Query Processing over Crowdsourced Data*

Hyunjung Park
Stanford University
hyunjung@cs.stanford.edu

Aditya Parameswaran
Stanford University
adityagp@cs.stanford.edu

Jennifer Widom
Stanford University
widom@cs.stanford.edu

ABSTRACT

We are building *Deco*, a comprehensive system for answering declarative queries posed over stored relational data together with data gathered from the crowd. In this paper we present Deco's query processor, building on Deco's data model and query language presented earlier. In general, it has been observed that query processing over crowdsourced data must contend with issues and tradeoffs involving *cost*, *latency*, and *uncertainty* that don't arise in traditional query processing. Deco's overall objective in query execution is to maximize parallelism while fetching data from the crowd (to keep latency low), but only when the parallelism will not issue too many tasks (which would increase cost). Meeting this objective requires a number of changes from traditional query execution. First, Deco's query processor uses a *hybrid execution model*, which respects Deco semantics while enabling our objective. Our objective also requires *prioritizing accesses to crowdsourced data*, which turns out to be an interesting NP-hard problem. Finally, because Deco incorporates *resolution functions* to handle the uncertainty in crowdsourced data, query execution bears as much similarity to incremental view maintenance as to a traditional iterator model. The paper includes initial experimental results, focusing primarily on how our query execution model and access prioritization scheme maximize parallelism without increasing cost.

1. INTRODUCTION

Crowdsourcing [4] provides a programmatic way of incorporating human computation to accomplish a variety of tasks that are difficult for computer algorithms to perform, e.g., evaluating search results and labeling images. Even though crowdsourcing is considered a promising tool for many applications, programmers encounter some common challenges in taking advantage of crowdsourcing in practice: resolving inconsistencies in crowdsourced data, seamlessly integrating crowdsourced data with existing data, and reducing the monetary cost and latency of crowdsourcing.

To address these challenges, we proposed *Deco* (for "declarative crowdsourcing") [12, 13, 14], a system that answers declarative queries posed over stored relational data together with data gathered from the crowd. In [12], we defined a data model for Deco that is *general* (it can be instantiated to other proposed models), *flexible* (it allows methods for data cleansing and external access to be plugged in), and *principled* (it has a precisely-defined semantics). We also defined a query language for Deco as a simple extension to SQL with constructs necessary for crowdsourcing, and with a semantics that directly follows the data-model and SQL semantics.

*This work was supported by the NSF (IIS-0904497), the Boeing Corporation, and a KAUST research grant.

In this paper, we describe Deco's query processor. While at a high level Deco's query processor resembles its counterpart in traditional database systems, we had many significant new challenges to address:

- As a data source, the crowd has unique characteristics that are not found in conventional sources (like disks): very high latency and abundant parallelism. Thus, it is important for a crowdsourcing infrastructure (like Deco) to hide the latency and exploit the parallelism by invoking "access methods" in parallel.
- Accessing crowdsourced data incurs monetary cost. However, reducing monetary cost and latency at the same time is not straightforward. It is critical to exploit the right degree of parallelism to optimize for both monetary cost and latency.
- The query execution engine should attempt to answer a given query using existing data before it collects more data through crowdsourcing. This requirement seems trivial, however it is not trivial to implement. All query operators must buffer existing data and combine it correctly with new data.
- Deco's data model is general and flexible enough to invalidate some key assumptions behind traditional iterator-based query execution, discussed shortly.

In response to these challenges, we set the overall objective for Deco's query execution as follows: exploit as much parallelism as possible when accessing the crowd (to reduce latency), but only when the parallelism will not waste work (to minimize monetary cost). We designed and implemented a query processor for Deco that respects Deco semantics while meeting this objective.

- Deco's query processor executes a query plan using a novel *hybrid execution model*. In this model, each query operator can "asynchronously pull" more tuples from its child operator: The parent operator proceeds without waiting for new tuples, and the child operator can "asynchronously push" new tuples to its parent later. This model helps us meet our objective by precisely adjusting the degree of parallelism.
- To maximize parallelism but not incur extra cost, we use a technique based on prioritization of accesses to crowdsourced data. This prioritization problem is unique to the crowdsourcing setting, and it turns out to be critical to performance when Deco must combine existing data with newly crowdsourced data. The solution to this NP-hard problem should be effective and easily incorporated into the query execution engine. We show experimentally that our heuristic algorithm can achieve a near-optimal prioritization.
- Deco's query execution bears as much similarity to incremental view maintenance as to a traditional iterator model: Query operators can remove or modify output tuples that were passed to their parent previously. This feature is key to supporting the way Deco handles uncertainty and inconsistencies in crowd-

sourced data. Moreover, not only do Deco's "access methods" insert new tuples into a single table during query execution, but as a side effect they may provide new tuples spanning multiple tables. Changes based on these new tuples propagate up the plan similar to incremental view maintenance.

In this paper we show some alternative valid plans for a given query, and explain how different plans affect query execution. (Query optimization is a large and complex challenge on its own; in [14] we describe plan costing and enumeration.)

The rest of the paper proceeds as follows:

- We review Deco's data model and query language (Section 2), summarizing materials from [12, 13].
- We establish the goals for Deco's query execution, discuss several challenges, and describe our approach (Section 3).
- We describe how Deco executes queries using its hybrid execution model, when there is no existing data (Section 4).
- We extend query execution for the general case where existing data must be combined with new data (Section 5).
- We formalize the prioritization problem and describe how Deco prioritizes accesses to crowdsourced data to minimize monetary cost (Section 6).
- We experimentally evaluate Deco's query execution model and access prioritization scheme in various settings (Section 7).

Related work is covered in Section 8, and we conclude in Section 9.

2. DATA MODEL AND QUERY LANGUAGE

We begin by reviewing each of the Deco data model components using a running example, then we describe Deco's query language and semantics. For more details see [12].

Conceptual Relation: *Conceptual relations* are the logical relations specified by the Deco schema designer and queried by end-users and applications. The schema designer also partitions the attributes in each conceptual relation into *anchor attributes* and *dependent attribute-groups*. Informally, anchor attributes typically identify "entities" while dependent attribute-groups specify properties of the entities.

As a running example, suppose our users want to query two conceptual relations with information about countries and cities:

Country(country, [language], [capital])
City(city, country, [population])

Each dependent attribute-group (single attributes in this case) is enclosed within square brackets. In the Country relation, the anchor attribute country is a country name, while language and capital are properties of the country. In the City relation, the pair of city and country names identifies a city, while population is a property of the city.

Raw Schema: Deco is designed to use a conventional RDBMS as its back-end. The *raw schema*—the schemas for the data tables actually stored in the underlying RDBMS—is derived automatically from the conceptual schema, and is invisible to both the schema designer and end-users. (Later we will see that the back-end RDBMS is also used for intermediate storage during query execution.) Specifically, for each relation R in the conceptual schema, there is one *anchor table* containing the anchor attributes, and one *dependent table* for each dependent attribute-group; dependent tables also contain anchor attributes.

In our example, we have the raw schema:

CountryA(country)
CountryD1(country, language)
CountryD2(country, capital)
CityA(city, country)
CityD1(city, country, population)

Fetch Rules: *Fetch rules* allow the schema designer to specify how data can be obtained from humans. A fetch rule takes the form $A_1 \Rightarrow A_2 : P$, where A_1 and A_2 are sets of attributes from one conceptual relation (with $A_1 = \varnothing$ permitted), and P is a *fetch procedure* that implements access to human workers. (P might generate HITs (Human Intelligence Tasks) to Mechanical Turk [1], for example.) When invoked, the fetch rule $A_1 \Rightarrow A_2$ obtains new values for A_2 given values for A_1, and populates raw tables using those values for $A_1 \cup A_2$. The schema designer also specifies a fixed monetary cost for each fetch rule, to be paid to human workers once they complete the fetch rule.

Here are some example fetch rules and their interpretations for our running example.

- [Country] $\varnothing \Rightarrow$ country: Ask for a country name, inserting the obtained value into raw table CountryA.
- [Country] country $\Rightarrow$ capital: Ask for a capital given a country name, inserting the resulting pair into table CountryD2.
- [Country] language $\Rightarrow$ country: Ask for a country name given a language, inserting the resulting country name into CountryA, and inserting the country-language pair into CountryD1.

For a full description of the allowable fetch rules in Deco, see [12].

The schema designer may add or remove fetch rules at any time during the lifetime of a database—they are more akin to "access methods" than to part of the permanent schema.

Resolution Rules: Suppose we've obtained values for our raw tables, but we have inconsistencies in the collected data. We use *resolution rules* to cleanse the raw tables—to get values for conceptual relations that are free of inconsistencies. For each conceptual relation, the schema designer can specify a resolution rule $\varnothing \rightarrow A : f$ for the anchor attributes A treated as a group, and one resolution rule $A \rightarrow D : f$ for each dependent attribute-group D. Resolution function f is a black-box that adheres to a simple API, taking as input a set of values for the right-hand side attributes (corresponding to a specific value for the left-hand side) and returning a "cleaned" set of values. If the empty set is returned, more input values are needed to produce an output.

In our example, we might have the following resolution rules:

- [Country] $\varnothing \rightarrow$ country : *dupElim*
- [Country] country $\rightarrow$ language : *majority-of-3*
- [Country] country $\rightarrow$ capital : *majority-of-3*
- [City] $\varnothing \rightarrow$ city,country : *dupElim*
- [City] city,country $\rightarrow$ population : *average-of-2*

Resolution function *dupElim* produces distinct country values for Country and distinct city-country pairs for City. Resolution function *majority-of-3* produces the majority of three or more language (or capital) answers for a given country. We assume a "shortcutting" version that can produce an answer with only two values, if the values agree. On the other hand, sometimes more than three values are input to the function, in which case a majority is needed to produce an output. Resolution function *average-of-2* produces the average of two or more population answers for a given city. Note any resolution functions are permitted, not just the types used here for illustration.

Data Model Semantics: The semantics of a Deco database is defined as a potentially infinite set of *valid instances* for the conceptual relations. A valid instance is obtained by a *Fetch-Resolve-Join* sequence: (1) *Fetching* additional data for the raw tables using fetch rules; this step may be skipped. (2) *Resolving* inconsistencies using resolution rules for each of the raw tables. (3) *Outerjoining* the

resolved raw tables to produce the conceptual relations.

It is critical to understand that the Fetch-Resolve-Join sequence is a *logical concept only*. When Deco queries are executed, not only may these steps be interleaved, but only those portions of the conceptual data needed to produce the query result are actually materialized.

Query Language and Semantics: A Deco query Q is simply a SQL query specified over the conceptual relations. Deco's query semantics dictate that the answer to Q must represent the result of evaluating Q over some (logical) valid instance of the database. Because our Fetch-Resolve-Join database semantics is based on outer-joins, conceptual relations may logically include numerous NULL values. Thus, we restrict query results to include only those conceptual tuples whose attribute values are non-NULL, although this restriction could be lifted if desired.

One valid instance of the database can be obtained by resolving and joining the current contents of the raw tables, without invoking any further fetch rules. Thus, it appears a query Q could always be answered correctly without consulting the crowd at all. The problem is that this "correct" query result may be very small, or even empty. To retain our straightforward semantics over valid instances, while still forcing answers to contain some amount of data, we add one of the following *constraints* to a Deco query:

- "MaxCost c" specifies to spend up to c dollars (or other cost unit) to answer the query, while attempting to maximize the number of tuples in the result.
- "MaxTime t" specifies to spend up to t seconds (or other time unit) to answer the query, while attempting to maximize the number of tuples in the result.
- "MinTuples n" specifies that at least n tuples should be in the result, while attempting to minimize cost (or time).

In this paper we focus on the third type of constraint: producing a minimum number of (non-NULL) result tuples while minimizing cost. This problem alone is quite challenging; as future work we will address the other constraint types.

3. QUERY EXECUTION OVERVIEW

Having defined the Deco data model and query language, we now consider how to build a query execution engine that implements the defined semantics while executing queries efficiently. The query execution engine must support constraints such as MinTuples while dealing with the inherent challenges in crowdsourcing, such as monetary cost and latency.

In this section, we first establish the goals and objectives for query execution, then we discuss several challenges in query execution as well as our approach to tackle them. Lastly we walk through execution of an example query plan at a high level.

3.1 Goals

Given a Deco query plan with "MinTuples n" constraint, our primary goal in query execution is to produce at least n result tuples while minimizing monetary cost. In addition, our secondary goal is to reduce latency by exploiting parallelism when accessing the crowd. Achieving both the primary and secondary goals translates to the following two fundamental objectives for Deco's query execution engine:

- **Objective #1**: Never parallelize accesses to the crowd if it might increase the monetary cost.
- **Objective #2**: Always parallelize accesses to the crowd if it cannot increase the monetary cost.

We will see in the next subsections how Deco's query execution strategy is driven by these objectives. Note these objectives define Deco's default behavior. Users can trade higher cost for lower latency by overriding the degree of parallelism; see Section 7.1.

3.2 Challenges and Approach

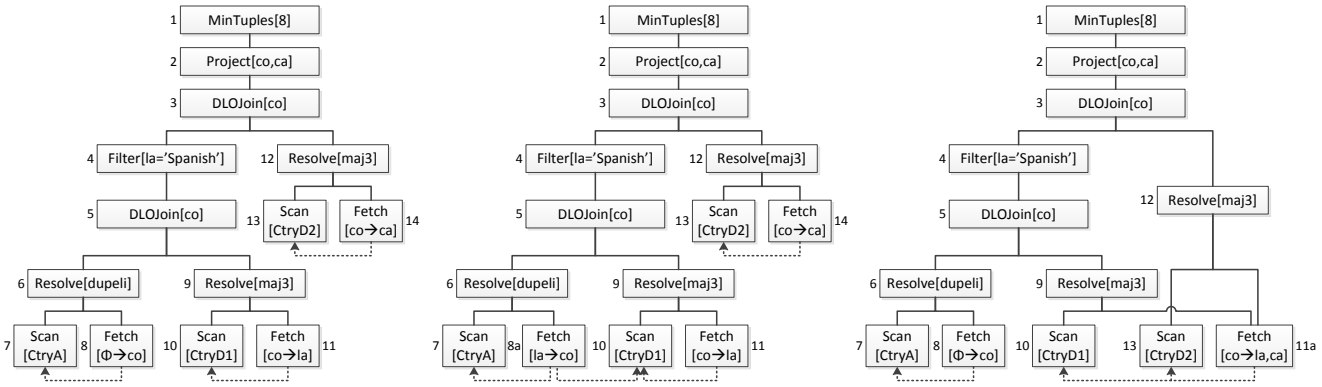
Deco's data model and query semantics along with the objectives defined above give us several unique challenges to address. We describe those challenges and how Deco's execution model addresses them. Like a traditional query plan, a Deco query plan is a rooted DAG of *query operators*. Each operator produces "output tuples" based on "input tuples" that are the outputs of its children.

Executing Queries in Two Phases: To minimize monetary cost, Deco's query execution engine has to ensure that fetches are issued only if the raw tables do not have sufficient data to produce n result tuples. To do so, Deco executes queries in two phases. In the *materialization* phase, the "current" result is materialized using the existing contents of the raw tables without invoking additional fetches. If this result does not meet the MinTuples constraint, the *accretion* phase invokes fetch rules to obtain more results. This second phase extends the result incrementally as fetch rules complete, and invokes more fetches as necessary until the constraint is met.

Enabling Parallelism Using Asynchronous Pull: To reduce latency, it is important for Deco's query execution engine to exploit parallelism when accessing the crowd, as discussed in Section 1. However, the traditional *iterator* model cannot enable this kind of parallelism because *getNext* calls do not return until data is provided. (The solution used in parallel database systems does not apply in our setting; see Section 8.) In Deco's *hybrid execution model*, query operators do not expect an immediate response to a "pull" request; the child operator will respond whenever a new output tuple becomes available. This built-in asynchrony in query plan execution ultimately allows Deco to ask multiple questions to the crowd in parallel, without having to wait for individual crowd answers. The concept of *asynchronous iteration* introduced in [7] also aims to enable parallelism when accessing outside sources during query execution. However, our specific setting led us to a somewhat different solution; see Section 8.

Choosing Right Degree of Parallelism: To reduce latency while still minimizing monetary cost, it is critical to choose the right degree of parallelism: too much parallelism might waste work (and therefore increase monetary cost), while too little increases latency. As described in Section 3.1, our approach is to maximize the number of fetches being executed in parallel, as long as all of them may be required to produce the query result. For example, to produce n output tuples, a *Filter* operator starts by "pulling" n input tuples in parallel from its child, then initiates another pull whenever it receives an input tuple not satisfying the predicate. Similarly, a *Resolve* operator first pulls the minimum number of input tuples required for the resolution function to produce an output value, then pulls additional input tuples as long as the resolution function indicates that more are needed for an output value.

Initiating Good Fetches: In certain cases where existing data must be combined with new data to produce the result, minimizing monetary cost is especially difficult because existing data can make some fetches more profitable than others. Thus, Deco's query execution engine has to choose not only the right degree of parallelism, but also the specific "good" fetches to invoke in parallel. Individual query operators do not always have enough information to choose the good fetches, so our approach is to invoke more fetches than needed, but prioritize them so the better fetches are more likely to complete first (thus minimizing monetary cost). The query engine cancels any outstanding fetches once the MinTuples constraint is met, which for our model we assume incurs no extra cost. (Note



(a) Basic **(b) Reverse** **(c) Combined**

Figure 1: Query plans

this assumption largely holds in, e.g., Mechanical Turk [1].)

Changing Result Incrementally: Due to the flexibility of Deco's fetch rules and resolution rules, query operators sometimes have to remove or modify output tuples that were passed to their parents previously. For example, fetch rules such as country ⇒ language,capital can provide tuples to multiple raw tables. Even if this fetch rule is invoked based on the need for a language value, data may as a side effect be inserted into the raw table for capital. This insertion can update tuples already produced because resolution functions are not necessarily monotonic. In our example, if we've already computed *majority-of-3* for the capital of a country and passed the result to the parent, we may need to propagate an update to modify the capital if the majority changes. The process of propagating updates up the plan becomes similar to *incremental view maintenance* [2].

3.3 Example Query Plan

We now describe our execution model in the context of a basic query plan, depicted in Figure 1a. The plan is for the following query on the example database from Section 2:

```
SELECT country, capital FROM Country
WHERE language='Spanish' MINTUPLES 8
```

We use three fetch rules: ∅ ⇒ country (operator 8), country ⇒ language (operator 11), and country ⇒ capital (operator 14). Abbreviations in the query plan should be self-explanatory.

At a high level, the plan performs an outerjoin (operator 5) of a resolved version of CountryA (operator 6) and a resolved version of CountryD1 (operator 9), followed by a filter on language (operator 4). This result is outerjoined (operator 3) with a resolved version of CountryD2 (operator 12). Lastly, country and capital attributes are projected (operator 2). The *Scan-Fetch* operator pairs at the leaves of the plan will be explained shortly.

To keep things simple, in this example we illustrate the case where there are no existing tuples in any of the raw tables. First, the root operator sends eight "pull" requests to its child operator in parallel. Starting with eight requests based on MinTuples meets our two objectives in Section 3.1. These requests propagate down the left (outer) side of the joins, and eventually invoke fetch rule ∅ ⇒ country eight times, without waiting for answers. At this point, there are eight outstanding fetches in parallel.

As these outstanding fetches complete, the new country values are inserted into raw table CountryA and "pushed" into the plan by the *Scan* operator. Through the *DLOJoin* (for Dependent Left Outerjoin [5, 7]), new countries trigger invocations of fetch rule country ⇒ language. For each country value, two instances of this fetch rule are invoked in parallel because the resolution function *majority-of-3* requires at least two language values to produce an output value. At this point, we may have many fetches going on in parallel: some to fetch more countries, and some to fetch languages for given countries.

Until the MinTuples constraint is met, the query plan invokes additional fetches as needed to exploit as much parallelism as possible while minimizing monetary cost. For example, if the two instances of fetch rule country ⇒ language for a given country return two different language values, the plan invokes another instance of the same fetch rule to obtain the third language value. Likewise, as soon as a resolved language value for a certain country turns out to not be Spanish, or fetch rule ∅ ⇒ country gives a duplicated country value, the plan invokes a new instance of fetch rule ∅ ⇒ country. For countries whose resolved language value is Spanish, the plan obtains capital values for the country, in parallel with other fetches similarly to how language values were obtained. Once the MinTuples constraint is met, the result tuples are returned to the client.

In Section 4, we provide further details of query execution for the case where there are no existing tuples in any of the raw tables. Then, in Section 5, we extend query execution for the general case where there may be existing tuples in raw tables.

4. QUERY EXEC. WITH NO EXISTING DATA

In this section, we describe in detail how to execute a Deco query plan starting with empty raw tables. Under this assumption, the "current" query result computed in the materialization phase is always empty and thus does not satisfy the "MinTuples n" constraint. Therefore, we focus on the accretion phase, which fetches new data to obtain n result tuples. Section 5 addresses the general case of existing raw data.

We first describe the basics of Deco query operators. Then we explain how those query operators work together during the accretion phase in the context of the basic query plan from Figure 1a as well as two alternative plans using more sophisticated fetch rules.

4.1 Query Operators

We start by describing how Deco query operators communicate with each other and store intermediate tuples, then we describe the behavior of individual operators.

Operator Overview: Each query operator has a queue that stores messages received from other operators, and runs on its own thread that dequeues and processes one message at a time. Processing a

message typically involves changing the operator's local state as well as sending messages to its parent or child operators.

Messages: A message consists of a method to be run at the target operator and an optional argument. In the accretion phase covered in this section, bind messages pull more tuples from child operators, and add and remove messages push incremental changes to parent operators.

Buffers: Some operators have a local buffer that stores all input tuples to the operator. (Note *DLOJoin* and *DepJoin* have two local buffers, one for input tuples from the outer child and another for input tuples from the inner child.) These buffers are needed to determine the incremental changes to be propagated up the plan. The buffers are initially populated and indexed in the materialization phase, incrementally maintained in the accretion phase, and cleaned up when query execution terminates. All operators store their buffers in the same back-end RDBMS used for the raw tables, so large buffers can be handled efficiently.

Partial Result: We define the buffer contents at the root MinTuples operator as the *partial result* of the query: It contains the answer to the query computed so far, but may include tuples with NULL values. The goal is for the buffer to contain at least n tuples with no NULL values, to satisfy the "MinTuples n" constraint.

Since our operators must deal with asynchrony and handle both push and pull requests, their details differ significantly from their iterator model counterparts. Table 1 summarizes the behavior of our operators for the case of initially empty raw tables. The entries in the tables will be explained in the next subsections.

4.2 Basic Query Plan

We now provide additional details of query execution using the example query plan in Figure 1a.

Initial Fetches: Initially, the *MinTuples* operator sends n bind[$\varnothing$] messages to its child operator, where n is the MinTuples constraint, and $\varnothing$ denotes an empty tuple. When an operator receives a bind message, its job is to produce at least one output tuple for its parent. Under the assumption that query execution starts with empty raw tables, all operators except *Fetch* simply pass the responsibility (i.e., the bind message) on to a child (the outer child for *DLOJoin*/*DepJoin* and *Fetch* child for *Resolve*), and *Fetch* operators invoke their fetch rules to obtain tuples from the crowd.

In our example plan, *MinTuples* operator 1 initiates eight bind messages, and these bind messages propagate down to *Fetch* operator 8, which invokes eight instances of its fetch rule $\varnothing \Rightarrow$ country in parallel.

Populating Result: When an outstanding fetch completes, the *Fetch* operator sends an add message with the new tuple to its corresponding *Scan* operator. The *Scan* operator inserts the tuple into its raw table, then the change is propagated up the plan via add and remove messages, similar to incremental view maintenance. (In Section 4.3 we will see that a single fetch can actually result in multiple changes.)

In addition to bind messages from the *MinTuples* root, some operators may initiate additional bind messages based on the tuples propagating up, in the following two cases:

- *DLOJoin* and *DepJoin* are dependent join operators [5, 7]: they send bind messages to their inner children when they receive outer tuples that need to be matched.
- *Filter* and *Resolve* operators may initiate an additional bind message if an input tuple does not produce a new output tuple to propagate up. To minimize monetary cost, these operators have to ensure that the additional bind message is in fact necessary to satisfy the MinTuples constraint.

As a result, the set of outstanding fetches at any given time maintains the right degree of parallelism according to the objectives in Section 3.1.

Continuing our example, suppose an outstanding fetch $\varnothing \Rightarrow$ country completes with answer Peru. First, *Fetch* operator 8 sends an add message with tuple (Peru) to *Scan* operator 7. The *Scan* inserts the tuple into its raw table CountryA and forwards the add message to its parent. Then, *Resolve* operator 6 (duplicate elimination) forwards the add to its parent because its buffer contains no other (Peru) tuples. Upon receiving this add from the outer child, *DLOJoin* operator 5 sends add with NULL-padded tuple (Peru,NULL) to its parent because there are no matching tuples in its inner buffer. (Even though pushing padded tuples may seem unnecessary for this plan, in general all query operators must push all output tuples to their parents because they have no global view of the plan they belong to.) *Filter* operator 4 does not forward the padded tuple further because the tuple does not satisfy predicate language='Spanish'.

In addition to pushing new data up the plan, *DLOJoin* operator 5 sends a bind message with Peru to its inner child to obtain a language value for Peru. The job of *Resolve* operator 9 is to ultimately pass up an add message with tuple (Peru,X), where X is a resolved language value for Peru. It does so by sending two bind messages to *Fetch* operator 11, which invokes two instances of fetch rule Peru $\Rightarrow$ language in parallel.

Now suppose both outstanding fetches Peru $\Rightarrow$ language complete with answer Spanish. For each completed fetch, *Fetch* operator 11 sends an add message with (Peru,Spanish) to *Scan* operator 10, which extends its raw table CountryD1 and forwards the add to the parent. Once *Resolve* operator 9 receives both adds with (Peru,Spanish), it sends add with (Peru,Spanish) to its parent.

Next, *DLOJoin* operator 5 modifies its output tuple (Peru,NULL) to (Peru,Spanish) using a remove and an add message. The new tuple passes through *Filter* operator 4 and reaches *DLOJoin* operator 3, which pushes a padded tuple (Peru,Spanish,NULL) up the plan. Also, *DLOJoin* operator 3 sends a bind message with Peru to its inner child. Once receiving an add message with (Peru,Y) from *Resolve* operator 12, the *DLOJoin* incorporates Y into the partial result by modifying its output tuple (Peru,Spanish,NULL) to (Peru,Spanish,Y).

As a final example, suppose an outstanding fetch $\varnothing \Rightarrow$ country completes with answer Korea. Then, similarly to how Peru is processed, two instances of Korea $\Rightarrow$ language are invoked in parallel. When both instances complete with the same answer Korean, *DLOJoin* operator 5 sends its parent a remove message with (Korea,NULL) and an add message with (Korea,Korean). At this point, *Filter* operator 4 finds out that the new input tuple does not pass its predicate, so it initiates a bind message to obtain another country-language pair. This bind message propagates down the plan and invokes another instance of fetch rule $\varnothing \Rightarrow$ country. (Note that *Filter* operator 4 does not initiate bind messages for input tuples with NULL language values: an additional bind message is initiated only if the predicate is evaluated as "false" in a three-valued logic.)

Signaling Termination: Once the partial result at the root operator satisfies the MinTuples constraint, all query operators are terminated, and the operator buffers in the back-end RDBMS are cleaned up. We will see later that in the general case, outstanding fetches may need to be canceled, but in the special case of empty raw tables, there cannot be outstanding fetches. Finally, all non-NULL result tuples in the buffer at the *MinTuples* operator buffer are returned to the client, and query execution terminates.

Operator	On receiving bind[t] (from parent)	On receiving add[t] or remove[t] (from child)
MinTuples	–	For add[t], add t to buffer. For remove[t], remove t from buffer. If the MinTuples constraint is met, terminate execution and return all non-NULL tuples in the buffer to the client.
Project	Forward bind[t] to child.	Forward add/remove[$\Pi_A(t)$] to parent.
Filter	Forward bind[t] to child. (For our space of plans, t=$\varnothing$ always.)	For add[t], if $p(t)$ is true (where p denotes the filter's predicate), forward add[t] to parent; if $p(t)$ is false, send bind[$\varnothing$] to child. For remove[t], if $p(t)$ is true, forward remove[t] to parent.
DLOJoin	Forward bind[t] to outer child.	For add[t], add t to outer or inner buffer. For remove[t], remove t from outer or inner buffer. Propagate any changes to outerjoin result to parent using add/remove. For add[t], suppose t is from outer and has no matching tuple in inner buffer. If the join values $\Pi_A(t)$ are being seen for the first time, send bind[$\Pi_B(t)$] to inner child (where A denotes the joining anchor attributes from outer, and B denotes all anchor attributes from outer).
DepJoin	Forward bind[t] to outer child. (For our space of plans, t=$\varnothing$ always.)	If the join values in t contain one or more NULLs, do nothing and return. For add[t], add t to outer or inner buffer. For remove[t], remove t from outer or inner buffer. Propagate any changes to join result to parent using add/remove. For add[t], suppose t is from outer and has no matching tuple in inner buffer. If the join values $\Pi_A(t)$ are being seen for the first time, send bind[$\Pi_A(t)$] to inner child (where A denotes outer attributes in the join predicates). Otherwise, if bind[$\Pi_A(t)$] has failed to obtain matching inner tuples, send bind[$\varnothing$] to outer child. For add[t], if t is from inner and has no matching outer tuples, send bind[$\varnothing$] to outer child.
Resolve	Forward bind[t] to child *Fetch* operator.	Add $\Pi_{L\cup R}(t)$ to buffer (where $L \rightarrow R$ denotes the resolution rule). Propagate any changes to resolution result to parent using add/remove. If the resolution function indicates that more input tuples are needed to produce an output, send bind[t] to child *Fetch* operator.
Scan	–	Insert $\Pi_A(t)$ into raw table (where A denotes attributes in the raw table), and send add[t] to parent.
Fetch	Invoke the fetch rule $L \Rightarrow R$ with argument $\Pi_L(t\|\|c)$ as left-hand side, where $\|\|$ denotes tuple concatenation, and c is a tuple consisting of constant value v's in all Where clause predicates of form $S.A$=v.	When the fetch completes, send add[t] to corresponding *Scan* operators. (See dotted arrows in Figures 1a, 1b, and 1c.)

Table 1: Message exchanges during the accretion phase (empty raw tables)

4.3 Alternative Plans

In addition to standard plan transformations based on relational algebra [12], our Fetch-Resolve-Join semantics enables additional plan alternatives based on the selection of fetch rules. In this section, we describe two example alternative plans for our query.

Reverse Fetches: Suppose the predicate language='Spanish' is very selective. If we use the query plan in Figure 1a, even obtaining a single answer could be expensive in terms of monetary cost and latency, because we are likely to end up fetching many countries and languages that do not satisfy the predicate.

Instead, we can use the "reverse" fetch rule language ⇒ country underneath the *Resolve* operator to obtain countries with a certain language, rather than random countries. Figure 1b shows a query plan that uses this approach. Note the only change from Figure 1a is operator 8a. Whenever *Fetch* operator 8a receives a bind message from its parent, it invokes the fetch rule language ⇒ country with Spanish as the language value. (The association of predicate language='Spanish' with the *Fetch* operator is made when the query plan in Figure 1b is built.) When completed with a new country name Z, this fetch rule invocation adds tuples to both CountryA and CountryD1 via *Scan* operators 7 and 10, and the two added tuples propagate up the plan separately. Assuming the country name Z is not a duplicate, *Resolve* operator 6 pushes Z up to *DLOJoin* operator 5, which sends a bind message to its inner child to complete the language of Z. Meanwhile, *Scan* operator 10 pushes (Z,Spanish) to *Resolve* operator 9. Since the *Resolve* already has one raw language value for Z, it ends up asking for one or two more language values using the fetch rule country ⇒ language (*Fetch* operator 11) to compute a resolved language value for Z.

Combined Fetches: It may be less expensive to use a fetch rule that gathers multiple dependent attributes at the same time, rather than fetching attributes separately. For the example query, we can use the "combined" fetch rule country ⇒ language,capital instead of the two fetch rules country ⇒ language and country ⇒ capital. Figure 1c shows a plan that uses this approach. Note that Figure 1c differs from Figure 1a only in operator 11a and the absence of operator 14. Both *Resolve* operators 9 and 12 send bind messages to *Fetch* operator 11a when they need more tuples. (*Fetch* operators keep track of outstanding fetches to ensure that redundant fetches are not invoked.) Once an outstanding fetch completes, *Fetch* operator 11a sends add messages to both *Scan* operators 10 and 13.

To illustrate a more interesting scenario, let us consider the query plan in Figure 1c but with *majority-of-5* as the resolution function for capital in *Resolve* operator 12 (with shortcutting, so three matching values are needed). Suppose an outstanding fetch ∅ ⇒ country completes with answer Bolivia. *DLOJoin* operator 5 initiates a bind message, and *Fetch* operator 11a invokes two instances of Bolivia ⇒ language,capital in parallel. Suppose both fetches complete with the same answer (Spanish,La Paz). Then, a new output tuple (Bolivia,Spanish) reaches *DLOJoin* operator 3, and

a partial result tuple (Bolivia,NULL) is stored at *MinTuples* operator 1. At the same time, another instance of Bolivia ⇒ language,capital is invoked to obtain another capital value. Upon receiving (Quechua,Sucre) as the third answer, the same fetch rule is invoked again. Suppose the fourth answer is (Aymara,La Paz). While *Resolve* operator 12 finally produces La Paz as the resolved capital value, *Resolve* operator 9 no longer has a majority for the language of Bolivia. Thus it sends a remove message with (Bolivia,Spanish) to its parent, which propagates up and eventually invalidates the partial result tuple (Bolivia,NULL). More bind messages are initiated until resolved values for country and capital are sufficient to produce the query result.

4.4 Join of Conceptual Relations

Although our example query from Section 3.3 contains only one conceptual relation Country in its From clause, Deco's query execution engine also supports joining conceptual relations using the *DepJoin* operator. While *DLOJoin* handles outerjoins between anchor and dependent tables according to Deco's data model semantics, *DepJoin* handles join predicates explicitly specified in Where clauses. Both join operators are variants of dependent join, so they send bind messages with join values extracted from outer tuples to their inner children to receive matching inner tuples. However, *DepJoin* is somewhat more complex than *DLOJoin*. By definition, *DLOJoin* is always an equijoin over anchor attributes, whose values are fixed by the time a bind message is issued to the inner child, i.e., no additional fetches or resolution functions are applied for these anchor values. On the other hand, *DepJoin* predicates can be over any attributes (although restricted to equijoins; non-equijoins are handled as filters). When a *DepJoin* sends a bind message with join attribute values to the inner child, due to the behavior of resolution functions, it cannot be assured that the inner tuple returned will have matching join values. If the values do not match, additional binds must be sent to produce the needed join result tuple.

5. QUERY EXEC. WITH EXISTING DATA

Now we describe how to execute a Deco query in the general case where there may be existing data in raw tables. As discussed in Section 3.2, this general case is significantly more difficult to handle than the special case of empty raw tables, in terms of minimizing monetary cost and reducing latency.

In this section we first describe how an initial query result is computed in the materialization phase and how the accretion phase differs from the special case described in Section 4.

5.1 Materialization Phase

The materialization phase computes an initial query result based on the existing contents of the raw tables, and as a side effect populates operator buffers. Starting from *Scan* operators at the bottom, each operator in the plan pushes its initial output tuples to its parent using populate messages, then sends a shift message to the parent indicating the end of the initial output tuples at the operator (thus "shifting" to the accretion phase, if needed). Table 2 summarizes the behavior of operators for materialization. When the root *MinTuples* operator receives a shift message, its buffer contains the initial partial result. If the partial result satisfies the MinTuples constraint, execution terminates. Otherwise, execution continues to the accretion phase.

Although our current approach for computing the initial result is fairly naive, we can easily incorporate many conventional techniques into the materialization phase to improve performance. For example, we can cache the resolved versions of the raw tables across queries so that *Scan* operators do not have to send all raw tuples again for each query. In this case, the materialization phase starts from *Resolve* operators, and *Scan* operators do not participate. We could also incorporate a more traditional iterator model for the materialization phase, as long as it is properly extended to populate the operator buffers. Note that unless we have sufficient raw data, the bulk of query execution time is spent waiting for human answers, so latency improvement from speeding up the materialization phase is marginal.

As an example, suppose we execute the query plan in Figure 1a with the following initial contents for the raw tables:

CountryA

country
Chile
Italy
Korea
Peru
Spain
Spain

CountryD1

country	language
Chile	Spanish
Chile	Spanish
Chile	English
Italy	Italian
Italy	Italian
Peru	Spanish
Spain	Spanish
Spain	Spanish

CountryD2

country	capital
Italy	Rome
Korea	Seoul
Spain	Madrid
Spain	Barcelona
Spain	Madrid

Recall the resolution function for both language and capital is *majority-of-3*, with shortcutting. During the materialization phase, *DLOJoin* operator 5 accumulates the following input tuples in its buffers:

Outer buffer

country
Chile
Italy
Korea
Peru
Spain

Inner buffer

country	language
Chile	Spanish
Italy	Italian
Spain	Spanish

Among the five output tuples of the *DLOJoin*, three of them do not pass *Filter* operator 4: (Italy,Italian), (Korea,NULL), and (Peru, NULL). Thus, *DLOJoin* operator 3 accumulates the following input tuples in its buffers:

Outer buffer

country	language
Chile	Spanish
Spain	Spanish

Inner buffer

country	capital
Spain	Madrid

The initial partial result at MinTuples operator 1 contains (Chile, NULL) and (Spain,Madrid).

5.2 Accretion Phase

Similarly to how the special case of empty raw tables proceeds (Section 4), the accretion phase first invokes some initial fetches to get started. Then, it extends result based on newly fetched data, possibly invokes more fetches as necessary, and finally signals termination once the MinTuples constraint is met. We will later discuss how our approach meets the two objectives from Section 3.1.

Initial Fetches: As specified in Table 3, initial bind messages are generated for two distinct purposes:

- **Gathering Completely New Tuples**: The *MinTuples* operator initiates k bind messages, where k is the minimum number of additional partial result tuples needed to satisfy the MinTuples constraint (based on the partial result after materialization).
- **Joining Existing Tuples with New Tuples**: The other method of increasing the size of the result is to attempt to join existing outer tuples with new inner tuples. (For *DLOJoin*, this means replacing NULL values with actual values.) The bind messages to do so are generated by the *DLOJoin* and *DepJoin* operators. Each *DLOJoin* or *DepJoin* operator sends a bind

Operator	On receiving populate[t] (from child)	On receiving shift (from child)
MinTuples	Add t to buffer.	If the "MinTuples n" constraint is met, terminate execution and return all non-NULL tuples in the buffer to the client. Otherwise, proceed to the accretion phase.
Project	Forward populate[$\Pi_A(t)$] to parent.	Forward shift to parent.
Filter	If $p(t)$ is true (where p denotes the filter's predicate), forward populate[t] to parent.	Forward shift to parent.
DLOJoin	Add t to outer or inner buffer.	Send the left outerjoin of the two buffers to parent using populate messages. Then send shift to parent.
DepJoin	If all join attribute values are non-NULL, add t to outer or inner buffer.	Send the join of the two buffers to parent using populate messages. Then send shift to parent.
Resolve	Add t to buffer.	Group all tuples in buffer by the left-hand side attributes of the resolution rule, apply the resolution function for each group, and send the resolved tuples to parent using populate messages. Then send shift to parent.
Scan	At the start of the materialization phase, for each t in the raw table, send populate[t] to parent. Then send shift to parent.	

Table 2: Message exchanges for materialization

Operator	At the start of accretion phase
MinTuples	Send $\max(n-m, 0)$ bind[$\varnothing$] messages to the child, where n is the MinTuples constraint, and m is the number of tuples in the buffer.
DLOJoin	For each set of values $\Pi_A(t)$ in outer buffer with no matching inner tuples, send bind[$\Pi_B(t)$] to inner child (where A denotes the joining anchor attributes from outer, and B denotes all anchor attributes from outer).
DepJoin	For each set of values $\Pi_A(t)$ in outer buffer with no matching inner tuples, send bind[$\Pi_A(t)$] to inner child (where A denotes outer attributes in the join predicates).

Table 3: Message exchanges to start accretion phase

message to its inner child for each join attribute values in its outer buffer with no matching tuples in its inner buffer.

Note that in the special case of empty raw tables, Table 3 says for *MinTuples* to initiate n binds, and none from joins, consistent with Section 4.2.

For most operators, behavior in the general case is the same as for the special case (Table 1). However, for *Filter* and *DepJoin*, the behavior upon receiving a bind message differs from the special case: These operators might be able to produce an output tuple without passing the bind message on to their child because of existing data. As mentioned above, *DLOJoin* operators initiate bind messages to replace NULL values with actual values. If a NULL is replaced with a value that satisfies the predicate of a *Filter* higher up in the plan, the *Filter* produces an output tuple spontaneously. Thus, *Filter* operators do not necessarily propagate bind messages down the plan. Instead, they keep track in local variables of how many bind messages have been received and how many tuples might be generated from below as NULL values are replaced with actual values, and send bind messages only if they have to. *DepJoin* operators also do not necessarily propagate bind messages down the plan, for similar reasons. Further details are omitted, but our algorithm guarantees that whenever a *Filter* or *DepJoin* operator sends a bind to its child (the outer child for *DepJoin*), the MinTuples constraint could not be satisfied without that bind (Objective #1 from Section 3.1).

Continuing our example from the end of Section 5.1, the accretion phase proceeds as follows:

- *MinTuples* operator 1 needs at least eight result tuples, but its buffer contains only two partial result tuples. To obtain six more partial result tuples, it sends six bind messages to its child. Among these six binds, *Filter* operator 4 stops two binds because its local variables indicate that two input tuples may pass the predicate once their actual language values replace NULLs: (Korea,NULL) and (Peru,NULL). Eventually, four bind messages reach *Fetch* operator 8 and invoke fetch rule $\varnothing \Rightarrow$ country four times.
- *DLOJoin* operator 3 scans its outer buffer and finds one tuple (Chile,Spanish) that does not match any inner tuples. Thus, it sends a bind message to its inner child to complete the capital value of Chile. This message reaches *Fetch* operator 14, which invokes two instances of Chile $\Rightarrow$ capital in parallel.
- Similarly, *DLOJoin* operator 5 sends two bind messages to its inner child to complete the language values for Korea and Peru. *Fetch* operator 11 invokes two instances of Korea $\Rightarrow$ language and one instance of Peru $\Rightarrow$ language.

Once these initial fetches are invoked, the query execution engine handles each completed fetch similarly to the examples from Section 4, possibly invoking additional fetches until eight result tuples are produced.

Now let us further discuss Objective #1, considering the fetches resulting from the binds initiated by *DLOJoin* and *DepJoin* operators. It may appear that *DLOJoin* and *DepJoin* clearly violate the objective, since the number of binds they issue depends only on the number of non-joining tuples (which could be very large), and not on the "MinTuples n" constraint. As discussed in Section 3.2, our approach to this specific case relies on two features:

- *prioritizing* outstanding fetches, so the ones most likely produce useful data are returned first
- *canceling* outstanding fetches (without incurring cost) once sufficient data has been obtained

(Both of these capabilities are dependent on the crowdsourcing platform; we discuss Mechanical Turk specifically in Section 6.4.) Given the limited information at each *DLOJoin* and *DepJoin* operator, it is impossible for those operators to choose exactly the right number of bind messages to maximize parallelism while minimizing cost. Thus, we allow *DLOJoin* and *DepJoin* to issue bind messages to their inner children for *all* non-matching outer tuples, but we carefully prioritize the resulting fetches, and cancel any that are outstanding once the MinTuples constraint is met. The prioritization problem turns out to be quite interesting in our setting, so it is discussed in detail in the next section.

6. FETCH PRIORITIZATION

We now explain how we prioritize fetching data from the crowd, in order to minimize cost. Recall that all fetches are the result of bind messages passed down the plan until they reach *Fetch* operators. After a fetch rule has been invoked and before it returns, we refer to that instance as an "outstanding fetch." As discussed earlier, at any given time there may be a large number of outstanding fetches executing in parallel; our goal is to profitably influence the order in which these outstanding fetches are handled. To separate our optimization goal from the details in crowdsourcing platforms, we assign *scores* to each outstanding fetch, reflecting our prioritization. How the scores result in actual fetch prioritization is platform-specific.

Based on our discussion in the previous section, all outstanding fetches have one of two purposes:

(1) To create new partial result tuples. These fetches may be a result of bind messages originating from *MinTuples*, *DepJoin*, or *DLOJoin* operators.

(2) To fill in NULL values in the partial result. These fetches are always a result of binds originating from *DLOJoin* operators.

For a "MinTuples n" constraint, our overall prioritization strategy is to first create at least n partial result tuples (purpose 1), then fill in NULL values (purpose 2) until we have n result tuples. Although this strategy may not be optimal in all cases, intuitively we must have n partial result tuples regardless in order to produce a query result. Thus, we focus our optimization on filling in NULL values in a fashion that minimizes cost. As future work, we plan to consider the more difficult problem of globally optimizing purposes 1 and 2 together, which will undoubtedly depend in complex ways on the query plan itself.

To find the optimal set of fetches that can fill in enough NULL values to generate the query result, there are several important factors to consider:

- Our goal is to generate tuples with no NULL values, so we may prefer to fill in NULL values for tuples that are "nearly" complete.
- Sometimes a single fetch can fill in multiple NULL values.
- Since resolution rules often require multiple input values in order to produce one output value, multiple fetches may be needed to fill in one NULL value.

We first formalize our fetch prioritization problem and show that it is NP-hard. We then propose two heuristic scoring functions and describe their implementation in the context of Deco's query execution engine. Lastly we describe how fetch prioritization is implemented in one crowdsourcing platform, Mechanical Turk.

6.1 Formal Problem Definition

Suppose we have m partial result tuples for a query plan with "MinTuples n". As described above, we are interested in the case where $m \geq n$, but fewer than n tuples are non-NULL. The query processor creates a set of outstanding fetches, each one associated with one or more NULLs in the partial result. (For formalizing the problem, we assume resolution functions require a fixed number of input tuples, however we will see that our heuristics allow us to drop this assumption.) Our goal is to select a subset of the outstanding fetches that completes the result at minimum cost.

Finding the optimal solution for our fetch prioritization problem turns out to be NP-hard in the data size and the number of desired result tuples, using a reduction from the three-dimensional matching problem. A theorem and proof is given in Appendix A. Thus, we use a heuristic approach, described in Section 6.2. Here we formulate the fetch prioritization problem as a *polynomial zero-one program* to motivate our heuristics. (In fact, the fetch prioritization problem can be posed as an integer linear program, making it NP-complete; however, we use the polynomial zero-one program for ease of exposition.)

Let $\text{NULL}_{i1}, \ldots, \text{NULL}_{ip_i}$ denote the p_i NULL values of the i-th partial result tuple ($p_i \geq 0$). To fill in NULL_{ij}, $q(i,j)$ identical outstanding fetches $f_{g(i,j)1}, \ldots, f_{g(i,j)q(i,j)}$ must complete. (Note that an outstanding fetch f_{hk} contributes to all NULL_{ij}'s with $g(i,j) = h$ and $q(i,j) \geq k$.) Finally, let x_{hk} be an indicator variable specifying if fetch f_{hk} is chosen. Then, the fetch prioritization problem is directly translated to the following:

$$\text{minimize} \sum_h \sum_k x_{hk} \quad \text{subject to} \sum_{i=1}^{m} \prod_{j=1}^{p_i} \prod_{k=1}^{q(i,j)} x_{g(i,j)k} \geq n$$
$$x_{hk} = 0, 1 \quad \forall h, k$$

The objective function is the number of chosen fetches. The inequality constraint says that at least n tuples have to be completed.

Example: Consider the following raw tables for the Country and City relations. Recall that the resolution functions for the language, capital, and population attributes are *majority-of-3*, *majority-of-3*, and *average-of-2*, respectively.

CityA

city	country
Istanbul	Turkey
Venice	Italy
Trento	Italy

CityD1

city	country	population
Venice	Italy	270660

CountryA

country
Turkey
Italy

CountryD1

country	language
Italy	Italian

CountryD2

country	capital
Turkey	Istanbul

Suppose that we have the following five fetch rules:

- [Country] $\varnothing \Rightarrow$ country
- [Country] country $\Rightarrow$ language
- [Country] country $\Rightarrow$ capital
- [City] $\varnothing \Rightarrow$ city,country
- [City] city,country $\Rightarrow$ population

Further suppose our query asks for any two cities along with their population and language:

```
SELECT city, country, population, language
FROM City, Country
WHERE City.country = Country.country
MINTUPLES 2
```

Evaluating the query over the conceptual relations implied by the current contents of the raw tables, we get:

city	country	population	language
Istanbul	Turkey	NULL	NULL
Venice	Italy	NULL	NULL
Trento	Italy	NULL	NULL

(None of the population or language values have sufficient raw data to satisfy the corresponding resolution function.)

To fill in NULL values, the following ten fetches are initiated during query execution:

- f_{11}, f_{12}: (Istanbul,Turkey) $\Rightarrow$ population
- f_{21}: (Venice,Italy) $\Rightarrow$ population
- f_{31}, f_{32}: (Trento,Italy) $\Rightarrow$ population
- f_{41}, f_{42}, f_{43}: Turkey $\Rightarrow$ language
- f_{51}, f_{52}: Italy $\Rightarrow$ language

Formulating this case as a polynomial zero-one program, we get:

$$\begin{aligned}\text{minimize } & x_{11}+x_{12}+x_{21}+x_{31}+x_{32}\\ & +x_{41}+x_{42}+x_{43}+x_{51}+x_{52}\\ \text{subject to } & x_{11}x_{12}x_{41}x_{42}x_{43}+x_{21}x_{51}x_{52}\\ & +x_{31}x_{32}x_{51}x_{52}\geq 2\\ & x_{hk}=0,1 \quad \forall h,k\end{aligned}$$

Recall the objective is to minimize the number of chosen fetches out of all f_{hk}'s. Each term in the constraint indicates if its corresponding partial result tuple is completed; for example, $x_{21}x_{51}x_{52}$ corresponds to the second partial result tuple for (Venice,Italy). The optimal solution is $x_{21}{=}x_{31}{=}x_{32}{=}x_{51}{=}x_{52}{=}1$, which translates to actual outstanding fetches (Venice,Italy) ⇒ population, (Trento, Italy) ⇒ population, and Italy ⇒ language. □

Note that the number of outstanding fetches $q(i,j)$ required to fill in a NULL value may not be fixed as in our formulation, depending on the resolution function. Even in our simple running example, *majority-of-3* can stop after obtaining two raw values if they agree with each other. We will see that our heuristic approach accommodates variable values for $q(i,j)$.

6.2 Heuristic Algorithm

Our practical solution to the NP-hard prioritization problem is based on assigning scores to outstanding fetches. The scores can then be used by the crowdsourcing platform to influence which fetches are most likely to complete (Section 6.4). Initial scores are assigned to outstanding fetches at the start of accretion phase based on a heuristic solution to the problem formalized in Section 6.1. As fetches complete and the partial result changes, scores for the remaining outstanding fetches may be adjusted. We will see in Section 7 that performance with our online heuristic approach can be close to optimal. We present two scoring functions. The first one assumes that only one fetch is needed to complete each NULL value, i.e., $q(i,j)=1$. The second scoring function takes the resolution function into account and therefore multiple fetches may be needed, i.e., $q(i,j)\geq 1$.

Our first scoring function, $score_1$, is expressed in terms of p_i, the number of remaining NULL values in each partial result tuple. Specifically, we regard the contribution of f_{hk} to the i-th partial result tuple as $1/p_i$ (if f_{hk} contributes to the tuple at all):

$$score_1(f_{hk})=\sum_{i=1}^{m}([\exists j: g(i,j)=h]\times\frac{1}{p_i})$$

In our example in Section 6.1, we have $p_i{=}2$ for $i{=}1,2,3$, so $score_1(f_{hk})$ depends on the number of partial result tuples to which f_{hk} contributes. Thus, we have $score_1(f_{hk}){=}1/2$ for $h{=}1,2,3,4$ and $score_1(f_{5k}){=}1$.

Our second scoring function, $score_2$, is expressed in terms of the number of remaining fetches to complete each partial result tuple, $\sum_{j=1}^{p_i}q(i,j)$. The contribution of f_{hk} to the i-th partial result tuple is $1/\sum_{j=1}^{p_i}q(i,j)$:

$$score_2(f_{hk})=\sum_{i=1}^{m}([\exists j: g(i,j)=h]\times\frac{1}{\sum_{j=1}^{p_i}q(i,j)})$$

In our example in Section 6.1, we have $\sum_{j=1}^{p_i}q(i,j){=}5,3,4$ for $i{=}1,2,3$, respectively. Since each of $f_{1k},\ldots,f_{4k}$ contributes to a single partial result tuple, we get $score_2(f_{1k}){=}score_2(f_{4k}){=}1/5$, $score_2(f_{2k}){=}1/3$, and $score_2(f_{3k}){=}1/4$. Since f_{5k} contributes to two partial result tuples, we get $score_2(f_{5k}){=}1/3{+}1/4$. Notice the top-5 initial $score_2$ values correspond to the optimal solution.

6.3 Query Execution Engine Extension

We now explain how we have extended Deco's query execution engine to compute scoring function $score_1$ or $score_2$ for each outstanding fetch. Actual prioritization of fetches based on the scores depends on fetch procedures and crowd interfaces. For Mechanical Turk, our fetch procedure always presents the outstanding fetch with the highest score whenever a worker arrives (see Section 6.4).

Since $score_1$ relies on the entire set of current partial result tuples, the *MinTuples* operator is responsible for computing it. However, computing $score_1$ incurs little overhead due to the nature of the execution model: the *MinTuples* operator can incrementally maintain the scores as partial result tuples are updated by add and remove messages from its child operator. Specifically, when a partial result tuple t is added or removed, the *MinTuples* operator can adjust $score_1(f)$ for each outstanding fetch f that can fill in NULL values in the tuple t.

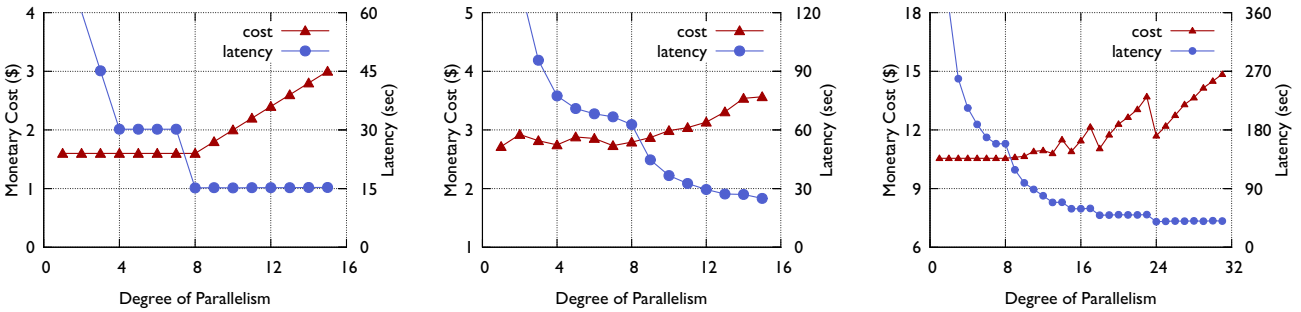
Our approach requires us to track all outstanding fetches that can fill in a NULL value in a given partial result tuple t. To do so, we assign a unique identifier for each outstanding fetch f and embed the identifier in the NULL values that f can fill in. *DLOJoin* and *Fetch* operators cooperate to perform this embedding.

For $score_2$, we can use the same overall approach as for $score_1$ except we need to manage q, the number of remaining fetches to complete each NULL value. *Resolve* operators calculate q based on the numbers of required input tuples for the resolution function (set by the schema designer), and the tuples currently in its buffer. *Resolve* operators must propagate calculated q values up to the *MinTuples* operator so that $score_2$ can reflect up-to-date q values. In this case, simply embedding q in its corresponding NULL value is not enough: Whenever q changes, *Resolve* operators must modify the q part of the NULL value using a remove plus an add message. When these messages reach the *MinTuples* operator, the $score_2$ values can be updated without affecting the partial result. Due to the additional computation and messages, computing $score_2$ is somewhat more expensive than computing $score_1$; however, we will see in Section 7 that $score_2$ is a better heuristic.

6.4 Mechanical Turk Support

We now describe how Deco's generic Mechanical Turk (MTurk) fetch procedure supports fetch prioritization based on scoring as described in the previous subsection. The MTurk fetch procedure translates fetch rule invocations from the query execution engine into *HIT*s (*Human Intelligence Task*s, unit tasks on MTurk) so that workers can answer them. For prioritization, the goal of the MTurk fetch procedure is to present the outstanding fetch with the highest score whenever a worker "accepts" one of the HITs. To do so, the MTurk fetch procedure works together with a dedicated *Deco form server*, which hosts HTML forms that the workers fill in, and keeps track of scores for outstanding fetches.

More specifically, when the MTurk fetch procedure is invoked by a *Fetch* operator, the procedure instantiates a form template for the fetch rule, sends the HTML form and its score to the form server using a web service API, and creates a HIT that points to the form server. The MTurk fetch procedure also forwards any changes in scores for outstanding fetches from the query execution engine to the form server. When a worker accepts any of the HITs, the worker's web browser loads the address of the form server, which then chooses the HTML form with the highest score and serves it to the worker. Typically MTurk workers accept a series of HITs within their chosen HIT type, presented by MTurk in random order. Overall, our approach replaces random scheduling with score-based prioritization using our form server to delay the binding of HTML forms to HITs.



(a) Reverse plan, correct answers **(b) Reverse plan, erroneous answers** **(c) Basic plan, correct answers**

Figure 2: Experiment 1

7. EXPERIMENTAL EVALUATION

In this paper we focus our experimental evaluation of the Deco execution model on the interactions among parallelism, cost, and latency. (In [12] we presented experiments showing Deco's capability of executing various plans, using Mechanical Turk.) Also, we evaluate the effectiveness of our fetch prioritization scheme, compared against the optimal prioritization and random prioritization.

To enable a large number of experiments without significant latency and dollar cost, we built a *crowd simulator* that responds to fetch requests by selecting values from a predetermined set. (Note that repeating our experiments on a real crowdsourcing platform would be extremely costly.) We can either set our simulator to always give "correct" answers, or specify a fixed probability for each fetch rule that "incorrect" answers are given.

7.1 Parallelism, Cost, and Latency

Experiment 1: Varying Degrees of Parallelism Our first experiment determines whether Deco's query execution engine accomplishes the two objectives in Section 3.1, by comparing monetary cost and latency of executing the same query plan with varying degrees of parallelism. We use the example query from Section 3.3:

```
SELECT country, capital FROM Country
WHERE language='Spanish'  MINTUPLES 8
```

For this experiment we start with empty raw tables. Thus, Deco begins by invoking eight anchor-value fetches in parallel, so the crowd can contribute to all eight (potential) result tuples at the same time. Additional fetches are invoked as needed when some of the original eight complete, but never more fetches than would contribute to eight result tuples. In our graphs, the x-axis corresponds to the degree of parallelism d, defined as the maximum number of result tuples being produced in parallel. Thus, Deco's behavior for our example query is at d=8.

Figure 2a shows the monetary cost and latency of executing the reverse plan in Figure 1b for d=1..15, with our crowd simulator configured to always give correct answers. We assume each fetch takes 5 seconds and costs $0.05, for all fetch rules. Since each result tuple needs three rounds of answers (e.g., Spanish ⇒ Peru, Peru ⇒ Spanish, and two instances of Peru ⇒ Lima in parallel), the minimum cost and latency are $8 \times 4 \times \$0.05 = \$1.6$ and $3 \times 5\text{s} = 15\text{s}$, respectively. In fact, Deco's behavior (d=8) minimizes both monetary cost and latency. As discussed in Section 3.2, too much parallelism (d>8) increased monetary cost, while too little (d<8) increased latency. Compared to no parallelism (d=1, equivalent to the traditional iterator model), Deco reduced latency dramatically without increasing the cost.

Figure 2b shows the cost and latency of executing the reverse plan, with our simulator configured to give incorrect answers with 25% chance. Each data point reported is the average of 50 trials. Due to incorrect answers, Deco often ends up invoking fetch rule language ⇒ country more than eight times, so the cost remains at the minimum until d=9, which is the best degree of parallelism. Although Deco did not quite achieve the minimum, latency is still very close to the minimum across d=1..9.

Figure 2c shows the cost and latency of executing the basic plan in Figure 1a, with our simulator set to always give correct answers. Since cost and latency of executing this plan depend on the order in which countries are obtained, we picked a random order and used the same order for all data points. As in Figure 2a, Deco found the best degree of parallelism (d=8), reducing latency as much as possible while minimizing cost, thereby meeting the objectives laid out in Section 3.1. (As a side note, the non-monotonicity of cost increase for d>8 is related to the positions Spanish-speaking countries appear in the random order of countries obtained.)

7.2 Effectiveness of Fetch Prioritization

Now we present two additional experiments evaluating the effectiveness of fetch prioritization. Experiment 2 evaluates our two scoring functions for varying amounts of existing data in the raw tables, while Experiment 3 evaluates the scoring functions for different data distributions. In both experiments, we compare our scoring functions against the optimal prioritization computed using a brute-force enumeration, and against random prioritization (i.e., equal scores).

For both experiments, we use the following fetch rules:

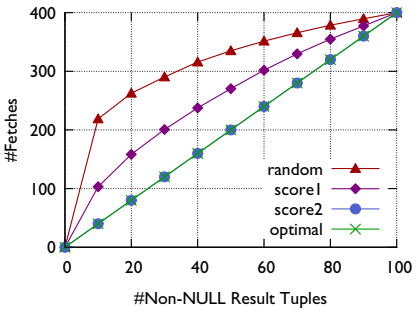
- [Country] country ⇒ language, and country ⇒ capital
- [City] city,country ⇒ population

Recall the resolution functions for the language, capital, and population attributes are *majority-of-3*, *majority-of-3*, and *average-of-2*. Also, we set our simulator to always give correct answers, so that comparison against the optimal case makes sense. Each data point in the figures is the average of ten trials, which had little variance.

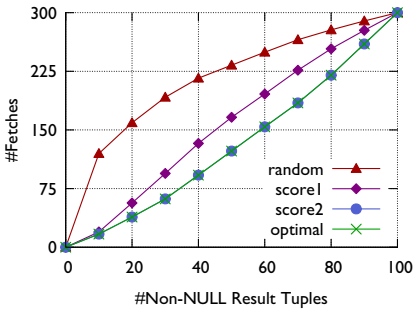
Experiment 2: Varying Amount of Existing Data We use the following simple query:

```
SELECT country, language, capital  FROM Country
MINTUPLES X
```

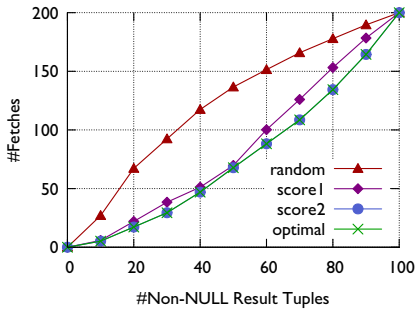
We seed anchor table CountryA with 100 different country names. In this setting, each outstanding fetch contributes to only one NULL value (either language or capital for a particular country), so the partial result tuples are independent from each other. We can achieve the optimal prioritization by completing first those partial result tuples requiring fewer overall fetches to fill in. In fact, $score_2$ does exactly this in this experiment: For a partial result tuple requiring k fetches to fill in, each of those k fetches has a $score_2$ of $1/k$. On the other hand, $score_1$ first completes partial result tuples with fewer NULLs, ignoring the effect of resolution functions on number of overall fetches.



(a) Empty dependent tables

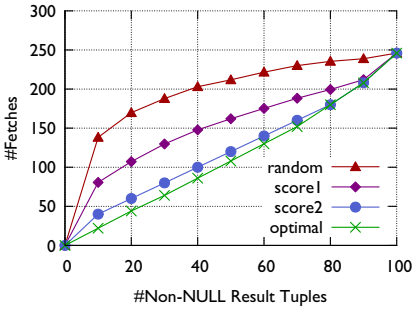


(b) 100 tuples in dependent tables

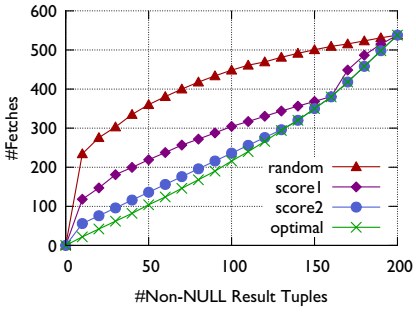


(c) 200 tuples in dependent tables

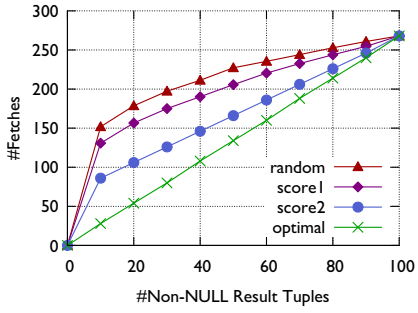
Figure 3: Experiment 2



(a) 100 European cities



(b) 200 World cities



(c) 100 Synthetic cities (worst case)

Figure 4: Experiment 3

Figure 3a shows the number of fetches completed to obtain X result tuples using $score_1$ and $score_2$, starting with empty dependent tables. Because our simulator gives correct answers only, we always need 400 fetches (two fetches for each NULL value) to obtain 100 result tuples. We observe that prioritization based on $score_1$ and $score_2$ needed 22% and 34% fewer fetches on average than random prioritization. As expected, $score_2$ achieves the optimal prioritization for this particular experiment.

In Figures 3b and 3c, we start the query with 100 and 200 tuples, respectively, in the two dependent tables combined. These tuples are randomly chosen from 400 correct tuples that would fill in all NULL values. In Figure 3b, the overall trends are similar to Figure 3a: prioritization based on $score_1$ and $score_2$ needed 28% and 41% fewer fetches on average than random prioritization. In Figure 3c, prioritization based on $score_1$ and $score_2$ needed 32% and 39% fewer fetches on average than random prioritization. In Figure 3c the difference between $score_1$ and $score_2$ is much smaller because the simplifying assumption behind $score_1$ holds more often: As we seed more tuples in the dependent tables, more NULL values can be filled in by completing one outstanding fetch.

Experiment 3: Different Data Distributions We use the following join query:

```
SELECT city, country, population, language
FROM Country, City
WHERE City.country = Country.country  MINTUPLES X
```

Anchor tables CountryA and CityA are already populated with a varying number and distribution of values. In this query, some outstanding fetches for language might complete multiple NULL values in the partial result, depending on the distribution of city-country pairs. Because the previous experiment showed that existing data has little impact on the overall trends, we start with empty dependent tables.

Figures 4a and 4b show the number of fetches to obtain X result tuples for two real datasets: the 100 largest European cities and the 200 largest cities in the world. Each country in the European and world city dataset has 4.3 and 2.9 cities on average, respectively. The European city dataset contains eight countries (out of 23) with only one city, while the world city dataset contains a long tail of 39 countries (out of 69) with only one city. In Figure 4a, $score_2$-based and optimal prioritization needed 34% and 40% fewer fetches on average than random prioritization. In Figure 4b, $score_2$-based and optimal prioritization needed 37% and 42% fewer fetches on average than random prioritization. Overall, prioritization based on $score_2$ is quite close to the optimal across the entire range of X.

For Figure 4c, we deliberately generated a synthetic set of 100 city-country pairs to make our $score_2$-based prioritization work as poorly as possible: all language values must be completed before any population values. Considering the resolution functions *majority-of-3* and *average-of-2*, $score_2$ for country $\Rightarrow$ language can be as low as $k/5$ where k is the number of cities for the country value. Since $score_2$ for city,country $\Rightarrow$ population can be as high as $1/2$ in this scenario, k should be at least 3 for all countries. Thus, the worst-case dataset contains 32 countries with three cities and one country with four cities. In Figure 4c, $score_2$-based prioritization and the optimal schedule needed 19% and 35% fewer fetches on average than random prioritization.

8. RELATED WORK

Among prior work in the general area of query processing, WSQ-DSQ [7] and incremental view maintenance [2] are most relevant to Deco's query execution. WSQ-DSQ enables an iterator execution model to concurrently access high-latency data sources, in the context of integrating web search results into a relational database. However, the WSQ-DSQ "placeholder" solution does not apply to Deco because of Deco's flexible fetch and resolution rules. Parallel database systems [3] also access data sources in parallel. However, they typically rely on static data partitioning and operator replication, so their approach is not applicable to Deco, where arbitrary

and dynamically adjustable degrees of parallelism must be supported. Some query processors for streaming data [9, 15] take a hybrid push-pull execution approach by designating each operator as either push or pull-based and enabling them to work together; in contrast, Deco's hybrid execution model uses both push and pull within each operator. View maintenance algorithms propagate base table updates to a materialized view. Deco's query execution engine similarly applies given base (raw) table changes to a partial query result, but in Deco base-data changes also influence further query execution.

Recently, several data-oriented systems leveraging crowdsourcing have been proposed. CrowdDB [6] closely resembles Deco, but Deco opts for more generality and flexibility and thus requires the novel query processing techniques described in this paper. (A detailed comparison between the two systems can be found in [12].) Qurk [10] is a workflow system that supports crowd-powered operations on existing relational data.

Finally, there have been several papers describing crowd-powered algorithms for database operations such as filtering items [11], finding max [8], and sorts and joins [10]. Some of these algorithms may be incorporated into our Deco prototype to improve individual query operators.

9. CONCLUSION

We presented Deco's query processor, focusing on how to minimize monetary cost and reduce latency when executing a query plan. We incorporated several novel techniques to answer Deco queries correctly and efficiently, including a hybrid execution model, dynamic fetch prioritization, two-phase query execution, and incremental view maintenance.

10. REFERENCES

[1] Mechanical Turk. *http://mturk.com*.

[2] J. A. Blakeley, P. Larson, and F. W. Tompa. Efficiently updating materialized views. In *SIGMOD*, 1986.

[3] D. J. Dewitt and J. Gray. Parallel database systems: the future of high performance database systems. *CACM*, 35(6):85–98, 1992.

[4] A. Doan, R. Ramakrishnan, and A. Halevy. Crowdsourcing systems on the world-wide web. *CACM*, 54(4):86–96, 2011.

[5] D. Florescu, A. Levy, I. Manolescu, and D. Suciu. Query optimization in the presence of limited access patterns. In *SIGMOD*, 1999.

[6] M. J. Franklin, D. Kossmann, T. Kraska, S. Ramesh, and R. Xin. CrowdDB: Answering queries with crowdsourcing. In *SIGMOD*, 2011.

[7] R. Goldman and J. Widom. WSQ/DSQ: A practical approach for combined querying of databases and the web. In *SIGMOD*, 2000.

[8] S. Guo, A. Parameswaran, and H. Garcia-Molina. So who won? dynamic max discovery with the crowd. In *SIGMOD*, 2012.

[9] S. Madden and M. J. Franklin. Fjording the stream: An architecture for queries over streaming sensor data. In *ICDE*, 2002.

[10] A. Marcus, E. Wu, D. Karger, S. Madden, and R. Miller. Human-powered sorts and joins. *PVLDB*, 5(1):13–24, 2011.

[11] A. Parameswaran, H. Garcia-Molina, H. Park, N. Polyzotis, A. Ramesh, and J. Widom. Crowdscreen: Algorithms for filtering data with humans. In *SIGMOD*, 2012.

[12] A. Parameswaran, H. Park, H. Garcia-Molina, N. Polyzotis, and J. Widom. Deco: Declarative crowdsourcing. In *CIKM*, 2012.

[13] H. Park, R. Pang, A. Parameswaran, H. Garcia-Molina, N. Polyzotis, and J. Widom. Deco: A system for declarative crowdsourcing. *PVLDB*, 5(12):1990–1993, 2012.

[14] H. Park and J. Widom. Query optimization over crowdsourced data. *PVLDB*, 6(10), 2013.

[15] N. Trigoni, Y. Yao, A. J. Demers, J. Gehrke, and R. Rajaraman. Hybrid push-pull query processing for sensor networks. In *GI Jahrestagung (2)*, 2004.

APPENDIX

A. PROOF OF HARDNESS OF THE FETCH PRIORITIZATION PROBLEM

THEOREM 1. *The Fetch Prioritization Problem is NP-hard.*

PROOF. We now reduce the NP-hard three-dimensional matching problem to the fetch prioritization problem, showing that the fetch prioritization problem is NP-hard.

In the three-dimensional matching problem, there are three sets of items A, B, and C, of equal size n. We are given a set of triples $S = \{(a_i, b_i, c_i)\} \subseteq A \times B \times C$, $|S| = m$. The goal is to check if a *perfect matching* exists, i.e., a subset $R \subseteq S$ of size n such that each a_i, each b_i and each c_i appear exactly once.

We reduce the three-dimensional matching problem to the following instance of the fetch prioritization task: We create a conceptual relation $G(A_1, A_2, A_3, A_4, [D_1], [D_2], [D_3], [D_4])$, such that the following resolution rules hold (all correspond to *majority-of-1* function):

$$A_1 \rightarrow D_1 \quad A_2 \rightarrow D_2 \quad A_3 \rightarrow D_3 \quad A_1A_2A_3A_4 \rightarrow D_4$$

and the single fetch rule:

$$A_1A_2A_3A_4 \Rightarrow D_1D_2D_3D_4$$

Based on the schema and the resolution rules, the data is stored in five tables (corresponding to the raw schema): one anchor table T_0 corresponding to A_1, A_2, A_3, A_4, and one dependent table T_i for each D_i (along with the left-hand-side of the corresponding resolution rule.)

The current data in these five tables is the following: T_0 consists of all tuples $(a_i, b_i, c_i, 0)$ and $(a_i, b_i, c_i, 1)$ such that $(a_i, b_i, c_i) \in S$ in the corresponding three-dimensional matching problem. Additionally, T_4 consists of tuples $(a_i, b_i, c_i, 1, d)$ for all $(a_i, b_i, c_i) \in S$; none of T_1, T_2, T_3 contain any tuples.

Now, in the fetch prioritization problem, our goal is to select the smallest set of fetch invocations such that $m + n$ output tuples are produced. Note first that the optimal set of fetch invocations must have $A_4 = 0$. To see this, if there are fetch invocations with $A_4 = 1$, then we can replace them with fetch invocations with $A_4 = 0$ to only possibly increase the number of output tuples, and then reduce the number of fetch invocations. (Recall that we already know the D_4 values for all tuples in T_0 with $A_4 = 1$.)

Next, note that we need at least n fetch invocations: We already have m tuples in T_0 whose D_4 values are known (all with $A_4 = 1$). In order to complete n more tuples, we must issue at least n more fetch invocations, each of which will give us the D_4 value for precisely one tuple. Furthermore, as we saw earlier, all of these invocations must have $A_4 = 0$.

We now show that if the solution to the fetch prioritization problem requires only n fetch invocations, then the fetch invocations correspond to the solution for the three-dimensional matching problem. Specifically, if $a_i, b_i, c_i, 0 \Rightarrow D_1, D_2, D_3, D_4$ is issued as a fetch, then (a_i, b_i, c_i) is part of R, the solution to the three-dimensional matching problem. To see this, note that if only n invocations are used, then each $a_i \in A_1, b_i \in A_2, c_i \in A_3$ appears precisely once in the fetch invocations. Only then will we complete all m tuples in T_0 with $A_4 = 1$.

Furthermore, we always invoke fetches corresponding to complete tuples $\{(a_i, b_i, c_i, 0)\} \in T_0$ in order to fill in as many D_4 values as possible. Thus, our selection of fetch invocations corresponds to a perfect matching.

The converse is also true. That is, if there is a perfect matching, then the corresponding set of fetch invocations will be of size n and will form a solution to the fetch prioritization problem. $\square$