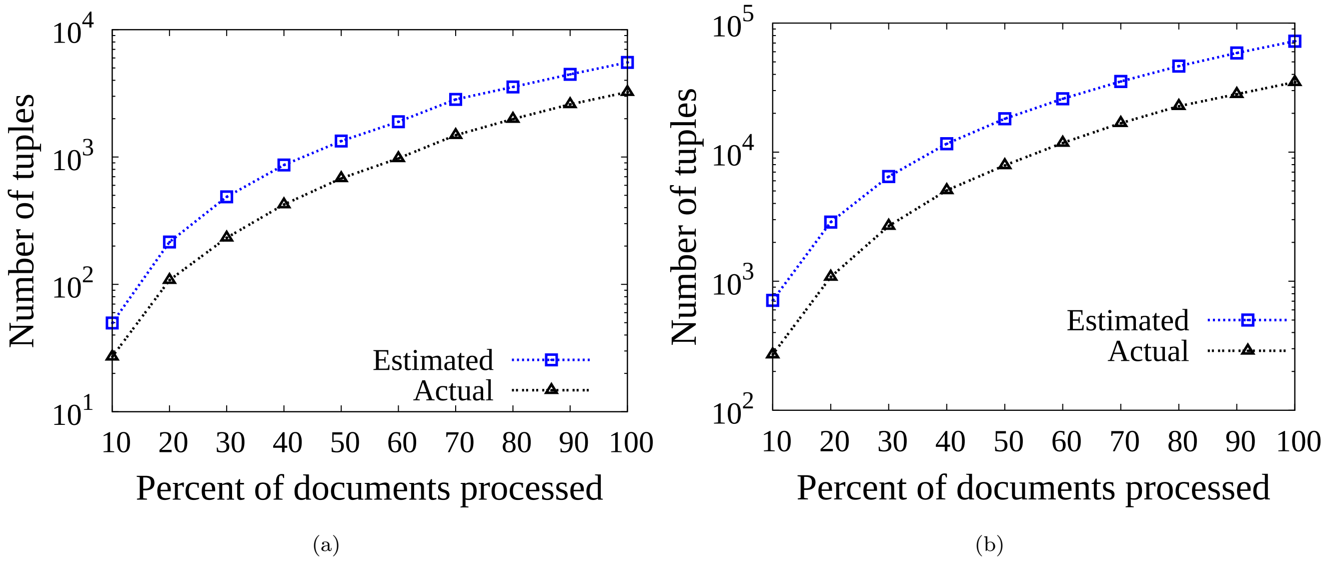


Figure 13: Estimated and actual number of (a) good tuples and (b) bad tuples for $HQ \bowtie EX$, using IDJN with *Scan* and $minSim = 0.4$.

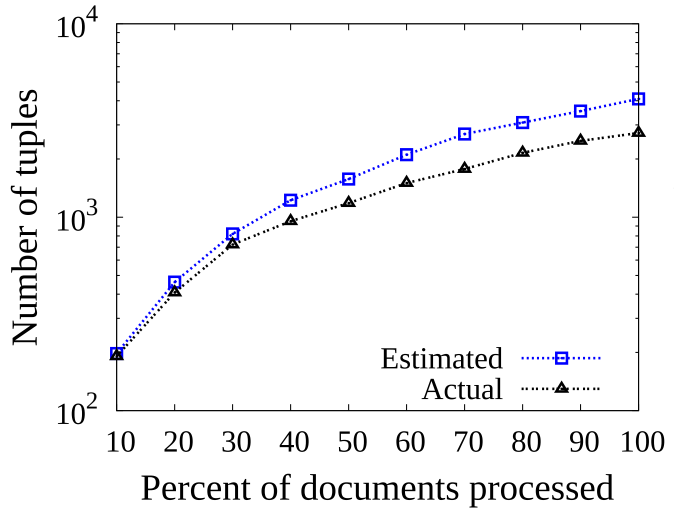
"CNN Center," appears 895 and 2765 times in HQ and EX, respectively. When using OIJN and processing 50% of the database documents for the outer relation, our estimated frequencies of the bad occurrences of this value was 28.3 and 29.7 times, respectively; in reality, this attribute value was not extracted, thus resulting in an overestimate of 812 join tuples. This difference is further expanded for ZGJN due to a modeling choice: we assume that all queries used in ZGJN will match some documents and the execution will not *stall*. We can account for stalling by incorporating the reachability of a ZGJN execution based on the single-relation analysis in [17, 18].

We further break down our evaluation and study the estimated number of join tuples that we will observe for each attribute occurrence after processing $|Dr|$ documents. Specifically, given $|Dr|$, we use our analysis from Section 4 to estimate, for each attribute occurrence, the expected number of join tuples that we will observe in the output after processing $|Dr|$ documents. For each attribute occurrence, we also derive the actual number of join tuples that we observe in the output. Given the estimated and the actual number of join tuples that we observe, we studied the distribution of the estimation error computed as the number of actual observations minus the estimated number of observations, across all attribute occurrences. Figure 17 shows this distribution for the case of good attribute occurrences for IDJN (Figure 17(a)), OIJN (Figure 17(b)), and ZGJN (Figure 17(c)); Figure 18 shows the corresponding graphs for bad attribute occurrences and IDJN (Figure 18(a)), OIJN (Figure 18(b)), and ZGJN (Figure 18(c)).

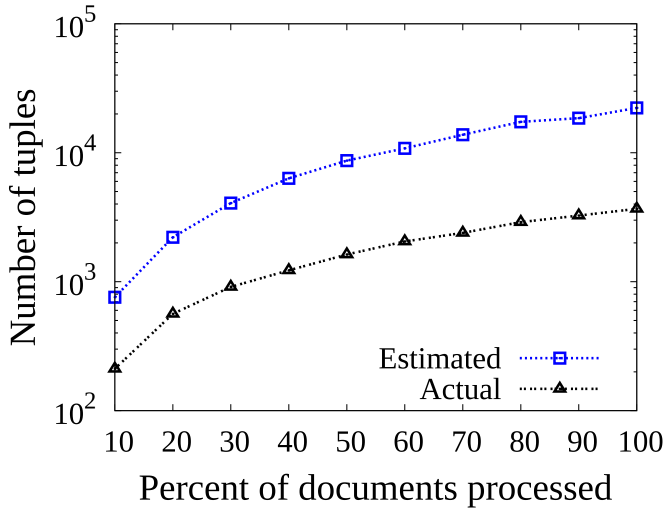
In general, we observe that the estimation error is centered around zero and, more importantly, for a significant fraction of attribute occurrences the estimated error is 0 (note that the y-axis is on a log-scale). For good attribute occurrences, often the estimated value is an overestimate. On the other hand, for bad attribute occurrences there were relatively more numerous cases of overestimation due to the reasons discussed above. Thus, the observations from this analysis are largely in line with our previous observations on the accuracy of the overall estimation model.

Reachability of Zig-Zag Join: Next, we study the reachability of the ZGJN algorithm (Section 6.1) using the analysis in [3]. For this, we construct a reachability graph [3] for EX. The analysis in [3] relies on the knowledge that reachability graphs of a text database belong to the general family of power law graphs. As a first step, we verify whether the reachability graph is a power law graph. Figure 19 reports the outdegree distribution of the nodes in the reachability graph for different number of matching documents retrieved for each query issued during the execution. We observed that a power law distribution indeed best fits the data. Similarly, we also examine the size of the connected components in the reachability graph [3]. Figure 20 reports the distribution of the size of the connected components for different number of matching documents retrieved for each query issued during the execution.

As the next step, we study the estimated and the actual reachability of the graph using the reachability metric defined in [3]. Specifically, we estimate this metric using the analysis presented in [3] and also derive the actual reachability. Figure 21 reports the estimated and actual values for the reachability for different number of matching documents retrieved for each query issued during the execution. As seen in the figure, in general, the ZGJN execution can successfully reach a significant fraction of the attributes in the database, as denoted by a value of above 70% when more than 5 documents are retrieved per query. Furthermore, the estimated value, as noted in [3], is an overestimate of the actual value. (Refer to [3] for a detailed discussion on the reasons for this overestimation.) In summary, the



(a)



(b)

Figure 14: Estimated and actual number of (a) good tuples and (b) bad tuples for $HQ \bowtie EX$, using OIJN with *Scan* and $minSim = 0.4$.

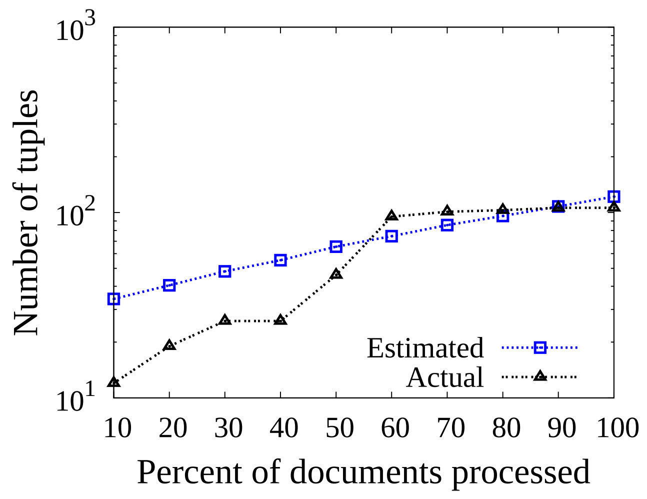
reachability analysis in [3] allows us to examine whether a ZGJN-based execution for the given databases is desirable.

Effectiveness of the Optimization Approach: After verifying our modeling, we studied the effectiveness of our optimization approach, which uses our models along with the parameter estimation process outlined in Section 6. Specifically, we examine whether the optimizer picks the fastest execution strategy for a given output quality requirement. For this, we provided the optimizer with two thresholds, τ_g and τ_b, which specify the minimum number of good tuples requested and the maximum allowable bad tuples for the resulting join.

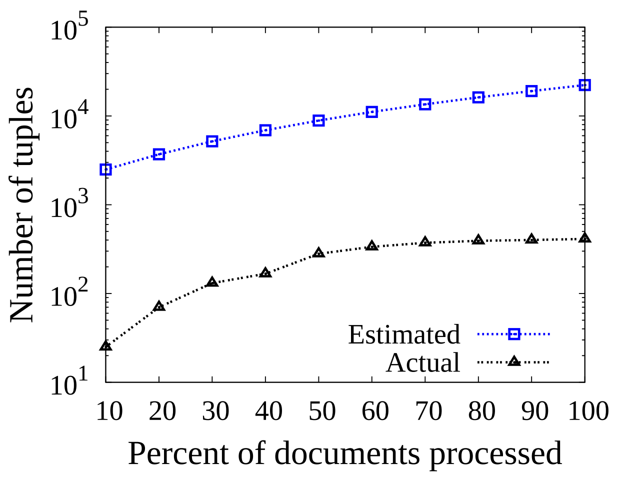
To evaluate the choice of execution strategy for a specified τ_g and τ_b pair, we compare the execution time for the chosen plan S against that of the alternate executions plans that also meet the τ_g and τ_b requirements. Table 2 shows the results for $HQ \bowtie EX$, for varying τ_g and τ_b. For each τ_g and τ_b pair, we show the number of candidate plans that meet the τ_g and τ_b requirement. Furthermore, we show the number of candidate plans that result in faster executions than the plan chosen by our optimizer and the number of candidate plans that result in slower executions than the chosen plan. Finally, to highlight the difference between the associated execution times, we show the range of relative difference in time for both faster and slower execution plans.

As shown in the table, our optimizer selects OIJN for low values of τ_g and τ_b, and progresses towards selecting IDJN coupled with *AQG* or *FS*, eventually picking IDJN coupled with *SC* for high values of τ_g and τ_b. For most cases, our optimizer selects an execution strategy that is the fastest strategy or close to the fastest strategy, as indicated by having either no candidates with faster executions than the chosen plan or a small number of such executions. For cases where the chosen plan is not the fastest option, the execution time of the faster candidates is close to the one of the chosen plan, as indicated by the relative difference values (e.g., a value of 1 indicates the execution times for both the candidate and the chosen plans were identical). An important observation is that the plans eliminated by the optimizer were an order of magnitude (10 to 35 times) slower than the chosen plans.

An intriguing outcome of our experiments is that the choices for execution strategies do not involve ZGJN. Interestingly, for our test data set, ZGJN is not a superior choice of execution algorithm as compared to other algorithms. Intuitively, ZGJN does not specifically focus on filtering out any bad documents; therefore, ZGJN does not meet the quality requirements as closely as other query-based strategies that use IDJN or OIJN along with *AQG* or *FS*. Furthermore, the maximum number of tuples that can be extracted using ZGJN is limited, which makes it a poor choice for higher values of τ_g and τ_b. ZGJN would be a competing choice for scenarios involving databases that only provide query-based access (e.g., search engines or hidden-Web databases) and also for cases where the generated queries match a relatively large number of good documents. Extending ZGJN to derive queries that focus on good documents remains interesting future work.

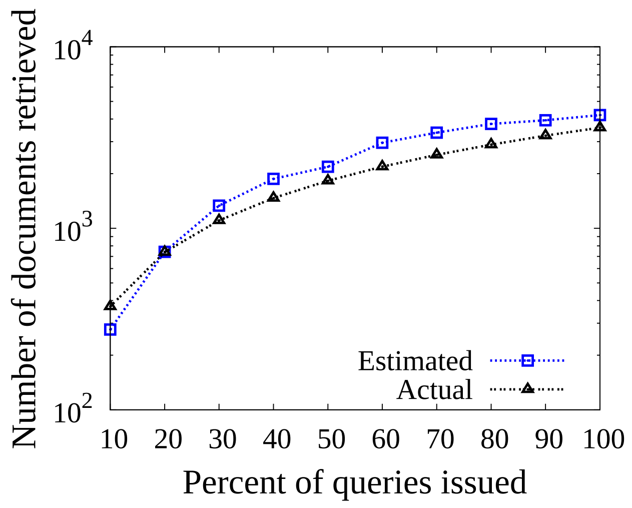


(a)

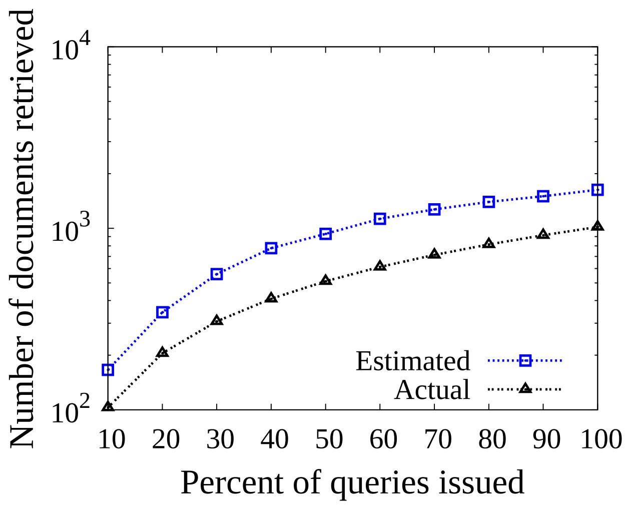


(b)

Figure 15: Estimated and actual number of (a) good tuples and (b) bad tuples for ZGJN.



(a)



(b)

Figure 16: Estimated and actual number of documents retrieved by (a) *HQ* and (b) *EX* for ZGJN.

9 Related Work

Information extraction from text has received much attention in the database, AI, Web, and KDD communities (see [8, 12] for tutorials). The majority of the efforts have considered the construction of *a single extraction system* that is as accurate as possible (e.g., using HMMs and CRFs [8, 22]). Approaches to improve the efficiency of the IE process have developed specialized document retrieval strategies; one such approach is the QXtract system [2], which uses machine learning to derive keyword queries that identify documents rich in target information. We use QXtract in our work.

Related efforts to this paper are [17, 18] and [21], but this earlier work studied the task of extracting just one relation, not our *join* problem. Specifically, in [17, 18] we studied the document retrieval strategies considered in this paper for the goal of efficiently achieving a desired *recall* for a single-relation extraction task. The analysis in [17, 18] assumes a *perfect* extraction system (i.e., all generated tuples are good). On the other hand, in [21] we studied document retrieval strategies for single-relation extraction while accounting for extraction imprecision. Our current work builds upon the statistical models presented in [17, 18, 21], extending them for multiple extraction systems.

Real-world applications often require *multiple extraction systems* [12, 24]. Hence, the problem of developing and optimizing IE programs that consist of multiple extraction systems has received growing attention. Some of the existing solutions write such programs as declaratively as possible (e.g., UIMA [13], GATE [10], Xlog [24]), while considering only the execution time in their analysis.

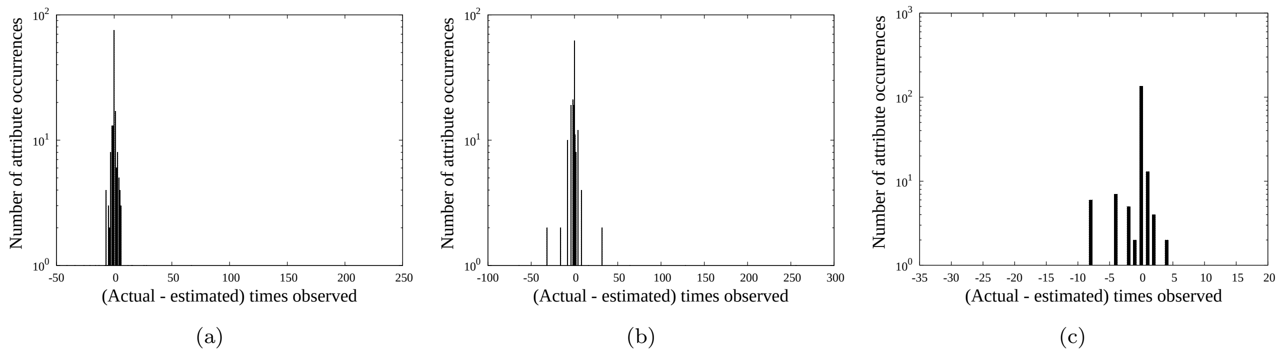


Figure 17: Distribution of the estimation error, on a log-scale, for a good attribute occurrence using (a) IDJN, (b) OIJN, and (c) ZGJN.

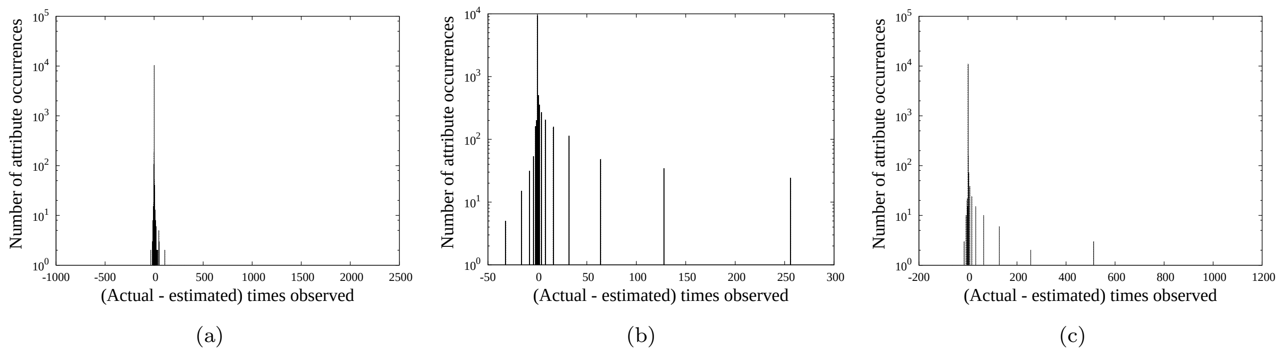


Figure 18: Distribution of the estimation error, on a log-scale, for a bad attribute occurrence using (a) IDJN, (b) OIJN, and (c) ZGJN.

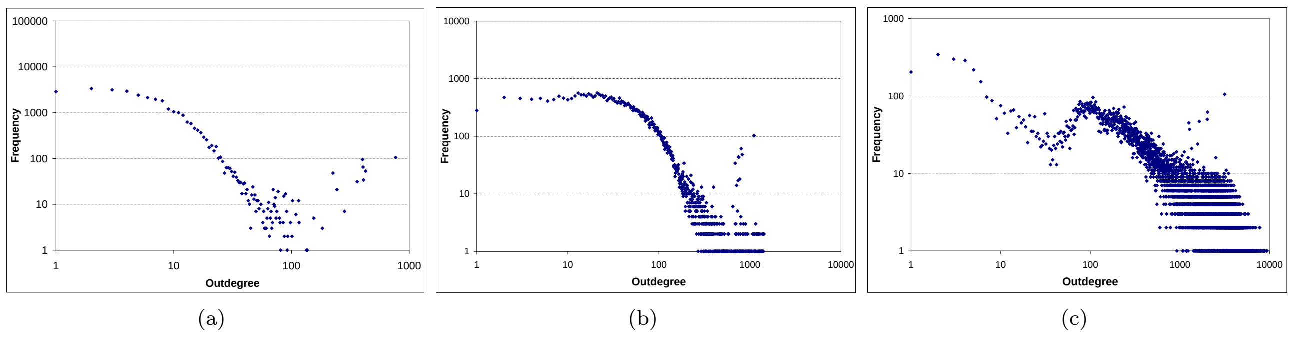
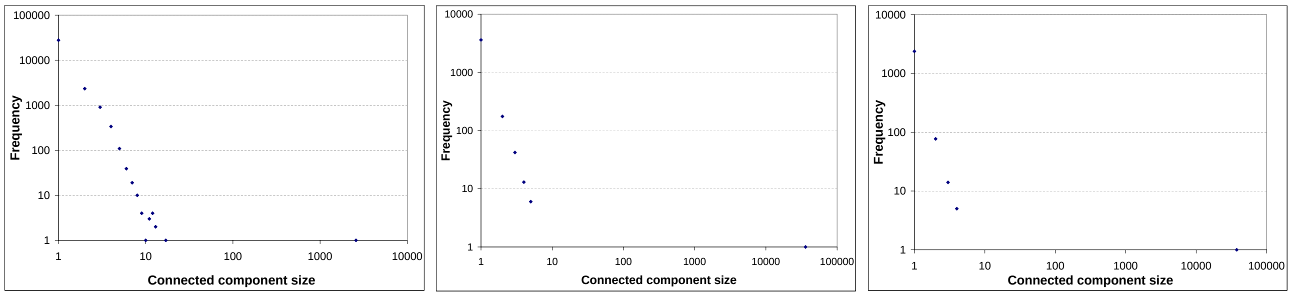


Figure 19: The outdegree distribution of the reachability graph for *Executives* when the maximum number of documents retrieved for each query is (a) 5, (b) 10, and (c) 50.



(a) (b) (c)

Figure 20: The component size distribution of the reachability graph for *Executives* when the maximum number of documents retrieved for each query is (a) 5, (b) 10, and (c) 50.

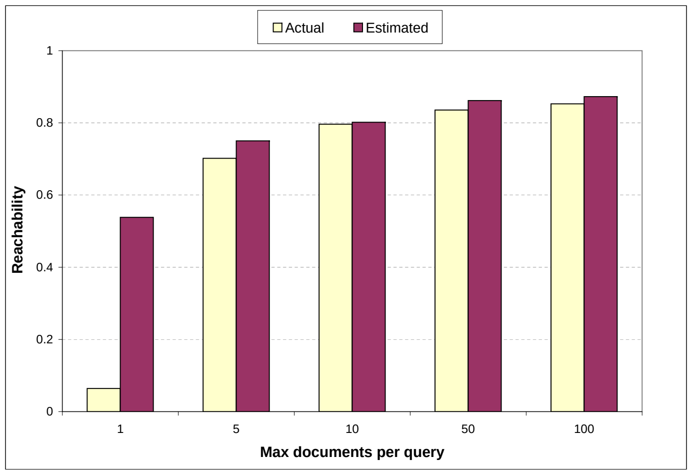


Figure 21: Estimated and actual reachability for *Executives* for different number of matching documents retrieved per query issued during an execution.

Criteria		**Candidate plans**	**Chosen plan**					**# Faster plans**	**# Slower plans**	**Relative time range for faster plans**		**Relative time range for slower plans**	
τ_g	τ_b		**JN**	θ_1	θ_2	X_1	X_2			*min*	*max*	*min*	*max*
1	20	46	OIJN	0.4	0.4	FS	*(OIJN)*	5	36	0.68	0.80	1.20	27.48
2	30	46	OIJN	0.8	0.4	AQG	*(OIJN)*	10	32	0.19	0.75	1.78	11.91
2	50	47	OIJN	0.8	0.4	AQG	*(OIJN)*	11	33	0.19	0.75	1.78	11.91
4	20	39	OIJN	0.4	0.4	FS	*(OIJN)*	3	29	0.34	0.34	1.59	35.76
4	40	42	OIJN	0.4	0.4	FS	*(OIJN)*	3	37	0.34	0.34	1.59	35.76
8	40	40	OIJN	0.8	0.4	AQG	*(OIJN)*	3	33	0.19	0.19	1.15	22.20
8	80	44	OIJN	0.8	0.4	AQG	*(OIJN)*	4	38	0.19	0.19	1.15	22.20
16	50	26	IDJN	0.4	0.4	FS	AQG	-	21	-	-	1.22	11.62
16	80	36	IDJN	0.4	0.4	FS	AQG	3	30	0.66	0.94	1.10	11.62
16	160	39	IDJN	0.4	0.4	FS	AQG	3	34	0.66	0.94	1.10	11.62
32	84	26	IDJN	0.4	0.4	FS	AQG	-	22	-	-	1.26	13.30
32	160	36	OIJN	0.8	0.4	AQG	*(OIJN)*	-	35	-	-	1.55	20.62
32	320	40	OIJN	0.8	0.4	AQG	*(OIJN)*	-	39	-	-	1.55	20.62
64	320	35	IDJN	0.8	0.4	AQG	AQG	-	34	-	-	1.50	27.16
64	640	41	IDJN	0.8	0.4	AQG	AQG	-	40	-	-	1.50	27.16
128	640	21	IDJN	0.4	0.4	FS	AQG	-	20	-	-	1.19	9.41
128	1280	26	IDJN	0.4	0.4	FS	AQG	-	25	-	-	1.19	9.41
256	1280	14	IDJN	0.4	0.4	SC	AQG	-	13	-	-	1.18	2.89
256	2560	18	IDJN	0.4	0.4	SC	AQG	-	17	-	-	1.01	2.89
512	1024	1	IDJN	0.8	0.8	SC	SC	-	-	-	-	-	-
512	2560	3	IDJN	0.8	0.4	SC	SC	-	2	-	-	1.02	1.15
512	5120	4	IDJN	0.4	0.4	FS	SC	-	3	-	-	1.46	1.69
1024	5120	2	IDJN	0.8	0.4	SC	SC	1	-	0.99	0.99	-	-
1024	10240	2	IDJN	0.8	0.4	SC	SC	1	-	0.99	0.99	-	-

Table 2: Choice of execution strategies for varying output quality requirements expressed as τ_g and τ_b thresholds (Section 2.3), and comparing the execution time of the chosen strategy against that of alternative execution strategies that also meet the τ_g and τ_b requirements, for $HQ \bowtie EX$.

In prior work [20], we presented a query optimization approach for simple SQL queries involving joins while accounting for both execution time and output quality. Our earlier paper considered only *one* simple heuristic to estimate the quality of *one* simple join algorithm, namely, the IDJN algorithm, discussed and analyzed in this paper (Section 3). Our current work substantially expands on [20] by modeling an extended family of join algorithms and showing how to pick the best option dynamically. To the best of our knowledge, our current work is the first to carry out an in-depth output quality analysis of a variety of join execution plans over multiple extraction systems.

Our work is also related to research on the "loose integration" of relational DBMSs and text databases (e.g., [6, 14, 11]), generally achieved via careful querying of the text databases. Our focus is different, on the explicit extraction of structured data from plain-text documents, which requires that we understand and model the output quality that results from the extraction and join processing plans, in addition to their extraction efficiency.

10 Conclusions

In this paper, we addressed the important problem of optimizing the execution of joins of relations extracted from natural language text. As a key contribution of our paper, we developed rigorous analytical models to analyze the output quality of a variety of join execution strategies. We also showed how to use our models to build a join optimizer that attempts to minimize the time to execute a join while reaching user-specified result quality requirements. We demonstrated the effectiveness of our optimizer for this task with an extensive experimental evaluation over real-world data sets. We also established that the analytical models presented in this paper demonstrate a promising direction towards building fundamental blocks for processing joins involving information extraction systems.

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