Approximating Aggregated SQL Queries With LSTM Networks

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Abstract—Despite continuous investments in data technologies, the latency of querying data still poses a significant challenge. Modern analytic solutions require near real-time responsiveness both to make them interactive and to support automated processing. Current technologies (Hadoop, Spark, Dataflow) scan the dataset to execute queries. They focus on providing a scalable data storage to maximize task execution speed. We argue that these solutions fail to offer an adequate level of interactivity since they depend on continual access to data. In this paper we present a method for query approximation, also known as approximate query processing (AQP), that reduce the need to scan data during inference (query calculation), thus enabling a rapid query processing tool. We use LSTM network to learn the relationship between queries and their results, and to provide a rapid inference layer for predicting query results. Our method (referred as “Hunch“) produces a lightweight LSTM network which provides a high query throughput. We evaluated our method using 12 datasets. The results show that our method predicted queries’ results with a normalized root mean squared error (NRMSE) ranging from approximately 1% to 4%. Moreover, our method was able to predict up to 120,000 queries in a second (streamed together), and with a single query latency of no more than 2ms.

Index Terms—Approximate query processing (AQP), Deep learning, LSTM, SQL, Supervised Learning

I. INTRODUCTION

While Big Data opens new possibilities for extracting unprecedented insights, this may come at the price of high processing latency and increased computational resource requirements for answering queries over large data sets [1]. That said, the concept of approximate query processing is vigorous and offers disruptive market potential. Therefore, the possibility of answering analytic queries “approximately”, at a fraction of the cost of executing the query in the traditional way, is alluring. If we can leverage the potential of approximate query processing, we may be able to speed up our ability to explore a vast amount of data swiftly and inexpensively [2]. That can be particularly useful for data analysts, who often need to discover and explore large new data sets. This task requires a fast, efficient, and cost-effective query engine and does not necessarily rely on exact answers. In these scenarios a ballpark estimation is enough for, among other things, reporting, visualization, fast decision making, and even process simulation. Additionally, there are other considerations when examining query approximation application: (1) raw data is not always available (sometimes due to privacy constraints, or compliance with GDPR regulations), (2) raw data is costly to persist or process in a database; and (3) raw data sets might suffer from inconsistent or missing data. In addition, when data becomes too large to fit in a single machine, data processing platform vendors (e.g., Hadoop, Spark, Google Cloud Dataflow) address this challenge by scaling out resources. However, this strategy may be increasingly cost-prohibitive and could be inefficient for large and distributed data sources [3]. Moreover, this approach poses a challenge when users or systems need to interact with data in real-time and with a high level of responsiveness. As a result, it has been shown that data exploration could be successfully performed in an approximate fashion [4]. This new paradigm introduces new ways to strike a balance between speed, resource consumption, and computation accuracy.

Previous methods for query approximation focused on building representative data samples. The strength of these approaches relies on the ability to use statistical methods to provide a confidence interval for the approximated result. However, for complex and dynamic datasets, novel sampling methods must be utilized and recalculated to keep in sync with the database [5]. Other methods utilized data summaries in advance to represent raw data in a compact and aggregated form [6]. However, the solutions developed so far with this approach are aimed at approximating predefined query configurations [7], the same way online analytical processing (OLAP) cubes are designed. This raises questions regarding the usefulness of these solutions for generic data explorations [8]. Other systems were aimed to support query approximation in streaming, transnational, and interactive systems using distributed data processing engines (e.g., Hive, Spark SQL, Impala, Amazon Redshift, Presto, etc.) [9], [10]. Although this method yields accurate and rapid results (depending on Spark cluster size and tuning), it can be cost prohibitive and still requires both storing and accessing the data. In this research we introduce a new method that can produce high-value approximated results for SQL queries by training a LSTM network, without a-priori domain knowledge, to learn the relationship between the different elements of SQL queries and their results. The proposed method consists of three main phases. In the first phase, a rich set of analytical (aggregated)
SQL queries are randomly generated. We argue that this set of queries, being generated randomly and in high volumes, represent different perspectives of the raw data. The queries’ structure consists of categorical "WHERE" statements, i.e., `WHERE col IN (val1, val2,...)`, or continuous "WHERE" statements, i.e., `WHERE col BETWEEN (min, max)`. In the second phase we use hot encoding technique to encode the queries into meaningful numeric matrices. Finally, we utilize a neural network (NN) model to learn queries results approximation based on the training set.

Our proposed approach uses neither summaries nor samples to aggregate the data. Instead, by generating a very large and rich training set of SQL queries, we represent many different user perspectives on possible data exploration paths. Consequently, we believe that this method can generalize to approximate new queries. Moreover, our method processes queries on large datasets rapidly and in a fixed response time, regardless of the required rows scan. Post model training, our proposed method does not require persisting nor accessing the data during query processing time, another advantage over previous methods.

We applied the proposed method on 12 different datasets. We evaluated the method predictions (approximations) using large hold-out testing sets of queries. To evaluate model accuracy, we used the normalized root mean square error (NRMSE) metric. For assessing the method execution performance, we used queries throughput (QT) and query latency (QL). Our results show that the proposed solution approximates query results within a controlled range of normalized error (NRMSE), between 1% to 4%. In terms of execution latency, query latency (QL) ranges from approximately 2 ms/q (millisecond per query) to 30 ms/q. We also evaluated method performance on large batches of queries (processed in parallel on a GPU). Our method demonstrated a query throughput (QT) of approximately 2,000 queries per second to 120,000 queries per second, depending on input dimension and the LSTM network architecture (number of neurons and number of hidden layers).

In summary, the contributions of this paper are as follows:
- we introduce a novel approach for producing lightweight data representation layer in the form of a NN;
- we propose an effective query processing method, with lightning-fast query response times for big data platforms;
- we present a forceful concurrent approach to process SQL queries with GPU technology;
- Finally, we make our code and datasets publicly available.

II. RELATED WORKS

Query approximation by sampling. Previously, different approaches to approximate database queries have been introduced, with the majority based on executing queries over smart samples of data [5]. These approaches rely on the ability to use a statistical method to deliver an approximated result within confidence interval. However, for datasets with many columns, those samples need to be quite large, consequently limit both the performance and the applicability of this approach. While several research projects have explored the benefits in data sampling [11], [12], [13], these methods are not widely used in streaming engines [14], [15] with the noteworthy exception found in the SnappyData project [9], which uses the notion of High-level Accuracy Contract (HAC), which is also used in VerdictDB [16]. When memory is limited (as is often the case), sampling may help to enable in-memory processing.

However, majority of AQP systems use stratified sampling based on prior knowledge (which might not be always available) of the data distributions [17], [18], [19]. Specifically, it had been demonstrated that uniform random samples are less effective for answering "Group By" which are important when conducting data exploratory analysis while biased sampling show better efficiency for these sort of tasks [20]. Moreover, these methods usually require a substantial preprocessing time for data preparation towards known set of queries. While effective for some use-cases, this approach might lack this efficiency when dealing with interactive data exploration, characterized by the unknown queries [21], [20].

Query approximation by data summaries. With this approach, query approximation is based on preparing data summaries in advance [6]. This approach and the previous one (sampling) are complementary [9]. However, the solutions developed so far for building data summaries are aimed at approximating predefined query configurations [7], the same way OLAP cubes are designed. This raises questions regarding the effectiveness of these solutions for generic data explorations, for which a rich range of query structures are needed to address the raw data from many views [8]. In contrast, with our approach we make no assumptions as to which data aspects are more interesting. The idea of summarizing data to reduce query latency, introduced by this project [22], was to build histograms. Practically, there is a substantial body of research on the use of data summaries in relational database management system (DBMS) optimizer added [23].

Batch-approximate query processing. The field of query approximation is closely related to the field of approximate computing, where the main goal is to produce results good enough to be accepted while minimizing cost and latency [24]. An example for reducing cost and latency introduced in this project [25], includes a rough query feature that, given a query, determines the bounds for actual query results. This idea was inspired by a previous database paradigm [26] in which summary rows were classified as relevant, partially relevant, or irrelevant to a specific SQL query.

Interactive approximate query processing. The SnappyData [9] engine, developed in 2015, was designed to support query approximation in streaming, transnational, and interactive systems. It is based on many insights gained from the BlinkDB project [10]. Spark, a contemporary distributed in-memory data processing engine, manages smart query caching (referred to as delta update queries) with confidence intervals utilized to minimize loss. It also handles on-line aggregation to reduce processing latency by presenting preliminary approx-
imated results immediately on processing a small portion of the whole dataset. Oracle Database uses the HyperLogLog (HLL) algorithm for approximate ‘count distinct’ operations. Processing a large volume of data is significantly faster using HLL compared with the exact aggregation, especially for datasets with a large number of distinct values. Also, HLL requires a significant number of samples to determine data cardinality, consuming time and computational resource. It is uncertain how effective HLL is when used with a rapidly changing data with high entropy.

Query approximation with ML. As mentioned above, the database research community has proposed novel techniques for AQP that could give approximate query results in orders of magnitude faster than the time needed to calculate exact results. In this work, the usage of deep generative model, specifically Variational auto-encoder (VAE), for answering aggregate queries specifically for interactive applications such as data exploration and visualization. As much as this method is similar to our proposed method, one significant difference rely in the way the DL model is being used: while in this method the model is used to generate samples distributed tightly similar to the dataset distributions and then execute the queries on these samples, our method relies on the intrinsic structure of the LSTM network to both learn the dataset distributions and answer the approximated result. Similar to our approach, this work utilized ML models to approximate aggregated SQL queries. Specifically, gradient Boosting Machines (GBM), XGBoost and LightGBM were trained to predict the aggregated queries’ result. These models have scalable implementation which allows handling large, high dimensional and sparse input. However, our method, not only scales to high dimensions and large input, but it can also be executed concurrently on a GPU.

III. PROPOSED METHOD

The proposed method uses a process to generate the training set which is used for fitting the query approximation model. This process is divided into four phases: (1) generating artificial SQL queries (Section III-C), (2) obtaining the labels for the training set by executing the queries on the database (Section III-D), (3) inducing an encoder for transforming the queries into numeric matrices (Section III-E) and finally (4) training a neural network to approximate the queries labels (Section III-F).

A. Query template and notations

As an example, assume a table ‘transactions’ that includes computer sales from either physical or online shops. The table includes the attributes: ‘hour’ (time of transaction), the ‘store_type’ (physical or online), the ‘computer_type’, the ‘harddisk_size’ (hard disk size in Gb), and the ‘sales’ (amount in $). The method is designed to generate many instances of queries conforming to a query template defined by the following:

- \( attr^{(n)} \) – denotes a nominal data attribute in the dataset (e.g., ‘computer_type’, ‘store_type’).
- \( A = \{a_1, a_2, \ldots\} \) – denotes the set of optional aggregation functions (e.g., avg, count).
- \( a_i(attr) \) – denotes an aggregation function \( a_i \in A \) that is applied on valid attribute \( attr \) (either \( attr^{(c)} \) or \( attr^{(n)} \)) in a select query (e.g., avg(‘sales’), max(‘revenue’), or count(‘id’)).
- \( between_{attr^{(c)}}(l, u) \) - a ‘between’ constraint argument defined on a continuous data attribute \( attr^{(c)} \), where \( l \) is a lower bound and \( u \) is an upper bound on the values of \( attr^{(c)} \).
- \( in_{attr^{(n)}}(v_k) \) - an ‘in’ constraint argument defined on a nominal data attribute \( attr^{(n)} \), where \( v_k \) is a single possible member of \( attr^{(n)} \).

B. Support “Group By” queries with multiple aggregations

We supported queries with “Group By” clause on multiple \( attr^{(n)} \). This enables flexibility in exploring and analyzing large datasets on one side, but poses the following two challenges on the other side: (1) learning different data distribution (characterized by the aggregation functions), and (2) learning an output which may have varying dimensions (while NN models expects fixed output types and dimension). The latter results from the fact that a “Group By” query can return a table of one or more rows as shown by the example in Table II which is the result of the following running example query:

\[
SELECT computer_type, store_type, AVG(sales), MEDIAN(revenue)
FROM transactions WHERE hour BETWEEN (20 and 23) AND harddisk_size between (121 and 820)
GROUP BY computer_type, store_type
\]

To tackle these challenges, we transform each “Group By” query to multiple ‘flat’ queries which returns one scalar, i.e., a result of a single aggregation function \( a_i(attr) \). This way every LSTM network has an output layer which consists of a single linear output neuron to approximates the query result.

To explain this in more details we refer to our example above. Assuming Table II is a result set returned by this query. Consequently, eight reduced ‘flat’ queries will be extracted from this table as follows (squared brackets contains the reduced query results):

1) \( SELECT AVG(sales) \) FROM transactions WHERE store_type IN (‘online’) AND computer_type IN (‘Mac’) AND hour BETWEEN (20 and 23) AND harddisk_size BETWEEN (121 and 820) \[102\]
2) \( SELECT AVG(sales) \) FROM transactions WHERE store_type IN (‘online’) AND computer_type IN (‘IBM’) AND hour BETWEEN (20 and 23) AND harddisk_size BETWEEN (121 and 820) \[180\]
3) \( SELECT AVG(sales) \) FROM transactions WHERE store_type IN (‘physical’) AND computer_type IN (‘Mac’) AND
TABLE I: AQP project benchmark comparison table.

| Paper | Name          | Flat Query Latency in sec. | Guaranteed Error bound | GPU Support | Training Requirement | Preprocessing/Sampling Requirement | Queries Batch Processing Support | Result Confidence |
|-------|---------------|-----------------------------|-------------------------|-------------|----------------------|------------------------------------|----------------------------------|-------------------|
| [29]  | Hive Hadoop   | 400                         | no                      | yes         | no                   | yes                                | yes                              | NA                |
| [31]  | Hive Spark    | 40                          | no                      | yes         | no                   | yes                                | yes                              | NA                |
| [32]  | BlinkDB       | 2                           | 2-10%                   | no          | no                   | yes                                | yes                              | 95%               |
| [9]   | SnappyData    | 1.5                         | NA                      | no          | no                   | yes                                | yes                              | NA                |
| [18]  | VerdictDB     | 1                           | 2.6%                    | no          | no                   | yes                                | yes                              | 95%               |
| [34]  | DICE          | 0.5                         | 10%                     | no          | no                   | yes                                | no                               | NA                |
| [25]  | DeepGen       | NA                          | 0.1-1.25%               | yes         | yes                  | yes                                | yes                              | No                |
| [19]  | ML AQP        | 20                          | 1-5%                    | no          | yes                  | yes                                | no                               | NA                |
| Our method | Hunch (DL) AQP | 10                          | <2.5%                   | yes         | yes                  | yes                                | yes                              | NA                |

TABLE II: An example for a group by result set.

| store_type | computer_type | AVG(sales) | MEDIAN(revenue) |
|------------|---------------|------------|-----------------|
| online     | MAC           | 102        | 85              |
| online     | IBM           | 80         | 82              |
| physical   | MAC           | 95         | 61              |
| physical   | IBM           | 94         | 50              |


C. SQL queries generation

The goal of this phase is to generate a large representative set of aggregated SQL queries $q_i$ that broadly represents the raw data.

**Define query template parameters.** A query template is define by the domain expert which provides for each query template: (1) the SELECT clause parameters, and (2) the filter template (i.e., the WHERE clause parameters).

In this phase, first, the domain expert choose a set of aggregation functions and a set of data attributes. Then, the method constructs a SELECT clause consisting of the selected aggregation functions, which are applied on a set of valid data attributes, either continuous or nominal, $\{a_i(\text{attr}_j)\}$.

All aggregation functions can be applied on continuous data attributes, whereas the only aggregation functions that can be applied on a nominal attribute are ’count’ and ’countDistinct’. In our example, assuming the domain expert chooses to apply all aggregation functions $\text{AVG(sales)}, \text{MEDIAN(sales)}$, $\text{AVG(revenue)}, \text{MEDIAN(revenue)}$

As mentioned, each $\{a_i(\text{attr}_j)\}$ will have a designated model (see Section III-F) fitted to learn its distribution. This means that the training set will be split for each $\{a_i(\text{attr}_j)\}$ and learned separately. In our example the first training set will consist of queries with AVG(sales) in the select clause, the second training set will consist of queries with MEDIAN(sales) and so on.

Next, the domain expert can choose a filter template which includes the list of continuous data attributes $\text{attr}^{(c)}$ and nominal data attributes $\text{attr}^{(n)}$ that can be included in each query. Then, for each querytemplate defined by the domain expert, the method generates a set of queryinstances as follows.

**Generating filter.** In this step, the method generates a rich set of filters applied on (1) continuous data attributes $\text{attr}^{(c)}$ and (2) nominal data attributes $\text{attr}^{(n)}$ in the following manner.

1. For each $\text{attr}^{(c)}$, we calculate the intervals defined by: the minimum value, the first quartile (25%), the median, the third quartile (75%), and maximum value (four intervals). In order to select the lower and upper bounds of a
continuous attribute constraint \( \text{between}_{\text{attr}}(l, u) \) we select two intervals randomly. Then, from each selected interval, we randomly choose a value (from a uniform distribution). This results into two numeric values which form a filter, such that the smaller value will define the lower bound and the larger value will define the upper bound. For instance, assume the \( \text{harddisk}\_\text{size} \) continuous attribute values spanning from 1 to 1000. Given those values, minimum=0, 25% quartile=250, median=500, the 75% quartile=750 and maximum=1000, and assuming the selected intervals are [0,250] and [750,1000] the continuous constraint might take the values \( \text{between}_{\text{harddisk}\_\text{size}}(121,820) \)

2) To construct a nominal filter, the method uses an "IN" constraint argument defined on a nominal data attribute \( \text{attr}^{(n)} \), filtered by \( v_k \) - a possible member of \( \text{attr}^{(n)} \). To determine which member to use in each filter, the method constructs a "Group By" term on the nominal attribute and once the query is executed against the dataset, the method systematically extracts all possible combinations of members which exists in the result set and constructs a nominal filter for each one. In our example, one combination of members for \( \text{store}\_\text{type} \) and \( \text{computer}\_\text{type} \):

\[
\{ \text{in}_{\text{store}\_\text{type}}(\text{online}), \text{in}_{\text{computer}\_\text{type}}(\text{Mac}) \}
\]

3) Finally, each of these combinations of nominal filters is paired with each of the continuous filters to form a query filter; for example, \( \{ \text{between}_{\text{harddisk}\_\text{size}}(121,820), \text{in}_{\text{store}\_\text{type}}(\text{online}), \text{in}_{\text{computer}\_\text{type}}(\text{Mac}) \} \).

D. Obtaining labels for the training set

To build a supervised dataset for training the proposed method needs to obtain real query results; therefore, our method runs the set of generated queries \( Q \) against the data source. As LSTM model requires a relatively large number of training examples, the system needs to generate and execute hundreds of thousands of queries. However, by using "Group By" queries, the actual size of \( Q \) is much smaller.

E. Encoding queries

At this stage, a list of "flat" SQL queries and their real label (result) is available. Since neural networks can take only numeric input, we encode the queries into numeric matrices (see Figure 4) via an encoder model which is constructed on the fly (during SQL queries generation), making use of a multi-hot encoding technique. The reason for choosing this type of encoding is to enable a distinctive representation for discrete data entities. That way, entities like 'Mac' and 'IBM' will be represented by perpendicular bit-wise vectors to signal the LSTM which entity exists in the input (query). The encoding process starts by mapping all unique query tokens that exist in the training set \( Q \) and assigns each with a numeric sequential value, as illustrated in Figure 4 (for example, the token \( \text{avg(sales)} \) is mapped to the value 00001). Each numeric value is then transformed into binary (base 2) representation. Numeric query tokens (scalars) are also transformed into their binary (base 2) representation. Using this representation method, each query token is represented as a vector stacked into a matrix, as presented in Figure 1; this vector is the input, representing a query to the LSTM network. We exclude tokens that do not change over queries, e.g. SELECT, table name, FROM, etc.

F. LSTM network generation and training

At this point, the algorithm pipeline builds an LSTM network. The network weights were initialized according to the Xavier initialization method [36]. The primary reason for choosing this architecture was related to the language aspects of the problem, where SQL queries are treated as sentences with a structured order of clauses and tokens. Moreover, the LSTM was required to learn the query structure (i.e. SELECT, FROM, WHERE, etc.) and the irrelevancy of WHERE clause statements order (since only AND operator is used). A 50% dropout was configured on all training processes to reduce over-fitting.

An LSTM network has proved its efficiency in learning complex sequential data, which was our initial motivation for selecting this architecture [37]. Upon data updates, we retrain the LSTM from its last state on a training set consists of queries which span on the new data. We will carry out future research to optimize approach to tackle frequently changing datasets.

IV. EVALUATION

A. Datasets

The system was evaluated using 12 unique data sets, both proprietary and open source. The data sets characteristics are presented in Table III.

B. Training set partitioning

For each dataset, a training set was generated and split, using python package sklearn cross_validation (train_test_split), to three datasets: (1) training set - 70% of the queries, (2) validation set - 15% and (3) testing set - 15%. The training set was used for training the LSTM network, the validation set was used to assess the LSTM loss (MSE) during training and the testing set was used for model validation, where we evaluated the success of the entire training process.

C. LSTM training cost function

The LSTM network is trained to minimize a quadratic cost function, defined as:

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2
\]

where \( Y_i \) is the real query result, \( \hat{Y}_i \) is the model approximated query result, and \( n \) is the batch size.
D. Evaluation metrics

Since the target variable (query result) is continuous, a simple regression cost function such as MSE or RMSE can yield an unnormalized range of values and is greatly influenced by the problem scale. For this reason, we have chosen a normalized version of RMSE (NRMSE), defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n}}$$  \hspace{1cm} (2)

where $i$ represents a query from the testing set, $Y_i$ is the real query result, $\hat{Y}_i$ is the model approximated query result, and $n$ is the number of testing set queries.

$$NRMSE = \frac{RMSE}{Y_{max} - Y_{min}}$$  \hspace{1cm} (3)

where $Y_{max}$ is the max query result and $Y_{min}$ is the min query result. Normalizing the RMSE facilitates the comparison between data sets with different scales.

In addition, we calculated $QL$ – the duration of a single query execution in milliseconds, as well as the queries throughput at batch mode (using GPU), referred to as $QT$ and measured as follows:

$$QT = \frac{T}{Q}$$  \hspace{1cm} (4)

where $T$ is the total latency of the batch mode prediction operation and $Q$ is the number of queries used in the testing set.

Lastly we calculate $ME$ mean entropy $\overline{H}$ for data set predictors (all columns in where clause), while for each categorical column entropy is calculated as:

$$H(X) = -\sum_{i=1}^{n} P(X_i) \log_2 P(X_i)$$

Where $i$ varies from 1 to $n$ – number of distinct values for a categorical column and $P(X_i)$ – is the number of rows containing value $i$ divided by total number of rows. For continuous columns, we first discretize them to categorical columns using 10 equal-length bins and then use the above entropy calculation. We chose 10 bins to allow enough bins to capture the column variance, but not so many as to prevent reasonable calculation time.

$$\overline{H} = \frac{1}{M} \sum_{j=1}^{M} H(X)_j$$

Finally, we calculated the LSTM input layer variance using Tensorflow moments:

$$H(X) = -\sum_{i=1}^{n} P(X_i) \log_2 P(X_i)$$

Data complexity which is expressed by the data mean entropy $ME$, target column STD (standard deviation) determine the problem complexity and influences how well and how quick the LSTM can learn the data converge. According to these measures, we have configured a hyper-parameters heuristic that we found, by trial and error, to be effective. We use this heuristic to tune the models and as a baseline value for a reasonable and practical search space. We have decided not to pursue costly grid-search strategies due to budget limitations and time constraints. In future work, optimizing the search using more advanced search methods can be beneficial.

https://www.tensorflow.org/api_docs/python/tf/nn/moments
TABLE III: Datasets characteristics.

| Dataset              | Proprietary data source | Target function | # attr\((n)\) | # attr\((c)\) | # rows | queries | Mean Entropy | Input Tensor variance | Target column STD |
|----------------------|-------------------------|-----------------|---------------|---------------|-------|---------|--------------|----------------------|------------------|
| average_revenue      | Yes                     | avg (revenue)   | 3             | 2             | 1000000000 | 5205078 | 6.293        | 0.154                | 404000000         |
| average_success_rate | Yes                     | avg (build_time)| 2             | 3             | 2333293    | 415791  | 2.264        | 5.421                | 19.196           |
| count_product_pass   | Yes                     | count (machine_id) | 1             | 5             | 4000000000 | 811928  | 0.942        | 0.151                | 2350516          |
| count_product_fail   | Yes                     | count (machine_id) | 1             | 5             | 95484     | 451173  | 0.942        | 0.153                | 8613             |
| count_product_false_calls | Yes                      | count (machine_id) | 1             | 5             | 350232    | 378111  | 0.942        | 0.202                | 215315           |
| count_churn_customers | Yes                     | count (customer_id) | 4             | 3             | 9263836   | 62092   | 2.782        | 0.13267              | 530              |
| sum_duration_call    | Yes                     | sum (duration)  | 3             | 2             | 9349      | 100000  | 3.198        | 0.167                | 861              |
| average_ibm_price    | No                      | avg (close_price) | 1             | 2             | 1048575   | 340489  | 0.343        | 0.125                | 471              |
| average_realestate_price | No                    | avg (price)    | 3             | 2             | 22489348  | 508086  | 2.113        | 0.105                | 236              |
| avg_stock_close_price | No                      | avg (close_price) | 2             | 1             | 63267     | 8721    | 5.703        | 0.157                | 118              |
| average_paid_days    | Yes                     | avg (actual_paid_days) | 3             | 2             | 100000000 | 508365  | 0.451        | 0.099                | 25667553         |
| average_build_duration | Yes                    | avg(duration)  | 1             | 3             | 22276094  | 325935  | 0.993        | 0.129                | 7487             |

E. LSTM Hyper-Parameters tuning

We found that hyper-parameters tuning decision are greatly affected by data set characteristics. These characteristics, which naturally vary between data sets, determine how well the LSTM can learn the data and approximates queries, and how fast it will converge. Specifically we have identified that the following metrics mentioned above, best define the model complexity: (1) \( ME \) (mean entropy), (2) LSTM input tensor variance, and (3) target column variance. Notably, the latter determines the model time to converge, and the risk of converging to sub-optimal solution and mitigated by \( LR \) (learning rate) and LSTM number of neurons, as detailed next.

- **Learning rate** – varies between 0.000001 to 0.01, depending on the LSTM cost function (explained next) fluctuation over batches and on the number of epochs (derived from the time frame we allow for training). We allow smaller learning rate, if the number of epochs is sufficiently high to enable a reasonable loss convergence to an optimal solution.
- **Batch size** – varies from 32 to 2048, depending on an input dimension (query length and embedding space). We noticed that larger batches, if there is sufficient GPU memory, are preferable to shorten learning processes.
- **Optimizer** – we chose RMSProp, which decays slower and is adapted to our typical range of learning rate [26]. This optimizer has proved better than any other optimizer that we tried (Adam, Nadam, AdaGrad, AdaDelta, AdaMax, SGD).
- **Weights initialization method** – Initial weights values have been determined by state-of-the-art Xavier’s method [38].

TABLE IV: LSTM hyper-parameters tuning

| Target Variable       | STD range                    | Learning Rate | LSTM size (# neurons) |
|-----------------------|------------------------------|---------------|-----------------------|
|                       | [10 , 1000)                  | 0.001         | 125                   |
|                       | [1000 , 100000)              | 0.0001        | 256                   |
|                       | [1000000 , INF)              | 0.000001      | 512                   |

- **Number of lstm neurons** – varies from 128 to 512, depending on target variable distribution standard deviation.
- **Dense layer** – one dense layer with 200 or 400 neurons. Regarding LR (learning rate) and number of LSTM neurons, we saw a soft trend (based only on these 12 points) where a higher target variable STD requires a finer (smaller) LR and possibly more computation units (LSTM neurons), as seen in the following Table [IV]

F. DNN training cost function

The DNN is trained to minimize a quadratic cost function, which is also known as mean squared error, maximum likelihood, and sum squared error, defined as:

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2
\]

\(Y_i\) – real query result
\(\hat{Y}_i\) – model approximated query result
\(n\) – batch size

Baseline methods and metrics. We have chose three baseline methods: (1) VerdictDB [16], a novel AQP method which
accelerates analytical queries, (2) a random sampling approach [5] where each dataset is sampled randomly without replacement down to 10% of the source rows count, and (3) a random LSTM which was not trained and tweaked to yield random output within target column distribution boundaries (min/max). We use mean query latency (QL) and NRMSE metrics to evaluate performance and accuracy respectively.

G. Experiment Results

For each data set, Table V specifies LSTM network training parameters and the trained model performance metrics.

Accuracy (NRMSE). As expected, NRMSE for the largest model (dataset #5) with 512 LSTM neurons layer and a dense layer with 400 neurons, was the smallest (most accurate) with a value of 0.12 while for the smallest model (dataset #6) with 128 LSTM neurons layer and a dense layer with 200 neurons, was the largest with a value of 3.75. The results were obtained on a hold-out set (the testing set) which was not present during training. However, since no methodical hyper-parameters grid search had been performed (due to limited resources) we cannot make a clear statement as for the relation between the LSTM architecture and the accuracy.

Predictions vs. query results. In Figure 2 the method predicted values are visualized with comparison to the original query result per dataset. Overall we see that the method approximations are well correlated with the query results. However, in specific cases (Figure 2 dataset #2), for the same query result the LSTM yields different approximations (not desired).

Model loss convergence. We saved multiple model checkpoints along the training to explore how the LSTM loss converges along epoch progression as seen in figure 3. It is evident that loss decays exponentially as epochs progress, which might suggest a desired learning process.

Query latency performance. Using GPU, a throughput (QT) of approximately 121k queries per second was measured, while a single query latency (QL) for our largest (slowest) model lasted 28 ms. Generally and as can be expected, as the LSTM network is more complex (more layers, more neurons, larger input), latency goes up and throughput goes down.

Baseline comparison results. Figure 4 and Figure 5 depicts the accuracy and latency of Hunch, as well as of the baseline methods: VerdictDB [16], random 10% sampling, and the random LSTM on all datasets. We used the same test set of SQL queries on the same twelve reported datasets which were used to evaluate our method. In addition, all benchmarking results are listed in Table VI. All methods (except Hunch) ran on Windows Server with 16 CPU cores with 64Gb RAM. LSTM based methods ran on Nvidia GeForce GTX 1060. It is evident that our method show dominance both from accuracy and performance perspective over the majority of the experiments.

H. Discussion

Our proposed solution predicts query results within a controlled accuracy (NRMSE), ranging between approximately 1% to 4%. QT ranges from approximately 2.0 ms/q to 30.0 ms/q for a single query. Moreover, for large datasets (20M - 4B records), our method is two orders of magnitude faster from the compared methods. In batch mode (utilizing GPU batch processing) the method was capable of calculating results at up to 120,000 queries per second. These encouraging results led us to consider this solution as a novel query approximation tool, capable of saving heavy-lifting database processing and data transfer from the consumer to the database and back. Our method can predict missing data points and data points that span in the future. For instance, when the system was trained on temporal dimensions (e.g., dates in where clause), our 10th dataset (named avg_stock_close in Table III) results shows a NRMSE of approximately 0.2% for testing set with future dates (which were not available during training). Comparing our method to other methods, our method is resilient to growing scale of datasets (2M rows). This is because our method uses the LSTM network to calculate SQL query’s result and is decoupled from the dataset after training process.
Table V: Datasets models performance and accuracy metrics.

| #  | Dataset name          | LR  | Batch size | LSTM neurons | Dense Neurons | input shape | GPU Type | QT (q/s) | QL (ms/q) | NRMSE | LSTM size (Mb) |
|----|-----------------------|-----|------------|--------------|---------------|-------------|----------|----------|-----------|-------|----------------|
| 1  | average_venue         | 1.E-05 | 2048 | 512 | 200 | (7,17) | GTX | 25501 | 2.79 | 1.57 | 3.51 |
| 2  | average_access_ate    | 1.E-02 | 1024 | 128 | 200 | (7,17) | GTX | 43512 | 2.55 | 3.75 | 2.51 |
| 3  | count_redact_ass      | 1.E-04 | 2048 | 512 | 400 | (16,18) | GTX | 1881 | 27.41 | 0.07 | 3.84 |
| 4  | count_redact_all      | 1.E-03 | 1024 | 512 | 400 | (16,18) | GTX | 6185 | 28.60 | 0.51 | 3.84 |
| 5  | count_redact_also_all | 1.E-04 | 1024 | 512 | 400 | (16,18) | GTX | 1889 | 28.2 | 0.12 | 3.84 |
| 6  | count_hurn_customers  | 1.E-02 | 2048 | 128 | 200 | (17,17) | GTX | 21304 | 3.55 | 0.14 | 2.56 |
| 7  | sum_uuration_all      | 1.E-02 | 128 | 256 | 200 | (7,20) | GTX | 1877 | 2.84 | 0.01 | 2.58 |
| 8  | average_bm_price      | 1.E-02 | 128 | 256 | 200 | (7,62) | GTX | 26667 | 3.29 | 0.17 | 2.91 |
| 9  | average_realestate    | 1.E-02 | 1024 | 128 | 200 | (13,61) | GTX | 76086 | 2.81 | 0.32 | 2.9 |
| 10 | avg_tock_lose_rice    | 1.E-02 | 2048 | 128 | 200 | (6,61) | GTX | 121259 | 4.03 | 0.17 | 2.9 |
| 11 | average_oil_als       | 1.E-05 | 2048 | 128 | 200 | (27,7) | GTX | 62046 | 2.05 | 0.97 | 2.63 |
| 12 | average_uild_uation   | 1.E-04 | 1024 | 256 | 200 | (10,32) | GTX | 12159 | 4.01 | 0.15 | 2.74 |

Table VI: Baseline comparisons results.

| Dataset Name (# rows) | NRMSE Hunch | NRMSE Random (no training) LSTM | NRMSE 10% Sampling Method | NRMSE VerdictDB | Verdict Latency | Hunch Latency | Latency 10% Sampling Method |
|-----------------------|-------------|---------------------------------|---------------------------|-----------------|----------------|--------------|---------------------------|
| sum_duration_call (1K)| 0.01 | 6.95 | 121.50 | 0.25 | 4.51 | 2.84 | 120.50 |
| avg_stock_close_price (63k)| 0.17 | 10.20 | 102.60 | 0.51 | 35.53 | 4.03 | 102.60 |
| count_product_fail (95k)| 0.51 | 1.06 | 185.50 | 0.85 | 736.10 | 27.41 | 185.50 |
| count_product_false_calls (350k)| 0.12 | 1.48 | 145.60 | 1.15 | 45.75 | 28.60 | 145.60 |
| average_tbm_price (1M)| 0.61 | 61.50 | 180.40 | 0.55 | 4.79 | 3.29 | 180.40 |
| average_success_rate (2M)| 3.75 | 30.15 | 170.20 | 1.55 | 0.21 | 2.55 | 170.20 |
| count_customer (10M)| 0.14 | 1.06 | 125.20 | 0.56 | 50.08 | 3.55 | 125.20 |
| average_build_duration (20M)| 0.15 | 7.30 | 185.10 | 0.25 | 122.25 | 4.01 | 185.10 |
| average_realestate_price (20M)| 0.32 | 0.85 | 175.40 | 0.62 | 660.24 | 2.81 | 175.40 |
| average_paid_days (100M)| 0.97 | 29.10 | 202.50 | 0.83 | 890.45 | 2.05 | 202.50 |
| average_revenue (1B)| 1.57 | 2.02 | 250.20 | 2.50 | 867.90 | 2.79 | 250.20 |
| count_product_pass (4B)| 0.07 | 2.51 | 1500.10 | 0.05 | 7361.04 | 27.41 | 1500.10 |

is done. From accuracy point of view, our method expected consistency shows lower NRMSE than the sampling method and versus the random LSTM network. One shortcoming is the limited query structure model which currently does not support join, exist operation and other sub-queries operations. This limitation is on our road map for future research.

V. Conclusion and Future Research

The primary goal of this research was to develop a novel approach for AQP over massive datasets. A secondary goal was to show how our method can serve as an interactive analytical tool, demonstrating rapid responses processing a queries on large datasets. Existing querying methods require ongoing access to the underlying data. Once training is done, our proposed method does not require online connection to the data to approximate SQL queries. This opens up an array of potential use cases for big data analytics. Going forward, we aim to develop our method to scenarios where dataset changes frequently, thus the model should adapt more quickly to new data. In addition, we plan to enrich the method to support additional SQL operations. 

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Fig. 2: Visualizing LSTM model SQL queries approximations results on all datasets.

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Fig. 3: Model loss (NRMSE) convergence along epochs.