Resilient Disaggregated Network Flow Monitoring

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ABSTRACT

Sketch has been extensively used for scalable network monitoring, which unfortunately, is sensitive to hash collisions. Deploying the sketch involves fine-grained performance control and instrumentation. This paper presents a new class of sketch structure that proactively minimizes the estimation error and reduces the error variance. We develop a disaggregated monitoring application that natively scales the sketching deployment. Testbed and real-world trace-driven simulations show that LSS achieves close-to-optimal performance under hash collisions.

CCS CONCEPTS

• **Networks** → **Network monitoring**; *Network services*.

KEYWORDS

Network flow, sketch, hash function, disaggregated application

ACM Reference Format:
Yongquan Fu, Dongsheng Li, Siqi Shen, Yiming Zhang, and Kai Chen. 2019. Resilient Disaggregated Network Flow Monitoring. In *SIGCOMM '19: ACM SIGCOMM 2019 Conference (SIGCOMM Posters and Demos '19), August 19–23, 2019, Beijing, China.* ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/3342280.3342305

1 INTRODUCTION

Network flow monitoring needs a variety of traffic measurement, such as flow delay, flow queueing time, flow frequency, flow entropy, and heavy hitters [2, 5, 10, 15, 21, 28–30, 33, 34]. Traffic statistics tasks require advanced data structures and traffic statistical algorithms due to ever-increasing line rates, massive traffic volumes, and large numbers of active flows [16, 25, 26, 35]. Many space- and time-efficient approaches have been studied, e.g., traffic sampling, traffic counting, traffic sketching [3, 8, 11, 13, 14, 18–20, 24]. Compared to other approaches, the sketch has received extensive attentions due to their competitive trade-off between resource consumption and performance guarantees [1, 22, 32], which is widely used in traffic engineering, network diagnosis, network forensics, intrusion detection and prevention. The sketch internally builds a memory-efficient and constant-speed bucket array to accumulate incoming flow counters [4, 6, 7, 23, 31]. A fundamental question is that, the sketch is sensitive to hash collisions, where multiple keys are mapped to the same bucket, as this noisy bucket no longer returns exact results for any of inserted keys. Recently, ElasticSketch [31] and SketchLearn [17] separates large flows from the sketch structure but need to allocate dedicated space for new items.

We present a new class of sketch called locality-sensitive sketch LSS that is resilient to hash collisions with a constant-size data structure. Real-world deployment experiments and trace-driven simulation confirms that LSS dramatically reduces the estimation error under the same memory footprint. More details are provided in the technical report [12].

2 NETWORK FLOW MONITORING

LSS turns from passively tolerating noisy buckets to proactively recovering the noisy buckets. A bucket array consists of a number of buckets, where each bucket has two fields: (i) A ValSum field that records the sum of values; (ii) A KeyCount filed that records the number of unique keys inserted to this bucket. LSS maps each item to only one bucket array that corresponds to the nearest cluster center for this item. Each bucket array corresponds to a cluster of similar items. LSS averages the bucket's counter to produce an unbiased estimator for noisy buckets. Figure 1 shows the main processes in LSS.

Clustering: We represent the clusters with k cluster centers, thus an LSS is organized as a number k of bucket arrays. The distance from the item to a cluster center is defined as the one-dimensional absolute difference between the item's value and the cluster center. Thus the overall time to find the nearest cluster centers is $O(k)$.

LSS learns the cluster structure based on transferred learning from network flow samples. We initialize the clustering model with

SIGCOMM Posters and Demos '19, August 19–23, 2019, Beijing, China

ACM ISBN 978-1-4503-6886-5/19/08…$15.00
https://doi.org/10.1145/3342280.3342305

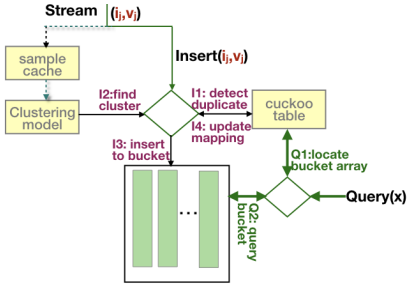
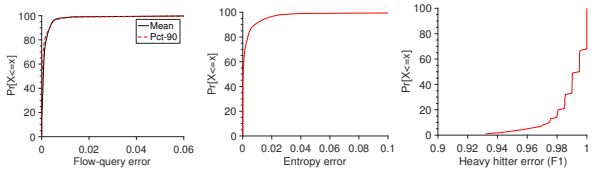


Figure 1: Illustration of LSS' main processes.



(a) Flow-size query (b) Flow entropy (c) Heavy hitters

Figure 2: Testbed performance metrics.

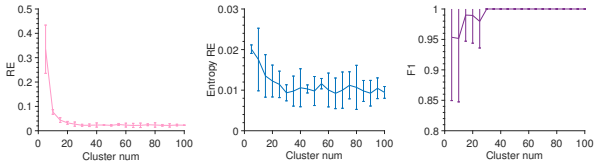
a set of sampled items from the stream. The clustering model is then fed to the LSS instance to produce the clusters. Next, we periodically refresh the clustering model with up-to-date sample cache to adapt to the variations of stream distributions. We select the well-studied K-means clustering method that clusters samples to minimizes the intra-cluster variance.

Insertion: To insert a key-value pair, LSS maps the value to the nearest cluster center, and accumulates the value to the corresponding bucket array. We increment the KeyCount field only once for each unique key to correctly count the number of keys. Further, we adapt to packets from the same network flow with a cuckoo table [9, 27, 36] that dynamically keeps the counters with the same key.

Query: To query the value of a key on the LSS, we first locate the bucket array with a Cuckoo hash table with the input key to get the cluster index of this key. Finally, we return the weighted value $\frac{ValSum}{KeyCount}$ as the approximated result.

Disaggregated Monitoring Framework: The proposed monitoring architecture splits the monitoring application into non-coherent ingestion, sketching, query runtime functions that can be horizontally scaled in the data center. A publish/subscribe (Pub/Sub for short) framework delivers ordered streaming messages across monitoring functions. We choose the Pulsar messaging system originally created at Yahoo as the Pub/Sub underlay.

Evaluation: We ran experiments on ten servers in two racks connected by a 10 Gbps switch. We choose three representative monitoring tasks to evaluate the sketch's performance, namely the flow-size query, the flow-entropy query, and the heavy-hitter query. We quantify the performance of the first two tasks with the relative error metric: defined as $|x_r - x_e| / (x_r)$, where x_r and x_e denoted the ground-truth metric and the estimated metric, respectively, and the last task based on the F1 score defined as the harmonic mean of the precision and the recall values.



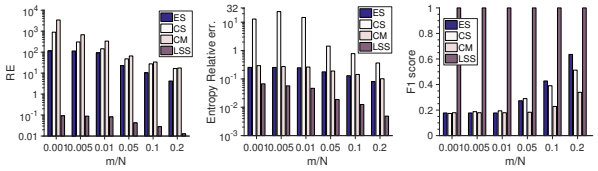
(a) Flow query (b) Entropy (c) Heavy hitters

Figure 3: LSS performance as a function of cluster numbers.

Figure 2(a) plots the Cumulative Distribution Function (CDF) of the mean relative errors. The relative errors of over 90% of all estimations are smaller than 0.01. Over 90% of estimations are smaller than 0.06, because of accurate estimations of flow sizes. Over 90% of tests are greater than 0.95. As LSS captures fine-grained flow distributions with clustered bucket arrays.

Next, we performed a trace-driven study that consists of 8.4 million flows collected on February 18, 2016 at the Equinix-Chicago monitor by CAIDA [31]. We evaluate LSS' accuracy with respect to the number of clusters. Figure 3 plots the variation of the estimation accuracy. We see that the estimation accuracy improves steadily with increasing numbers of clusters from two to ten. The diminishing returns occur when the number of cluster reaches 30.

Further, we compare LSS with count-min (CM) [7], count-sketch (CS) [4], and Elastic Sketch (ES) [31] that are most related with our work. We set the same memory footprint for all compared sketch structures. Figure 4 plots the performance of the flow-size, flow-entropy, and heavy-hitter query tasks, as we vary the ratio between the number of buckets in LSS and the number of unique flows. We see that LSS significantly outperforms other sketch structures in all cases.



(a) Flow-size query (b) Flow entropy (c) Heavy hitters

Figure 4: Simulation performance metrics.

3 CONCLUSION

We have proposed a new class of sketch that is resilient to hash collisions. We present a disaggregated monitoring application that allows for non-intrusive sketch deployment and native network-wide analytics. Extensive evaluation shows that LSS achieves close to optimal performance with a tiny memory footprint.

ACKNOWLEDGMENTS

This work was sponsored in part by National Key R&D Program of China under Grant No. 2018YFB0204300, and the National Natural Science Foundation of China (NSFC) under Grant No. 61602500, 61402509, 61772541, 61872376.

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