A benchmark for histogram building algorithms of numeric streams

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1 Introduction

The main goal of this paper is to provide a benchmark for algorithms that build histograms over continuous streams of numeric data. The main goals of the benchmark is to measure both performance and accuracy in conditions resembling real streams of data: large volumes, varying data distribution, concurrent additions and queries. The benchmark is implemented as a separate application which generates data and communicates with the histogram clients using Kafka streams and http requests for queries. It is applied over two algorithms taken from practical industry-tested environments: the Numeric Histogram[1] from the Apache Hive project and the Optimal Streaming Histogram from the Amplitude's company blog[2]. The algorithms provide different approaches to solving the main issues of stream bucketing algorithms, enuntiated above, however, after being put through the benchmark they seem to behave very similarly in terms of execution times and approximation error.

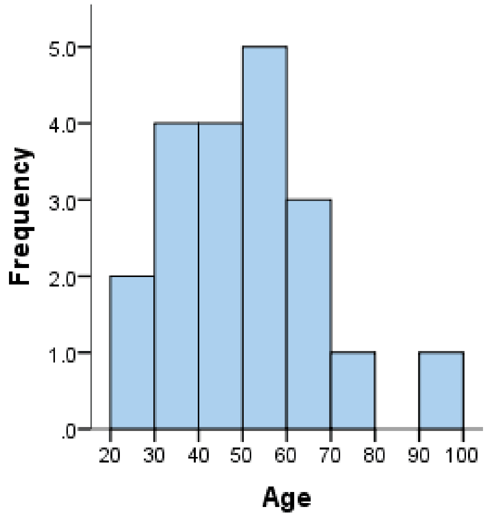
1.1 Histograms

A histogram is a type of plot that shows the underlying distirbution of a set of data[3]. In this paper the actual meaning of the term is the data structure out of which this plot can be built. An example of such a plot can be seen in figure 1.1. The main use of such methods is to provide a quick and easy to interpret summary of the data, which can then be analyzed by a domain expert to aid in various business decisions. The supporting data structure can also be used by other more complex algorithms. For example, Bel-Haim et al.[4] proposed an algorithm for classification of streaming data which leverages histograms for obtaining a light weight summary of the incoming data.

Most algorithms and mehtods for building histograms are thought out with the presumption that the data set is known in advance and has a reasonable size. However, this does not hold in the case of data streams, where data is accumulated over time in huge volumes, which causes a number of issues for the classic algorithms. First of all, the size of the data can be gigantic, meaning that it is not reasonable to store each point and its occurences, and an approximation heuristic is required. Furthermore, the distribution of the data is unknown beforehand, and this can cause issues if we can't properly store incoming data. Given the limitation of the first point, the algorithm needs to keep a limited number of buckets, but these must not be fixed in the beginning because the values represented by the buckets might not be relevant if the distribution of the data changes over time. Finally, these algorithms must be able to absorb data and perform queries constantly, meaning that performance is also an important factor.

A mathematical model for this data structure can be described as: a set of B pairs (called bins) of the form $(p_1, m_1), .., (p_B, m_B)$. The value of the m variables represent the number of points observed for the p variables. The meaning of the p variables depends upon the bucketing algorithm. For example, in the Ben-Haim's algorithm[4], p represents a central point for the interval and m the number of values around it. In the second algorithm discussed in the paper p_i represents the lower bound of the considered interval, with the upper bound being the the value of p_{i+1}.

Figure 1: Example of a histogram showing the frequency of age data[5]



1.2 Motivation

The field of data streams has been evolving at a very fast rate in order to match the explosion in continuous sources of data: user activity logs, web application metrics, sensor data from various domains like traffic or healthcare [6]. Given this recent development, a lot of algorithms that were designed for batch processing do not perform so well in a streaming environment. A class of such algorithms are the ones used to build histogram models. There is little research in this domain which causes developers to come out with their own in-house methods for the task. This article aims to contribute to the development of the field, to provide a comparison of the currently available algorithms and a baseline with which to compare future stream histogram methods.

1.3 Paper outline

The paper is organized in four main chapters. The first, contains an introduction into the topic and summarizes the goals of the experiment. The second chapter describes the algorithms which were put under the benchmark, providing snippets of implementation and covering advantages and disadvantages. The next chapter covers the benchmarking client, the methodology and the test results. Finally, the conclusion provides a short overview of the experiment and final results.

2 Algorithms

2.1 Numeric Histogram

2.1.1 Overview

The Numeric Histogram algorithm first appeared in the paper by Ben-Haim and Tom-Tov on building a streaming parallel decision tree algorithm[4]. The main focus was to describe a method for tree based classifiers for large data sets in a distributed environment, however they needed a data structure that can summarize large amounts of data accurately.

Thus, they proposed a histogram data structure that can adapt to the requirements of a streaming environment.

The histogram maintains a fixed number of bins of the shape (p, m) where p represents a central value of the interval and m the number of points in it. Initially the histogram has some bins allocated but the values are not known. They are filled as data comes is added into the structure and once the allocated number of bins is reached the central bin values are updated depending on incoming values. In this regard, the algorithm is robust to changes in data patterns over a longer period of time, which is one of the main concerns of streaming analysis algorithms.

2.1.2 Procedures

The proposed data structure contains four procedures: update, merge, sum and uniform. But for the purpose of this benchmark only two were needed: update and sum. The update procedure adds a new point to the histogram data structure and is described in algorithm 1.

Data: histogram $h = (p_1, m_1), .., (p_b, m_b)$, a point p
Result: a histogram that represents the set $S \bigcup \{p\}$
binary search for the closest p_i larger than p;
if $p_i = p$ **then**
  $m_i = m_i + 1;$
else
  add a new bin of shape (p, 1) to the histogram at the i-th position;
  find the closest two bins by their p values;
  merge those bins, moving p proportional to their m values;
end

Algorithm 1: add procedure

The sum procedure, depicted in algorithm 2, obtains the estimated number of points between $(-\infty, n]$ where n is the input value. In order to estimate the number of values in a range $[a, b]$ we can calculate $sum(b) - sum(a)$. The algorithm assumes that for each bin (p, m), there are $m/2$ points to the left of p and $m/2$ to the right. This means that the number of points in the interval $[p_i, i_{i+1}]$ is equal to $(m_i + m_{i+1})/2$, which is the area of the trapezoid $(p_i, 0), (p_i, m_i), (p_{i+1}, m_{i+1}), (p_{i+1}, 0)$, divided by $p_{i+1} - p_i$. Similarly, we can estimate the number of points in the interval $[p_i, p]$ by adding calculating its projection on the line from (p_i, m_i) to (p_{i+1}, m_{i+1}), then find the area of the new trapezoid and dividing again by $p_{i+1} - p_i$. The algorithm will not work properly if the point p is smaller than p_0 or larger than p_b. For this reason the data structure should be initialized with a lower and upper bound into which all incoming data should fit.

2.1.3 In practice

This algorithm was adapted and implemented into the open source project Apache Hive[7], which is a datawarehouse solution built on top of Hadoop to provide data query and analysis methods. The project is used actively in industry, handling reporting tasks for large volumes of data, for e.g. data produced by 435M monthly users of Chitika[8]. The version of the algorithm presented in this report is based on the Hive implementa-

Data: a histogram h, a point p such that $p_1 < p < p_b$
Result: estimated number of points in the interval $[-\infty, p]$
binary search to find i such that $p_i <= p <= p_{i+1}$;
set $s = (m_i + m_p) \cdot (b - p_i)/2 \cdot (p_{i+1} - p_i)$;
where $m_p = m_i + (m_{i+1} - m_i) \cdot (p - p_i)/(p_{i+1} - p_i)$;
for $j < i$ **do**
  $s = s + m_j$;
end
$s = s + m_i/2$;

Algorithm 2: sum procedure

tion, called NumericHistogram[1]. The optimal number of bins is left as a choice to the user, however the suggested range is between 20 and 80.

The algorithm is adaptable and can work with any ranges of data, however the access to its underlying structure must be synchronized which slows down execution in case of concurrent queries and insertions.

2.2 Optimal Streaming Histograms

2.2.1 Overview

This algorithm was presented in a blog post[2] by an engineer from the Amplitude company. Therefore, it was developed with industry requirements in mind, and tested in realistic conditions before being published. The main challenge was to avoid storing gigantic amounts of streaming data and to uncover an optimal bucketing solution. The key requirements they identified for the bucket boundaries were: to be useful and reasonable for any range of data and to remain useful upon changes in data distribution.

The algorithm was also designed with data visualization needs in mind. For this reason the buckets size and spacing have been thought out to look intuitive in a chart and be easy to interpret.

2.2.2 Iterations

In order to reach a satisfying solution they went through multiple iterations of the algorithm. The first one was to save the first 1000 distinct values on the stream and then make evenly spaced buckets using them. However, this method behaves poorly when distribution changes over time because the buckets are fixed. Also, this might have resolution issues when the distribution is skewed, for example: a lot of points in a small range of values.

The second technique was iterative merging of the closest values into buckets. This was done in order to solve the resolution problem. Basically, among the first 1000 values, the 2 closest ones are merged into a bucket. This process is repeated until only 50 buckets are left. This improves resolution, however it causes difficulties in interpreting the histograms as all buckets have different widths and the spacing seems arbitrary.

2.2.3 Algorithm

The final form of the algorithm is to pre-create buckets on a logarithmic scale. This requires the user to know the boundaries of the incoming data, and then, using those bounds, to create buckets that have 10% increments for every order of magnitude. For example, for the range 1 - 10, there will be buckets of size 0.1, for the range 10 - 100, of size 1 and so forth. This solves the resolution issues because each value will be in a bucket in a 10% range of its true value. The spacing issues are also solved, and data visualization is easier and more intuitive. The fixed size of the buckets should not be a problem in this scheme, which should work with a variety of data set types.

2.2.4 Implementation

The blog post did not provide an implementation so a variant will be proposed in this report. The initialization step is done with a given lower and upper bound. The smallest power of 10 larger than the upper bound and the largest power of 10 smaller than the lower bound are found and for each value p between them 90 buckets of width $p/10$ are created.

For the add procedure, the bucket is found using binary search which provides a logarithmic complexity. The bin is the incremented by 1 for each addition. In order to estimate3 the number of values in a range $[a, b]$ two binary searches are performed, for the bin of a and the bin of b. We need to estimate the number of values in the range $[a, bUb]$, where bUb is the upper bound of the bucket which contains a, and in the range $[bLb, b]$ where bLb is the lower bound of the bucket which contains b. The approach is similar for both intervals, so only one will be described. In order to estimate the number of values in $[a, bUb]$, a ratio is calculated between the distance from a to the upper bound and the size of the bucket. This ratio is then multiplied with the number of values in the bucket. The values for the buckets contained in the range $[bUb, bLb]$ are added as they are.

Data: a histogram h, two points a, b
Result: estimated number of points in the interval $[a, b]$
estimate = 0;
bin1 = getBin(a), bin2 = getBin(b);
$lowerBound = bin1.val$, $upperBound = lowerBound \cdot 10$;
$ratio = (upperBound - a)/(upperBound - lowerBound)$;
$estimate = estimate + ratio \cdot bin1.count$;
for *each bin from bin1 to bin2* **do**
| $estimate = estimate + bin.count$
end
$lowerBound = bin2.val$, $upperBound = lowerBound \cdot 10$;
$ratio = (b - lowerbound)/(upperBound - lowerBound)$;
$estimate = estimate + ratio \cdot bin2.count$;

Algorithm 3: Estimated number of points in range

2.2.5 Remarks

In the current iteration this algorithm has some weak points. The main issue is that buckets are fixed before execution, which means that the building algorithm should be adapted to incoming data. For example, the algorithm currently does not support negative numbers and performs poorly for small ranges of very large values as illustrated in the benchmark.

3 Benchmark

This paper proposes a benchmark for histogram building algorithms over continuous data streams. The benchmark aims to address some issues which are specific to these types of problems: a large amount of data, which is usually not practical to store, varying distribution of data, meaning the algorithms must adapt to changes and have an efficient bucketing algorithm, and the mixing of input and queries from multiple channels, which means an ideal algorithm would have little overhead for doing multiple operations concurrently.

3.1 Metrics

The benchmark contains several test suites which attempt to cover all these situations. It is run as a separate application which communicates with the histogram building applications through a stream of data to be added, and a list of queries over the input data. The metrics measured are: average request time, mean squared error and mean absolute error.

Average request time represents the cumulated execution time of all queries divided with the number of queries. The time is measured by the benchmarking application from the moment the query request is sent to the moment the answer is received. This metric aims to measure algorithm performance and might also indicate issues with concurrency, caused by attempting to perform queries while the algorithm also performs additions from the input stream.

Mean absolute error[9] is defined as $MAE = \frac{1}{n} \cdot \sum |y - \hat{y}|$ and it's one of the simplest regression metrics. It calculates the residual for every query result compared to actual expected answer and takes the absolute value so that positive and negative values don't cancel each other out.

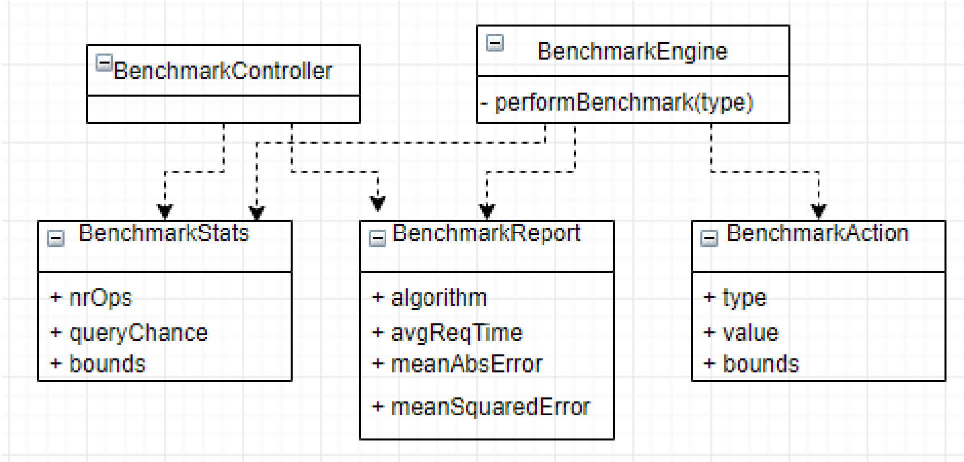
Mean squared error[9] can be calculated as $MSE = \frac{1}{n} \sum (y - \hat{y})^2$. It is similar to MAE, however it instead squares the difference. The main consequence of squaring the difference is that MSE is more sensitive to outliers in the results, because the error grows quadratically. Thus, the model is punished more if it makes predictions which are far from the expected value.

3.2 Implementation

For this benchmark two histogram algorithms with proven practical results were implemented in the Java programming language using the libraries provided by the Spring Boot framework. The aforementioned algorithms are the Numeric Histogram[1] from the Hive project and Optimal Streaming Histogram[2] developed by software engineers from Amplitude. The algorithms are contained in a standalone application which provides two input channels: a HTTP Rest API and a Kafka reader.

The application API exposes methods for initializing the bucketing algorithms, which requires the expected range into which the data will fall, and methods for queries. A query is of the type 'approximately how many points were observed in the given range?' and in realistic scenarios they are used for statistics and data mining processes started by users and don't come into the application as a continuous stream. Apache Kafka[10] is a distributed streaming platform used for building real time data pipelines with strong

Figure 2: Architectural diagram of the benchmarking application



fault-tolerance guarantees. This message queue was selected to model incoming data streams, which, in this case represent values to be added into the histogram.

The benchmarking component runs as a separate Spring Boot application which exposes an API that starts the different available benchmarks. The user can provide some parameters: which benchmark to perform, how many operations, what's the ratio of queries to additions, and which are the bounds of the data that is generated. An overlook of the architecture is given in figure 3.2. The entry point is the BenchmarkController which reads from the user a list of parameters, contained in the stats class. The actual work is done by the BenchmarkEngine which generates a list of actions, executes them, records response times and query values and then generates a report for each algorithm in the system. Input data for the histogram algorithms is sent through a Kafka queue, on a different topic for each algorithm.

3.3 Tests and results

The benchmark contains tests that can be divided into two main categories: for performance and for accuracy. The accuracy tests are designed to cover some distribution which might appear over time on a data stream. The first such distribution is uniform, which is the simplest one and should not cause any issues. A second test in this category is with a skewed distribution, where the first 80% of operations cover the first 20% of the value range and the rest 20% of the operations cover the remaining range. A third scenario for the value range to change twice at a third and two thirds of the testing interval. These last two scenarios are designed to test the ability of the algorithm to adapt to changes in the distribution of the incoming data stream.

The performance oriented tests are focused on testing the system under a lot of queries, which tends to be the most costly operation. Another situation is with a large range of possible data values, which means that in case of dynamic bucketing, the values might have to change more often as the chance of the same value arriving multiple times is reduced.

A special test case was designed to point out a weakness of the OptimalStreamingHistogram in its current form, which uses a small range of large values (1000000, 1000100).

We can observe that both algorithms behave surprinsingly similar in all test cases. The average response time seems to be very close for all tests, at around 3 milliseconds for

Table 1: Uniform distribution; 1mil operations, 1% of them queries, bounds (0, 100)

Algorithm	Avg Req Time	MAE	MSE
NumericHistogram	3.09	161536	52098973486
OptimalStreamingHistogram	3.14	161624	52131831979

Table 2: Skewed distribution; 1mil operations, 1% of them queries, bounds (0, 100)

Algorithm	Avg Req Time	MAE	MSE
NumericHistogram	6.30	102856	23614668551
OptimalStreamingHistogram	4.81	103477	23626580730

Table 3: Twice changing distribution; 1mil operations, 1% of them queries, bounds (0, 100)

Algorithm	Avg Req Time	MAE	MSE
NumericHistogram	3.45	52115	5385128831
OptimalStreamingHistogram	3.13	51968	5344437433

Table 4: Uniform distribution; 1mil operations, 1% of them queries, bounds (0, 100000)

Algorithm	Avg Req Time	MAE	MSE
NumericHistogram	3.44	166381	54802576827
OptimalStreamingHistogram	3.03	166345	54665682814

Table 5: Uniform distribution; 1mil operations, 90% of them queries, bounds (0, 100)

Algorithm	Avg Req Time	MAE	MSE
NumericHistogram	3.37	16356	535437528
OptimalStreamingHistogram	2.83	16350	534797489

Table 6: Uniform distribution; 1mil operations, 1% of them queries, bounds (1000000, 1000100)

Algorithm	Avg Req Time	MAE	MSE
NumericHistogram	3.39	160078	50782133935
OptimalStreamingHistogram	3.04	491258	321320234951

tests which consider 1 million elements, with NumericHistogram being just a bit slower. An exception is the skewed distribution test case where OptimalStreamingHistogram is around 2 milliseconds faster than the other algorithm.

The last scenario points out the weakness of the OptimalStreamingHistogram, which lies in the way the buckets are built. For a small range of large values most of them fall into the same bucket, which causes the algorithm to give inaccurate responses. It can be seen that the error is around 3 times larger than that of the NumericHistogram algorithm.

4 Conclusions

The main goal of creating a benchmark for various scenarios of data stream bucketing was achieved. The benchmark was executed for two popular algorithms in the field and uncovered the fact that they behave very similar. A noticeable difference is when using large values, which causes the OptimalStreamingHistogram algorithm to give out inaccurate responses. In terms of speed NumericHistogram seems to be slightly slower than the other algorithm.

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