JENNER: Just-in-time Enrichment in Query Processing

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ABSTRACT

Emerging domains, such as sensor-driven smart spaces and social media analytics, require incoming data to be *enriched* prior to its use. Enrichment often consists of machine learning (ML) functions that are too expensive/infeasible to execute at ingestion. In this paper, we develop a strategy entitled Just-in-time ENrichmeNt in quERy Processing (JENNER) to support interactive analytics over data as soon as it arrives for such application context. JENNER exploits the inherent tradeoffs that ML functions often display between cost and quality to progressively improve answers during the query execution as more data is enriched using expensive enrichment functions. We describe how JENNER works for a large class of SPJ and aggregation queries that form the bulk of data analytics workload. Our experimental results on real datasets (IoT and Tweet) show that JENNER achieves progressive answers and performs significantly better compared to naive strategies of achieving progressive computation.

1 INTRODUCTION

Today, organizations have access to potentially limitless information in the form of web data repositories, continuously generated sensory data, social media posts, captured audio/video data, click stream data from web portals, and so on [2]. Often, before such data can be analyzed, it needs to be enriched. Functions used to enrich data (referred to as *enrichment functions* in the paper) could consist of (a combination of) custom-compiled code, declarative queries, and/or expensive machine learning techniques. Examples include mechanisms for sentiment analysis [37] over social media posts, named entity extraction [4] in text, and sensor interpretation such as face detection and face recognition [18, 29] from images, sensor data fusion [31], and data cleaning tasks such as missing value imputation in relational data [10].

Analytical applications that require raw data to be enriched prior to use can be built in several ways. One approach is to collect the data, periodically enrich it, and then load it into the database for analysis, as in done in traditional extract-transform-load (ETL) systems [41]. An alternate approach is to enrich the data as it arrives "on-the-fly" at insertion time. Systems (*e.g.*, Spark Streaming [46] often used for scalable ingestion) are capable of executing enrichment functions on newly arriving data prior to its storage in a DBMS and can be used to build such an approach.

Both these approaches suffer from several limitations. The periodic approach could significantly increase latency between when data arrives to when it is enriched and available for analysis. Such an approach does not support interactive analytics on the data as it is inserted.[1] The alternate approach of enriching data at insertion time suffers from a different limitation - it is only feasible when enrichment functions are simple. If complex functions such as Multi-layer Perceptron and Random Forest (often used to interpret data) are used for enrichment, it may result in ingestion bottleneck. To see this, let us consider the following motivating example.

[1]This is similar to the limitation of the traditional data warehouse applications wherein newly arrived data was not available for analysis until it was loaded into a warehouse which led to the emergence of HTAP systems [8] over the past decade.

Example 1.1. Recent work [25, 26] has explored how WiFi connectivity data between user device and an access point (AP) can be used for indoor localization to support applications such as real-time occupancy analysis and other location-based services. While coarse localization (i.e., at the level of the region covered by the AP) can be performed on-the-fly as data arrives (it only requires a table lookup), fine-grained localization (at the room level) requires complex queries to be executed (that extract features such as other devices in the vicinity, location history of the device, etc.) and ML models to be evaluated on the query results in order to estimate the current location of the device with high accuracy [25]. Such an execution is expensive - e.g., it takes approx. 200 ms per event [2]. In a medium size campus/organization, with 1000s of AP, even at data rates as low as one event per second per AP, we require roughly 4 minutes of compute time to process one second worth of WiFi data! In general, with more sensor types each of which may need enrichment (e.g., camera data used for event detection), the computation during insertion time may be even more complex. Clearly, such an insertion process is infeasible! □

Both the insertion time approach and periodic enrichment approach suffer from additional limitations − given the expensive nature of enrichment, both techniques waste resources since they indiscriminately enrich all data, irrespective of whether or not future analysis requires all data to be enriched or if the analysis is limited to a possibly (very) small portion of data. For instance, in the above example, the analyst may only be interested in executing adhoc queries that require fine-grained localization of a small number of individuals and/or spaces and that too over a small period of time instead of continuous fine-grained tracking of all individuals all the time. Finally, both approaches require that enrichment functions to be used be known in advance prior to data collection.

With the goal of supporting analytics on data as it arrives, recent work in EnrichDB [1] has proposed a different approach that supports "just-in-time" data enrichment during query processing. Such a technique eliminates several limitations of the insertion-time and periodic techniques mentioned above. It prevents wastage of resources since only data accessed by queries during analysis is enriched. Furthermore, by not performing enrichment at ingestion (or limiting it to very simple enrichment) the scheme does not create an ingestion bottleneck. Finally, data is available for analysis as soon as it is inserted without incurring long latency between when data is inserted and is available for analysis.

While the query-time enrichment has several advantages it, nonetheless, increases latency of individual queries since now enrichment of queried data may need to be performed at the time of the query execution (if, for instance, it has not already been

[2]On a a server of 64 core Intel Xeon CPU E5-4640, 2.40GHz, and 128GB memory.

enriched as part of another query). Interactive analytics can only be supported if the number of objects that need to be enriched to answer the query remains relatively small.

To overcome such a limitation of query-time enrichment, we develop Just-in-time ENrichmeNt in quERy Processing (JENNER) that interactively refines query answers based on progressively enriching data. To progressively enrich and answer queries, JENNER exploits the fact that often multiple functions can be used to enrich the same data for the same task which display a cost-quality tradeoffs. Consider, for instance our running example of location determination [25] from the WiFi connectivity data. One can map the region (coarse-grained) level location to a uncertain room (fine-grained) level location by assigning non-zero probability to the rooms present in the region and assigning zero probability otherwise. viewed this way, the coarse level localization can be used to get a fast but less accurate room level location. Such a coarse localization might itself be useful in query evaluation (e.g., in eliminating tuples that have zero probability of matching the query predicate). More accurate location, using a more expensive but much more accurate fine grained localization mechanism, may need to be computed for other tuples. In LOCATER [25] the quality of fine-grained localization improves by adding more complexity, *i.e.*, having more features by using a larger historical device location data. For instance, [25] shows the algorithm's accuracy to be 0.7 when the model considers only last 2 days of data, whereas, the accuracy is 0.92 when past 14 days are used. The algorithm cost, however, increases from 40 ms to about five times higher at 200 ms.

Such a trade-off is not specific to the technique in [25] - it is demonstrated by several ML functions as well. *E.g.*, a more complex neural network classifier (having a higher number of hidden layers and/or higher number of neurons in each layer) has better accuracy as compared to a less complex neural net. Similarly, a more complex random forest classifier (*i.e.*, that uses a higher number of decision tree models as the base-predictors) has better accuracy as compared to a less complex random forest classifier.[3] Furthermore, simple classifiers such as Bayes classifier, logistic regression are less accurate than more complex classifiers such as Extra Tree, Random Forest, and Neural Network classifiers.

JENNER supports adaptive data management technology that exploits this cost and quality trade-off between enrichment functions to support progressive query answering. JENNER prioritizes/ranks which enrichment functions should be evaluated on which objects first to improve the quality of the answer as quickly as possible for a query. To this end, JENNER divides the query execution into several *epochs* and analyzes the evaluation progress at the beginning of each epoch to generate an execution plan for it. Such a plan chooses tuples to enrich that have the highest potential of improving the quality of the answer in that epoch.

The deferred/lazy enrichment in JENNER is motivated by prior work on lazy query time data cleaning such as [7, 14]. Such works developed techniques to combine entity resolution/database repair using denial constraints with query processing to minimize the amount of data that needs to be cleaned. Likewise, [5] developed an approach to dynamically link entities in the context of top-k queries. Such approaches, however, do not support progressiveness that JENNER does. Since data cleaning tasks, such as entity linking, can be viewed as enrichment, the approach developed can also benefit query time data cleaning by supporting progressiveness. In summary, we make the following contributions in the paper:

- We propose a progressive approach to data enrichment and query evaluation that quantizes the execution time into epochs that are adaptively enriched.
- We present an algorithm for the problem of generating an execution plan that has the highest potential of improving the quality of the answer set in the corresponding epoch.
- We develop an efficient probabilistic strategy to estimate the benefit of executing various enrichment functions on objects.
- We experimentally evaluate JENNER in different domains (*i.e.*, images, tweets, and IoT) using real datasets and enrichment functions and demonstrate the efficiency of our solution.

JENNER has been integrated into the EnrichDB system [] and forms the basis of its progressive query evaluation strategy.

2 DATA MODEL TO SUPPORT ENRICHMENT

We consider an extended relational data model, wherein some of the attributes of a relation are ***derived*** (denoted as $\mathcal{A}_i$) and require enrichment (performed by executing a set of associated enrichment functions). The remaining attributes are ***fixed*** (denoted as A_j) and do not require enrichment. Without loss of generality, all relations contain an `id` attribute that uniquely identifies the tuples present in them. Table 1 shows a sample table with several fixed attributes (*e.g.*, id, user_id, time, wifi_ap) and a derived attribute `location` that could be derived using multiple localization functions that vary in cost and quality.

The enrichment functions are categorized based on their input types: (*i*) *single-tuple-input* and (*ii*) *multi-tuple-input*, that take as input a set of fixed attribute values of a single tuple or multiple tuples, respectively. Often classification and regression functions are of type single-tuple-input whereas clustering based functions are of multi-tuple-input type. Enrichment functions can also be categorized based on their output types: (*i*) *single-valued*, (*ii*) *multi-valued*, or (*iii*) *probabilistic*, that output as a prediction a single value (*e.g.*, as in a binary classifier [40]), multiple values (*e.g.*, as in top-k classifiers [22]), or probability distribution over a set of possible values, (as in a *e.g.*, probabilistic classifier). Of the three, probabilistic outputs are the most general since we can always interpret results of the other two as probability distributions. We, thus, assume that the enrichment functions output probabilities in the rest of the paper. *E.g.*, the value of `location` attribute in tuple t_1 of `wifi` in Table 2 is $[0.54, 0.35, 0.11]$ which corresponds to the locations of `L1`, `L2`, and `L3`. JENNER assumes that the probability outputs of enrichment functions are calibrated using calibration mechanisms such as [34, 45] on a labeled validation dataset. After calibration, the output of an enrichment function represents a real probability distribution that was learnt during calibration.

The enrichment functions for a derived attribute $\mathcal{A}_i$ are denoted by $F^i = \{f^i_1, f^i_2, \ldots, f^i_k\}$. Each function f^i_j is associated with a *cost* (denoted by c^i_j) which represents the average execution cost of the function on a single tuple. Since the output of an enrichment function is probabilistic, we can associate a notion of uncertainty

[3]Note that this phenomena is true until the point at which the model overfits the training data [13].

id	user_id	time	wifi_ap	location
t_1	24	09:14	56	L1
t_2	22	10:26	110	NULL
t_3	108	14:10	116	L4

Table 1: The `wifi` table where `location` is a derived attribute.

tid	location
t_1	L1:0.54, L2:0.35, L3: 0.11
t_2	L1: 0.1, L2: 0.1, . . ., L10: 0.1
t_3	L1:0.15, L2: 0.35, . . ., L6: 0.05

Table 2: State output for derived attributes.

tid	BitMap	LocationState Output
t_1	[1,0,0]	[[0.54, 0.35, 0.11, ...], [], []]
t_2	[1,0,1]	[[0.2,0.6,..., 0.2],[], [0.86,0.1, . . . 0.04]]
t_3	[1,1,0]	[[0.1,0.2,...,0.5,0.2], [0.2,0.5,0,...] ,[]]

Table 3: `wifistate` table (created for tuples in `wifi` table).

with the probabilistic outputs. An expensive enrichment function is expected to produce output with less amount of uncertainty. Given a probabilistic attribute value, we measure uncertainty using the entropy metric [17]. For a tuple t_k and derived attribute $\mathcal{A}_p$, entropy is calculated as follows:

$$h(t_i, \mathcal{A}_j) = -\sum_i p_i \cdot log(p_i) \qquad (1)$$

where, p_i represents the probability of the derived attribute taking the i-th domain value for the tuple t_i. The entropy of t_1 in the example above is, thus, $[-0.54 \times \log(0.54) - 0.35 \times \log(0.35) - 0.11 \times \log(0.11)] = 0.86$.

State and Value of a Derived Attribute. Enrichment state or state of a derived attribute $\mathcal{A}_j$ in tuple t_i (denoted by $state(t_i.\mathcal{A}_j)$) is the information about enrichment functions that have been executed on t_i to derive $\mathcal{A}_j$ and the output of execution of such functions. The state has two components: ***bitmap***, that stores the list of enrichment functions already executed on $t_i.\mathcal{A}_j$; and ***output***, that stores the output of executed enrichment functions on $t_i.\mathcal{A}_j$. As an example, consider that there are three enrichment functions f_1, f_2, and f_3 available for the derived attribute of `location` in Table 3. The state bitmap of t_2 is $\langle 101 \rangle$ signifying that only f_1 and f_3 have been executed on the tuple.[4] Further, the output of the state $\langle [0.2, 0.6, \ldots 0.2], [], [0.86, 0.1, \ldots, 0.04] \rangle$ signifies that the output of f_1 was a distribution $[0.2, 0.6, \ldots 0.2]$ and that of f_3 was $[0.86, 0.1, \ldots, 0.04]$ over the possible values of location.

The individual function outputs are aggregated into a combined value denoted by $\mathcal{A}_j.Value$ (*e.g.*, *Location.Value*) using a **combiner function** (*e.g.*, weighted average and majority voting). Since this value depends upon the state of the derived attribute, we denote $\mathcal{A}_j.Value$ by $Val(state(t_i.\mathcal{A}_j))$ and the probability of it taking a a particular value a_j by $Val(state(t_i.\mathcal{A}_j))[a_j]$. For instance, for the example in Table 3, the value of `topic` for t_1, is $Val(state(t_1.\text{location}))$ = [L1: 0.54, L2: 0.35, L2: 0.11]. The probability of t_1 taking the value of `location` as `L1`, *i.e.*, $Val(state(t_1.\text{location}))[\text{L1}]$ is 0.54.

State and Value of Tuples and Relations. The notions of state and value of derived attributes are generalized to tuples, relations, and the database in a straightforward way. The state (value) of a tuple t_i, denoted by $state(t_i)$ ($Val(state(t_i))$ is the concatenation of the state (value) of all derived attributes of t_i. Likewise, the state (value) of relation R_i and database D is denoted by $state(R_i)$ ($Val(state(R_i))$) and $state(D)$ ($Val(state(D))$), respectively.

Next Best Function at a State. Execution of an enrichment function on an attribute $\mathcal{A}_j$ in a tuple t_i in state $state(t_i.\mathcal{A}_j)$ reduces uncertainty in its value $Val(state(t_i.\mathcal{A}_j))$. This reduction in uncertainty depends upon $state(t_i.\mathcal{A}_j)$ and is learnt using a validation data set as a preprocessing step. Given $state(t_i.\mathcal{A}_j)$ we order the enrichment functions associated with $\mathcal{A}_j$ in the order of their uncertainty reduction and choose the one that reduces the uncertainty the most as the next-best function, denoted as $NBF(t_i, \mathcal{A}_j)$). Notice that the uncertainty reduction due to enrichment functions that have already executed in the past is zero and hence they cannot be the next best function at a particular state.

[4]The bitmap does not represent any order between the enrichment functions. It is possible to execute only the second enrichment function without executing the first enrichment function.

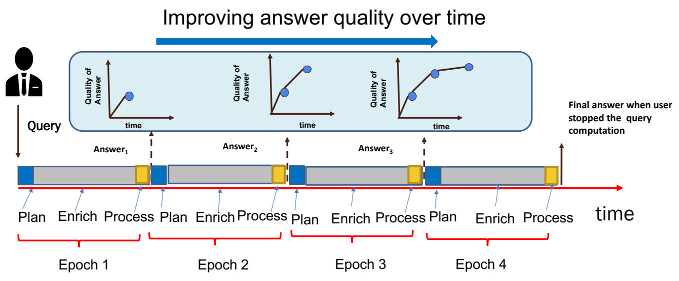


Figure 1: Progressive Query Processing Strategy.

Query Model. JENNER supports single block *select-project-join-aggregation* queries with conditions on both fixed and derived attributes, an example of which is shown in Code Listing 1.

```sql
SELECT wifi.location as p_location,
wifi.timestamp as p_time  FROM wifi
WHERE p_location = 'L1'
AND p_time BETWEEN ('10:00','12:00')
```

Code Listing 1: Example Query.

We focus the rest of the paper on queries containing at least derived attribute is present in either the `SELECT` or `WHERE` clause. *E.g.*, in the above query, it contains a condition on the derived attribute `location` in addition to that on the fixed attribute `timestamp`.

Since derived attributes have probabilistic values, JENNER interprets queries based on ***determinization-based*** semantics [24, 30, 44], wherein Q is evaluated over determinized values for derived attributes in tuples that are part of Q. The determinized value of a derived attribute $\mathcal{A}_j$ is determined by executing a determinization function $DET(.)$ on the associated value of the derived attribute (*i.e.*, $DET(Val(state(t_i.\mathcal{A}_j)))$). Several methods to determinize a probabilistic attribute have been previously studied [24, 30, 44]. We choose the function that returns the highest probable value (or NULL if highest probability value is ambiguous). [5]

[5]The techniques developed in the paper can be adopted to other determinization functions studied in [24, 30, 44] including those that return multiple values as used by the EnrichDB system [1].

Determinization concept naturally extends to a tuple and a relation. Determinized representation of a relation R is denoted as $DET(R)$:

$$DET(R) = DET(Val(state(t_i.\mathcal{A}_j))) \mid \forall t_i \in R, \forall \mathcal{A}_j \text{ of } R.$$

Thus, the execution of query Q is:

$$Q(R_1, R_2, \ldots, R_n) = Q(DET(R_1), DET(R_2), \ldots, DET(R_n))$$

where $DET(R_i)$ is the determinized representation of R_i.

Progressive Query Execution in Epochs. The complete strategy of progressive query execution is shown in Figure 1. The query execution time is discretized into multiple *epochs* (denoted by $e_1, e_2, \dots, e_z$) in which data enrichment is performed. We denote the time span of an epoch e_w by the notation $|e_w|$. [6]

During an epoch e_w, certain enrichment functions (that have not been executed so far) are chosen to be executed. Let $EP_w = \{\langle t_i, \mathcal{A}_j, f_k^j \rangle\}$ be such a set containing ⟨tuple, derived attribute, enrichment function⟩ triples. We refer to EP_w as the *enrichment plan* of epoch e_w. Let S be the state of the database at the end of the previous epoch e_{w-1} and, let S' be the state after the execution of enrichment plan EP_w in e_w. This execution results in state update of all the tuples $t_i \in EP_w$ as follows: $\forall \langle t_i, \mathcal{A}_j, f_k^j \rangle \in EP_w$, the $state(t_i.\mathcal{A}_j).bitmap$ is updated by setting the k-th bit to 1 to denote that k-th function is executed. Similarly, $state(t_i.\mathcal{A}_j).output$ is updated to reflect the execution of k-th enrichment function: $state(t_i.\mathcal{A}_j).output = (t_i.\mathcal{A}_j).output \oplus \langle t_i, \mathcal{A}_j, f_k^j \rangle$, where $\oplus$ signifies that the state is updated using k-th array, as well as the update on the derived attribute value of the tuple. At the end of each epoch e_w, the user receives a query result, denoted as Ans_w, based on the current state of the database. Note that a tuple that was part of the answer in previous epoch, may no longer be part of Ans_w. In the rest of the paper, to disambiguate between different states/values of the data during different epochs, we will denote the original database D on which Q executes at D_0 to signify its status at the beginning prior to query being executed. We will refer to the database after the execution of epoch e_w as D_w which will correspond to the database after all enrichment functions until e_w have executed.

Since in a progressive approach, users may stop query evaluation at any instance of time, performing enrichments that impact the answer quality as early as possible is desirable.

Definition 2.1. Progressive Score. The effectiveness of JENNER is measured using the following progressive score (similar to other progressive approaches used in [6, 32]):

$$\mathcal{PS}(Ans(q,E)) = \sum_{i=1}^{|E|} W(e_i) \cdot [Qty(Ans(Q,e_i)) - Qty(Ans(Q,e_{i-1}))] \tag{2}$$

where $E = \{e_1, e_2, \dots, e_k\}$ is a set of epochs, $W(e_i) \in [0,1]$ is the weight allotted to the epoch e_i, $W(e_{i-1}) > W(e_i)$), Qty is the quality of answers, and $[Qty(Ans(Q,e_i)) - Qty(Ans(Q,e_{i-1}))]$ is the improvement in the quality of answers occurred in epoch e_i. Assigning higher weights to the earlier epochs provide higher importance to the improvement in quality in such epochs as compared to the later epochs. ■

Since weights W_i in the progressive score defined above are decreasing, optimizing the progressive score is equivalent to selecting a set of enrichment functions (that have previously not executed) which can result in maximum increase in quality in the following epoch, that is, $Maximize(Qty(Ans(Q,e_i)) - Qty(Ans(Q,e_{i-1})))$.

The quality Qty in Equation 2, for a set-based query answer corresponds to a set-based quality metrics such as precision, recall, F_α-measure [35], or Jaccard similarity coefficient [20]. We define the F_α measure (calculated by the weighted harmonic mean of precision and recall)and Jaccard's similarity below.

$$\begin{aligned} F_\alpha(Ans_w) &= \frac{(1+\alpha)\cdot Pre(Ans_w)\cdot Rec(Ans_w)}{(\alpha \cdot Pre(Ans_w) + Rec(Ans_w))} \\ \mathcal{J}(Ans_w) &= \frac{|Ans_w \cap Ans^{real}|}{|Ans_w \cup Ans^{real}|} = \Big[\frac{1}{Pre(Ans_w)} + \frac{1}{Rec(Ans_w)} - 1\Big] \end{aligned} \tag{3}$$

where Ans^{real} is the real answer of the query in ground truth set G, Pre corresponds to precision, *i.e.*, $Pre(Ans_w) = |Ans_w \cap Ans^{real}|/|Ans_w|$, and Rec corresponds to recall, *i.e.*, $Rec(Ans_w) = |Ans_w \cap Ans^{real}|/|Ans^{real}|$, and $\alpha \in [0,1]$ is the weight factor assigned to precision in calculating F_α-measure. In the rest of the paper, for computing the quality of set-based query result, we restrict our discussion to F_α-measure. The quality of an aggregation query could be measured using root-mean-square error [19] or mean-absolute-error [42].

Quality Guarantees in JENNER. At each epoch JENNER strives to choose the best set of object to enrich that can improve quality of the query result most. Since the ground truth of objects are not known, JENNER can neither directly measure the quality of the results returned so far, nor can it precisely determine the improvement in quality by executing an enrichment function. Instead, JENNER estimates both the quality of results (returned during the previous epoch) and the improvement in quality if a selected set of objects are enriched in the current epoch. Based on these estimates, JENNER chooses and executes the enrichments that are guaranteed to maximize the improvement in quality of the resulting query answer from the previous epoch.

Below we discuss how JENNER estimates the quality for set-based queries. For aggregation queries, JENNER optimizes the enrichment process using a set-based metric (*e.g.*, F_α-measure) and then applies the aggregation function on resulting tuples.

Definition 2.2. Estimated Quality Let Ans_w^{MAX} be the set of tuples that have non-zero probability to be in the answer to query Q, Ans_w be a set of tuples returned as an answer to the user. Let $\mathcal{P}_i$ be the probability of a tuple $t_i \in Ans^{real}$ (we discuss ways to compute $\mathcal{P}_i$ later). Furthermore, let m be the cardinality of Ans_w, and n be the cardinality of Ans_w^{MAX}. We compute the estimated precision and recall of Ans_w, denoted by $\widehat{Pre}$ and $\widehat{Rec}$, as follows:

$$\widehat{Pre} = \frac{\sum_{t_i \in Ans_w} \mathcal{P}_i}{m}, \quad \widehat{Rec} = \frac{\sum_{t_i \in Ans_w} \mathcal{P}_i}{\sum_{t_j \in Ans_w^{MAX}} \mathcal{P}_j} \tag{4}$$

Given the above estimates of precision and recall, we can next define estimate of F_α measure denoted as $\widehat{F}_\alpha$.

$$\widehat{F}_\alpha(Ans_w) = \frac{(1+\alpha) \sum_{t_i \in Ans_w} \mathcal{P}_i}{\alpha \sum_{t_i \in Ans_w^{MAX}} \mathcal{P}_j + m} \tag{5}$$

The above definition of estimated quality depends upon determining the probability $\mathcal{P}_i$ of an answer tuple t_i to be in the real

[6]For simplicity, we will consider the duration of each epoch $|e_w|$, $w \in 1, 2, \dots, n$ to be of fixed size in the remainder of the paper, though, the approach does not require this to be the case.

answer of the query. For a selection query with a single condition $(t_i.\mathcal{A}_j = a_j)$ on a derived attribute $\mathcal{A}_j$, the $\mathcal{P}_i$ of t_i is simply $Val(state(t_i.\mathcal{A}_j))[a_j]$ if the determinized value of $t_i.\mathcal{A}_j$ corresponds to a_j, else it is zero. For queries with selection conditions on multiple derived attributes, the probability of t_i satisfying the predicate is computed under the assumption of independence of derived attributes by appropriately combining the probabilities of t_i satisfying the predicates on single derived attributes. For a join query, $\mathcal{P}_i$ is calculated by computing the product of constituting tuples that formed the answer tuple t_i as done in [39] in the context of probabilistic databases.

Progressive Enrichment Problem. Given the notations above, we can now formally state the problem of progressive enrichment. Let Q be a query and let $e_1, e_2, \ldots, e_n$ be the epochs used to execute Q. Let $state(D)$ be the state of the database after the execution of epoch e_{w-1}, where $w \leq n-1$. Let CS_w be the set of tuples in D that are not fully enriched, *i.e.*, for each $t_i \in CS_w$, there exists an enrichment function f_k^j that can be used to enrich a derived attribute $\mathcal{A}_j \in Q$ of t_i, which was not executed before.

The progressive enrichment problem consists of determining a set of ⟨tuple, derived attribute, enrichment function⟩ triples EP_w such that, when executed in epoch e_w, results in a new database value of: $(Val(state(D)) \oplus EP_w)$ that optimizes the following objective function:

$$\max_{\langle t_i, \mathcal{A}_j, f_k^j \rangle} \Big[\widehat{Qty}(Q(DET(Val(state(D)) \oplus EP_w))) - \widehat{Qty}(Q(Val(state(D))))\Big]$$
$$\text{subject to} \quad \sum_{\langle t_i, \mathcal{A}_j, f_k^j \rangle \in EP_w} cost(\langle t_i, \mathcal{A}_j, f_k^j \rangle) \leq |e_w| \tag{6}$$

where $\widehat{Qty}(Q(Val(state(D)) \oplus EP_w))$ is the expected quality of the query result when it is executed on the updated state of the database in epoch e_w and $\widehat{Qty}(Q(Val(state(D))))$ is the expected quality of the query result at the end of previous epoch of e_{w-1}.

3 PROGRESSIVE ENRICHMENT IN JENNER

This section describes how JENNER solves the progressive enrichment problem formalized above. We distinguish between the zero-th epoch and the other subsequent epochs in the epoch-based processing of the query. The zero-th epoch performs pre-processing in order for answers to be generated in the later epochs. The later epochs e_w, $w > 0$, iteratively enriches the tuples and compute the query results. The overall algorithm is presented in Algorithm 1.

Zero-th Epoch (Lines 6 - 13): The goal of the zero-th epoch is to seed JENNER with the tuples that may need to be enriched in the upcoming epochs (*i.e.*, epoch 1 and onwards). It also sets up the data structures used in the later epochs. JENNER does not require any enrichment function to be executed on the data before. During the zero-th epoch, JENNER identifies for each relation R_i a *minimal set* of candidate tuples whose enrichment in subsequent epochs may influence the query result (denoted as $CandidateSet(R_i)$). Such a $CandidateSet(R_i)$ is identified by executing *probe queries* (Lines 3-5) $pq(R_i)$. Generation of probe queries are discussed in §3.1.

Next, for each t_i in the *CandidateSet* for each relation, for each derived attribute $\mathcal{A}_j$ in t_i that is part of Q, JENNER estimates the

Algorithm 1: Overall Algorithm.

```
   Inputs: Query $Q$ and the duration of each epoch $epoch\_duration$.
   Outputs: An enrichment plan for each epoch that optimizes
     progressive score.
1  Function $Optimize\_Enrichment()$ begin
2      $CandidateSet^M \leftarrow \emptyset$
       // Beginning of epoch 0.
3      for each $R_i \in Q$ do
4          $pq(R_i) \leftarrow GenerateProbeQuery(Q, R_i)$
5          $CandidateSet(R_i) \leftarrow Execute(pq(R_i))$
6      for each $R_i \in Q$ do
7          for each $t_j \in CandidateSet(R_i)$ do
8              for each $\mathcal{A}_k$ in $R_i$ that is element of $Q$ do
9                  $match\_prob \leftarrow ComputeProb(t_j, \mathcal{A}_k)$
10                 $cost \leftarrow Cost(NBF(t_j, \mathcal{A}_k))$
11                 $benefit \leftarrow ComputeBenefit(NBF(t_j, \mathcal{A}_k))$
12                 $CandidateSet^M \leftarrow CandidateSet^M \cup$
                     $\langle t_j, \mathcal{A}_k, NBF(t_j.\mathcal{A}_k), benefit, cost, match\_prob \rangle$
13     $CandidateSet^M \leftarrow Sort_{match\_prob}(CandidateSet^M)$
       // End of epoch 0 and beginning of epoch w, $w \geq 1$.
14     for each epoch $e_w$ do
15         $EP_w \leftarrow ChooseEnrichmentPlan(CandidateSet^M)$
16         for each entry $\in EP_w$ do
               $ExecuteEnrichment(t, \mathcal{A}, f)$; $UpdateState(t, \mathcal{A}, f)$;
17             $Determinize(t, \mathcal{A})$;
               $UpdateBenefit(CandidateSet^M, t, \mathcal{A}, f)$;
18             // $\langle t, \mathcal{A}, f \rangle$ is the ⟨tuple, derived attribute,
                  enrichment function⟩ of the entry.
19         $Ans_w \leftarrow ProduceQueryResult(Q)$
20     Return $Ans$
```

probability of t_i matching the condition on $\mathcal{A}_j$ (listed in the code as *match_prob*). For each such attribute $\mathcal{A}_j$ in t_i, JENNER also computes the *benefit* and *cost* of executing the next best function (*NBF*) associated with $t_i.\mathcal{A}_j$ based on its current state (Line 10- 11).

The *match_probability* of a derived attribute $t_i.\mathcal{A}_j$ is determined using the probability $Val(state(t_i.\mathcal{A}_j)).prob[a_j]$ where the selection condition is $\mathcal{A}_j = a_j$. For derived attributes, that do not appear in any selection condition, the value of *match_probability* is 1.

The cost $Cost(NBF(t_i, \mathcal{A}_j))$ of the next best function for each tuple t_i and the derived attribute $\mathcal{A}_j$ is specified as part of the enrichment function specification as discussed in §2 (Line 10).

The benefit of enrichment of tuple t_i using the next best function (as shown in Line 11) for attribute $\mathcal{A}_j$ is computed by estimating the improvement in quality from the previous epoch. We describe this step in details in §3.2. The benefit, cost, and matching probability for each candidate in $CandidateSet(R_i)$ is stored in the corresponding $CandidateSet^M$ to represent the metadata of candidates, viz. benefit, cost, and probability (Lines 9-12). Candidates in $CandidateSet^M$ are sorted based on their *match_prob* values (Line 13).

Later epochs $e_w, w \geq 1$, (Lines 14 - 19): The later epochs (*i.e.*, $e_1, e_2, \ldots, e_n$) consist of a sequence of the following three steps: (*i*) *Choose Enrichment Plan:* that selects a set of candidate tuples from $CandidateSet^M$ to generate an enrichment plan EP_w for execution during e_w (Line 15); We discuss choosing the enrichment plan in details in §3.2 and in §3.3; (*ii*) *Execute Enrichment Plan:* that enriches the tuples in EP_w, update their state, determinized representations and their benefit in *CandidateSet*^{M} (Lines 16 - 17); We discuss them in details in §3.4; (*iii*) *Produce Query Results:* produce a query result by executing the query on determinized representation of the tuples and then choosing a subset of tuples that maximizes the quality of the result measured using $E(F_1)$ measure (Line 19); We discuss this step in §3.5. Progressive approach for aggregation queries is realized by developing a progressive approach for the corresponding set-based query on which the aggregation is performed.

3.1 Probe Query Generation

In order to populate *CandidateSet*(R_i) for relation R_i, *i.e.*, to find out the set of tuples that may have impact on the query results, one could add all the tuples that have not been fully enriched to this set. However, such an approach would result in significant number of redundant enrichments, *i.e.*, the tuples that do not satisfy predicates on the fixed attributes of a query may be added to this set for enrichment. To avoid such situations, JENNER exploits the predicates over fixed attributes to filter out tuples whose enrichment has no consequence on the results. For instance, considering a query that contains a selection condition on a fixed attribute, a tuple that does not satisfy the predicate on the attribute could be dropped from considerations for enrichment. Likewise, we can also exploit join predicates on fixed attributes to filter away tuples in a relation that would not satisfy the join predicate. This is achieved by using a semi-join program as discussed in [9]. We perform filtering of redundant tuples whose enrichment will not affect the query answer by executing a *probe query* for each relation in the query Q.

The `probe queries` identify a "minimal" subset of tuples (as small a subset as possible) for each $R_i \in Q$ that need to be enriched to execute Q (denoted as $pq(R_i)$). Let us illustrate how probe queries are generated using a sample query in Figure 5a.

To generate a probe query for say relation R_1, we first identify the selection conditions on fixed attributes of R_1. In the query of Figure 5a, this is the condition $R_1.A_2 = a_2$. Thus, we can limit the tuples that require enrichment in R_1 using this condition as shown in Figure 2b. We further exploit join conditions on fixed attributes. For instance, in Figure 5a, an R_1 tuple must join with at-least one of the R_2 tuples that satisfy the restriction on fixed attributes, *i.e.*, $R_2.A_5 = a_5$. A tuple of R_1 will possibly be part of the query answer if it joins some tuples of R_2 which satisfy the join condition $R_1.A_4 = R_2.A_4$. We can determine such a set by computing semi-join with other relations in the query with which R_1 joins using conditions on fixed attributes. Utilizing such a semi-join optimization will result in a nested query as shown in Figure 2c. We restrict the description of probe query generation simply to illustrate how it works using an example since the algorithm to generate probe queries is a direct adaptation of the technique proposed in [9] for semi-join optimization. We have described the algorithm in Appendix 6.1.

In addition to exploiting selection and join conditions on fixed attributes, we exploit the current state of the tuples to avoid repeating enrichment of tuples that are completely enriched for a derived attribute. This is achieved as shown in Figure 2d by rewriting the selection condition on derived attribute, *i.e.*, $R_1.\mathcal{A}_1 = a_1$ by the condition of: $\big[R_1.id = R_1State.id$ AND $R_1.array\_sum(\mathcal{A}_1StateBitmap)! = R_1.array\_length(\mathcal{A}_1StateBitmap)\big]$. This condition checks if a derived attribute of a tuple is completely enriched using the *StateBitmap* column of the R_iState table. For a *StateBitmap* value with all the bits set to 1, the sum of the array and the length of the array becomes equal. All the tuples with bitmap having the sum of elements not equal to the length of the array, are not completely enriched. Hence, such tuples can be part of the probe query result.

SELECT * FROM R_1, R_2 WHERE $R_1.\mathcal{A}_1 = a_1$ AND $R_1.A_2 = a_2$ AND $R_1.\mathcal{A}_3 = R_2.\mathcal{A}_3$ AND $R_1.A_4 = R_2.A_4$ AND $R_2.A_5 = a_5$ AND $R_2.\mathcal{A}_6 = a_6$

(a) Original query.

SELECT * FROM R_1 WHERE $R_1.A_2 = a_2$

(b) Step 1 of probe query generation for relation R_1.

SELECT * FROM R_1 WHERE $R_1.A_2 = a_2$
AND $R_1.A_4$ IN (SELECT A_4 FROM R_2 WHERE $R_2.A_5 = a_5$)

(c) Step 2 of probe query generation for R_1.

SELECT * FROM R_1, R_1State WHERE $R_1.A_2 = a_2$
AND $R_1.A_4$ IN (SELECT A_4 FROM R_2 WHERE $R_2.A_5 = a_5$)
AND $R_1.id = R_1State.id$
AND ($R_1State.array\_sum(\mathcal{A}_1StateBitmap)! = R_1State.array\_length(\mathcal{A}_1StateBitmap)$)

(d) Step 3 of probe query generation for R_1.

Figure 2: Steps of `probe query` generation for R_1 in Q.

3.2 Benefit Estimation

JENNER chooses the ⟨tuple, derived attribute, enrichment function⟩ triples from *CandidateSet*^{M} as an enrichment plan based on the *benefit* of the triple per unit cost. Benefit, discussed formally below, corresponds to the expected improvement in the quality of the answers compared to the previous epoch because of the execution of the enrichment plan. We restrict the choice of tuples to enrich in the enrichment plan to only those that are not in the answer set of the previous epoch to reduce the overhead of repeatedly computing benefits of $\langle tuple, attribute\rangle$ pairs that have already appeared in the answer. JENNER does so, since the expected benefit of further enriching such a tuple in e_w that already appeared in Ans_{w-1} is significantly lower compared to those that are not in the answer. We formally justify this decision using a theorem in Appendix 6.3 and show performance improvement due to reduced overhead of computing benefit in §4.

Definition 3.1. Benefit of an Enrichment Function. Let Q be a query, D_{w-1} be the database at the end of epoch e_{w-1}, and $\langle t_i, \mathcal{A}_j, f_k\rangle$ be a triple to be executed in epoch e_w. The benefit of $\langle t_i, \mathcal{A}_j, f_k\rangle$ is defined as follows:

$$Benefit(\langle t_i, \mathcal{A}_j, f_k\rangle) = \widehat{Qty}(Q(D_{w-1} \oplus \langle t_i, \mathcal{A}_j, f_k\rangle)) - \widehat{Qty}(Q(D_{w-1})) \quad (7)$$

where $\widehat{Qty}(Q(D_{w-1} \oplus \langle t_i, \mathcal{A}_j, f_k\rangle)$ is the estimated quality of the query answer after the triple $\langle t_i, \mathcal{A}_j, f_k\rangle$ is executed and $\widehat{Qty}(Q(D_{w-1}))$ is the estimated quality at the end of e_{w-1}. ∎

Thus, to determine the benefit of executing an enrichment function, we need to estimate (*i*) the quality of the answer after epoch

Algorithm 2: Benefit Calculation.

```
Inputs: A triple containing a tuple $t_i$, a derived attribute $\mathcal{A}_j$, the
  next best function $f_k$ for the tuple at the state of the attribute at
  the end of epoch $e_{w-1}$.
Outputs: The benefit of the ⟨tuple $t_i$, derived attribute $\mathcal{A}_j$,
  enrichment function $f_k$⟩ triplet.
1 Function Compute_Benefit() begin
2     $PreviousQuality \leftarrow \widehat{F}_\alpha(Ans_{w-1})$
3     $\mathcal{E}_{w-1} \leftarrow ComputeEntropy(t_i, \mathcal{A}_j)$
4     $\widehat{\mathcal{E}}_w \leftarrow \mathcal{E}_{w-1} - DeltaEntropy(t_i, \mathcal{A}_j, f_k)$
5     $Match\_Probability \leftarrow ComputeInverseOfEntropy(\widehat{\mathcal{E}}_w)$
6     $ExpectedAnswerQuality \leftarrow$
        $ComputeQuality(Match\_Probability, Ans_{w-1})$
7     $Benefit(t_i, \mathcal{A}_j, f_k) \leftarrow$
        $Max(ExpectedAnswerQuality - PreviousQuality, 0)$
8     Return $Benefit(t_i, \mathcal{A}_j, f_k)$
```

e_{w-1} and (*ii*) the expected quality of the answer set if that enrichment function is executed in the current epoch. Before we consider how we can estimate these two metrics for general queries, we first describe how to estimate them for selection queries.

3.2.1 ***Selection Queries***.

Given Ans_{w-1} (*i.e.*, $Q(D_{w-1})$), for selection queries, estimating its quality (*i.e.*, $\widehat{Qty}(Q(D_{w-1}))$ is straightforward, since for every tuple $t_i \in Ans_{w-1}$, the probability of the tuple t_i to be in the Ans^{real} is known, as discussed in §2 and illustrated using the following example.

Example 3.1. Consider the selection query in Code Listing 1 on `wifi` (see Table 1). Suppose at the end of epoch e_1, the state after enrichments that have executed is as shown in Table 3 and let t_1 be part of the query result. Since, t_1 value for `Location.Value` in Table 3 is [L1: 0.54, L2: 0.35, L3: 0.11] and, thus, its associated determinized value of location in Table 1 is `L1`. Hence, the combined probability of the tuple satisfying all the selection conditions in the query is 0.54. The expected precision of the answer is 0.54. The recall calculation requires probability of the tuples that are part of the answer as well as of the tuples that are outside of the answer. ■

To compute the benefit of a given triple $\langle t_i, \mathcal{A}_j, f_k \rangle$, we need to estimate the quality of the answer that would result if Q were to be executed on the database after executing f_k on t_i. Recall that with each enrichment function f_k, we have associated a measure of uncertainty reduction that is a function of the state of the derived attribute $\mathcal{A}_j$ of tuple t_i on which f_k executes. Let the uncertainty reduction for the function f_k executing over the state of the attribute $\mathcal{A}_j$ in tuple t_i in the current database D_{w-1} be Δ. Such an uncertainty reduction measure Δ can allow us to estimate the probability of the tuple satisfying the selection condition of the query after execution of f_k as follows. Let $\mathcal{E}_{w-1}$ be the entropy of attribute $\mathcal{A}_j$ of t_i prior to the execution of f_k. The tuple's entropy after the execution of f_k is thus $\mathcal{E}_{w-1} - \Delta$. We can thus estimate the new probability p of $t_i.\mathcal{A}_j$ satisfying the selection condition by solving the following equation:

$$\mathcal{E}_{w-1} - \Delta = -p \cdot log(p) - (1-p) \cdot log(1-p) \qquad (8)$$

Note that the equation above leads to two solutions, one that reduces the probability p of $t_i.\mathcal{A}_j$ satisfying the selection condition (denoted as p_{low}) and another that corresponds to the increase in probability (denoted as p_{high}).

Example 3.2. Consider tuple t_3 in Table 3 the value of which, based on the execution of the first two enrichment functions associated with the `location` attribute, is a distribution [0.15, 0.35, . . ., 0.05] over the possible values of locations. Given the query in Code Listing 1, the probability of t_3 satisfying the predicate on location is 0.15 and not satisfying the predicate is 0.85. As a result, entropy is calculated as 0.60. Let us consider executing the third enrichment function on `location` and, furthermore, let us assume that its associated entropy reduction is 0.3. With the new entropy value of (0.6-0.3) =0.3, JENNER solves Equation 1 to determine p_{low} and p_{high} as 0.05 and 0.95 respectively. ■

Given (p_{low} and p_{high}) and the probabilities of other tuples satisfying the query condition (which is the same as in the previous epoch e_{w-1}), JENNER can determine the answer that would be return to the user in order to maximize the answer quality (as discussed in §3.5). Thus, JENNER can determine the answers returned in both cases when the probability of $t_i.\mathcal{A}_j$ satisfying the query condition is p_{low} or it is p_{high}. Let these answers be Ans_{low} and Ans_{high} respectively.

We can now determine the estimated quality of the answer after execution of f_k on $t_i.\mathcal{A}_j$ as a weighted sum of the quality of the potential answers $\widehat{Qty}(Ans_{low})$ and $\widehat{Qty}(Ans_{high})$).

$$p_{w-1}\widehat{Qty}(Ans_{high}) + (1-p_{w-1})\widehat{Qty}(Ans_{low}) \qquad (9)$$

where p_{w-1} refers to the probability of $t_i.\mathcal{A}_j$ satisfying the query condition in its state in D_{w-1}.

Given the above expected quality of answers after execution of f_k on $t_i.\mathcal{A}_j$, we can now determine the benefit of its execution to the results. Note that such a value could potentially be negative depending upon the value of p_{w-1}. In this case, we consider benefit to be 0 and such a function would not be chosen for enrichment.

3.2.2 ***Generalizing to Other Queries*** .

To estimate benefit for general queries, we have to extend the model for both estimating the quality of query result in the previous epoch e_{w-1} and also the benefit of executing the triples in enrichment plan EP_w of the current epoch. Let us consider a query Q with conditions on n relations R_1, R_2, . . ., R_n. For each R_i, there could be multiple selection and join conditions on both fixed and derived attributes.

At epoch e_{w-1}, the tuples of R_i are classified as one of the following two types: (*i*) the tuples that have met the selection condition on derived attributes of R_i, denoted by R_i^σ, [7] and (*ii*) the tuples that do not satisfy such selection conditions, are denoted by $R_i^{\neg\sigma}$. The tuples of R_i^σ are further classified as those that were part of the answer set (*i.e.*, one of the tuple in the answer set was generated by this tuple) or not in the answer set (if there does not exist any tuple in the query's answer so far from this tuple).

To determine R_i^σ, JENNER determines the set of tuples in Ans_{w-1} and consider the tuples of R_i with the minimum *match_prob*, *i.e.*, probability of satisfying all the selection conditions of R_i, which is part of Ans_{w-1}. We refer to this minimum *match_prob* as the *relation-threshold* of R_i. The tuples with *match_prob* higher than this threshold compose R_i^σ and the tuples with *match_prob* less

[7]If there are no selection conditions on derived attributes then all the tuples are part of R_i^σ.

than the threshold compose $R_i^{\neg\sigma}$. Candidate tuples are chosen from $R_i^{\neg\sigma}$ of the relations.

To compute the probability of a tuple $t_i \in Ans_w$ to be part of the answer Ans^{real}, let us consider the projection of t_i to its constituent tuples in the relations of $R_1, R_2, \ldots, R_n$. Let us denote the corresponding tuple in R_j as $t_i[R_j]$. The probability of $t_i[R_j]$ satisfying the selection condition in Q on attributes in R_j is computed as discussed above in the context of selection queries. The probability of the join condition between two relations R_j and R_k (say $R_j.\mathcal{A}_m = R_k.\mathcal{A}_m$) being satisfied by t_i can be computed as follows: Let the determinized value of $t_i[R_j]$ be $Det(t_i[R_j])$. Its probability of $t_i[R_j]$ satisfying the join condition on the derived attribute $\mathcal{A}_m$ is $Val(state(t_i[R_j].\mathcal{A}_m)[Det(t_i[R_j].\mathcal{A}_m)]$. Likewise, suppose the determinized value of $t_i[R_k]$ be $Det(t_i[R_k])$. The probability of $t_i[R_k]$ satisfying the join condition on the attribute $\mathcal{A}_m$ is $Val(state(t_i[R_k].\mathcal{A}_m)[Det(t_i[R_k].\mathcal{A}_m)]$. Hence, the probability of tuple t_i to satisfy the join condition of $R_j.\mathcal{A}_m = R_k.\mathcal{A}_m$ is the product of the above two probabilities, *i.e.*, $Val(state(t_i[R_j].\mathcal{A}_m)[Det(t_i[R_j].\mathcal{A}_m)] \cdot Val(state(t_i[R_k].\mathcal{A}_m)[Det(t_i[R_k].\mathcal{A}_m)]$. The overall probability of tuple t_i is computed by computing the product of all the probabilities for the predicates present in Q.

Given the probability of all tuples $t_i \in Ans_w$ to be part of real answer set Ans^{real}, JENNER compute F_α measure using Equation 5. To compute benefit of a triple $\langle t_i, \mathcal{A}_j, f_k\rangle$, where tuple t_i belongs to relation R_p and it is part of $R_p^{\neg\sigma}$, JENNER needs to estimate the quality of the answer that would result if Q were to be executed on the database after executing f_k on $t_i.\mathcal{A}_j$. We follow the same strategy, as in selection query, we generate p_{low} and p_{high} for the condition on $t_i.\mathcal{A}_j$ to be met. In each case, we re-execute the query, generate the answers Ans_{high} and Ans_{low}. As in selection queries, we execute the pruning of answers to maximize F_α measure §3.5.

The above way of computing benefit for executing f_k on $t_i.\mathcal{A}_j$ requires (*i*) determining the probabilities p_{low} and p_{high} from the entropy reduction of f_k, (*ii*) re-executing Q on the database state resulting in $D_{e_{w-1}}$ with the probability of $t_i.\mathcal{A}_j$ matching the query condition modified to p_{low} (or p_{high}), and (*iii*) run *ProduceQueryResult* in both cases (the complexity, as will be clear in §3.5 is $|Ans|log(|Ans|)$, where $|Ans|$ is the size of the answer from which query result is selected). Thus, the complexity of the above three steps is $O(costQ + |Ans_w|log(|Ans_w|))$, where $costQ$ is the time taken to execute Q, $|Ans_w|$ is the size of answers returned. As a result, the overall complexity of benefit estimation is $O(n(costQ + |Ans_w|log(|Ans_w|))$ where n is the size of $CandidateSet^M$.

3.3 Selecting Enrichment Plan

This step chooses a set of ⟨tuple, derived attribute, enrichment function⟩ triples as the enrichment plan of epoch e_w. The problem of selecting an enrichment plan is a budgeted Knapsack problem as we need to find an enrichment plan with total cost less than or equal to *epoch_duration* and that has maximum sum of benefit values among all the possible subset of ranked tuples. We use a greedy approach to choose this enrichment plan for the epoch e_w. For the ⟨tuple, derived attribute, enrichment function⟩ triples in $CandidateSet^M$, we compute their benefit as described in the previous step of plan generation phase and sort them based on their benefit values. The triples in CandidateSet are sorted in decreasing order of their benefit/cost values. The enrichment plan is chosen from the sorted set starting from the triple with highest benefit. Once the running total cost of the chosen triples exceeds *epoch_duration*, the WSPT algorithm terminates and the chosen set is considered as the enrichment plan.

3.4 Execution of Enrichment Plan

In this step, the ⟨tuple, derived attribute, enrichment function⟩ triples present in EP_w are executed. While executing an enrichment function on a set of tuples, JENNER batches the tuples together and then execute the enrichment function on them. For each tuple $t_i \in EP_w$, JENNER updates the state of t_i. Next, the determinized representation of t_i is updated based on the output of all the enrichment functions executed on it. For each tuple for which a derived attribute value was enriched, the *NBF* function for that attribute changes. Hence, JENNER, calculates the new benefit of the tuple, if it is enriched using the *NBF* function at the current state. These updated benefit of the tuples that were enriched in epoch e_w are reflected in the $CandidateSet^M$ data structure. Hence, the next epoch can choose an enrichment plan by comparing the updated benefit of enriched tuples in e_w and the previous benefit of tuples that were not enriched. In an epoch, JENNER keeps executing the triples until the epoch duration is exhausted.

3.5 Produce Query Result

After updating the state of tuples enriched in the current epoch e_w, the original query Q is re-executed on the determinized representation to determine the set of potential answer. For each tuple t_i in Ans_w computed, JENNER determines the probability of t_i to be in Ans^{real}, based on the probability of tuples in the base relation R_i used to construct t_i. Instead of returning all tuples in Ans_w, we return a subset of them, in order to maximize the answer quality based on the quality metric (*i.e.*, F_α-measure for set-based queries). For aggregation queries, we first determine the set of answers that optimizes F_α-measure and then compute the aggregation function.

JENNER is based on the following observation (proved in Appendix 2) : Let $t_1 t_2, \ldots, t_n$ be the set of tuples in Ans_w sorted based on their probability of being in Ans^{real}. The $E(F_\alpha)$ measure of the query result increases monotonically with the inclusion of more tuples t_i starting with the highest probability value up to the inclusion of a certain tuple; beyond which the $E(F_\alpha)$ measure decreases monotonically with the inclusion of any more tuples.

We utilize this observation where we sort the tuples in Ans_w based on their probability of being in Ans^{real} and continue including answer tuples until $E(F_\alpha)$ measure of the answer is maximized. We refer to the probability of the last tuple that is part of the answer set of epoch e_w as the *answer-threshold*. The time complexity of this step is $O(nlog(n))$ where n is the size of $CandidateSet^M$.

Example 3.3. Let us consider the query of Figure 5a containing conditions on two relations of R_1 and R_2. Suppose R_1 contains five tuples that are in the probe query result of R_1: $\langle r_1^1, r_2^1, \ldots, r_5^1 \rangle$ and relation R_2 contains ten tuples in its probe query results: $\langle r_1^2, r_2^2, \ldots, r_{10}^2\rangle$. Without loss of generality, let us consider that the tuples of each relation are sorted based on their probability of satisfying all the selection conditions on the derived attributes. Considering the possible tuple pairs of $\langle\langle r_1^1, r_1^2 \rangle, \ldots, \langle r_5^1, r_{10}^2\rangle\rangle$, JENNER computes the probability of the tuples as described in Example 3.4. It keeps including the tuples in Ans_w as long as the $E(F_1)$ measure of the answer set keeps increasing. The tuple beyond which the $E(F_1)$ measure decreases, are not included in the answer set. The Ans_w chosen in this way has maximum $E(F_1)$ measure as described above.

We next discuss how the probability of a tuple $t_i \in Ans_w$ to be in the true answer based on the corresponding tuples in the base relations $R_i \in Q$ that resulted in the answer tuple t. For simple selection queries over derived attributes, it is simply the probability of the value of the tuple to match the query condition (*i.e.*, $Val(state(t.\mathcal{A}_j)) = a_j$ for a selection condition of $\mathcal{A}_j = a_j$).

For multiple selection conditions on derived attributes of a relation, the probability is estimated under the assumption derived attributes to be independent. For queries where answer tuple t_i is formed using tuples from multiple relations, the corresponding probability is based on the product of the probabilities of individual tuples to satisfy the individual selection and the join conditions. [8] An example of computing the probability of the tuples satisfying the query Q is shown below.

Example 3.4. Let us consider the query of Figure 5a on relations R_1 and R_2 and two tuples $r_1 \in R_1$ and $r_2 \in R_2$ which were part of the probe query results of R_1 and R_2. Suppose, the value of $r_1.\mathcal{A}_1$ is a_1 (*i.e.*, the value with highest probability after determinization) and the probability associated with the value is 0.9. Similarly, let the value of $r_2.\mathcal{A}_6$ is a_6 and the probability associated with it is 0.8. Now considering the join condition on derived attribute (*i.e.*, $R_1.\mathcal{A}_3 = R_2.\mathcal{A}_3$), suppose the attribute values of them after determinization match and corresponding probability values are 0.95 and 0.85. Hence, the probability of the tuple pair $\langle r_1, r_2\rangle$ satisfying all the query conditions in Q are as follows: $\mathcal{P}(\langle r_1, r_2\rangle) = 0.9 \times 0.8 \times 0.95 \times 0.85 = 0.58$. We compute these probabilities for all the tuple pairs in the probe query result of R_1 and R_2 and whose determinized representation of derived attribute matches the conditions in the query.

After determining the Ans_w that optimizes the quality metric $E(F_\alpha)$, JENNER prunes tuples from the candidate set whose impact on improving the quality of the answer set in subsequent epochs is expected to be low. This is achieved by finding out the tuples of each relation that already contributed to Ans_w of the current epoch and remove them from $CandidateSet^M$. Enriching such tuples have low impact on improving the quality of the query result as proved in a theorem Appendix 6.3.

3.6 Optimizing Benefit Computation

The techniques for benefit computation for an enrichment function f_k on attribute $t_i.\mathcal{A}_j$ as described in §3.2.1 and §3.2.2 used simulated execution of f_k to assess the impact of its execution on the overall quality of the answers. These techniques resulted in the overall time complexity of $O(n(costQ + |Ans_w| log(|Ans_w|))$ where n is the size of $CandidateSet^M$.

In this section, we present a strategy wherein *SelectEnrichmentPlan* can select the plan without explicitly calculating the benefit of the enrichment functions. We do so first for selection queries and then generalize to other queries.

[8]For duplicates, probability values are added up as in probabilistic databases [12]

Selection Query. In the modified strategy, for each $\langle t_i, \mathcal{A}_j, f_k\rangle \in$ *CanddiateSet*^{M}, we compute the *RelativeBenefit* defined below.

$$RelativeBenefit(t_i, \mathcal{A}_j, f_k) = \frac{\mathcal{P}_i(\mathcal{P}_i + \Delta\mathcal{P}_i)}{c_k} \tag{10}$$

where $\mathcal{P}_i$ is the probability of the tuple satisfying the selection conditions and $\mathcal{P}_i + \Delta\mathcal{P}_i$ is the new probability of tuple t_i if it is enriched in the current epoch. Here, Δ would be positive for p_{high} and negative for p_{low}.

We can show that if a triple has higher relative benefit than another, then the first triple will always have a higher benefit (viz., Equation 7) as stated in the following theorem.

Theorem 1. *A triple (t_i, $\mathcal{A}_j$, f_k) has higher benefit than a triple (t_q, $\mathcal{A}_s$, f_v) in epoch w irrespective of the values of $\mathcal{P}_i$, $\mathcal{P}_q$, $\Delta\mathcal{P}_i$ and $\Delta\mathcal{P}_q$ if the following condition holds:*

$$RelativeBenefit(t_i, \mathcal{A}_j, f_k) > RelativeBenefit(t_q, \mathcal{A}_s, f_v) \tag{11}$$

Proof. We prove this theorem as follows: for the given values of $\mathcal{P}_i$, $\mathcal{P}_q$, $\Delta\mathcal{P}_i$ and $\Delta\mathcal{P}_q$, there can be four possible orders among them. They are as follows: (*i*) $\mathcal{P}_i > \mathcal{P}_q$ and $\Delta\mathcal{P}_i > \Delta\mathcal{P}_q$, (*ii*) $\mathcal{P}_i > \mathcal{P}_q$ and $\Delta\mathcal{P}_i < \Delta\mathcal{P}_q$, (*iii*) $\mathcal{P}_i < \mathcal{P}_q$ and $\Delta\mathcal{P}_i > \Delta\mathcal{P}_q$, (*iv*) $\mathcal{P}_i < \mathcal{P}_q$ and $\Delta\mathcal{P}_i < \Delta\mathcal{P}_q$. For each of these orders, we determine the answer set and calculate the quality of the answer when the triple (t_i, $\mathcal{A}_j$, f_k) is executed. Similarly, we calculate the quality when triple (t_q, $\mathcal{A}_s$, f_v) is executed. We measure their benefit values using Equation 7.

Let m_1 be the number of tuples of Ans_{w-1} that move out of Ans_w as a result of increased probability of tuple t_i satisfying the query from $\mathcal{P}_k$ to $\hat{\mathcal{P}}_k$, where $m_1 \geq 0$. Furthermore, let $m_2 \geq 0$ be the number of tuples of Ans_{w-1} that move out of Ans_w as a result of changing the probability of t_q from $\mathcal{P}_q$ to $\hat{\mathcal{P}}_q$.

Given three possible cases of m_1 and m_2 (*i.e.*, $m_1 > m_2$, $m_1 < m_2$, and $m_1 = m_2$), we consider the possible combinations (16 possible combinations) of the values of $\mathcal{P}_k$, $\mathcal{P}_q$, $\Delta\mathcal{P}_k$, and $\Delta\mathcal{P}_q$ and show if Equation 11 holds, then the benefit of (t_i, $\mathcal{A}_j$, f_k) will be higher than the benefit of (t_q, $\mathcal{A}_s$, f_v). In the following we provide the proof of these scenarios:

For ease of notation, we take the following steps: Since, $E(F_\alpha(Ans_{w-1})) = \frac{(1+\alpha)(\mathcal{P}_1+\cdots+\mathcal{P}_\tau)}{\alpha(\mathcal{P}_1+\mathcal{P}_2+\cdots+\mathcal{P}_{|O|})+\tau}$, this expression is simplified as $\frac{X}{Y+\tau}$. We denote the value of $\frac{\mathcal{P}_k}{c_k}$ by v_k and the value of $\frac{\mathcal{P}_q}{c_v}$ by v_q.

Simplifying the expression of benefit the triples (*i.e.*, Equation 7) and quality measured using $\hat{F}_\alpha$ measure (*i.e.*, Equation 5), benefit of triple $\langle t_i, \mathcal{A}_j, f_k\rangle$ is higher than the triple $\langle t_q, \mathcal{A}_s, f_v\rangle$, when the following condition holds:

$$\begin{aligned} &v_k\Big(\frac{X - (1+\alpha)\cdot(\mathcal{P}_\tau + \mathcal{P}_{\tau-1} + \ldots\mathcal{P}_{\tau-(m_1-1)}) + (1+\alpha)\cdot(\mathcal{P}_k + \Delta\mathcal{P}_k)}{Y + (\tau - m_1) + \alpha\cdot\Delta\mathcal{P}_k}\Big) > \\ &v_q\Big(\frac{X - (1+\alpha)\cdot(\mathcal{P}_\tau + \mathcal{P}_{\tau-1} + \ldots\mathcal{P}_{\tau-(m_2-1)}) + (1+\alpha)\cdot(\mathcal{P}_q + \Delta\mathcal{P}_q)}{Y + (\tau - m_2) + \alpha\cdot\Delta\mathcal{P}_q}\Big) \end{aligned} \tag{12}$$

Case 1: $\Delta\mathcal{P}_k < \Delta\mathcal{P}_q$, $\mathcal{P}_k + \Delta\mathcal{P}_k > \mathcal{P}_q + \Delta\mathcal{P}_q$, **and** $m_1 > m_2$.
Comparing the denominators of Equation 12, we observe that $(\tau - m_1) < (\tau - m_2)$ and $\Delta\mathcal{P}_k < \Delta\mathcal{P}_q$. This implies that the denominator on the L.H.S. is smaller than the denominator on the R.H.S. In the numerator of L.H.S., the value of $(\mathcal{P}_\tau + \mathcal{P}_{\tau-1} + \ldots\mathcal{P}_{\tau-(m_1-1)})$ is

higher than $(\mathcal{P}_{\tau} + \mathcal{P}_{\tau-1} + ...\mathcal{P}_{\tau-(m_2-1)})$ as m_1 is higher than m_2. Furthermore, if $v_k(\mathcal{P}_k + \Delta\mathcal{P}_k) > v_q(\mathcal{P}_q + \Delta\mathcal{P}_q)$ then the numerator of the L.H.S. will be higher than the numerator of the R.H.S. Thus we conclude that Equation 12 is satisfied when condition $v_k(\mathcal{P}_k + \Delta\mathcal{P}_k) > v_q(\mathcal{P}_q + \Delta\mathcal{P}_q)$ is satisfied.

Case 2: $\Delta\mathcal{P}_k > \Delta\mathcal{P}_q$, $\mathcal{P}_k + \Delta\mathcal{P}_k > \mathcal{P}_q + \Delta\mathcal{P}_q$, and $m_1 > m_2$. In Equation 12, the value of $(\mathcal{P}_{\tau} + \mathcal{P}_{\tau-1} + ...\mathcal{P}_{\tau-(m_1-1)})$ on the L.H.S is higher than $(\mathcal{P}_{\tau} + \mathcal{P}_{\tau-1} + ...\mathcal{P}_{\tau-(m_2-1)})$ as m_1 is higher than m_2. In the denominator, although the value of $\Delta\mathcal{P}_k$ is higher than $\Delta\mathcal{P}_q$, the total value of $(\tau - m_1 + \alpha \cdot \Delta\mathcal{P}_k)$ is lower than $(\tau - m_2 + \alpha \cdot \Delta\mathcal{P}_q)$ as both $\Delta\mathcal{P}_k$ and $\Delta\mathcal{P}_q$ are less than one.

Case 3: $\Delta\mathcal{P}_k > \Delta\mathcal{P}_q$, $\mathcal{P}_k + \Delta\mathcal{P}_k < \mathcal{P}_q + \Delta\mathcal{P}_q$, and $m_1, m_2 = 0$. Let us compare the L.H.S and R.H.S. of Equation 12. In the numerator, if the term of $v_k(\mathcal{P}_k + \Delta\mathcal{P}_k)$ is higher than the value of $v_q(\mathcal{P}_q + \Delta\mathcal{P}_q)$, then the numerator of L.H.S will be higher than the numerator of R.H.S. Hence, the value of the expression in the left hand side will be higher.

Case 4: $\Delta\mathcal{P}_k < \Delta\mathcal{P}_q$, $\mathcal{P}_k + \Delta\mathcal{P}_k < \mathcal{P}_q + \Delta\mathcal{P}_q$, and $m_1, m_2 = 0$. In Equation 12, after simplifying some steps further, we derive that the condition in which the L.H.S. will be higher than the R.H.S. is as follows: $v_k(\mathcal{P}_k + \Delta\mathcal{P}_k)\Delta\mathcal{P}_q > v_q(\mathcal{P}_q + \Delta\mathcal{P}_q)\Delta\mathcal{P}_k$. According to the assumption $\Delta\mathcal{P}_q$ value is higher than the value of $\Delta\mathcal{P}_k$. This implies that, if the condition $v_k(\mathcal{P}_k + \Delta\mathcal{P}_k) > v_q(\mathcal{P}_q + \Delta\mathcal{P}_q)$ is satisfied, then L.H.S. will be higher than the R.H.S.

The above proofs will also hold for the scenarios where $m_1 = m_2$ and $m_1 > 0$. Only difference will be as follows: an additional constant term (*i.e.*, $\mathcal{P}_{\tau} + \mathcal{P}_{\tau-1} + \cdots + \mathcal{P}_{\tau-(m_1-1)}$) will be added to the numerators of both the sides of Equation 12. The remaining steps will remain the same as the proofs of Cases 1-4.

Case 5: $\Delta\mathcal{P}_k < \Delta\mathcal{P}_q$, $\mathcal{P}_k + \Delta\mathcal{P}_k > \mathcal{P}_q + \Delta\mathcal{P}_q$, and $m_1 < m_2$. Comparing both the denominators of Equation 12, we can see that $(\tau - m_1) < (\tau - m_2)$ and $\Delta\mathcal{P}_k < \Delta\mathcal{P}_q$. This implies that the denominator of L.H.S. is lower than the denominator of R.H.S. In the numerators, the value of $(\mathcal{P}_{\tau} + \mathcal{P}_{\tau-1} + ...\mathcal{P}_{\tau-(m_1-1)})$ is lower than $(\mathcal{P}_{\tau} + \mathcal{P}_{\tau-1} + ...\mathcal{P}_{\tau-(m_2-1)})$ as m_1 is less than m_2. This condition makes the numerator of L.H.S higher than R.H.S. Furthermore, if $v_k(\mathcal{P}_k + \Delta\mathcal{P}_k) > v_q(\mathcal{P}_q + \Delta\mathcal{P}_q)$ is satisfied then the numerator of L.H.S. is higher than R.H.S.

Case 6: $\Delta\mathcal{P}_k > \Delta\mathcal{P}_q$, $\mathcal{P}_k + \Delta\mathcal{P}_k > \mathcal{P}_q + \Delta\mathcal{P}_q$, and $m_1 < m_2$. From Equation 12, we can derive the following equation:

$$\begin{aligned} &v_k(X - (1+\alpha)\cdot(\mathcal{P}_{\tau} + \mathcal{P}_{\tau-1} + ...\mathcal{P}_{\tau-(m_1-1)}) + (1+\alpha)\cdot \\ &(\mathcal{P}_k + \Delta\mathcal{P}_k)) \cdot (Y + (\tau - m_2) + \alpha \cdot \Delta\mathcal{P}_q) > v_j(X - \\ &(1+\alpha)\cdot(\mathcal{P}_{\tau} + \mathcal{P}_{\tau-1} + ...\mathcal{P}_{\tau-(m_2-1)}) + (1+\alpha)\cdot \\ &(\mathcal{P}_q + \Delta\mathcal{P}_q)) \cdot (Y + (\tau - m_1) + \alpha \cdot \Delta\mathcal{P}_k) \end{aligned} \tag{13}$$

In the above equation, the value of $(\mathcal{P}_{\tau} + \mathcal{P}_{\tau-1} + ...\mathcal{P}_{\tau-(m_1-1)})$ is lower than $(\mathcal{P}_{\tau} + \mathcal{P}_{\tau-1} + ...\mathcal{P}_{\tau-(m_2-1)})$ as m_1 is smaller than m_2. This favors the value in the left hand side of the equation. Furthermore, if the value of $v_k(\mathcal{P}_k + \Delta\mathcal{P}_k)$ is higher than the value of $v_q(\mathcal{P}_q + \Delta\mathcal{P}_q)$, then the benefit of first triple is higher than the second triple.

Case 7: $\Delta\mathcal{P}_k > \Delta\mathcal{P}_q$, $\mathcal{P}_k + \Delta\mathcal{P}_k < \mathcal{P}_q + \Delta\mathcal{P}_q$, and $m_1 < m_2$. Comparing the L.H.S. of Equation 13 with the R.H.S., we observe that if the value of $v_k(\mathcal{P}_k + \Delta\mathcal{P}_k)$ is higher than the value of $(\mathcal{P}_q + \Delta\mathcal{P}_q)$, then the whole expression of L.H.S. becomes higher than the R.H.S.

Case 8: $\Delta\mathcal{P}_k < \Delta\mathcal{P}_q$, $\mathcal{P}_k + \Delta\mathcal{P}_k < \mathcal{P}_q + \Delta\mathcal{P}_q$, and $m_1 < m_2$. Let us consider Equation 12 and compare the L.H.S. with the R.H.S. After simplifying them, we can derive that the condition in which the left hand side will be higher than the right hand side is as follows: $v_k(\mathcal{P}_k + \Delta\mathcal{P}_k)\Delta\mathcal{P}_q > v_q(\mathcal{P}_q + \Delta\mathcal{P}_q)\Delta\mathcal{P}_k$. According to the assumption of this case, $\Delta\mathcal{P}_q$ value is higher than the value of $\Delta\mathcal{P}_k$. This implies that, if the condition $v_k(\mathcal{P}_k + \Delta\mathcal{P}_k) > v_q(\mathcal{P}_q + \Delta\mathcal{P}_q)$ holds, then Equation 12 is satisfied and the benefit of first triple is higher than the second triple.

The above proofs (*i.e.*, the proofs of Cases 5-8) will also hold for the scenarios where $m_1 > m_2$, due to the symmetric nature of the assumptions. Based on the proofs of Cases 1-8, we conclude that given two triples $(t_i, \mathcal{A}_j, f_k)$ and $(t_q, \mathcal{A}_s, f_v)$, if $RelativeBenefit(t_i, \mathcal{A}_j, f_k)$ $> RelativeBenefit(t_q, \mathcal{A}_s, f_v)$ then the first triple has higher benefit than the second triple. ∎

Given the above theorem, JENNER computes the *RelativeBenefit* of the triples and select enrichment plan (§3.3) based on relative benefit. Note that, the complexity of computing the *RelativeBenefit* for all the triples in the candidate set is $O(n)$, where n is the size of the $CandidateSet^M$ which is significantly lower compared to the approach based on computing benefits explicitly.

More General Queries. To exploit a strategy based on relative benefit for more general queries, we need to estimate the number of tuples that would be resulting from a tuple t_i in relation R_p. JENNER estimates the average number of tuples that were generated by the tuples in R_p^{σ} in the answer of Ans_{w-1}. We refer to this value as $\lambda^{w-1}(R_p)$. We measure the relative benefit of $\langle t_i, \mathcal{A}_j, f_k \rangle$, where $t_i \in R_p$ as follows:

$$RelativeBenefit(t_i, \mathcal{A}_j, f_k) = \lambda_{R_i} \cdot \Big[\frac{\mathcal{P}_i(\mathcal{P}_i + \Delta\mathcal{P}_i)}{c_k}\Big] \tag{14}$$

The relative benefit reflects the amount of improvement in the quality of the query result that is achieved by the answer tuples generated from tuple t_i in R_p. As for selection queries, the enrichment plan EP_w is chosen using the above *RelativeBenefit* metric.

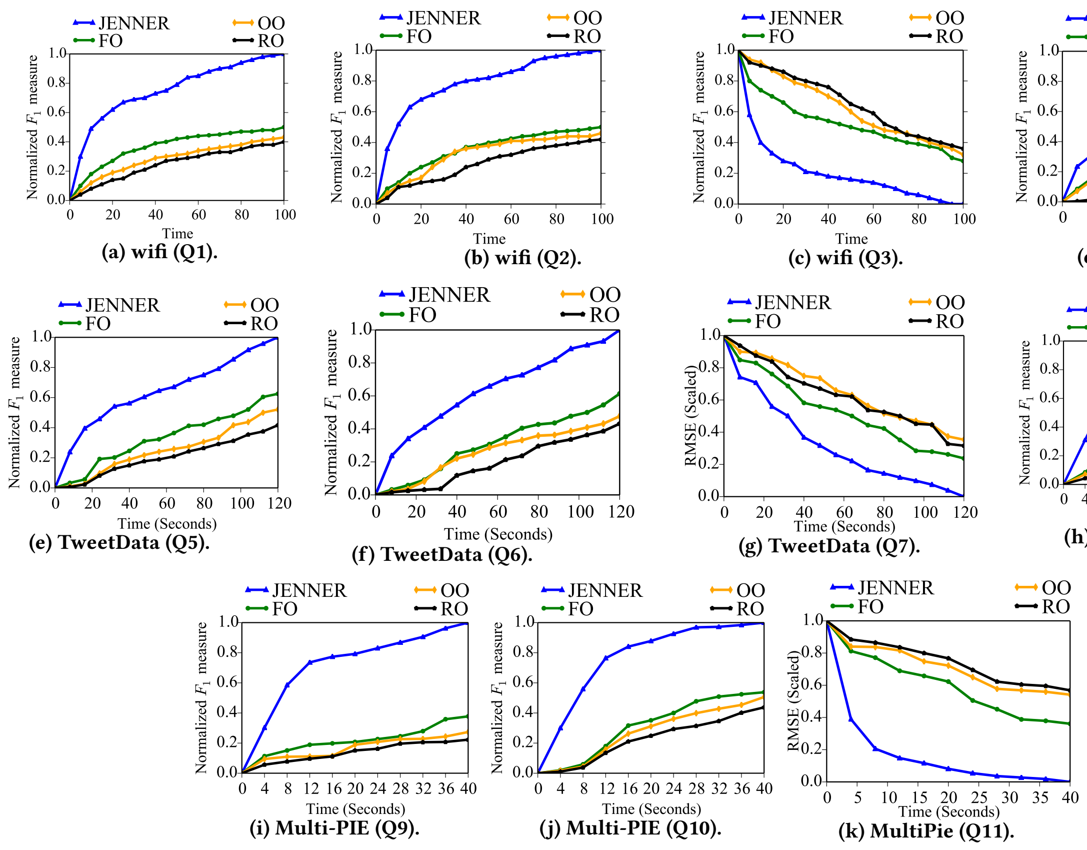
4 EXPERIMENTAL EVALUATION

Our experimental study evaluates JENNER in the following aspects.

- Quality improvement due to JENNER 's benefit based approach as compared to the other approaches (discussed later) of selecting enrichment during an epoch.
- Time and storage overhead of enrichment plan generation.
- Impact of different epoch sizes on the quality of query results.
- Impact of pruning of *CandidateSet* and calculating the benefit using the *RelativeBenefit* metric.

Datasets. We used the following datasets to evaluate JENNER: (*i*) WiFi data containing 10M connectivity events of user's mobile devices with WiFi access points installed inside a university campus (taken from the SmartBench benchmark[15]) and (*ii*) TweetData containing 11 million tweets.

Enrichment Functions. The enrichment functions chosen for the derived attributes of the dataset are presented in Table 5. For the wifi dataset, we have used the algorithm proposed in [25] as enrichment functions. We have used multiple versions of this function referred to as `LOC_n` in Table 5. The parameter of n signifies that the algorithm analyzed the data of past n days to predict the location of the



(a) wifi (Q1). (b) wifi (Q2). (c) wifi (Q3). (d) TweetData (Q4). (e) TweetData (Q5). (f) TweetData (Q6). (g) TweetData (Q7). (h) Multi-PIE (Q8). (i) Multi-PIE (Q9). (j) Multi-PIE (Q10). (k) MultiPie (Q11).

Figure 3: Performance results of different plan generation strategies.

user. We used the following probabilistic classifiers as enrichment functions in the image dataset: 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); as enrichment functions, as they are very commonly used in image analysis [11, 43]. The GNB classifier was calibrated using isotonic-regression model [45] and the remaining classifiers using Platt's sigmoid model [34] during cross-validation. After calibration, each classifiers outputs a real probability distribution.

Queries. As shown in Table 4, we selected seven queries, where ***Q1-Q3*** are on `wifi` dataset, ***Q4 - Q7*** are on `TweetData`, and ***Q8 - Q11*** are on `MultiPie` data. The queries on `wifi` data are taken from the SmartBench benchmark[15]. The epoch sizes in experiment 1 are set according to the optimal epoch sizes determined by Experiment 3 for different queries.

Implementation Details. In JENNER , we utilize two servers: (*i*) an enrichment server and (*ii*) a DBMS server. In current implementation, enrichment is performed in a separate server (outside the DBMS). JENNER could also be adapted to execute enrichment inside the DBMS, using UDF technology supported by modern databases, though such an approach raises additional implementation challenges [1] which we do not address in the paper. The benefits of using JENNER in both implementations, are, however, similar.

In the zero-th epoch, for a query Q, the enrichment server generates a set of probe queries and executes them on the DBMS to fetch the tuples that may require enrichment. The state of the tuples are replicated in both the DBMS and the enrichment server. This reduces the communication overhead without adding much storage overhead since the size of state tables are usually much lower than the size of data tables (as shown later in experiments). The enrichment is performed at the enrichment server in epochs resulting in changes to following tables: (*i*) the state tables stored in the enrichment server as well as the one stored in the database, and (*ii*) the combined derived attribute values in the data tables. At the end of an epoch, JENNER returns a query results to the user based on the updated derived attribute values.

Enrichment Plan Generation Strategies. For experiments, we compare JENNER with three different plan generation strategies: (*i*) *Sample-based with Object Order* (**OO**): that randomly selects tuples from the set of tuples satisfying predicates on fixed attributes. Selected tuples are completely enriched by executing all enrichment functions available for derived attributes present in the query. (*ii*) *Sample-based with Function Order* (**FO**): that selects enrichment functions based on the decreasing order of their $\frac{quality}{cost}$ values. The top-most function from the sorted enrichment functions is executed on all tuples (obtained after checking the predicates on fixed attributes), before executing the next function. (*iii*) *Sample-based with Random Order* (**RO**): that selects both tuples and enrichment functions randomly from a set of ⟨tuple, function⟩ pairs after checking predicates on fixed attributes.

4.1 Experimental Results

The experiments were performed on an enrichment server with 16 core 2.50GHz Intel Xeon CPU, 64GB RAM, and 1TB SSD. The datasets were stored in two tables of a PostgreSQL database. If we

ID	Query
Q1	SELECT u.name FROM wifi w1, wifi w2, users u WHERE w1.time between (?, ?) AND w1.user_id = w2.user_id AND w1.location = ? AND w2.location = ? AND w1.time < w2.time AND w1.user_id = u.id
Q2	SELECT w2.user_id FROM wifi w1, wifi w2 WHERE w1.time between (?, ?) AND w1.time=w2.time AND w1.user_id = ? AND w1.user_id != w2.user_id AND w1.location = w2.location
Q3	SELECT Avg(tSpent) FROM (SELECT trunc('day', w.time), count(*)*10 as tSpent FROM wifi w, Infrastructure I, Infrastructure_Type IType WHERE w.location = infra.id AND I.type_id=IType.id AND IType.name=? AND w.user_id=? AND w1.time between (?, ?) GROUP BY trunc('day', w.time)) AS tSpentPerDay
Q4	SELECT tid, UserID, Tweet, location, time from TweetData where sentiment = ? and and topic = ? and time between(?,?)
Q5	SELECT * from TweetData T1, TweetData T2 where T1.sentiment = T2.sentiment and T1.time between(?,?) and T2.time between (?,?)
Q6	SELECT * from TweetData T1, State S where T1.location = S.city and S.state= ? and T1.sentiment = ? and T1.time between(?,?)
Q7	SELECT topic, count(*) from TweetData where time between(?, ?) group by topic
Q8	SELECT * from MultiPie where gender=1 and CameraID <12
Q9	SELECT * from MultiPie where gender=1 and expression = 2 and CameraID <12
Q10	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
Q11	SELECT gender, count(*) from MultiPie where CameraID <12 group by gender

Table 4: Queries used. In this table (?) represents a user input.

Relation	Derived attrs.	Function	Cost (ms)	Quality
WiFi 10M tuples 9GB Size	location(304)	LOC_2	24.5	0.68
		LOC_4	46.4	0.75
		LOC_8	93.7	0.82
		LOC_16	186.4	0.91
TweetData 11M tuples 10.5GB Size	sentiment(3)	SVM	1.67	0.61
		KNN	2.81	0.72
		GNB	5.32	0.81
		MLP	6.26	0.89
	topic(40)	LDA	2.17	0.58
		LR	3.89	0.67
		KNN	5.48	0.75
		GNB	7.82	0.88
MultiPie[38] 100K tuples 16.9GB Size	gender(2)	DT	11.6	0.64
		GNB	18.7	0.71
		KNN	24.3	0.85
		MLP	32.7	0.92
	expression(5)	DT	10.4	0.62
		GNB	17.6	0.73
		RF	23.8	0.86
		KNN	28.7	0.9

Table 5: Datasets and cost/quality tradeoff of functions.

had to perform complete enrichment of 11M tweets of TweetData table for both `topic` and `sentiment` attributes, it would have taken ≈ **43 hours** to complete after using all the 16 cores of the server. Similarly, the complete enrichment of 100K wifi data for `location` derived attribute, would have taken ≈ 37 days on the same server. Hence, complete enrichment of the data is an infeasible option.

Q	**JENNER**	**FO**	**OO**	**RO**	**Q**	**JENNER**	**FO**	**OO**	**RO**
Q1	**0.87**	0.36	0.33	0.32	Q7	**0.74**	0.37	0.33	0.34
Q2	**0.84**	0.34	0.32	0.31	Q8	**0.85**	0.33	0.31	0.28
Q3	**0.76**	0.43	0.35	0.31	Q9	**0.82**	0.33	0.29	0.27
Q4	**0.80**	0.34	0.33	0.31	Q10	**0.78**	0.31	0.29	0.26
Q5	**0.73**	0.39	0.35	0.33	Q11	**0.71**	0.29	0.26	0.24
Q6	**0.72**	0.37	0.36	0.32					

Table 6: Progressive Scores.

Query	Q1	Q2	Q3	Q4	Q5	Q6
Time	31	44.5	40.6	22.1	67.1	39.2
Query	Q7	Q8	Q9	Q10	Q11	
Time	45.1	46	67	70	48	

Table 7: Exp 1. Query time without progressiveness (in Mins).

Experiment 1 (Need for a Progressive Approach). In this experiment, we compare JENNER with the traditional approach of executing the enrichment functions as UDFs in the DBMS. The enrichment functions of Table 5 are implemented as PostgreSQL UDFs. The queries in Table 4 are rewritten using these UDFs and are executed in the DBMS. The execution time of the queries are shown in Table 7. In contrast, if we execute the queries in JENNER, the variation of quality of the results are presented in Figure 3. It is clearly observed that in JENNER, the quality of the query result achieves very high value within few seconds of query execution. Hence, an application does not have to wait for a long time (as shown in Figure 7) to receive the query results.

Experiment 2 (Comparison with Different Progressive Approaches). This experiment compares JENNER with FO, OO, and RO approaches. Progressive score is computed as a weighted summation of F_1 measures with weight of the epoch e_w set as $(1-\frac{w}{w_{max}})$ where the w_{max} (corresponding to the maximum number of epochs) is set as 15. The results are shown in Figure 3 where we measure the quality of the query result using *normalized F_1 measure* for set based queries and *normalized root-mean-square-error* (RMSE) for aggregation queries (Q3 and Q7). The normalized F_1 measure is calculated as F_1/F_1^{max}, where F_1^{max} is the maximum F_1 measure that is achievable by executing all the enrichment functions.[9] Similarly, normalized root-mean-square-error is calculated by measuring $RMSE/RMSE^{min}$ where $RMSE^{min}$ is the minimum RMSE achievable by executing all enrichment functions. Furthermore, we report the progressive scores in Table 6.

Figure 3 and Table 6 show that JENNER outperforms the other approaches significantly for all queries. With JENNER , the answer achieves a high quality within the first few epochs of the execution as shown in Figure 3 for all queries. For example, Figure 3(a) shows that JENNER achieves F_1-measure of 0.9 within the first 20 seconds of query execution. Furthermore, JENNER achieves a high rate of quality improvement in the epochs in the beginning resulting in the highest progressive score compared to the sampling based approaches. We observe this performance gap as JENNER monitors and reassesses the progress of enrichment at the beginning of each epoch to identify and execute the triples that are expected to yield the highest improvement in quality. In Table 6, we observed that JENNER achieves high progressive scores for all queries.

[9]Recall that our evaluation of F_1 measure in experiments is based on the ground truth data since we have access to them.

Query	Plan Gen. Time	%age of Total Time	Query	Plan Gen. Time	%age of Total Time
Q1	0.52	0.64	Q7	1.6	1.33
Q2	0.26	0.93	Q8	0.12	0.3
Q3	1.4	0.96	Q9	0.26	0.65
Q4	0.58	1.45	Q10	0.64	1.31
Q5	1.58	1.32	Q11	0.68	1.7
Q6	0.85	0.71			

Table 8: Average plan generation time (in seconds).

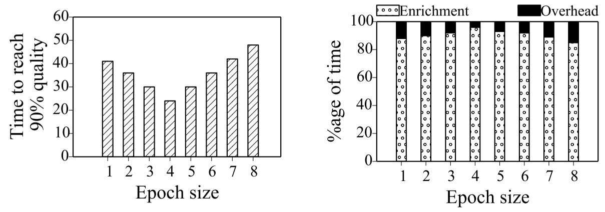


Figure 4: Effect of epoch sizes: (a) time to reach 90% of quality (Q2) and (b) %age of total time spent in plan generation.

Experiment 2 (Overhead). Table 8 measures the *time* overheads of enrichment plan generation in JENNER. This overhead is measured by calculating the average time taken by the enrichment plan generation step for different queries. The results show that (*i*) as expected, plan generation overhead increases as more tuples satisfy the query predicates (*e.g.*, see increase in planning time for $Q2$ and $Q3$ that have 500 vs. 10,000 tuples in $CandidateSet^M$) ; (*ii*) Irrespective of the selectivity, the plan generation time remains a small fraction of the overall execution time of queries (ranging from 0.3 % to 1.55%). Thus, JENNER 's adaptive approach of selecting tuples to enrich does not impose significant overhead. In terms of storage overhead, the *CandidateSet*, $CandidateSet^M$, and EP_w maintained by JENNER were less than 10 MB which is a small fraction of the data sizes (which were 9 GB and 16.9 GB as shown in Table 5). Furthermore, the state table sizes for the tuples in `wifi` and `TweetData` tables were 0.4 GB and 0.9 GB, respectively.

Experiment 3 (Epoch Size). The objective of this experiment is study how choice of epoch size affects progressiveness achieved for different queries. Figure 4 plots: 1) Time to reach (TTR) 90% quality by JENNER for Q2 and 2) Overhead as percentage of total query execution time. From Figure 4(a), we observe that when we reduce epoch size for Q2 from 8 to 4 seconds, the TTR value reduces. With reducing epoch size, JENNER becomes more adaptive choosing enrichment plans more frequently. This results in improved choices and hence increased progressiveness. However, when we reduce the epoch size even further from 4 to 2 seconds, the overheads due to frequent plan generation (which changes from 0.65 percent to 6 percent) reduces the effective time available to enrich data, thereby reducing the progressiveness achieved, thus increasing the TTR. While we focused the experiment description on query Q2, the behavior of other queries is similar though the optimal point (which for Q2 is 4 seconds) would differ from query to query. Given the impact of choosing epoch size to query performance, exploring a strategy that chooses epoch size based on query characteristics (as compared to a fixed strategy used in current JENNER) would be an interesting direction of exploration.

Experiment 4 (Impact of Pruning). As mentioned in §3.2, JENNER restricts the choice of tuples to enrich in the enrichment plan to only those that are not in the answer set of the previous epoch. We compare this strategy with the strategy of considering all tuples in $CandidateSet(R_i)$ for generating enrichment plans. Table 9 shows that the size of $CandidateSet^M$ in JENNER is significantly smaller therefore reducing the cost of enrichment plan generation. The entries in $CandidateSet^M$ that were pruned by JENNER were (almost) never chosen for enrichment. As a result, this cost reduction comes with no impact on the quality achieved by JENNER.

Query	JENNER	Naive	Query	JENNER	Naive
Q1	800	3000	Q7	500	1000
Q2	1200	5000	Q8	1000	2000
Q3	16000	50000	Q9	2000	4000
Q4	1200	2000	Q10	2400	4000
Q5	11000	20000	Q11	1000	2000
Q6	6000	10000			

Table 9: Average Number of Candidates in $CandidateSet^M$.

Query	rel. benefit	benefit	Query	rel. benefit	benefit
Q1	0.64%	32.17%	Q7	0.62%	43.14%
Q2	0.93%	61.45%	Q8	0.3%	25.45%
Q3	0.96%	82.38%	Q9	0.65 %	87.75 %
Q4	1.45%	88%	Q10	1.45%	100%
Q5	1.32%	94.17%	Q11	0.62 %	43.14 %
Q6	0.85%	58.96%			

Table 10: Percentage of enrichment plan generation time taken by using relative benefit as compared to benefit.

Experiment 5 (Impact of Optimized Benefit Estimation). This experiment compares JENNER when it uses the naive strategy (described in §3.2) for benefit estimation that has higher complexity with JENNER using the estimation approach optimized for benefit described in §3.6 (with complexity $O(n)$). Table 10 plots the percentage of time taken by enrichment plan generation of the total execution time when the benefit estimation is done using the naive versus optimized strategy. The figure shows that the naive strategy would have required 25% to 100 % of the total execution time just for benefit estimation, thereby making JENNER impractical. The optimized strategy for benefit estimation requires only a small fraction of the total execution time, enabling JENNER to allocate most of the time to enrich data and process query. As shown in Experiment 1, it results in significantly improved progressive scores.

Experiment 6 (Accuracy of Different Estimation Steps). This experiment measures the accuracy of different estimation steps used in JENNER. Recall that, at each epoch e_w, for a tuple $t_i \in R_j$ that was in the probe query result, JENNER estimates the probability that it will be in the answer of e_w (*i.e.*, generate at-least one answer tuple). Furthermore, JENNER estimates the cardinality, *i.e.*, the number of answer tuples that are generated by the tuple. Both estimations are based on the answer provided in the previous epoch e_{w-1}. We measure accuracy of both estimations by calculating the Standard Deviation from actual value (determined using the ground truth) and the estimated value.

In an epoch e_w, the deviation in estimated probability and cardinality is calculated for each tuple present in the result of probe query and then the SD is computed over all such tuples. This process is continued over all epochs and SD is reported in Table 11. We report the accuracy of probability estimation in Table 11 and the accuracy of cardinality estimation (for join queries) in Table 12. From

Query	Std. Dev.	Query	Std. Dev.
Q1	1.18%	Q7	2.43%
Q2	1.87%	Q8	1.72
Q3	2.03%	Q9	1.96
Q4	2.11%	Q10	2.05
Q5	2.31%	Q11	2.17
Q6	1.94%		

Table 11: Estimation accuracy of JENNER for the probability of satisfying the query condition.

Query	Std. Deviation	Query	Std.Deviation
Q1	2.06%	Q6	2.74%
Q2	2.37%	Q10	2.6%
Q5	3.14%		

Table 12: Estimation accuracy of JENNER for the number of answer tuples generated by the tuples in base tables.

these tables, we observe that JENNER provides accurate estimation of the probability values as well as cardinality of the answer tuples generated from the tuples in the result of probe queries.

5 RELATED WORKS

Our approach in JENNER related to several lines of prior research. Progressive query answering has been explored in approximate processing of aggregate queries [16]. Such techniques offer error bounds based on sampling [3, 33] which improves as larger samples are considered. Such techniques, however, do not consider the problem of enrichment in query processing and cannot be used in our setting. Progressive data processing has also been considered in data cleaning contexts such as entity resolution [6, 28, 32]. JENNER adapted the metric for progressive enrichment from these works on progressive data cleaning. JENNER (which explores progressive enrichment during query processing) differs from the above listed research which has not considered progressive data cleaning in the context of queries. As mentioned in §1, data cleaning during query processing has been studied in [36]. However, unlike JENNER these works have not considered progressive data processing.

JENNER is also related to work on expensive predicate optimization in [21, 23, 27]. These works have focused on both static and dynamic predicate reordering during query optimization / processing so as to minimize cost of query processing. In contrast, JENNER focused on progressive enrichment during query processing.

6 CONCLUSIONS

In this paper, we describe an approach, entitled JENNER, that optimizes data enrichment with progressive query processing. JENNER overcomes several limitations of both offline and at-ingest enrichment by optimally integrating enrichment during query processing. To overcome the increased query latency, JENNER exploits trade-off between quality and efficiency that is implicit in the realization of enrichment functions that are typically based on machine learning/signal processing techniques. Furthermore, JENNER hides latency by supporting progressive query answering that refines as data gets enriched. Our experimental section validates improvement achieved by JENNER over naive strategies to support progressiveness in query processing.

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6.1 Exploiting Joins in Probe Query

The steps for exploiting join conditions on fixed attributes for generating `probe queries` are as follows:

[Step 1]: ***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). For example, Figure 5b shows the query tree generated from the query of Figure 5a. 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 2]: ***Generating Join Graph***: This step and the next step 3 are performed to exploit the join conditions on fixed attributes in a query to filter out tuples of R_i that do not require enrichment. Given a query tree with selection conditions modified as in Step 2, 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 join graph, the nodes correspond to *reduced* relations, *i.e.*, relations with the selection conditions applied on them. If there exists a join condition between the two relations in the original query, an edge between two nodes is present and shows the join conditions between two relations expressed in CNF form.

Next, from each edge of the join graph, all the derived join conditions are removed. If after removing all derived conditions of a join node, the final condition becomes empty (*i.e.*, all the conjuncts were on derived attributes), then that edge is deleted from the graph, *i.e.*, none of the join conditions between the two relations can be exploited to reduce the set of tuples that require enrichment.[10]

E.g., in Figure 6a, we present a join-graph for the query tree shown in Figure 5b. This graph contains two nodes: $\langle N_1, N_2\rangle$, representing the reduced relations of $\langle R_1, R_2\rangle$, respectively, *i.e.*, after applying selection conditions on derived attributes of each relation. Here, the edge between N_1 and N_2 represents the join condition of ($R_1.A_4 = R_2.A_4$) (after removing the join condition on $R_1.\mathcal{A}_3 = R_2.\mathcal{A}_3$) from Figure 5b).

[10]If a query tree contains the operators of `union`, `set-difference`, or `cross product`, then they are ignored, as such operators can not be utilized to reduce the number of tuples in `probe queries` apart from the join conditions.

[Step 3]: ***Semi-join-based Reduction***: 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 a 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 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 (same as the graph shown in Figure 6a). In $ST(N_1)$, a semi-join between R_1 and the tuples of R_2 are performed based on the join condition of $R_1.A_4 = R_2.A_4$. Using this semi-join programs, this step is able to eliminate the tuples of R_1 that do not join with any tuple of R_2. This step for semi-join reduction we used is based on the seminal work on semi-join given in [9].

[Step 4]: ***Generating queries from semi-join program***: Given the semi-join programs generated an input, for each relation $R_i \in q$, this step generates a query based on the semi-join programs and the selection conditions on R_i in a straightforward manner. For example, in Figure 6b (bottom), we show the `probe query` generated for R_1, from the semi-join programs described in 6b (top) for R_1. All the tuples of R_1 that do not match with any possible values of $R_2.A_4$ are filtered out using this query.

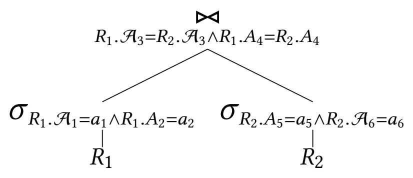
6.2 Threshold Selection

Theorem 2. *Let L be a list of tuples that can be part of the query answer and are sorted in a decreasing order of their probability of satisfying all the conditions on derived attributes of a query Q. Let L^k be a list of tuples consisting of only first k tuples from the sorted list of L. The expected quality of the possible subsets of L follow a monotonically increasing pattern with respect to k, up to a certain value of k and beyond that it decreases monotonically, i.e., it follows the pattern:* $E(Qty(L^1)) < E(Qty(L^2)) < \ldots < E(Qty(L^{\tau-1})) > E(Qty(L^{\tau})) > E(Qty(L^{\tau+1})) > \ldots > E(Qty(L))$.

Proof. We prove this theorem using F_α-measure as the quality metric of the answer set and show that if $E(F_\alpha)$ decreases for the first time due to the inclusion of a tuple in Ans_w, then it keeps decreasing monotonically with the inclusion of any further tuples. We denote $E(F_\alpha)$ of Ans_w, if τ-th tuple is included in Ans_w as F_τ. Similarly, the $E(F_\alpha)$ measures corresponding to the inclusion of $\tau+1$-th and $\tau+2$-th tuple are denoted as $F_{\tau+1}$ and $F_{\tau+2}$ respectively. We show that for a particular value of τ, if $F_{\tau+1} < F_\tau$, then it implies $F_{\tau+2} < F_{\tau+1}$.

SELECT * FROM R_1, R_2 WHERE $R_1.\mathcal{A}_1 = a_1$ AND $R_1.A_2 = a_2$
AND $R_1.\mathcal{A}_3 = R_2.\mathcal{A}_3$ AND $R_1.A_4 = R_2.A_4$
AND $R_2.A_5 = a_5$ AND $R_2.\mathcal{A}_6 = a_6$

(a) Original query.


$\bowtie_{R_1.\mathcal{A}_3=R_2.\mathcal{A}_3 \wedge R_1.A_4=R_2.A_4}$
$\sigma_{R_1.\mathcal{A}_1=a_1 \wedge R_1.A_2=a_2}$
$\sigma_{R_2.A_5=a_5 \wedge R_2.\mathcal{A}_6=a_6}$
R_1
R_2

(b) Query tree.

Figure 5: Original query and query tree for probe query generation.

(a) Join graph (Node $N_1 : \sigma_{R_1.A_2=a_2}(R_1)$ and Node $N_2 : \sigma_{R_2.A_5=a_5}R_2$).

Semi-join Programs for R_1:
$\langle N_1 \ltimes_{R_1.A_4=R_2.A_4} N_2; \rangle$

The query that filters out tuples of R_1 that do not join with any tuples of R_2:
SELECT * FROM R_1 WHERE $R_1.A_2 = a_2$ AND $R_1.A_4$ IN (SELECT A_4 FROM R_2 WHERE $R_2.A_5 = a_5$)

(b) Semi-join program and the query to filter out tuples of R_1 based on join conditions on fixed attributes (step 2 of `probe query` generation for R_1).

Figure 6: The join graph of R_1 and the semijoin program used to filter out tuples of R_1 in the `probe query` of R_1 (for the original query of Figure 5(a)).

$$F_\tau = \frac{(1+\alpha).\frac{k_1}{\tau}\cdot\frac{k_1}{k_2}}{\alpha\cdot\frac{k_1}{\tau}+\frac{k_1}{k_2}} = \frac{(1+\alpha)\cdot k_1}{\alpha\cdot k_2+\tau}, k_1 = \sum_{i=1}^{\tau}\mathcal{P}_i, k_2 = \sum_{i=1}^{|Ans_w^{MAX}|}\mathcal{P}_i \tag{15}$$

where $\mathcal{P}_i$ is the probability of a tuple satisfying all the conditions of Q and Ans_w^{MAX} is the set of tuples that have non-zero probability of being part of the query result.

Similarly the values of $F_{\tau+1}$ and $F_{\tau+2}$ are as follows:

$$F_{\tau+1} = \frac{(1+\alpha)(k_1+\mathcal{P}_{\tau+1})}{(\alpha k_2+\tau+1)}, F_{\tau+2} = \frac{(1+\alpha)(k_1+\mathcal{P}_{\tau+1}+\mathcal{P}_{\tau+2})}{(\alpha k_2+\tau+2)} \tag{16}$$

$$\begin{aligned} F_{\tau+1} < F_\tau &\Rightarrow \frac{(1+\alpha)\cdot(k_1+\mathcal{P}_{\tau+1})}{(\alpha k_2+\tau+1)} < \frac{(1+\alpha)\cdot k_1}{\alpha k_2+\tau} \\ &\Rightarrow (k_1+\mathcal{P}_{\tau+1})(\alpha k_2+\tau) < k_1(\alpha k_2+\tau+1) \\ &\Rightarrow \alpha k_1 k_2 + k_1\tau + \alpha k_2\mathcal{P}_{\tau+1} + \tau\mathcal{P}_{\tau+1} < \alpha k_1 k_2 + k_1\tau + k_1 \end{aligned} \tag{17}$$

Simplifying the above, we derive the following condition: $\frac{(k_1+\mathcal{P}_{\tau+1}+\mathcal{P}_{\tau+2})}{(\alpha k_2+\tau+2)} < \frac{(k_1+\mathcal{P}_{\tau+1})}{\alpha k_2+\tau+1}$, *i.e.*, $F_{\tau+2} < F_{\tau+1}$. □

6.3 Choosing Tuples

For each relation $R_i \in Q$, the tuples that did not contribute to the result of previous epoch, are considered for enrichment. Such tuples have higher probability of improving the quality of the query result. Below, we formalize this observation using a theorem.

Theorem 3. *Enriching a tuple t_k of a relation R_i that did not contribute to any tuple of the answer in epoch e_{w-1}, ensures that the quality of the answer set increases in epoch e_w as compared to the previous epoch of e_{w-1}. That is, $E(Qty(Ans_w)) >= E(Qty(Ans_{w-1}))$ irrespective of the outcome of enrichment on the tuple.*

Proof. We prove this theorem using the following lemmas.

Lemma 1. *If probability of a tuple $t_k \in R_i$ that contributed in Ans_{w-1} increases in e_w, then $E(F_\alpha)$ measure of Ans_w can increase or decrease from the result of previous epoch, i.e., Ans_{w-1}. If the probability decreases, then $E(F_\alpha)$ measure of Ans_w always decreases.*

If the probability of t_k increases from the previous epoch of e_{w-1}, it results in increment of the probability of the answer tuples (*i.e.*, in Ans_{w-1}) that were generated by t_k. Let the increase in sum of the probability values of the tuples that were part of Ans_{w-1} be Δ_1 and the increase in the summation of probabilities that were outside of Ans_{w-1} be Δ_2. Considering the expression of $\hat{F}_\alpha(Ans_w)$ in Equation 5, the numerator increases by the amount of Δ_1, whereas the denominator increases by a greater amount of Δ_2. Hence, the expected quality of $\hat{F}_\alpha(Ans_w)$ decreases from $\hat{F}_\alpha(Ans_{w-1})$. However, if some more tuples are added to Ans_{w-1} based on the new answer-threshold of e_w, then the value of Δ_1 can be higher than Δ_2, resulting in an increment of $F_\alpha(Ans_w)$. Similarly, when the probability of t_k decreases from previous epoch, the summation of probability values of the tuples that were part of Ans_{w-1} decreases resulting in a decrement of $\hat{F}_\alpha(Ans_w)$ value. ■

Lemma 2. *If the probability of a tuple $t_k \in R_i$ that did not contribute to any tuple in Ans_{w-1} increases or decreases in epoch e_w, then the $E(F_\alpha)$ measure of Ans_w will always be higher than Ans_{w-1}.*

If the probability of t_k increases from the previous epoch of e_{w-1}, it results in increment of the probability of the tuples that were generated by t_k and were not part of Ans_w. Let the sum of the probability values of the tuples that have probability higher than the answer threshold of epoch e_{w-1} be Δ_1 and the increase in the summation of probabilities that are still outside of Ans_{w-1} be Δ_2. Note that since the value of Δ_1 is the summation of the probability of all the newly added tuples to the answer set, the value of Δ_1 is much higher than the sum of delta values *i.e.*, Δ_2. Hence, considering the expression of $\hat{F}_\alpha(Ans_w)$ in Equation 5, the numerator increases by a greater amount of Δ_1, as compared to a lower amount of Δ_2 in the denominator. Hence, the expected quality of $\hat{F}_\alpha(Ans_w)$ increases from $\hat{F}_\alpha(Ans_{w-1})$ when t_k is enriched. ■