Supporting Complex Query Time Enrichment For Analytics

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ABSTRACT

Several application domains require data to be enriched prior to use. Data enrichment is often performed using expensive machine learning models to interpret low-level data (*e.g.*, models for face detection and person identification on image data) into semantically meaningful observation. Collecting and enriching data offline, prior to loading it to a database is infeasible if one desires online analysis on data as it arrives. Enriching data on the fly at insertion could result in redundant work (if applications require only a fraction of data enriched) and could result in an ingestion bottleneck (if enrichment functions are expensive). Any scalable solution requires enrichment during query processing. This paper explores two different architectures for integrating enrichment into query processing – a loosely coupled approach wherein enrichment is performed outside of the DBMS and a tightly coupled approach wherein it is performed within the DBMS. The paper also addresses the challenge of increased latency of queries that arise from executing enrichment while processing queries.

1 INTRODUCTION

Organizations, today, have access to potentially limitless data sources in the form of web data repositories, social media posts, and continuously generated sensory data [7]. Such data is often low-level/raw and needs to be enriched to be useful for analysis. Functions used to *transform* or *enrich* data (called *enrichment functions* in this paper) could consist of (a combination of) custom-compiled code, declarative queries, and/or expensive machine learning (ML) techniques. Examples include mechanisms for sentiment analysis [20] over social media posts, named entity extraction [12] in text, and sensor interpretation such as face detection and face recognition [28, 37] from images, sensor data fusion [40], and data cleaning tasks such as missing value imputation in relational data [29].

Data enrichment could be performed as a *periodic offline process* prior to loading the data into a database for analysis, and this approach is indeed common in enterprise data processing pipelines. For instance, in the enterprise data warehouses, data collected from diverse transactional databases running core organizational operations, is stored in the raw format at the time of data arrival. Such data is periodically loaded into an enterprise-wide warehouse [1–3, 9] through a transformation process. Such a strategy can be categorized as an *extract-transform-load* process. This offline process, however, adds a significant delay between the time data arrives (or is created) and when data is available for analysis. This limits the ability of organizations to analyze data in (near) real-time as it arrives. For example, enriching tweets to find sentiments and topics (using Multi-Layered Perceptron for sentiment and Gaussian Naïve Bayes for topic) over 11M tweets takes 43 hours on a machine with 16 core CPU, 64 GB ram and 1TB SSD, in our experiment.

In enterprise contexts, such a challenge has been well recognized, leading to the emergence of Hybrid Transaction and Analytical Processing (HTAP) systems (over the past decade [36, 45]) that exploits modern hardware and columnar storage to support both transactional and analytical capabilities in the same system. HTAP systems enable data analysis to be performed in *real-time as data arrives*. Systems (*e.g.*, Spark Streaming [56] often used for scalable ingestion) are capable of executing enrichment functions on newly arriving data prior to its storage into a DBMS. Recently, [52] has explored ways to optimize enrichment during ingestion.

Limitations of data enrichment at ingestion. Enriching data at arrival exhibits several limitations: (*i*) *Unnecessary enrichment*: Enriching data at ingestion could incur significant avoidable overhead of redundant data enrichment, if the analyst ends up using only (a small) portion of the data. In situations when workloads are predictable, one could potentially limit enrichment to only data that is expected to be used. However, accurate prediction of the workload, especially when analyst may execute adhoc queries, can be difficult, as argued in [22, 45]. (*ii*) *No support of complex enrichment:* Enriching data at ingestion is only feasible if enrichment functions are not computationally resource intensive. When functions require running one or more complex ML models (*e.g.*, Multi-layer Perceptron or Random Forest) to interpret data, executing them during ingestion would create a bottleneck. (*iii*) *Limited data ingestion:* Enriching all data as it arrives also limits the system to ingest only 10s of events per second.[1]

In order to reduce latency between the time when data arrives/is created and when data is available for analysis that *require data to be enriched before using*, ***this paper explores effective ways to integrate data enrichment into query processing in databases.***

Challenges of data enrichment at query execution. Integrating data enrichment with query processing raises several challenges, as:: (*i*) How to determine which data items/objects need to be enriched to answer a query correctly. (*ii*) Where should such enrichments be performed — either closer to the data at the DBMS possibly using stored procedures and user-defined functions (UDFs), or outside of the DBMS in an enrichment server. Both these options offer different pros and cons in terms of data movement, waste resources for enrichment, and the scope for parallelism in executing data enrichment. (*iii*) How to reduce the query execution time — while the ability of the system to enrich data at query time reduces the amount of work that needs to be performed at ingestion time (hence, scaling the ingestion process to higher data rates), it potentially causes an increased query execution time for individual queries.

Our contributions. This paper addresses the above-mentioned challenges. Our contributions in the paper are as follows:

(1) We develop and discuss pros/cons of two distinct solutions to support joint query processing and data enrichment. These two approaches address the above-mentioned first and second challenges. The first approach is a ***loosely coupled*** approach (referred to as

[1]The challenge of running complex ML functions on data as it arrives, was discussed extensively in the curated session on ML in databases in SIGMOD 2021 [38], leading to an observation that often organizations are forced to use simpler functions that can be performed at ingestion, even though such a choice results in poor quality.

tid	UserID	Tweet	feature	location	TweetTime	**topic**	**sentiment**
t_1	John	Uploading pics on Facebook.	[0.2, ..., 0.4]	US	16:08	social media	positive
t_2	Mark	Feeling great and listening to music.	[0.5, ..., 0.3]	US	16:48	entertainment	NULL
t_3	Richard	Sad about current pandemic.	[0.6, ..., 0.4]	UK	11:48	NULL	NULL

Table 1: `TweetData` table where `topic` and `sentiment` are the derived attributes.

$\mathbb{EQ}_{\mathbb{LC}}$) that performs data enrichment at an external server (different from a database server), called as *enrichment server*, and (*ii*) a ***tightly coupled*** approach (referred to as $\mathbb{EQ}_{\mathbb{TC}}$ approach) that exploits the mechanisms of pushing code to the database server using stored procedures and UDFs to co-process enrichment and queries at the database. Both strategies attempt to minimize the number of avoidable calls to the enrichment functions.

(2) We, then, address the challenge of increased query latency, which arises due to enrichment functions executed during query processing, and develop an iterative/progressive approach to answer queries. Particularly, the approach exploits the fact that often, enrichment of data can be performed using multiple enrichment functions, each of which may vary in their execution cost and quality of the output. Based on the query, simpler (*i.e.*, less costly), though possibly less accurate models may be applied first, and that can help to generate approximate answers. More accurate and expensive models can be used to refine such answers. Such an approach of hiding query latency for complex queries has been extensively explored in the area of approximate query processing [25, 47], where it is difficult to answer queries in real-time due to the size of data involved. We adopt a similar methodology of answering queries approximately based on partially enriched data and progressively improving them as data is enriched further.

(3) We experimentally evaluate the proposed approaches in various domains of social media and multimedia and use various enrichment functions to demonstrate the efficiency of our solutions. Results show that both proposed solutions outperform significantly than the approach of enriching data at ingestion by two orders of magnitude in terms of the time required to enrich the data for queries. Also, experiments show that the storage overhead (due to storing additional data supporting progressiveness) of the proposed solution is low — atmost 3%.

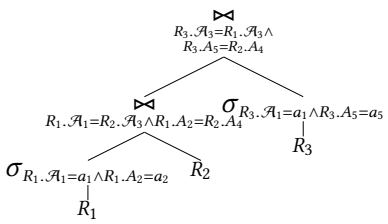
2 DATA ENRICHMENT DURING QUERY PROCESSING

Before presenting our approaches for data enrichment during query execution, we discuss our data model that is an extended relational model and the notion of enrichment functions. In our data model, some attributes of a relation are ***derived*** (denoted as $\mathcal{A}_i$) and require enrichment; the remaining attributes are ***fixed*** (denoted as A_j) and do not require enrichment. Enrichment is performed by a set of associated enrichment functions with $\mathcal{A}_i$. Without loss of generality, all relations contain an `id` attribute to uniquely identify tuples. *E.g.*, in a relation storing tweets, a derived attribute can be the tweet's `sentiment`, which is enriched using sentiment analysis functions on the tweet. Likewise, in a relation storing images, the identity of people in images can be the derived attribute, which is enriched using face recognition techniques for identifying a person.

In general, several *enrichment functions* could be used either independently or in combination to determine the value of a derived attribute. If an enrichment function is executed on a tuple, the derived attribute will take the value of the function output. *If the* ***enrichment function is not executed so far****, then the* ***attribute value will be*** **NULL**. For example, in Table 1, the values of two derived attributes `topic` and `sentiment` are NULL in t_3, since they are not enriched yet.

SELECT * FROM R_1, R_2, R_3
WHERE $R_1.\mathcal{A}_1 = a_1$ AND
$R_1.A_2 = a_2$ AND $R_1.\mathcal{A}_1 = R_2.\mathcal{A}_3$
AND $R_1.A_2 = R_2.A_4$ AND
$R_3.\mathcal{A}_1 = a_1$ AND $R_3.A_5 = a_5$ AND
$R_3.\mathcal{A}_3 = R_1.\mathcal{A}_3$ AND
$R_3.A_5 = R_2.A_4$

(a) Original query.



(b) Query tree.

Figure 1: Original query and its query tree.

Below, we develop two ways of enriching data during query processing: (*i*) loosely-coupled implementation ($\mathbb{EQ}_{\mathbb{LC}}$) that uses a separate enrichment engine (outside of databases) and (*ii*) tightly-coupled implementation ($\mathbb{EQ}_{\mathbb{TC}}$) that uses database programming features such as UDF to incorporate enrichment functions.

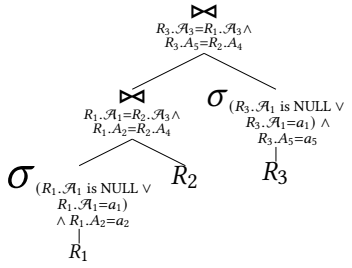
Running example. To explain $\mathbb{EQ}_{\mathbb{LC}}$ and $\mathbb{EQ}_{\mathbb{TC}}$, we consider a general query (Figure 1a), whose query tree is shown in Figure 1b. Using this query, we will explain different steps of $\mathbb{EQ}_{\mathbb{LC}}$ and $\mathbb{EQ}_{\mathbb{TC}}$ in the next subsections.

2.1 Query Processing in $\mathbb{EQ}_{\mathbb{LC}}$

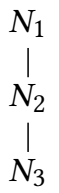
$\mathbb{EQ}_{\mathbb{LC}}$ executes enrichment outside of the DBMS at an enrichment server. Given a query q, the key step of $\mathbb{EQ}_{\mathbb{LC}}$ is to generate `probe queries` ($pq(R_i)$) — for each relation R_i whose derived attributed is a part of q — to identify a "minimal" subset of tuples (as small a subset as possible) that need to be enriched to execute q. The retrieved tuples by `probe queries` are enriched in the enrichment server, and the corresponding modified (enriched) values are updated at the DBMS. Finally, query q is executed at the DBMS.

$\mathbb{EQ}_{\mathbb{LC}}$ exploits the following three strategies to identify the minimal subset:

- *Exploiting Prior Work:* $pq(R_i)$ filters out all tuples of R_i that have been enriched earlier (*e.g.*, as part of prior queries), and hence, their derived attribute values in the database are not NULL.
- *Exploiting Selection Conditions on Fixed Attributes:* $pq(R_i)$ filters all tuples of R_i that do not satisfy selection conditions over fixed attributes of R_i. *E.g.*, for the query of Figure 1a, to identify the tuples of R_1 that require enrichment, $pq(R_1)$ retrieves only those tuples of R_1 that satisfy the condition $R_1.A_2 = a_2$.
- *Exploiting Join Conditions on Fixed Attributes:* $pq(R_i)$ filters out all tuples of R_i that would not join with any tuples in R_j, if a join condition exists between R_i and R_j in q based on fixed attributes. *E.g.*, for the query of Figure 1a, the tuples of relation R_1 that do not match with any tuples of R_3 based on the join condition of $R_3.A_1 = R_1.A_1$ do not need to be enriched.



(a) Step 1: Rewritten query tree for selection conditions.



(b) Step 2: Join graph (Node N_1 : $\sigma_{(R_1.\mathcal{A}_1 \text{ is NULL} \vee R_1.\mathcal{A}_1=a_1) \wedge R_1.A_2=a_2}(R_1)$, Node N_2 : R_2, and Node N_3 : $\sigma_{(R_3.\mathcal{A}_1 \text{ is NULL} \vee R_3.\mathcal{A}_1=a_1) \wedge R_3.A_5=a_5}(R_3)$).

$$\langle N_2 \ltimes_{R_2.A_4=R_3.A_5} N_3;\ N_1 \ltimes_{R_1.A_2=R_2.A_4} N_2; \rangle$$

(c) Step 3: Semi-join programs for R_1.

$$\sigma_{R_1.A_2=a_2 \wedge (R_1.\mathcal{A}_1 \text{ is NULL} \vee R_1.\mathcal{A}_1=a_1)}(R_1) \ltimes_{R_1.A_2=R_2.A_4} \left[R_2 \ltimes_{R_2.A_4=R_3.A_5} (\sigma_{(R_3.A_5=a_5) \wedge (R_3.\mathcal{A}_1 \text{ is NULL} \vee R_3.\mathcal{A}_1=a_1)}(R_3))\right]$$

(d) Step 4: The `probe query` for R_1.

Figure 2: Steps involved in EQLC.

Probe Query Generation Steps. The steps for generating `probe queries` (based on above three strategies) are as follows:

[Step 0]: *Query Tree Generation*: An input query q is first converted into a corresponding query tree, in which, selection conditions are pushed down as much as possible. The conditions present in selection and join nodes are converted into a conjunctive normal form (CNF), *i.e.*, $(C = C_1 \wedge C_2 \wedge \ldots \wedge C_z)$. Each condition $C_i \in C$ is characterized as either a ***fixed condition*** (*i.e.*, a condition containing only fixed attributes) or a ***derived condition*** (*i.e.*, a condition containing only derived or both fixed and derived attributes).

Figure 1b shows the query tree generated from the query of Figure 1a. In a CNF condition $R_1.\mathcal{A}_1 = a_1 \wedge R_1.A_2 = a_2$, the condition $R_1.A_2 = a_2$ is a fixed condition, while $R_1.\mathcal{A}_1 = a_1$ is derived.

[Step 1]: ***Rewrite of Selection Condition ($\sigma_C(R)$)*:** Given a CNF condition C at a selection node, for each derived condition $C_i \in C$ over derived attribute(s) $\mathcal{A}_1, \ldots, \mathcal{A}_n$, this step finds only those tuples for which there exists an attribute $\mathcal{A}_{i \in [1,\ldots,n]}$ that has not been enriched before. This filtering is achieved by replacing C_i by $\left[(\bigvee_{i=1}^{n} \mathcal{A}_i = \text{NULL}) \vee C_i\right]$. The fixed conditions are kept identical.

Figure 2a, for the CNF expression $R_1.\mathcal{A}_1 = a_1 \wedge R_1.A_2 = a_2$ as shown in Figure 1b, shows rewritten selection as: $((R_1.\mathcal{A}_1 \text{ is NULL} \vee R_1.\mathcal{A}_1 = a_1) \wedge R_1.A_2 = a_2)$. Note that only the first condition is modified as it is a derived condition, while the second condition is kept identical as it is fixed.

[Step 2]: *Generating Join Graph*: This step and the next step 3 exploits join conditions on fixed attributes in a query to filter out tuples of R_i that do not require enrichment. Given a modified query tree using Step 1 for selection conditions, now, a ***join-graph*** is generated from the tree. The purpose of the join graph is to find out for a relation R_i in the query: which join conditions (on fixed attribute) with other relations can be utilized to reduce the number of tuples of R_i that require enrichment.

In the join graph, the nodes correspond to *reduced* relations, *i.e.*, relations with the selection conditions applied on them. An edge between two nodes shows the join conditions between two relations (based on the original query) expressed in CNF form. Next, from each edge of the join graph, all the derived join conditions are removed. If all the conjuncts are on derived attributes, then we obtain just graph nodes that show none of the join conditions between the two relations can be exploited to reduce the set of tuples that require enrichment. (In a query tree `union`, `set-difference`, or `cross product` operators are ignored, since they cannot be utilized to reduce the number of tuples in `probe queries` apart from the join conditions.)

Figure 2b shows a join-graph for the query tree of Figure 2a. This graph contains three nodes: $\langle N_1, N_2, N_3 \rangle$, representing the reduced relations of $\langle R_1, R_2, R_3 \rangle$, respectively, *i.e.*, after applying selection conditions on each relation. Edge between N_1 and N_2 represents the join condition $R_1.A_2 = R_2.A_4$ (after removing the join condition $R_1.\mathcal{A}_1 = R_2.\mathcal{A}_3$ on derived attributes from Figure 2a).

[Step 3]: *Semi-join Program Generation*: Given the join graph as an input, for each node N_i in the graph, this step generates a set of semi-join programs for N_i to reduce the number of tuples of N_i that require enrichment. For N_i, semi-join programs are generated by exploiting join conditions among nodes of the graph. For node N_i, this step starts from node N_i in the join graph and generates a spanning tree, denoted as $ST(N_i)$, that contains all nodes of the graph with the minimum possible number of edges (using breadth-first traversal). From $ST(N_i)$, multiple semi-join programs are generated based on the join conditions in $ST(N_i)$.

Semi-join programs for a node N_i are generated in a bottom-up manner from $ST(N_i)$ starting from the children nodes and reaching upto N_i. For each node encountered in the path, a semi-join program is generated. The nodes in $ST(N_i)$ are traversed in a breadth-first order from the leaf node to the root node. All the semi-join programs between the leaf node and their immediate parent nodes are created first. This step is continued until all the paths from the leaf node to the root node are consumed.

For example, $ST(N_1)$ for node N_1, is a tree with root as the node N_1, the node N_2 as the child of N_1, and the node N_3 as the child of N_2 (same as the graph shown in Figure 2b). In $ST(N_1)$ (Figure 2b), a semi-join between relations N_2 and N_3 is performed first to identify the tuples of relation R_2 (part of N_2) that may result in the join output of R_2 and R_3 (as shown in Figure 2c). After this, a semi-join between R_1 and the tuples of R_2 output from the previous semi-join, is performed. Using these two semi-join programs, this step is able to eliminate two types of tuples from R_1: (*i*) the tuples of R_1 that do not join with any tuple of R_2 and R_3, and (*ii*) the tuples of R_1 that may join with some tuples of R_2 but ultimately do not join with any tuple of R_3. This step for semi-join reduction we used is based on the seminal work on semi-join given in [16].

[Step 4]: *Generating* `probe queries`: Given the semi-join programs (obtained in the previous step), this step generates a `probe query` based on the semi-join programs and the selection conditions on R_i in a straightforward manner. For example, in Figure 2d, we show the `probe query` generated for R_1, from the semi-join programs described in Figure 2c and the selection conditions added to the query tree of Figure 2a for R_1.

2.2 Query Processing in $\mathbb{EQ}_{TC}$

$\mathbb{EQ}_{TC}$ rewrites an input query q into a modified query q' that checks whether each derived attribute $\mathcal{A}_i \in q$ has been enriched earlier. If not, q' invokes a UDF, called $read_u$ UDF that executes enrichment functions and updates the value of $\mathcal{A}_i$.The $read_u$ is implemented as a generic function that takes as inputs: the name of the relation (*e.g.*, 'R_i'[2].), the name of the derived attribute (*e.g.*, '$\mathcal{A}_j$'), the tuple identity, and the identity of an enrichment function to execute. $\mathbb{EQ}_{TC}$ also rewrites selection and join conditions, as follows:

Rewrite of Selection Condition: $\mathbb{EQ}_{TC}$ rewrites each selection condition $(R.\mathcal{A}_i \ op\ a_i) \in q$ (where op is $\geq$, $>$, $=$, $\leq$, $<$, or $\neq$, and a_i is a constant value) that contains a derived attribute, by a modified selection condition denoted as $\omega_\sigma(R.\mathcal{A}_i \ op\ a_i)$, as follows:

$$R.\mathcal{A}_i \ op\ a_i \ \vee [R.\mathcal{A}_i \text{ is NULL} \wedge read_u(\text{'}R\text{'}, \text{'}\mathcal{A}_i\text{'}, R.id, f_{\mathcal{A}_i}.id) \ op\ a_i]$$

Here, $f_{\mathcal{A}_i}.id$ refers to the identity of an enrichment function for $\mathcal{A}_i$. In this rewritten condition, if a tuple's value in $\mathcal{A}_i$ is already enriched, then the original selection condition is evaluated (*i.e.*, $R.\mathcal{A}_i \ op\ a_i$). Otherwise, $read_u$ UDF is executed on the tuple to enrich the attribute $\mathcal{A}_i$ first, and then the selection condition is executed. Note that $read_u$ UDF is only invoked if the attribute value has not been enriched before.

Rewrite of Join Condition: We rewrite each join condition $R_p.\mathcal{A}_i \ op\ R_q.\mathcal{A}_j \in q$ that contains derived attributes $\mathcal{A}_i$ and $\mathcal{A}_j$, by a modified join condition, denoted as $\omega_\sigma(R.\mathcal{A}_i \ op\ a_i)$, based on whether one (or both) of the derived attributes in the condition have previously been enriched. If both the derived attributes have been enriched, $(R_p.\mathcal{A}_i \ op R_q.\mathcal{A}_j)$ is executed with no modification. If one of the attributes (say $R_p.\mathcal{A}_i$) is not enriched, then $R_p.\mathcal{A}_i$ is replaced with a call to UDF $read_u$ on $R_p.\mathcal{A}_i$ in order to enrich the attribute as part of checking the join condition. If both of the attributes (*i.e.*, $R_p.\mathcal{A}_i$ and $R_q.\mathcal{A}_j$) are not enriched, then both attributes in the join condition are replaced by calls to the $read_u$ UDF. The modified join condition of $\omega_{\bowtie}(R_p.\mathcal{A}_i \ op\ R_q.\mathcal{A}_j)$ is shown below:

$$\begin{aligned}
&R_p.\mathcal{A}_i \ op\ R_q.\mathcal{A}_j \ \text{/*Both } \mathcal{A}_i \text{ and } \mathcal{A}_j \text{ are enriched*/} \\
&\vee \big[R_p.\mathcal{A}_i \text{ is not NULL} \wedge R_q.\mathcal{A}_j \text{ is NULL} \quad \text{/* Only } \mathcal{A}_i \text{ is enriched */} \\
&\quad \wedge read_u(\text{'}R_q\text{'}, \text{'}\mathcal{A}_j\text{'}, R_q.id, f_{\mathcal{A}_j}.id,) \ op\ R_p.\mathcal{A}_i\big] \\
&\vee \big[R_p.\mathcal{A}_i \text{ is NULL} \wedge R_q.\mathcal{A}_j \text{ is not NULL} \quad \text{/*Only } \mathcal{A}_j \text{ is enriched*/} \\
&\quad \wedge read_u(\text{'}R_p\text{'}, \text{'}\mathcal{A}_i\text{'}, R_p.id, f_{\mathcal{A}_i}.id) \ op\ R_q.\mathcal{A}_j\big] \\
&\vee \big[R_p.\mathcal{A}_i \text{ is NULL} \wedge R_q.\mathcal{A}_j \text{ is NULL} \quad \text{/* None of } \mathcal{A}_i \text{ or } \mathcal{A}_j \text{ are enriched*/} \\
&\quad \wedge read_u(\text{'}R_p\text{'}, \text{'}\mathcal{A}_i\text{'}, R_p.id, f_{\mathcal{A}_i}.id) \ op\ read_u(\text{'}R_q\text{'}, \text{'}\mathcal{A}_j\text{'}, R_q.id, f_{\mathcal{A}_j}.id)\big]
\end{aligned}$$

Example. Below, we illustrate rewritten queries for the query of Figure 1a using modified selection (ω_σ) and join conditions ($\omega_{\bowtie}$) as described above.

SELECT * FROM R_1, R_2, R_3 WHERE $\omega_\sigma(R_1.\mathcal{A}_1 = a_1)$ AND $R_1.A_2 = a_2$ AND $\omega_{\bowtie}(R_1.\mathcal{A}_1 = R_2.\mathcal{A}_3)$ AND $R_1.A_2 = R_2.A_4$ AND $\omega_\sigma(R_3.\mathcal{A}_1 = a_1)$ AND $R_3.A_5 = a_5$ AND $\omega_{\bowtie}(R_3.\mathcal{A}_3 = R_1.\mathcal{A}_3)$ AND $R_3.A_5 = R_2.A_4$

3 PROGRESSIVE QUERY PROCESSING

While $\mathbb{EQ}_{LC}$ and $\mathbb{EQ}_{TC}$ reduce redundant enrichment of data and scale to higher ingestion rates (still supporting queries on data as it arrives), they increase query latency due to query time enrichment. To reduce query latency, this section explores ways to make $\mathbb{EQ}_{LC}$ and $\mathbb{EQ}_{TC}$ progressive that iteratively refines the query results as more enrichments are performed.

A progressive approach allows data to be consumed by analysts right away and to stop computation at any time they are satisfied with results [13, 42, 53]. Progressive query processing has been extensively explored in the approximate evaluation of aggregation queries (Approximate Query Processing – AQP) [25, 33, 41] to reduce *query latency arising from processing of massive datasets*. In contrast, *in this paper, the challenge is to reduce query latency arising from the execution of expensive enrichment functions.*

To develop a progressive approach, we exploit *a tradeoff between cost and quality*, which ML models often exhibit; cheaper (*i.e.*, low execution cost) functions produce prediction faster with low accuracy, compared to more expensive (*i.e.*, high execution cost) functions that produce slower but high-quality predictions. *E.g.*, a random forest classifier (RF) implemented using a small number of decision tree (DT) models is cheaper but less accurate compared to an RF classifier using many DT models.[3] Here, increased accuracy comes with a complex ML model, and, hence, higher execution time. (*E.g.*, in our experiments over Multi-PIE data [49], a DT classifier for classifying facial expression in an image with a tree depth of 5 (and 20) took ≈12 (and ≈35) ms/image. DT with large tree depth increases accuracy from 72% to 81%.) Based on this tradeoff, we achieve progressive answering by running cheap ML functions on (a subset of) data to generate initial answers and subsequently selecting additional data to enrich and/or enrich the data already selected using more complex functions to refine the answers.

Below, we develop a progressive approach of enriching data and answering queries for both $\mathbb{EQ}_{TC}$ and $\mathbb{EQ}_{LC}$. We begin by precisely defining the semantics of progressive query processing and then describe the ways to achieve progressiveness in $\mathbb{EQ}_{TC}$ and $\mathbb{EQ}_{LC}$. From here,*we use the notation* $\mathbb{EQ}^{\mathbb{P}}$ *to refer to both* $\mathbb{EQ}^{\mathbb{P}}_{TC}$ *or* $\mathbb{EQ}^{\mathbb{P}}_{LC}$, where $\mathbb{EQ}^{\mathbb{P}}_{TC}$ and $\mathbb{EQ}^{\mathbb{P}}_{LC}$, where $\mathbb{P}$ stands for progressive versions.

3.1 Progressive Queries

This section first describes notations that help in defining $\mathbb{EQ}^{\mathbb{P}}$.

Notations. We now permit multiple enrichment functions to be associated with each derived attribute.[4] Suppose $\mathcal{A}$ is a derived attribute and the set of enrichment functions associated with $\mathcal{A}$ is $\{f_1, f_2, \ldots, f_n\}$. This set of enrichment functions is called ***function-family*** of $\mathcal{A}$. For example, the `sentiment` derived attribute of `TweetData` (Table 1) may form a function-family with decision tree (DT), a k-nearest neighbor (KNN), multi-layered perceptron (MLP), or a support vector machines (SVM) classifier.

At any instance of time, for a given tuple t and for a given derived attribute $\mathcal{A}$ of a relation, multiple enrichment functions might have been executed, resulting in the value for $\mathcal{A}$ in t. We refer to the set of functions in the function-family that have executed as the ***state of the derived attribute*** (denoted as $state(t.\mathcal{A})$) in the tuple t. The state of a derived attribute $state(t.\mathcal{A})$ contains two components: ***state-bitmap*** that stores a list of enrichment functions that have

[2] We use quotes to refer to the names of relations R_i and attributes $\mathcal{A}_j$

[3] Similar tradeoff is shown by multi-layer perceptrons (where accuracy increases by additional layers and a number of perceptrons/layer, until the model over-fits training data [21]), k-NN classifiers (accuracy increases with increasing k), or DT (accuracy increases with the depth of the tree).

[4] Progressive approach is still possible when there is a single enrichment function associated with derived attributes since the system can choose a subset of data to enrich progressively. However, it is much more effective when it is able to exploit the tradeoffs between execution time and quality.

been executed on $t.\mathcal{A}$; and ***state-output*** that stores the output of executed enrichment functions on $t.\mathcal{A}$.

Each function-family is associated with a ***determinization function*** that finds the value of $\mathcal{A}$ in t based on $state(t.\mathcal{A})$. The determinization function (denoted by $DET(*)$) could use any ensemble technique [35, 54] for generating a value based on enrichment functions executed so far, *e.g.*, it could use a most likely value, or a value based on majority consensus [35]. We treat the determinization function as a black-box and is independent of the specific function used. Note that $DET(state(t.\mathcal{A}))$ returns a single or a NULL value. NULL value represents a situation when state of the attribute does not provide enough evidence to the determinization function to assign any value for $t.\mathcal{A}$. As more functions execute, the state of $\mathcal{A}$ changes, $DET(state(t.\mathcal{A}))$ computes a new value of $\mathcal{A}$ in t.

The notion of the state of a derived attribute generalizes to the state of tuples, relations, and databases in a straightforward way. The state of a tuple t (or a relation R or a database D) denoted by $state(t)$ (or $state(R_i)$ or $state(D)$) is the concatenation of the state of all derived attributes of t (or the concatenation of the state of all tuples or the concatenation of the state of all relations). Likewise, the concept of determinization also generalizes to a tuple, a relation, and a database, denoted by $DET(state(t))$, $DET(R_i)$, and $DET(D)$,

Progressive Query Processing. Now, we concretely develop the concept of progressive query processing. We discretize the query execution time into *epochs*: $\{e_0, e_1, e_2, \ldots, e_z\}$. e_0 is a special epoch to initialize data structures.[5] In each epoch, we select a set of derived attributes and functions to execute to enrich those attributes.

Let q be a query, and let $R_1, R_2, \ldots, R_n$ be the set of relations that are used in q. Let $state(D, e_k)$ be the resulting state of the database based on all the enrichment functions that have executed in (or before) epoch e_k. Let $DET(state(D, e_k))$ be the corresponding determinized representation of the database, where all derived attributes take a value based on their states.

Progressive query execution in an epoch e_k returns the results of query executed over the determinized representation of data, *i.e.*, returning answers to $q(DET(state(D, e_k))$, where the determinized representation of D include outputs of all enrichment functions that have been executed so far. Answers to query q differ from epoch e_{k-1} to e_k, due to the database's state change by enrichment functions in the epoch e_k.

Realizing progressive approach in $\mathbb{EQ}^{\mathbb{P}}$ raises two related issues (given below) that we address in this section.

- **Managing State.** State represents the current state of enrichment of all tuples in the database. In other words, the state refers to the information about enrichment functions that have been executed and their outputs. The state helps us to avoid repeated execution of expensive enrichment functions on objects. Since the number of objects and the outputs of enrichment functions can be large (a probability distribution — the probability of an object is a specific person/value in an image), efficient ways to represent the state are also needed.
- **Incremental Execution of Enrichment and Queries.** The following two problems are needed to be addressed to execute enrichment and queries in an incremental manner: (*i*) *Selection of objects and enrichment functions:* We need to select a set of ⟨object, enrichment function⟩ pairs that improve the quality of existing query results across different epochs. Sampling-based approaches can be used to select objects/enrichment functions (similar to AQP systems [11, 43]), or a benefit-based approach [23] can be used to optimize specific quality metrics of results (*e.g.*, F_α-measure). (*ii*) *Maintaining query results incrementally to avoid the overhead of computing query results from scratch:* As in each epoch the state of the database changes, a straightforward strategy to compute progressive answers is to simply execute the query at the end of each epoch over the entire determinized representation of the database. Such an approach, however, is wasteful, due to re-executing the query in each epoch without exploiting the work of the previous epochs. Instead, we explore a strategy based on Incremental View Maintenance (IVM) [17, 31, 39] that is supported by several database systems. Such a strategy computes answers as a *delta answer* over the previously reported query answers.

[5] For simplicity, we will consider epochs $\{e_1, e_2, \ldots, e_z\}$ to be fixed size in the remainder of the paper, though, the approach does not require this to be the case.

3.2 State Management

In $\mathbb{EQ}^{\mathbb{P}}$, the state of derived attributes of tuples for a relation R is stored as a separate table, $State(R)$. For each derived attribute, $State(R)$ contains a (state) bitmap and a (state) output vector. As mentioned in §3.1, the bitmap contains a bit for each enrichment function associated with the attribute, where 1 means the function was already executed and 0 means it is yet to execute. The output vector contains the results of the execution of enrichment functions. Enrichment functions are characterized by their output cardinality: (*i*) A *single-valued* function (*e.g.*, a binary classifier [50]) outputs a single value. (*ii*) A *multi-valued* function (*e.g.*, top-k classifiers [32]) outputs a set of values as a prediction. (*iii*) A *probabilistic* function outputs a probability distribution over the possible values, *e.g.*, probabilistic classifiers [19].

In both $\mathbb{EQ}^{\mathbb{P}}_{\text{TC}}$ and $\mathbb{EQ}^{\mathbb{P}}_{\text{LC}}$, the state table is maintained in the database. In $\mathbb{EQ}^{\mathbb{P}}_{\text{LC}}$, since enrichment is performed outside of the database, an in-memory cache for the state table is maintained at the enrichment server to reduce the number of database updates, each time an enrichment is performed. This cache only contains tuples that may need to be enriched during the entire query execution (*i.e.*, the result of probe queries, as will be discussed in §3.3), and the updates are pushed to the database at the end of the epoch. State table or cache makes sure that the same derived attribute of a tuple is never enriched using the same enrichment function multiple times in both approaches.

Example. Table 2 shows a state table for `TweetData` table (see Table 1) for `topic` and `sentiment` derived attributes. Consider tuple t_2 bitmap for `sentiment` attribute; that shows enrichment functions 1 and 3 were executed while function 2 is not yet executed. Enrichment functions 1 and 2 are probabilistic classifiers and their outputs were probability distributions $[0.2, 0.6, 0.2, \ldots]$ and $[0.86, 0.1, 0.04,]$, respectively, over an ordered domain of values. ■

Compressed State Representation. In the case of a large domain size of a derived attribute, the columns corresponding to its state output can be large. *E.g.*, if domain size of `topic` in `TweetData` is 40 and there are 3 enrichment functions, then `TopicStateOutput` column (see Table 2) could contain 120 values in each row. Such a large domain could incur high storage overhead and read/write cost

tid	Topic BitMap	TopicOutput	Sentiment BitMap	Sentiment Output
t_1	[1,0,0]	[[0.18,0.64,0.05,...],[],[]]	[1,0,0]	[[0.94, 0.06,0], [], []]
t_2	[1,0,1]	[[0.5,0.2,0.1, ...],[],[0.1,0.6,0.1, ...]]	[1,0,1]	[[0.2,0.6,0.2],[], [0.86,0.1,0.04]]
t_3	[0,1,0]	[[], [0.78,0.06,0.02, ...], []]	[1,1,0]	[[0.1,0.7,0.2], [0.2,0.8,0],[]]

Table 2: `TweetDataState` table (created for `TweetData` table).

of the states. Instead, $\mathbb{EQ}^{\mathbb{P}}$ uses a compressed representation for state output when domain sizes are large. It sets a ***cutoff threshold*** and only stores the domain values whose probability is above that threshold. Domain values are appropriately mapped to integers using a dictionary encoding and the probabilities are stored as key-value pairs. The compressed representation does not store large tails of a probability distribution.[6]

3.3 Joint Enrichment and Query Execution

In $\mathbb{EQ}^{\mathbb{P}}$, tuples are enriched in each epoch and require query results to be updated at the end of each epoch. Instead of re-executing the query to compute the modified answers, we use an incremental query processing approach based on Incremental View Maintenance (IVM). Below, we discuss how IVM can support incremental processing, and then, discuss ways to incorporate IVM in $\mathbb{EQ}^{\mathbb{P}}$.

Background on Incremental View Maintenance (IVM). Given a view corresponding to a query q, for each table $R_i \in q$, IVM algebraically derives an incremental query Δq that is executed (*e.g.*, using triggers as in [31]) whenever the base tables change. Δq query computes only the delta changes of the materialized view q. Correctness of IVM is characterized by ensuring that: $[q(D+\Delta D) = q(D) + \Delta q(D, \Delta D)]$, where D is an instantiation of a database, ΔD are the updates to D, $q(D)$ is the prior query results based on D, Δq is the modified query that needs to be executed on ΔD, and the notation '+' in the expression $q(D) + \Delta q(D, \Delta D)$ refers to the way of combining answers of the two queries to generate the overall answer to q over the modified data.

[17, 31, 39] provide a comprehensive description of how Δq can be algebraically derived from q. Below, to provide intuition, we provide examples of how operators are transformed. Let ΔR_1 and ΔR_2 be the set of tuples updated to relations R_1 and R_2, respectively.

- Let $q = \sigma_C(R_1)$, where C represents a set of selection conditions, then $\Delta q = \sigma_C(\Delta R_1)$, *i.e.*, the selection condition needs to be applied only on the updated tuples of R_1.
- Let $q = R_1 \bowtie R_2$, then $\Delta q = (\Delta R_1 \bowtie R_2 + R_1 \bowtie \Delta R_2 + \Delta R_1 \bowtie \Delta R_2)$, *i.e.*, only the updated tuples of R_1 needs to be joined with relation R_2, the updated tuples of R_2 with R_1 and between the updated tuples of R_1 and R_2.
- Let $q = \gamma_g(R)$, then $\Delta q = \gamma_g(\Delta R_1)$, where γ is an aggregation function, g is a `group by` attribute. The aggregation function γ_g needs to be applied directly on the updated tuples.

Recall that for each of the above queries, the result of the query Δq needs to be merged with the previous results of the query q. Hence, the result of $q(D + \Delta D)$ is obtained by merging the results of $q(D)$ and $\Delta q(D, \Delta D)$. This post-processing step is performed by IVM techniques itself in the DBMS. IVM techniques have been integrated in several popular databases: PostgreSQL [4], Oracle [6], and Amazon Redshift [5]. IVM implementations can be more efficient than recomputing the original query. For example, a rewritten selection query using the above rules requires only selections to be performed on updated tuples (that may be few), compared to re-execute selection over the entire table. Likewise, incremental computation of joins and other operators may be significantly efficient compared to the naïve implementation. DBToaster [31] shows ≈90 times improvement for certain queries in TPC-H benchmark [10], in terms of the number of refreshes supported by IVM, compared to a full refresh of materialized view after each update of base tables.

Incremental Processing in $\mathbb{EQ}^{\mathbb{P}}$. $\mathbb{EQ}^{\mathbb{P}}$ exploits IVM to incrementally compute modified query answers, as enrichments performed on the data during epochs. The query execution consists of four steps, discussed in the following subsections. Only one of the four steps (*i.e.*, query setup) is performed once in the zero-th epoch e_0 (this is a special epoch where only query setup is performed), and all other steps are executed iteratively, once per epoch.

3.3.1 ***Query Setup.*** During the query setup, $\mathbb{EQ}^{\mathbb{P}}$ initializes a materialized view q_v for the query q based on the current state of the database. Results of q_v are incrementally updated as more data is enriched in future epochs.

In addition, during query setup, to determine the set of possible candidate enrichments to be performed in future epochs, probe queries $pq(R_i)$ (discussed in §2.1) are executed for each relation $R_i \in q$. The query $pq(R_i)$ needs to be appropriately modified since simply checking if the value of a derived attribute is not NULL, no longer suffices if a tuple is fully enriched. Instead, the probe queries need to exploit the state of derived attributes to determine if the derived attribute can be further enriched by exploiting other enrichment functions that have not been executed yet on the attribute value. The test for whether a given attribute an enrichment function has not yet been executed (and hence the tuples can be further enriched) is performed by checking if the sum of the bits in the array of $\mathcal{A}jStateBitmap$ column of a tuple is equal to the length of the array in $\mathcal{A}jStateBitmap$ column.

Example 3.1. Considering the probe query of Figure 2d for relation R_1, the modified probe query is shown in Figure 3. In the modified query, if some of the bits in the array of $\mathcal{A}_1StateBitmap$ column of a tuple is not equal to the length of the array in $\mathcal{A}_1StateBitmap$ column, then that tuple is not completely enriched and hence it is returned in the probe query result. ■

$$\sigma_{R_1.A_2=a_2 \wedge (array\_sum(\mathcal{A}_1StateBitmap)!=array\_length(\mathcal{A}_1StateBitmap))} (R_1 \bowtie R_1State) \ltimes_{R_1.A_2=R_2.A_4} \Big[R_2 \ltimes_{R_2.A_4=R_3.A_5} (\sigma_{(R_3.A_5=a_5) \wedge (array\_sum(\mathcal{A}_1StateBitmap)!=array\_length(\mathcal{A}_1StateBitmap))} (R_3 \bowtie R_3State))\Big]$$

Figure 3: Updated probe query for R_1.

`PlanSpaceTable`. The result of the probe queries are stored in a table entitled `PlanSpaceTable`; an example of which is shown in Table 3. This table stores a set of candidate tuples of relations $R_i \in q$ that are considered for enrichment to answer q. Rows in `PlanSpaceTable` correspond to the name of the relation (R_i) included in q, the tuple ID, and the list of derived attributes for which the tuple needs to be enriched for q (see Table 3).

[6] Though, at times, it may require re-execution of enrichment functions, if the determinization process requires a probability value from the corresponding enrichment function for the domain value that has been pruned out. [30] uses a similar strategy compressed representation to store some tuples (with probability higher than a threshold) of a relation in a faster primary index, called *Uncertain Primary Indexing* (UPI), and the remaining tuples in a slower secondary index.

Rel	TID	Attribute
'R_1'	1	'$\mathcal{A}_1$', '$\mathcal{A}_3$'
...		
'R_1'	100	'$\mathcal{A}_1$', '$\mathcal{A}_3$'
'R_2'	1	'$\mathcal{A}_2$'
...		
'R_3'	200	'$\mathcal{A}_1$', '$\mathcal{A}_3$'

Table 3: `PlanSpaceTable`.

Rel	TID	Attr-FID
'R_1'	2	$\langle$'$\mathcal{A}_1$', $f_2.id\rangle$, $\langle$'$\mathcal{A}_3$', $f_5.id\rangle$
'R_1'	3	$\langle$'$\mathcal{A}_1$', $f_4\rangle$, $\langle$'$\mathcal{A}_3$', $f_6.id\rangle$
'R_2'	1	$\langle$'$\mathcal{A}_2$', $f_7.id\rangle$
'R_3'	2	$\langle$'$\mathcal{A}_1$', $f_3.id\rangle$, $\langle$'$\mathcal{A}_3$', $f_5.id\rangle$

Table 4: `PlanTable`.

3.3.2 ***Enrichment Planning.*** At the beginning of each epoch, based on the state of the tuples, $\mathbb{EQ}^{\mathbb{P}}$ moves a set of tuples from `PlanSpaceTable` to a `PlanTable` for (potential) enrichment during this epoch. `PlanTable` contains three columns: `RelationName`, `TID` (tuple identifier), and `Attr-FID` (stores a list of pairs of name of derived attribute and enrichment function identifier), which helps for each tuple and each derived attribute that require enrichment in selecting an enrichment function. A sample `PlanTable` in Table 4 is based on selecting tuples from `PlanSpaceTable` of Table 3. The cost of the selected plan is the summation of the cost of enrichment functions part of `PlanTable`. Note that for the plan to be valid (*i.e.*, executable during the epoch), the cost of the selected plan *must* be smaller than epoch duration.

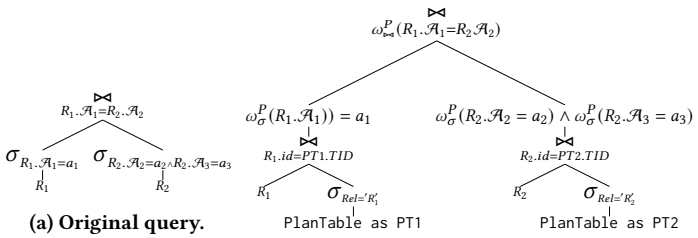
In order to populate `PlanTable` from `PlanSpaceTable`, we select a set of ⟨tuple, derived attribute, enrichment function⟩ triplets for enrichment during an epoch. Sample selection methods have been extensively studied for AQP [11, 25, 43]. In such systems, typically a random sample of tuples is selected based on which the approximate aggregate values are computed. Then, such aggregate values are improved as the system progressively chooses a larger sample size and computes the aggregate function on them [25]. Similar to such techniques, we also choose tuples randomly to enrich during a given epoch. However, in contrast to AQP, we need to further select a derived attribute to enrich, as well as, an enrichment function to execute on the chosen attribute (in case more than one enrichment functions are available to enrich). We modify the sampling-based selection policy of AQP for this purpose, leading to three distinct strategies. In each strategy, the tuples to be enriched are chosen randomly from `PlanSpaceTable` by simple random sampling.

Sampling-based Object Ordered (SB(OO)), where we randomly select a derived attribute from the chosen tuples and enrich it using all the associated functions with the attribute.

Sampling-based Random Ordered (SB(RO)), where we randomly select a derived attribute and randomly select an enrichment function for each of the chosen tuples. The enrichment is continued until the epoch time is exhausted.

Sampling-based Function Ordered (SB(FO)), where we enrich each attribute of the chosen tuples based on an ordered execution of the corresponding functions associated with the attributes. Enrichment functions associated with the attributes are ordered based on their $\frac{quality}{cost}$, where quality is measured using any classifier metrics such as accuracy and cost is measured using the average execution time of the function per object. This strategy is motivated by the optimization of multi-version predicates as proposed in [34].

3.3.3 ***Computing Progressive Answers.*** To compute q progressively, we need to compute delta answers for q_v based on the modified data due to enrichment in the epoch. Computing delta answers in $\mathbb{EQ}^{\mathbb{P}}_{\text{TC}}$ is more complex than in $\mathbb{EQ}^{\mathbb{P}}_{\text{LC}}$, which we discuss first.



(a) Original query. **(b) Query used in IVM for $\mathbb{EQ}^{\mathbb{P}}_{\text{TC}}$.**

Figure 4: The incremental query used by IVM in $\mathbb{EQ}^{\mathbb{P}}_{\text{TC}}$.

Progressive Answering in $\mathbb{EQ}^{\mathbb{P}}_{\text{LC}}$: In $\mathbb{EQ}^{\mathbb{P}}_{\text{LC}}$, enrichments are performed independently at the enrichment server and the modified attribute values of enriched tuples are updated in the tables stored in the DBMS. This update triggers the recomputation of the query answers at the end of each epoch. In $\mathbb{EQ}^{\mathbb{P}}_{\text{LC}}$, the IVM query q_v is simply the original query of q. During each epoch e_k, the ⟨tuple, derived attribute, enrichment function⟩ triplets of `PlanTable` are executed, followed by the execution of appropriate determinization function *DET*. The resulting updates are reflected in the database by replacing the current values of the derived attributes of enriched tuples based on the functions executed upto that time. Hence, the determinized representation of the database changes from $DET(state(D, e_{k-1}))$ to $DET(state(D, e_k))$. Such an update, triggers IVM to update the materialized view based on ΔD that consists of all the changes that took place in e_k (*i.e.*, $\big[DET(state(D, e_k))$ - $DET(state(D, e_{k-1}))\big]$). Specifically, $\Delta q(DET(D, e_{k-1}), DET(\Delta D))$ is executed to compute $q(DET(D, e_k))$, *i.e.*, the query result at the end of epoch e_k.

Progressive Answering in $\mathbb{EQ}^{\mathbb{P}}_{\text{TC}}$. In $\mathbb{EQ}^{\mathbb{P}}_{\text{TC}}$, enrichment of tuples are performed within the query q as part of the UDF execution. Therefore, enrichment of tuples and the subsequent updates to the state tables can not be used to trigger the incremental evaluation. To overcome this issue, $\mathbb{EQ}^{\mathbb{P}}_{\text{TC}}$, uses the updates to `PlanTable` to trigger the incremental evaluation of the query results.

In particular, the query q is rewritten to use `PlanTable` as follows: all relation $R_i \in q$, that require enrichment, R_i is replaced by the expression : $R_i \bowtie_{R_i.TID=PlanTable.TID} (\sigma_{RelName='R_i'}(PlanTable))$.

Example 3.2. Consider the query of Figure 4a. The tuples of both R_1 and R_2 require enrichment because of the conditions on attributes $\mathcal{A}_1$ and $\mathcal{A}_2$. In the rewritten query of q to support incremental evaluation, both relations are joined with `PlanTable`, as shown in Figure 4b (other rewrites of selection and join conditions are denoted as ω^P_σ and $\omega^P_\bowtie$ will be clear soon). Now, suppose in epoch e_k, a ⟨tuple, derived attribute, enrichment function⟩ triplet is added to `PlanTable` where the tuple belongs to relation R_1. The addition of this triplet triggers a view update as `PlanTable` is part of the view definition in Figure 4b. ■

In $\mathbb{EQ}^{\mathbb{P}}_{\text{TC}}$, each relation R_i is joined with the plan table to determine the set of enrichments to be performed during each epoch. We could potentially reduce the cost of such a join by maintaining plan tables associated with each table separately and joining the relation with its associated plan table. Since plan tables are relatively small (less than 0.1% in size of the database in our experiments), we maintain a single plan table for all the relations.

While the approach to create q_v by rewriting q using PlanTable results in desired incremental updates, it suffers from a subtle complexity. Specifically, for a given tuple t, when enrichment functions execute, the change in the state table, results in a new determinized value for the derived attribute $t.\mathcal{A}_j$ in R. If we update the current value of $t.\mathcal{A}_j$ in R, the change would cause the refresh to the view to cascade resulting in a duplicate update to the results. To see this, consider the following example.

Example 3.3. In Example 3.2, suppose a row $\langle t, \mathcal{A}_i, f_j \rangle$ where $t \in R$ is added to PlanTable in epoch e_k. Hence, the incremental query execution is triggered. During the execution of incremental query, enrichment function is executed on t and the condition of $(R.\mathcal{A}_1 = a_1)$ is evaluated on it. As a result, the state of t and the determinized value of $t.\mathcal{A}_1$ is updated. Now, if we update the new attribute value of t in R, it will cause another trigger to incremental query execution (as R is part of the q_v), causing duplicate results. ■

To prevent such a situation, we cannot update the value of attribute $t.\mathcal{A}_j$ directly during the execution of q_v. We instead store the value of determinized representation of $t.\mathcal{A}_j$ separately as part of state table R_iState. To do so, we extend the schema of R_iState to include a new field $\mathcal{A}_j$Value for each derived attribute in R_i.[7]

Since we do not modify the value of a derived attribute in place, we need to define additional UDFs for q_v to read the value of attribute $\mathcal{A}_j$. Note that if $\mathcal{A}_j$ is modified (due to enrichment) during the execution of the query, its value resides in the $\mathcal{A}_j$Value column of the R_iState table. Otherwise, if $\mathcal{A}_j$ is not modified in an epoch, its most recent value is available in $\mathcal{A}_j$ column of table R_i. To enable q_v to correctly retrieve the value of $\mathcal{A}_j$, we define two UDFs entitled *CheckState* and *GetValue* as described below.

***CheckState* UDF**: The objective of this UDF is to check if a particular tuple was enriched for a particular derived attribute present in the query. The input to the UDF is a relation name, a derived attribute name, a tuple identity, and Attr-FID value retrieved from PlanTable for the corresponding tuple. Attr-FID column of PlanTable, is used to get the enrichment function that needs to be executed. If that enrichment function was executed before, then it returns true, otherwise false. Note that *CheckState* retrieves this information from the state bitmap column of the derived attribute in the state table §3.2.

***GetValue* UDF:** The purpose of *GetValue* UDF is to retrieve the latest value of a derived attribute for a given tuple. *GetValue* takes as input a relation name (*e.g.*, 'R_i'), attribute name (*e.g.*, '$\mathcal{A}_j$'), and a tuple identity and returns the determinized value of $\mathcal{A}_j$ stored in the $\mathcal{A}_j$Value column of R_iState table.

Apart from the above two UDFs, we further need to appropriately modify the $read_u$ function shown in §2.2 (that enriches derived attributes as a side effect of reading them) to account for the way the state and data value are stored when multiple enrichment functions can be associated with a derived attribute.

Modified $read_u$ UDF: Given a tuple, a derived attribute $\mathcal{A}_j$, and an enrichment function, the modified $read_u$ UDF executes the enrichment function on the tuple, updates the state, and returns the determinized representation of the tuple for the derived attribute.

[7] R_iState, thus, contains three fields: $\mathcal{A}_j$Bitmap, $\mathcal{A}_j$Output, and $\mathcal{A}_j$Value, for attribute $\mathcal{A}_j$.

The modified $read_u$ function takes the following inputs: the name of the relation, the name of the derived attribute, the tuple identity, and the list of ⟨derived attribute, function ID⟩ pairs (stored in *Attr_FID* column of PlanTable). It executes the enrichment function on the input tuple for the derived attribute (parsed from *Attr_FID*), updates the state of the tuple, and returns the derived attribute value. In the state table, it updates the state bitmap, state output, and attribute-value columns. The state-bitmap is updated by setting the bit corresponding to the enrichment function executed on it. The state output is updated by the output of the executed enrichment function. The attribute-value column is updated by the latest determinized representation of the derived attribute value of the tuple. The determinized representation of the derived attribute is returned by the $read_u$ function.

Selection Query. Using $read_u$ UDF as shown above, we now describe how query q_v is rewritten. Essentially, the selection conditions are rewritten appropriately to check if the corresponding derived attribute was enriched during the epoch from the state table (enrichment is only performed if the enrichment function was not executed earlier). This check is performed using *CheckState* and *GetValue* UDFs as defined earlier. The complete rewrite logic of a selection condition ($\omega^P_\sigma(R.\mathcal{A}_i \ op \ a_i)$) is presented below:

$$\begin{aligned}&\big[CheckState(\text{'}R\text{'}, \text{'}\mathcal{A}_i\text{'}, R.id, Attr\_FID) \quad /^*\ \mathcal{A}_i \text{ is enriched.}^*/\\ &\quad \wedge\ GetValue(\text{'}R\text{'}, \text{'}\mathcal{A}_i\text{'}, R.id)\ op\ a_i\big]\\ \vee\ &\big[!CheckState(\text{'}R\text{'}, \text{'}\mathcal{A}_i\text{'}, R.id, Attr\_FID) \quad /^*\ \mathcal{A}_i \text{ is not enriched.}^*/\\ &\quad \wedge\ read_u(\text{'}R\text{'}, \text{'}\mathcal{A}_i\text{'}, R.id, Attr\_FID)\ op\ a_i\big]\end{aligned}$$

In the above rewrite logic, the rewritten condition first checks if the tuple is already enriched or not for a given derived attribute $\mathcal{A}_i$ using the *CheckState* function. If it is already enriched, then the *GetValue* UDF is used to retrieve the latest attribute value of the tuple and then the selection condition is executed. This rewrite logic is achieved by: $\big[CheckState(\text{'}R\text{'}, \text{'}\mathcal{A}_i\text{'}, R.id, Attr\_FID) \wedge GetValue(\text{'}R\text{'}, \text{'}\mathcal{A}_i\text{'}, R.id)\ op\ a_i\big]$. If a tuple is not enriched before (*i.e.*, *CheckState* UDF output is 0), then the $read_u$ UDF is executed to enrich the tuple and finally the selection condition is executed based on the output of $read_u$ UDF. It is achieved by the condition of $\big[!CheckState(\text{'}R\text{'}, \text{'}\mathcal{A}_i\text{'}, R.id, Attr\_FID) \wedge read_u(\text{'}R\text{'}, \text{'}\mathcal{A}_i\text{'}, R.id, Attr\_FID)\ op\ a_i\big]$.

Join Query. The rewrite logic for join condition $\omega^P_{\bowtie}(R_p.\mathcal{A}_i \ op \ R_q.\mathcal{A}_j))$ is shown below (similar to rewrite logic of selection condition). In the following rewrite logic, given a join condition of $(R_p.\mathcal{A}_i \ op \ R_q.\mathcal{A}_j)$, for a tuple pair, the rewritten condition first checks if both the derived attributes were enriched (*i.e.*, *CheckState* returning true for both tuples). If they were, then the join condition is executed on the output of the *GetValue* function as it returns the latest attribute value of the tuples. In the second and third conditions of the rewrite, only one tuple of the tuple pair is enriched. For the tuple that was enriched before, the value was retrieved using *GetValue* UDF. The other tuple is enriched first using the modified $read_u$ function and the join condition between the tuple pair is executed. In the fourth condition of the rewrite, both the tuples were not enriched in the epoch. Hence, both the tuples were enriched using the modified $read_u$ function and the join condition is executed.

$[CheckState(`R_p`, `\mathcal{A}_i`, R_p.id, Attr\_FID)$
$\wedge CheckState(`R_q`, `\mathcal{A}_j`, R_q.id, Attr\_FID)$ /* Both of $\mathcal{A}_i$ and $\mathcal{A}_j$ are enriched*/
$\wedge GetValue(`R_p`, `\mathcal{A}_i`, R_p.id)\ op\ GetValue(`R_q`, `\mathcal{A}_j`, R_q.id)]$
$\vee [CheckState(`R_p`, `\mathcal{A}_i`, R_p.id, Attr\_FID)$
$\wedge !\ CheckState(`R_q`, `\mathcal{A}_j`, R_q.id, Attr\_FID)$ /* Only $\mathcal{A}_i$ is enriched.*/
$\wedge GetValue(`R_p`, `\mathcal{A}_i`, R_p.id)\ op\ read_u(`R_q`, `\mathcal{A}_j`, R_q.id, Attr\_FID)]$
$\vee [!\ CheckState(`R_p`, `\mathcal{A}_i`, R_p.id, Attr\_FID)$
$\wedge\ CheckState(`R_q`, `\mathcal{A}_j`, R_q.id, Attr\_FID)$ /* Only $\mathcal{A}_j$ is enriched.*/
$\wedge read_u(`R_p`, `\mathcal{A}_i`, R_p.id, Attr\_FID)\ op\ GetValue(`R_q`, `\mathcal{A}_j`, R_q.id)]$
$\vee [!\ CheckState(`R_p`, `\mathcal{A}_i`, R_p.id, Attr\_FID)$
$\wedge !\ CheckState(`R_q`, `\mathcal{A}_j`, R_q.id, Attr\_FID)$ /* None of $\mathcal{A}_i$ and $\mathcal{A}_j$ are enriched.*/
$\wedge read_u(`R_p`, `\mathcal{A}_i`, R_p.id, Attr\_FID)\ op\ read_u(`R_q`, `\mathcal{A}_j`, R_q.id, Attr\_FID)]$

Example 3.4. Considering the query of Figure 4a, the rewritten query of q_v is shown in Figure 4b. In q_v, the selection and join conditions are rewritten using the rewrite logic of ω_σ and $\omega_{\bowtie}$ and contains `PlanTable` as we described above. In an epoch e_k, when a set of ⟨tuple, derived attribute, enrichment function⟩ triplets are added to `PlanTable`, a re-execution of query q_v is triggered. During the execution of q_v, the enrichment of triplets in `PlanTable` take place and the state of the tuples are updated (*i.e.*, using $read_u$ UDF), and IVM maintained for query q_v is updated. Hence, the delta query used to compute the delta changes to the result of q at the end of each epoch e_k is created using the same query of q_v. ■

3.3.4 ***Fetching Results.*** In $\mathbb{EQ}^{\mathbb{P}}$, users can fetch complete query results at the end of an epoch by querying the IVM. If the complete answer set is large, users can retrieve delta changes of answers, *i.e.*, inserted/deleted/updated tuples from the previous epoch. The current implementation allows users to fetch delta answers only from the last epoch. Fetching delta answers from any arbitrary epoch using a cursor is complex (will be supported in a future version), since the query processing in $\mathbb{EQ}^{\mathbb{P}}$ are not demand-driven, as in SQL databases. The refined answers due to $\Delta q(DET(D, e_{k-1}), DET(\Delta D))$, may result in retraction of previously returned tuples, or addition of new tuples, or updates to the previously reported answers.

4 COMPARISON BETWEEN $\mathbb{EQ}_{\mathbb{LC}}$ AND $\mathbb{EQ}_{\mathbb{TC}}$

While $\mathbb{EQ}_{\mathbb{LC}}$ enriches tuples prior to query processing (by identifying tuples that might need to be enriched using probe queries), $\mathbb{EQ}_{\mathbb{TC}}$ enriches tuples during query processing when the need to enrich the tuple arises. $\mathbb{EQ}_{\mathbb{TC}}$ may perform lesser number of enrichments compared to $\mathbb{EQ}_{\mathbb{LC}}$ since tuples may get eliminated during query processing and, thus, do not need to be enriched. As an example, consider a conjunctive selection query on derived attributes $\mathcal{A}_1$ and $\mathcal{A}_2$. Now, $\mathbb{EQ}_{\mathbb{TC}}$, after enriching attribute $\mathcal{A}_1$ of a tuple, will not enrich $\mathcal{A}_2$ of the tuple if the tuple does not satisfy the selection condition on $\mathcal{A}_1$. Also, compared to $\mathbb{EQ}_{\mathbb{TC}}$, $\mathbb{EQ}_{\mathbb{LC}}$ incurs additional overhead of moving data from DBMS to an enrichment server and vice versa. Such benefits, that are more pronounced when enrichment is expensive, are validated by experiments in §5.

While $\mathbb{EQ}_{\mathbb{LC}}$ incurs overhead due to potentially higher number of enrichment and data movement, $\mathbb{EQ}_{\mathbb{LC}}$ also has certain advantages compared to $\mathbb{EQ}_{\mathbb{TC}}$.

The rewritten queries in $\mathbb{EQ}_{\mathbb{TC}}$ are significantly more complex. For instance, in $\mathbb{EQ}_{\mathbb{TC}}$, join conditions in the rewritten query contain (potentially complex) disjunctions and UDFs compared to the conditions in the original query. This makes queries harder to optimize by the standard optimizers supported by the underlying DBMS on which $\mathbb{EQ}_{\mathbb{TC}}$ is built. Different DBMSs provide different levels of optimization support for UDFs. Systems such as PostgreSQL offer ways to specify cost per tuple for executing a UDF, which is then factored into the overall plan by the query optimizer. For instance, if a UDF is expensive it may be pulled up in the tree [27]. Disjunctions in rewritten query may also affect the choice of join algorithm chosen by the optimizer in the query plan. The DBMS may choose to implement the join using a nested loop join while the corresponding join in the plan associated with the original query (which is used to execute $\mathbb{EQ}_{\mathbb{LC}}$) may use a hash join instead. Thus, $\mathbb{EQ}_{\mathbb{TC}}$ and $\mathbb{EQ}_{\mathbb{LC}}$ potentially offer a tradeoff of reduced enrichment cost and reduced data movement versus possibly complex queries that are harder for existing systems to optimize. We study such a tradeoff in the experiments of §5.

5 EXPERIMENTAL EVALUATIONS

This section evaluates the performances of both $\mathbb{EQ}_{\mathbb{LC}}$ and $\mathbb{EQ}_{\mathbb{TC}}$ approaches. Specifically, we address the following questions:

- How does $\mathbb{EQ}_{\mathbb{TC}}$ perform compared to $\mathbb{EQ}_{\mathbb{LC}}$ approach in terms of savings in the enrichment? Does exploiting query semantics during enrichment really pay off?
- How does progressive query processing help in reducing query response time for queries with expensive UDFs compared to the traditional approaches of query processing?
- Which approach between $\mathbb{EQ}_{\mathbb{TC}}$ and $\mathbb{EQ}_{\mathbb{LC}}$ is well suited for supporting progressive query processing? What are their advantages and limitations in terms of overheads?
- How do enrichment plan generation strategies affect progressive query processing? Are there scopes for improvement?

5.1 Experimental Setup

Datasets. We used two datasets to evaluate $\mathbb{EQ}_{\mathbb{LC}}$ and $\mathbb{EQ}_{\mathbb{TC}}$: (*i*) TweetData collected using APIs with 11 million rows, two derived attributes: ⟨`sentiment` and `topic`⟩, and six fixed attributes: ⟨`tid`, `UserID`, `Tweet`, `feature`, `location`, and `TweetTime`⟩ (*ii*) MultiPie [49] dataset with 500K facial images, two derived attributes: ⟨`gender` and `expression`⟩, and five fixed attributes: ⟨`ImageID`, `UserID`, `CameraID`, `Image`, and `ImageTime`⟩ (see Table 5).

Relation	#tuples	Size(GB)	Derived attrs.	Functions used
TweetData	11M	10.5	sentiment(3)	GNB,KNN,SVM,MLP
			topic(40)	GNB,KNN,LDA,LR
MultiPie[49]	500K	84.5	gender(2)	DT,GNB,KNN,MLP
			expression(5)	DT, GNB, RF, KNN

Table 5: Datasets used in experiments.

Enrichment Functions. We used the following probabilistic classifiers as enrichment functions: Gaussian Naïve Bayes (GNB), Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multi-Layered perceptron (MLP), Linear Discriminant Analysis (LDA), Logistic Regression (LR), and Random Forest (RF). GNB classifier was calibrated using isotonic-regression model [55], and

Q1	SELECT * from MultiPie where gender=1 and CameraID < c_1
Q2	SELECT * from MultiPie where gender = 1 and expression = 2 and CameraID < c_1
Q3	SELECT tid, UserID, Tweet, location, TweetTime from TweetData where sentiment = s_1 and topic = t_1 and TweetTime between(t_1,t_2)
Q4	SELECT * from TweetData T1, TweetData T2 where T1.sentiment = T2.sentiment and T1.topic = T2.topic and T1.TweetTime between(t_1,t_2) and T2.TweetTime between (t_1, t_2)
Q5	SELECT * from MultiPie M1, MultiPie M2 where M1.expression = M2.expression and M1.gender = M2.gender and M1.CameraID < c_1 and M2.CameraID < c_1
Q6	SELECT * from MultiPie M1, MultiPie M2 where M1.gender = M2.gender and M1.expression = 1 and M2.expression = 2 and M1.CameraID < c_1 and M2.CameraID < c_1
Q7	SELECT * from TweetData T1, State S where T1.location = S.city and S.state='California' and T1.sentiment = 1 and T1.TweetTime between(t_1,t_2)
Q8	SELECT * from TweetData T1, TweetData T2, State S where T1.sentiment = T2.sentiment and T1.topic = T2.topic and T1.location = S.city and S.state='California' and T1.TweetTime between(t_1,t_2)
Q9	SELECT topic, count(*) from TweetData where T1.TweetTime between(t_1,t_2) group by sentiment

Table 6: Query templates.

Query	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
Baseline	500K	1M	22M	22M	1M	1M	11M	22M	11M
$\mathbb{EQ}_{\mathrm{LC}}$	10K	20K	200K	200K	20K	20K	4K	120K	100K
$\mathbb{EQ}_{\mathrm{TC}}$	10K	13K	164K	127K	12K	12K	4K	114K	100K

Table 7: Exp 1. Number of enrichments in $\mathbb{EQ}_{\mathrm{LC}}$, $\mathbb{EQ}_{\mathrm{TC}}$, and the *Baseline* approach where the data is completely enriched.

other classifiers were calibrated using Platt's sigmoid model [44] during cross-validation to output probability distribution.

Queries. Table 6 shows nine queries, where ***Q1-Q3*** are ***selection queries***, ***Q4-Q8*** are ***join queries***, and ***Q9*** is an ***aggregation query***.

5.2 Experimental Results

We setup PostgreSQL database on an AWS server with 16 core 2.50 GHz Intel Xeon CPU, 64GB RAM, and 1TB SSD. We used another AWS server with the same configuration as an enrichment server in $\mathbb{EQ}_{\mathrm{LC}}$. Enrichment functions were implemented as PostgreSQL UDFs in $\mathbb{EQ}_{\mathrm{TC}}$ and as Python functions in $\mathbb{EQ}_{\mathrm{LC}}$.

5.2.1 $\mathbb{EQ}_{\mathrm{TC}}$/ $\mathbb{EQ}_{\mathrm{LC}}$ ***VS Complete Enrichment***. To compare $\mathbb{EQ}_{\mathrm{LC}}$ /$\mathbb{EQ}_{\mathrm{TC}}$ against the strategy of complete enrichment before query execution (referred to as ***Baseline***), we used MLP for `sentiment` (100 ms/tweet), GNB for `topic` (125 ms/tweet), MLP for `gender` (1536 ms/image), and RF for `expression` attribute (1380 ms/image). Here, enriching all 11M tweets of TweetData table for both `topic` and `sentiment` attributes takes ≈**43 hours**, when we run these functions in parallel using all 16 cores of the server. Similarly, complete enrichment of MultiPie data takes ≈**26 hours**.

Exp 1: Number of enrichments. Table 7 shows the number of enrichments in the *Baseline* approach, $\mathbb{EQ}_{\mathrm{LC}}$, and $\mathbb{EQ}_{\mathrm{TC}}$. Both $\mathbb{EQ}_{\mathrm{TC}}$ and $\mathbb{EQ}_{\mathrm{LC}}$ perform significantly better than the *Baseline* approach. $\mathbb{EQ}_{\mathrm{TC}}$ needs either the same or less number of enrichments than $\mathbb{EQ}_{\mathrm{LC}}$ due to exploiting query semantics to avoid redundant enrichments. For queries with multiple predicates (*i.e.*, Q2-Q6 and Q8) on derived attributes, the tuples that did not satisfy a subset of query predicates were not enriched for the remaining derived attributes in $\mathbb{EQ}_{\mathrm{TC}}$, resulting in the savings in enrichment as compared to $\mathbb{EQ}_{\mathrm{LC}}$. However, in Q1, Q7, and Q9, the number of enrichments were same in both $\mathbb{EQ}_{\mathrm{LC}}$ and $\mathbb{EQ}_{\mathrm{TC}}$, as Q1 and Q7 had a single predicate on derived attribute and Q9 was an aggregation query with a selection condition on a fixed attribute.

Approach	Selectivity	`topic` ≤ 10	`topic` ≤ 20	`topic` ≤ 30	`topic` ≤ 40
Baseline	1%	22M	22M	22M	22M
$\mathbb{EQ}_{\mathrm{LC}}$	1%	20K	20K	20K	20K
$\mathbb{EQ}_{\mathrm{TC}}$	1%	11.4K	14.7K	15.4K	16.8K
Baseline	10%	22M	22M	22M	22M
$\mathbb{EQ}_{\mathrm{LC}}$	10%	200K	200K	200K	200K
$\mathbb{EQ}_{\mathrm{TC}}$	10%	100.1K	103.9K	104.6K	139K
Baseline	100%	22M	22M	22M	22M
$\mathbb{EQ}_{\mathrm{LC}}$	100%	22M	22M	22M	22M
$\mathbb{EQ}_{\mathrm{TC}}$	100%	11.16M	12.14M	13.6M	15.8M

Table 8: Exp 1. Number of enrichments performed in EQ_{TC}, EQ_{LC} as compared to *Baseline* with varying selectivity of a fixed condition (*i.e.*, `TweetTime` between (t_1, t_2)) in Q3.

Query	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
$\mathbb{EQ}_{\mathrm{LC}}$	378	684	1291	1319	736	705	32	910	652
$\mathbb{EQ}_{\mathrm{TC}}$	306	572	944	905	627	582	28	924	612

Table 9: Exp 1. Query latency in $\mathbb{EQ}_{\mathrm{LC}}$ and $\mathbb{EQ}_{\mathrm{TC}}$ (seconds).

Number of enrichments with varying selectivity. We define selectivity as the ratio of input-cardinality to the output-cardinality of a predicate. We used Q3 for this experiment, where we replace the predicate of (`topic` = t_1) with the predicate of (`topic` ≤ k) where k is varied from 10 to 40 to control the selectivity of `topic` predicate. Table 8 shows the results, where we observe that as the predicate selectivity increases (*i.e.*, passes fewer input tuples), the savings in terms of enrichment for both $\mathbb{EQ}_{\mathrm{LC}}$ and $\mathbb{EQ}_{\mathrm{TC}}$ increases as compared to the *Baseline* approach. $\mathbb{EQ}_{\mathrm{TC}}$ approach starts to outperform $\mathbb{EQ}_{\mathrm{LC}}$ more, when selectivity increases, since all tuples that do not satisfy the predicate of (`topic` ≤ k) are not further enriched for attribute of `sentiment` in $\mathbb{EQ}_{\mathrm{TC}}$. For $\mathbb{EQ}_{\mathrm{LC}}$, increasing selectivity does not reduce the number of enrichments, since all the tuples that were part of the result of probe queries are enriched for all derived attributes present in the original query. Thus, for highly selective predicates, $\mathbb{EQ}_{\mathrm{TC}}$ performs better compared to $\mathbb{EQ}_{\mathrm{LC}}$, and both $\mathbb{EQ}_{\mathrm{TC}}$ and $\mathbb{EQ}_{\mathrm{LC}}$ perform significantly better than *Baseline* for high selectivity values (*i.e.*, 1% and 10%).

Execution time/Server load. Table 9 shows the latency of queries Q1 to Q9 in $\mathbb{EQ}_{\mathrm{LC}}$ and $\mathbb{EQ}_{\mathrm{TC}}$, where latency is the average execution time of 50 queries generated from each template of Table 6. *E.g.*, we chose 50 queries of $Q2$ by setting different values in the condition on `CameraID` attribute. The latency of queries in $\mathbb{EQ}_{\mathrm{TC}}$ and $\mathbb{EQ}_{\mathrm{LC}}$ are much lower (*i.e.*, two orders of magnitude lower) than the time required to completely enrich the datasets (*i.e.*, 43 hours for tweet datasets and 26 hours for Multipie dataset).

The latency difference between $\mathbb{EQ}_{\mathrm{TC}}$ and $\mathbb{EQ}_{\mathrm{LC}}$ arise due to three reasons: (*i*) the number of enrichments (shown in Table 7), (*ii*) the data movement cost — transfer of data from DBMS to the

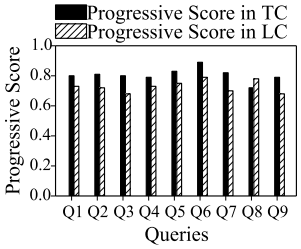


Figure 5: Exp 2. Progressive score achieved by queries in $\mathbb{EQ}_{TC}$ and $\mathbb{EQ}_{LC}$.

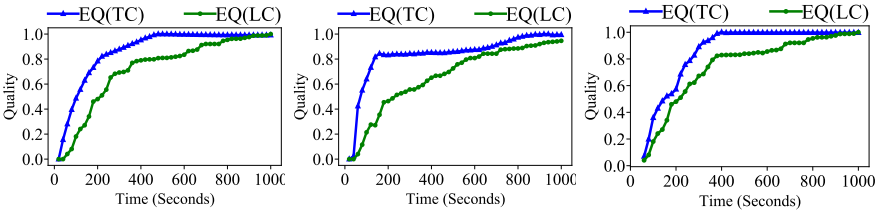


Figure 6: Exp 2. Progressiveness achieved in $\mathbb{EQ}_{LC}$ and $\mathbb{EQ}_{TC}$ for (a) Q2, (b) Q3, and (c) Q4.

enrichment server vice versa (see Table 11), and (*iii*) UDF invocation cost. Table 11 provides the breakdown of the execution time spent in the enrichment server and in the DBMS, and the data transfer cost in $\mathbb{EQ}_{LC}$. As expected, in $\mathbb{EQ}_{LC}$, the majority of the query execution time is spent at the enrichment server for all queries. In Q2-Q6, $\mathbb{EQ}_{LC}$ has higher query latency due to more enrichments (see Tables 7 and 11). Furthermore, due to additional data transfer cost, the total time in $\mathbb{EQ}_{LC}$ is higher than $\mathbb{EQ}_{TC}$ even for queries that have the same number of enrichments in both $\mathbb{EQ}_{TC}$ and $\mathbb{EQ}_{LC}$, *i.e.*, Q1, Q7, and Q9 (see Table 7). Additionally, observe that for these three queries Q1, Q7, Q9, the enrichment costs in $\mathbb{EQ}_{LC}$ is slightly lower than $\mathbb{EQ}_{TC}$ since, the enrichment functions are executed in batch in $\mathbb{EQ}_{LC}$ as compared to the execution of enrichment function UDFs on single rows in $\mathbb{EQ}_{TC}$.[8]

For Q8, while the number of enrichments performed by both $\mathbb{EQ}_{LC}$ and $\mathbb{EQ}_{TC}$ are identical (see Table 7), $\mathbb{EQ}_{LC}$ performs better than $\mathbb{EQ}_{TC}$. For Q8, in $\mathbb{EQ}_{TC}$, the optimizer is not able to optimize the rewritten join condition containing UDFs and disjunctions (discussed in §3.3.3) and uses a nested loop join instead of a hash join. However, in $\mathbb{EQ}_{LC}$ the optimizer is able to use a hash join since the queries that $\mathbb{EQ}_{LC}$ runs on the underlying database have no UDFs.

5.2.2 ***Progressiveness.*** This section considers all enrichment functions for the derived attributes as shown in Table 5. We present progressive quality improvement of queries Q1-Q9 in two ways: (*i*) plotting the quality of query results with respect to time and (*ii*) quantifying the quality improvement over time using a metric of *progressive score*, denoted by $\mathcal{PS}$. This metric was used in previous literature to measure progressiveness [13, 42].

$$\mathcal{PS}(Ans(q,E)) = \sum_{i=1}^{|E|} W(e_i)\cdot[\mathcal{Q}(Ans(q,e_i)) - \mathcal{Q}(Ans(q,e_{i-1}))] \quad (1)$$

where, $E = \{e_1, e_2, \ldots, e_z\}$ be the epochs, $W(e_i) \in [0,1]$ is the weight allotted to epoch e_i, $W(e_i) > W(e_{i+1})$, *i.e.*, initial epochs have higher weights, $\mathcal{Q}$ is the quality of query answers, and $[\mathcal{Q}(Ans(q,e_i)) - \mathcal{Q}(Ans(q,e_{i-1}))]$ is the improvement in the quality of answers occurred in the epoch e_i. We chose a linearly decreasing function with a negative slope of 0.05 to assign weights to epochs.

Exp 2: Progressiveness of different queries. Figure 6 evaluates $\mathbb{EQ}^{\mathbb{P}}_{LC}$ and $\mathbb{EQ}^{\mathbb{P}}_{TC}$ in terms of progressive quality improvement achieved. Figures 6(a), 6(b), and 6(c) show the results for queries Q2, Q3, and Q4, where the quality of answers is measured using ***normalized F_1 measure*** *i.e.*, F_1/F_1^{max}, where F_1^{max} is the maximum F_1 measure achieved during query execution. We plot normalized measures as a function of time to emphasize the rate at which the quality of query results are improved across different queries and datasets, instead of actual F_1-measures. Actual F_1-measure varies across different queries based on the quality of classifiers chosen for enrichment (*e.g.*, maximum F_1 measures for queries were: Q1 0.73, Q2 0.81, Q3 0.74, Q4 0.89, Q5 0.78, Q6 0.83, Q7 0.82, Q8 0.79). For aggregation query Q9, the quality is measured using normalized root mean square error.

[8] Recent, research has optimized queries with UDFs by executing them on a batch of tuples [52], inlining [46], or executing in parallel. Such optimizations can be applied to optimize $\mathbb{EQ}_{TC}$ further.

State Cut-off	State size (GB)	Progressive Score
0.4	1.4	0.802
0.6	0.9	0.800
0.8	0.7	0.710

Table 10: Exp 6. Effect of state cutoff in state table size and the query performance for Q3.

Query	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
$\mathbb{EQ}_{LC}$(DBMS)	3	4	9	11	6	5	2	14	7
$\mathbb{EQ}_{LC}$(Network)	72	72	37	37	72	72	3	44	37
$\mathbb{EQ}_{LC}$(ES)	303	608	1245	1271	658	628	27	852	608
$\mathbb{EQ}_{TC}$(DBMS)	306	572	944	905	627	582	28	924	612

Table 11: Exp 1. Times spent in enrichment server(ES) and DBMS in seconds.

From Figures 6, we observe that both $\mathbb{EQ}^{\mathbb{P}}_{LC}$ and $\mathbb{EQ}^{\mathbb{P}}_{TC}$ achieve a high-quality improvement within the first few epochs of query execution. The progressive scores achieved for queries (measured using Equation 1) are presented in Figure 5. $\mathbb{EQ}^{\mathbb{P}}_{TC}$ achieves a higher progressive score since the number of redundant enrichment in $\mathbb{EQ}^{\mathbb{P}}_{TC}$ is lower than that of $\mathbb{EQ}^{\mathbb{P}}_{LC}$. This experiment shows that the progressive query processing approach is beneficial, due to achieving high-quality results within a few epochs, without waiting for complete enrichment. Note that the progressive scores in Figure 5 for $\mathbb{EQ}^{\mathbb{P}}_{TC}$ and $\mathbb{EQ}^{\mathbb{P}}_{LC}$ are similar, as the value of the slope in the progressive score (*i.e.*, Equation 1) was set to a lower value of 0.05. The progressive score depends on the weights assigned to epochs. If we use a steeper function (*e.g.*, exponential) the difference in progressive scores between $\mathbb{EQ}^{\mathbb{P}}_{TC}$ and $\mathbb{EQ}^{\mathbb{P}}_{LC}$ will also be high.

Exp 3: Effect of Different Plan Generation Strategies. Figure 7 studies different plan generation strategies (as described in §3.3.2) and their impact on progressiveness. Figure 7 plots progressive improvement of quality for all the nine queries: Q1-Q9. Figures 7(a)- 7(i) show that SB(FO) performs the best and SB(OO) performs the worst since SB(FO) chooses functions based on the criteria of $\frac{quality}{cost}$ that allows SB(FO) to select the functions with the highest ratio of quality and cost to enrich the tuples in the beginning before selecting the other functions. In contrast, SB(OO) selects all enrichment functions of a given attribute that results in the enrichment

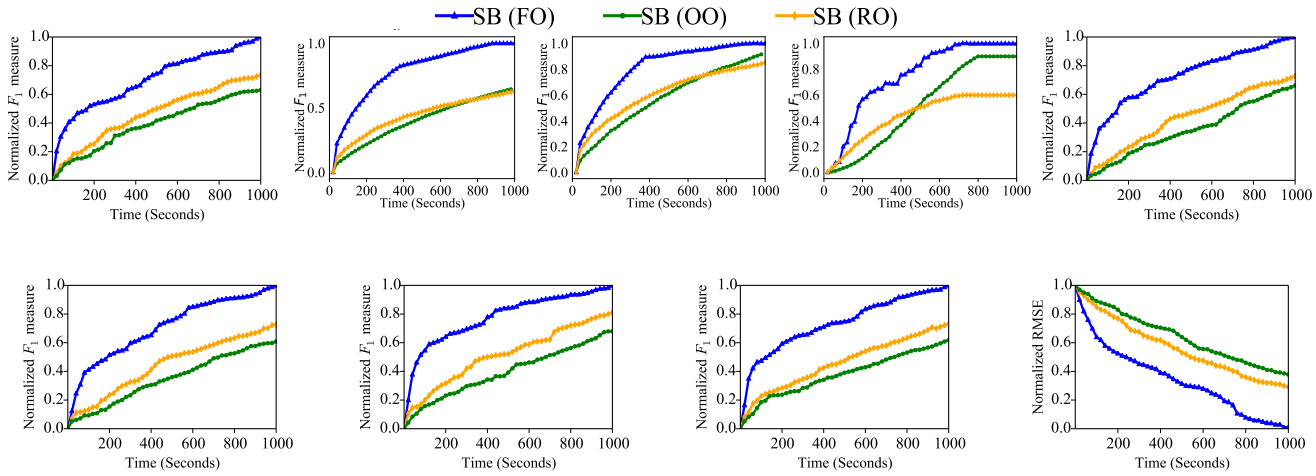


Figure 7: Exp 3. Comparing different plan generation strategies in $\mathbb{EQ}_{TC}$ for all the nine queries: (a) Q1, (b) Q2, (c) Q3, (d) Q4, (e) Q5, (f) Q6, (g) Q7, (h) Q8, (i) Q9.

of only a smaller number of tuples in an epoch. SB(RO) performs only marginally better than SB(OO), because of the randomness associated with the method of choosing the enrichment functions and derived attributes.

5.2.3 ***System Overhead***. We measure the overhead incurred by progressive query processing in both $\mathbb{EQ}^{\mathbb{P}}_{LC}$ and $\mathbb{EQ}^{\mathbb{P}}_{TC}$ approaches.

Exp 5: Time overhead measures the amount of time spent in *non-enrichment tasks*, *i.e.*, query setup, plan selection, delta computation, state update, and UDF invocation (only in $\mathbb{EQ}^{\mathbb{P}}_{TC}$) to compare against the time involved in data enrichment. The overhead of UDF invocation only exists in $\mathbb{EQ}^{\mathbb{P}}_{TC}$ as the enrichment function UDFs are executed on a single row as compared to the batched execution in $\mathbb{EQ}^{\mathbb{P}}_{LC}$. Particularly, across all epochs, the total time in query setup, plan selection, delta answer computation, state update, and UDF invocation took at most 3s, 4s, 5s, 17s, and 12s respectively, while the total time spent across all epochs in enrichment was 1000s (*i.e.*, almost 3% of the total time was spent in overhead). This result shows that both $\mathbb{EQ}^{\mathbb{P}}_{LC}$ and $\mathbb{EQ}^{\mathbb{P}}_{TC}$ have low overhead in terms of the non-enrichment tasks performed during query processing.

Exp 6: Storage overhead measures the size of all temporary tables (`PlanSpaceTable` and `PlanTable`), IVM, and the state tables used during query processing to compare against the size of data tables. The maximum storage overheads of `PlanSpaceTable`, `PlanTable`, and IVM at any epoch for the queries of Q1-Q9 were 1.48 MB, 56 KB, and 1.2 MB respectively. The state table sizes for TweetData and Multi-Pie were 2.4 GB and 500 MB, respectively, which are much smaller than the data tables (of 10.5GB and 84.5GB, respectively). Furthermore, using the state cutoff (§3.2) strategy, state storage overhead was reduced significantly. For TweetData, the state overhead was reduced from 2.4 GB (22.9% of the size of TweetData) to 0.9 GB (*i.e.*, 8.6% of the size of TweetData), due to the large domain size (*i.e.*, 40) of `topic` derived attribute.

For `Topic` attribute, we vary the value of cutoff-threshold and examine its effect of it on the query performance for only Q3. Table 10 shows the results. Observe that setting a very high threshold (*i.e.*, 0.8) results in a low storage overhead (*i.e.*, 0.7 GB) of the state table , (but requires re-execution of enrichment functions when queries are posted on the attribute values whose values are not stored in the state table). Hence, it also reduces progressive score (*i.e.*, 0.802 to 0.710) due to more enrichments.

6 RELATED WORK

At the motivational level, our approach of decoupling enrichment from data ingestion, by enabling it to be performed at query time, is related to the data flow in HTAP systems [36, 45]. HTAP systems maintain high transactional rates, instead of pre-computing aggregates, as part of the query during query execution time. Our approach of hiding increased query-time latency due to performing enrichment at query time, by exploiting progressive computation is motivated similarly by AQP systems. We discussed such connections in §1 and §3.

Similar works have also been proposed in the past but in a different context of entity resolution [14, 18, 24, 48]. They showed that the query context can be used to eliminate the cleaning of object blocks (residing in the disk) that cannot satisfy the query predicates. [14] utilized an approximate statistic for the objects residing in each disk block. Such statistics are used during query processing to dictate the cleaning tasks. In contrast, we consider a general class of enrichment functions with deterministic as well as probabilistic outputs. We consider state management of tuples that were enriched in the context of previous queries resulting in the elimination of repeated execution of enrichment functions. Furthermore, such frameworks do not consider a progressive approach to query processing when the cost of cleaning functions is high.

Several systems in the past have employed a tightly coupled approach, where application code is pushed down to the DBMS as UDFs [8, 26, 51]. Systems implemented using a loosely coupled

approach are also common, where the system was portable to any database system [11, 15, 43].

7 CONCLUSION

In this paper, we proposed a new data management system that supports enrichment during query processing. We explore two different layered architectures for integrating enrichment into query processing: a loosely coupled approach $\mathbb{EQ}_{\mathrm{LC}}$ where enrichment is performed outside of the DBMS, and a tightly coupled approach $\mathbb{EQ}_{\mathrm{TC}}$ where enrichment is performed within the DBMS. Both data enrichment strategies come with progressive query processing mechanism. Experimental results on real datasets show the efficacy of both architectures over the naive strategy of complete enrichment and then highlights the tradeoff between the two. When the queries are complex and the enrichment costs are the same between $\mathbb{EQ}_{\mathrm{LC}}$ and $\mathbb{EQ}_{\mathrm{TC}}$, $\mathbb{EQ}_{\mathrm{LC}}$ is preferable. In contrast, when the enrichment functions are complex, $\mathbb{EQ}_{\mathrm{TC}}$ outperforms the other due to the saving in enrichment by exploiting query semantics. This paper provides experiments only for single block SPJAG queries. While our approach applies to other types of queries including nested queries, we are restricted by the open-source implementation of Incremental View Materialization (IVM) of the chosen DBMS that only supported single block SPJAG queries. In the future, if the IVM supports nested queries, our implementation will be able to support such queries. Further, the implication of both the loosely and tightly coupled architectures to transactions and mechanisms to leverage enrichment due to concurrent execution of queries are interesting directions of future exploration.

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