Energy-Aware Allocation of Approximate Query Processing over Data Streams with Error Guarantee

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***Abstract*—With increasing real-time and resource-intensive requirements, approximate computing is widely adopted to improve the performance of query processing over data streams. However, existing works concentrate on simple queries with single-step operations, such as point or join queries. There are a large number of nested queries with selection or filtering operations before aggregation. In this poster, we focus on approximate *nested* stream queries. We first propose a novel approximate model, SCM-sketches, that makes two-stage approximation for nested query answering with guaranteed errors. In the first stage for nested filtering operations, we use the sampling method to compress the arriving data. Then in the second stage, a sketch is used for further aggregation or join operations. We also theoretically analyze the effect of error propagation on approximate errors. Compared with existing sketch-based methods, experiment results with real-life datasets verify the effectiveness of SCM-sketches.**

I. Introduction

Recently, online query processing techniques over high-volume data stream have been commonly applied to extract valuable information in various emerging applications. To meet the low-latency requirement of data stream processing, most data analytics applications are based on distributed stream processing systems (DSPS), such as Apache Spark, and Flink. However, explosive data volume and real-time requirements make it challenging to meet the desired Quality of Service (QoS). Thus, approximate computing emerges as an effective solution paradigm, and can be applied to DSPS for achieving low latency and efficient resource utilization.

To meet QoS in DSPS, approximate techniques such as sampling [1] and sketches [2], are employed to build data summary for aggregate queries. The combination of approximate computing and DSPS can effectively satisfy the real-time and resource intensive requirements. Most existing works consider approximate queries for single-step operations and focus on simple query processing statistics. Common operations include point (*e.g.,* frequency and heavy hitters), inner-product and self-join queries. In typical queries, a large number of queries need to perform selection or filtering before aggregation, which we refer to as nested stream query. For example, Figure 1 computes online order statistics that counts orders made by consumers whose salary are greater than 1500 ($R.Salary > 1500$). In DSPS, dependencies between query operators constrain the usage of approximate techniques in multiple stages. Because errors generated by the previous operations are propagated to the next operation, which makes it hard to control the output quality. For approximate query processing, it is of vital importance to obtain an approximate result with guaranteed accuracy specified by the user, so as to avoid the loss of information value.

For efficient query processing, we first observe that two approximate techniques, sampling and sketches, can be combined to achieve guaranteed-error for nested stream queries: when running queries in stream computing environments, sampling and sketches can be applied at different stages. Based on this observation, we propose a novel approximate model, sampled count-min sketches (SCM-sketches) for efficient query processing over data streams. For example, in Figure 1, we first use the sampling method to compress the arriving data and produce the intermediate output. Then with the sampling result as an input, a sketch-based method is utilized for later operations (*e.g.,* point or join) to obtain the approximate result. A sketch summary is efficient for estimating point, self-join and inner product queries in high-speed data streams. To control the quality of query results, we consider the dependency between operations in stream processing and analyze the effect of error propagation based on error estimation. To optimize the query execution in DSPS, we focus on the resource scheduling problem in terms of energy consumption with response time and error bound constraints.

II. Sampled Sketch-based Query

The query operations over large-scale stream data, especially joins are computationally expensive. To some extent, sketch-based method can effectively summarize stream data with small space and update time [2]. Based on sketch structures, we propose a two-stage approximation strategy, *SCM-sketches*, a sampled count-min sketch for maintaining data stream statistics over sliding windows. The approximate scheme combines the functionalities of sampling and ECM-sketch to make efficient and guaranteed-error query answering. At the first stage, the input stream data is compressed using sampling. The second stage computes the result by a sketch-based operation. The execution time of both two stages can be shortened because of the compressed data stream.

Figure 1 details the projected DAG of the query with approximation operations. Two streams R and S can be executed concurrently by τ_1 and τ_2, which can be seen as a general preprocessing operation. Task τ_3 or τ_4 respectively executes a sketch-based summary to select customers (CID) that meets the query constraint. With the sampled results from the upstream nodes, the operations, τ_3 and τ_4 process

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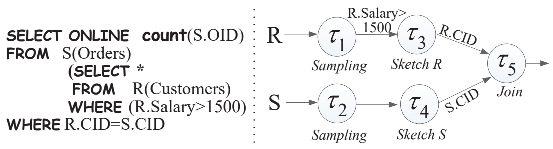

Figure 1: Two-stage approximation for sample data query.

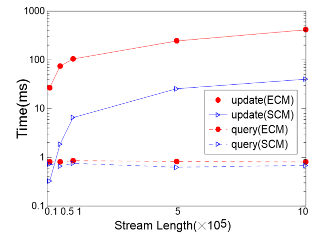

Figure 2: Update and Query Time for Self-join

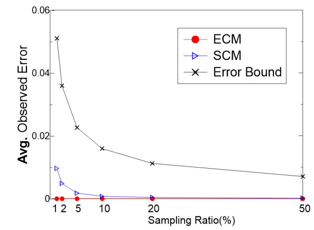

Figure 3: Avg Error vs Sampling Ratio for Self-join

compressed data. Then task τ_5 is to make a join operation with two sketches generated by τ_3 and τ_4. In order to ensure the required accuracy specified by users, we first analyze the effect of error propagation on approximation errors. Take the point query as an example, a point query (x, r) is a combination of an data item identifier x, and the query range r. Denote $\|a_r\|_1$ as the number of data items within r. We mainly analyze two commonly used types and detailed proofs are omitted in this poster due to the limited space.

(1) **Serial operation**. The serial operation corresponds to general point or range queries. In a complex query, it is possible that the result of intermediate input stream has already been approximated, with the evaluated error ε_k, confidence value δ_k and sampling ratio γ, assuming the error caused by the next sketch operation is ε^s_{k+1} with probability δ_{k+1}, then we analyze the way error generated by the upstream node affects the result of the downstream node.

Theorem 1. *For serial operation, the estimate from $k+1$ operation has the following guarantee: $|\hat{f}_{k+1}(x,r) - f(x,r)| \leq (\varepsilon_k + \varepsilon^s_{k+1} \cdot \gamma) \cdot \|a_r\|_1$, with probability at least $\delta_k + \delta_{k+1} - 1$, where $f(x,r)$ denotes the true value without approximation.*

(2) **Join operation**. The join operation corresponds to the inner-product or self-join queries (*i.e.,* WHERE colA=colB in the query). For data streams, the inner product of stream a and b in range r is defined as the Cartesian product, $a_r \odot b_r = \sum_{x \epsilon D} f_a(x,r) f_b(x,r)$. In the same way, we give error bound analysis for the error propagation of the join operations. In the following we assume the errors of sampling streams a and b are, respectively, ε^a_k and ε^b_k with the compressed ratio γ_a,γ_b and confidence value δ^a_k, δ^b_k.

Theorem 2. *For the join operation, the estimate from $k+1$ operation has the following guarantee: $|\widehat{a_r \odot b_r} - a_r \odot b_r| \leq (\varepsilon^a_k + \varepsilon^b_k + \varepsilon^a_k \varepsilon^b_k + \varepsilon^s_{k+1} \gamma_a \gamma_b) \|a_r\|_1 \|b_r\|_1$, with probability at least $\delta^a_k \delta^b_k + \delta_{k+1} - 1$*

Using the controllable error for query processing in DSPS, we can model the energy consumption model to efficiently allocate resource for approximate queries with response time and error bound constraints. To allocate resource on demand, one must consider the relation between resource demands and approximate degree, to ensure that the output error does not exceed the bound. In our optimization, the problem of resource allocation with approximate operations is reduced to assigning reasonable approximate ratios for input streams. To address the problem, we can propose a simulated annealing method to search for feasible resource allocation. It can quickly search for better solutions, which naturally fits our case of querying large-scale data stream in DSPS.

III. Performance Evaluation and Conclusion

The experiments are driven with real CAIDA Internet traffic traces 2016 datasets that consist of Internet traces collected from the Chicago monitors [3]. The sketch-based query estimates the number of packets sent by each IP address. The error generated by sketches is fixed to 0.01, with $\delta = 0.05$. Figure 2 illustrates the change of update and query time for point and self-join operations with SCM and ECM sketches respectively. The results show that the update time grows logarithmically with the increase of stream length while the query time is mostly unchanged. It can be seen that both the update and query time of SCM-sketch are lower than those of ECM. Specifically, the SCM sketch requires significantly less update time compared to ECM sketches. For instance, as shown as Figure 2, ECM requires about 104.3 ms to update stream items with length 100,000 while SCM only takes about 6.5 ms for point queries. It is more efficient to process those applications that require fast response time within a certain accuracy loss.

Figure 3 shows the average observed error with SCM sketches decreases and gradually approaches the result of ECM sketches when increasing sampling ratios. Error propagation causes the amplification of error and the larger sampling ratio leads to larger approximate error that further influences the final error. Thus, the average error with SCM sketches is higher, but it is much less than the given error bound.

In this paper, we proposed a novel approximate model, SCM-sketches, to address the complex nested stream query. The model combined sampling and sketches by making two-stage approximation, and also provided accuracy guarantee for the final result based on the analysis of error propagation.

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References

[1] D. R. Krishnan, D. L. Quoc, P. Bhatotia *et al.*, “IncApprox: A data analytics system for incremental approximate computing,” in *International Conference on WWW*, 2016, pp. 1133–1144.
[2] O. Papapetrou, M. Garofalakis *et al.*, “Sketch-based querying of distributed sliding-window data streams,” vol. 5, no. 10, pp. 992–1003, 2012.
[3] “CAIDA. center for applied internet data analysis,” http://www.caida.org/home/, [Online; accessed 26-June-2017].