SketchLearn: Relieving User Burdens in Approximate Measurement with Automated Statistical Inference

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ABSTRACT

Network measurement is challenged to fulfill stringent resource requirements in the face of massive network traffic. While approximate measurement can trade accuracy for resource savings, it demands intensive manual efforts to configure the right resource-accuracy trade-offs in real deployment. Such user burdens are caused by how existing approximate measurement approaches inherently deal with resource conflicts when tracking massive network traffic with limited resources. In particular, they tightly couple resource configurations with accuracy parameters, so as to provision sufficient resources to bound the measurement errors. We design SketchLearn, a novel sketch-based measurement framework that resolves resource conflicts by learning their statistical properties to eliminate conflicting traffic components. We prototype SketchLearn on OpenVSwitch and P4, and our testbed experiments and stress-test simulation show that SketchLearn accurately and automatically monitors various traffic statistics and effectively supports network-wide measurement with limited resources.

CCS CONCEPTS

• **Networks** → **Network measurement**;

KEYWORDS

Sketch; Network measurement

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1 INTRODUCTION

Network measurement is indispensable to modern network management in clouds and data centers. Administrators measure a variety of traffic statistics, such as per-flow frequency, to infer the key behaviors or any unexpected patterns in operational networks. They use the measured traffic statistics to form the basis of management operations such as traffic engineering, performance diagnosis, and intrusion prevention. Unfortunately, measuring traffic statistics is non-trivial in the face of massive network traffic and large-scale network deployment. Error-free measurement requires per-flow tracking [15], yet today's data center networks can have thousands of concurrent flows in a very small period from 50ms [2] down to even 5ms [56]. This would require tremendous resources for performing per-flow tracking.

In view of the resource constraints, many approaches in the literature leverage approximation techniques to trade between resource usage and measurement accuracy. Examples include sampling [9, 37, 64], top-k counting [5, 43, 44, 46], and sketch-based approaches [18, 33, 40, 42, 58], which we collectively refer to as *approximate measurement* approaches. Their idea is to construct compact sub-linear data structures to record traffic statistics, backed by theoretical guarantees on how to achieve accurate measurement with limited resources. Approximate measurement has formed building blocks in many state-of-the-art network-wide measurement systems (e.g., [32, 48, 55, 60, 62, 67]), and is also adopted in production data centers [31, 68].

Although theoretically sound, existing approximate measurement approaches are inconvenient for use. In such approaches, massive network traffic competes for the limited resources, thereby introducing measurement errors due to *resource conflicts* (e.g., multiple flows are mapped to the same counter in sketch-based measurement). To mitigate errors, sufficient resources must be provisioned in approximate measurement based on its theoretical guarantees. Thus, *there exists a tight binding between resource configurations and accuracy parameters*. Such tight binding leads to several practical limitations (see §2.2 for details): (i) administrators need

to specify tolerable error levels as input for resource configurations; (ii) each configuration is tied to specific parameters (e.g., thresholds); (iii) the theoretical analysis only provides worst-case analysis and fails to guide the resource configurations based on actual workloads; (iv) each configuration is fixed for specific flow definitions; and (v) administrators cannot readily quantify the extent of errors for measurement results. How to bridge the gap between theoretical guarantees and practical deployment in approximate measurement remains a challenging yet critical issue [13].

We address this issue by focusing on sketch-based measurement, which fully records the chosen statistics of all observed packets in fixed-size data structures (i.e., *sketches*). We propose SketchLearn, a sketch-based measurement framework that addresses the above limitations in approximate measurement through a fundamentally novel methodology. Its idea is to characterize the inherent statistical properties of resource conflicts in sketches rather than pursue a perfect resource configuration to mitigate resource conflicts. Specifically, SketchLearn builds on a multi-level sketch [17] to track the frequencies of flow records at bit-level granularities. The multi-level structure leads to multiple bit-level Gaussian distributions for the sketch counters, which we justify with rigorous theoretical analysis (see §4). SketchLearn leverages the Gaussian distributions to address the limitations of state-of-the-arts. It iteratively infers and extracts large flows from the multi-level sketch, until the residual multi-level sketch (with only small flows remaining) fits some Gaussian distribution. By separating large and small flows, SketchLearn eliminates their resource conflicts and improves measurement accuracy. Such iterative inference can be done without relying on complicated model parameters, thereby relieving administrators to a large extent from configuration burdens. SketchLearn further allows arbitrary flow definitions, provides error estimates for measurement results, and supports large-scale network-wide measurement (see §5). To our knowledge, SketchLearn is the first approximate measurement approach that builds on the characterization of the inherent statistical properties of sketches.

We prototype SketchLearn atop OpenVSwitch [52] and P4 [53] (see §6) to show its feasibility of being deployable in both software and hardware switches, respectively. Our testbed experiments and stress-test simulation show that with only 64KB of memory and 92 CPU cycles of per-packet processing, SketchLearn achieves near-optimal accuracy for a variety of traffic statistics and addresses the limitations of state-of-the-arts (see §7).

2 MOTIVATION

We start with measuring *per-flow frequencies* of network traffic across time intervals called *epochs*. Each flow is identified by a *flowkey*, which can be defined based on any combination of packet fields, such as 5-tuples or source-destination address pairs. We obtain the per-flow frequencies, in terms of packet or byte counts, for all or a subset of flows of interest in each epoch. Based on per-flow frequencies, we can derive sophisticated traffic statistics (see §5.1), such as heavy hitters [43], heavy changers [17], superspreaders and DDoS [19], cardinality [66], flow size distribution [38], and entropy [30].

2.1 Design Requirements

We first pose the design requirements for practical network measurement deployment.

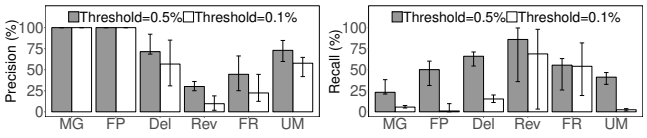
Requirement 1 (R1): Small memory usage. Network measurement should limit memory usage in both hardware and software deployments. For hardware devices (e.g., switching ASICs and NetFPGA), high memory usage aggravates chip footprints and heat consumptions, thereby increasing manufacturing costs. Even though modern switching ASICs have larger SRAM (e.g., 50-100MB) [45], the available SRAM size remains limited for per-flow tracking. Software switches in servers [54] can leverage abundant server-side DRAM. However, high memory usage not only depletes the memory of co-located applications (e.g., VMs or containers), but also degrades their performance due to more severe cache contentions [27].

Requirement 2 (R2): Fast per-packet processing. Network measurement must process numerous packets at high speed. For example, a fully utilized 10Gbps link corresponds to a packet rate of 14.88Mpps for 64-byte packets; equivalently, the time budget for each packet is only around 200 CPU cycles in a 3GHz processor. As the packet buffer size is limited, any packet that significantly exceeds the time budget can cause subsequent packets to be dropped.

Requirement 3 (R3): Real-time response. Some measurement tasks, such as anomaly detection, necessitate real-time statistics to respond quickly to potentially catastrophic events. Lightweight measurement solutions are more preferred to avoid unexpected delays [20, 57].

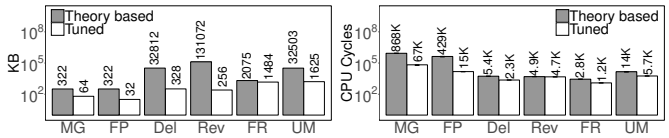
Requirement 4 (R4): Generality. Designing and deploying specific solutions for each type of traffic statistics is ineffective and also requires sophisticated resource allocation across different solutions to provide accuracy guarantees [47, 48]. Instead, a practical measurement solution should be applicable to general types of traffic statistics [40, 41].

Also, resource requirements vary between hardware and software. For example, ASIC switches have high throughput but limited memory (see R1); in contrast, commodity hosts generally have sufficient memory but limited CPU processing power (see R2). Enabling unified measurement for both software and hardware platforms is critical.



(a) Precision (b) Recall

Figure 1: (L2) Accuracy with smaller thresholds.



(a) Memory (b) Peak per-packet CPU cycles

Figure 2: (L3) Resource usage of theory-based and empirically-tuned configurations.

2.2 Limitations of Existing Approaches

Approximate measurement makes design trade-offs between resource usage and measurement accuracy (see §1). However, existing approximate measurement approaches (including sampling, top-k counting, and sketch-based approaches) still fail to address the following limitations.

Limitation 1 (L1): Hard to specify expected errors. Existing approximate measurement approaches mostly provide theoretical guarantees that the estimated result has a relative error ϵ with a confidence probability $1-\delta$, where ϵ and δ are configurable parameters between 0 and 1. How to parameterize the "best" ϵ and δ requires domain knowledge for different scenarios.

Limitation 2 (L2): Hard to query different thresholds. Some measurement tasks are threshold-based. For example, heavy hitter detection [43] finds all flows whose frequencies exceed some threshold. However, existing heavy hitter detection approaches take the threshold as input for configurations, thereby making both the theoretical analysis and actual measurement accuracy heavily tied to the threshold choice. Figure 1 shows the precision and recall for six representative heavy hitter detection approaches (see their details in §7). We first configure the threshold as 1% of total frequency. Then all approaches can achieve 100% in both precision and recall (not shown in the figure). If we decrease the threshold to 0.5% and 0.1% of total traffic without changing the configuration, then the figure shows that the precision and recall sharply drop to less than 80% and 20%, respectively.

Limitation 3 (L3): Hard to apply theories to tune configurations. Even though we can precisely specify the errors and query thresholds, it remains challenging to apply the theoretical results for two reasons. First, some measurement approaches (e.g., [7, 40, 58]) only provide asymptotic complexity results but not closed-form parameters for configurations. Second, most approximate measurement approaches perform worst-case analysis and do not take into account actual workloads. Some studies (e.g., [23, 44]) address heavy-tailed traffic distribution, but they need the exact distribution models as input and cannot readily adapt to actual network conditions. SCREAM [48] dynamically tunes configurations based on prior runtime behaviors, but it requires complicated coordination of a centralized controller to collect sketch statistics and fine-tune sketch configurations.

To justify this limitation, we consider heavy hitter detection with threshold 1%, relative error 1%, and error probability 5%. We employ two configurations: one exactly follows theoretical results, while the other is empirically tuned to achieve the configured errors. Figure 2 compares their memory consumption and peak per-packet processing overhead (in CPU cycles), measured by testbed experiments (see §7). It shows that the actual memory and CPU usage is much less than the theoretically proposed. However, tuning a resource-efficient configuration is labor-intensive.

Limitation 4 (L4): Hard to re-define flowkeys. Each approximate measurement configuration can support only one flowkey definition at a time in deployment. For example, if we want to perform heavy hitter detection on both 5-tuple flows and source-destination address pairs, we need to deploy two configurations, even though they both run the same algorithm. Some hierarchical heavy hitter detection approaches [5, 16] can detect multiple levels of flow keys, with one level being the prefix of another, but the levels must be pre-defined. In general, for a given configuration, we cannot choose any combination of packet fields once the flowkey definition is determined (e.g., switching from source-destination address pairs to source IP-port tuples).

Limitation 5 (L5): Hard to examine correctness. Existing approximate measurement approaches provide predefined error guarantees for the overall measurement results. Although they can tell the expected errors, they cannot quantify the actual extent of errors for individual flows. For example, in heavy hitter detection, we may estimate the frequency of a flow with a relative error ϵ and confidence probability $1-\delta$ (see L1). However, the estimation has a high confidence probability only if the flow has no hash collision with others, and the confidence probability drops as there are more hash collisions. Thus, we cannot measure exactly how likely a specific flow belongs to a true heavy hitter.

3 SKETCHLEARN OVERVIEW

3.1 Design Features

SketchLearn is a novel sketch-based measurement framework that addresses all design requirements (see §2.1) and the limitations of existing approaches (see §2.2). Recall from §1 that existing approximate measurement approaches tightly

bind resource configurations and accuracy parameters in their designs. In sketch-based measurement, it allocates a *sketch* in the form of a fixed matrix of counters, followed by hashing packet or byte counts to each row of counters. The sketch size (and hence the resource usage) is configured by the input of accuracy parameters, in which the errors are caused by hash collisions (i.e., the resource conflicts for tracking all packets in a fixed number of counters). Existing sketch-based measurement approaches focus on how to pre-allocate the minimum required sketch size so as to satisfy the accuracy requirement. In contrast, SketchLearn takes a fundamentally new approach, in which it characterizes and filters the impact of hash collisions through statistical modeling. It does not need to fine-tune its configuration for specific measurement tasks or requirements (e.g., expected errors, query thresholds, or flow definitions). Instead, it is self-adaptive, via statistical modeling, to various measurement tasks and requirements with a single configuration. It comprises the following design features, which address the design requirements R1-R4 and the limitations L1-L5.

Multi-level sketch for per-bit tracking (§3.2 and §5.2). SketchLearn borrows the idea from Deltoid [17], and maintains a multi-level sketch composed of multiple small sketches, each of which tracks the traffic statistics of a specific bit for a given flowkey definition. Combined with statistical modeling, SketchLearn not only reduces the sketch size and hence resource usage (R1-R3), but also enables flexible flowkey definitions (L4 addressed). In the multi-level sketch, each flowkey is composed of all candidate fields of interest (e.g., 5-tuples), and we can extract the traffic statistics for any combination of the packet fields by examining the levels for the corresponding bits.

SketchLearn differs from Deltoid by extracting flowkeys via statistical modeling. In contrast, Deltoid is tailored for heavy hitter/changer detection based on deterministic group testing, which requires a large sketch size to avoid hash collisions. Also, it cannot be readily generalized for flexible flowkey definitions. We show that SketchLearn incurs much less resource overhead than Deltoid (see §7).

Separation of large and small flows (§4.2 and §5.1). The multi-level sketch provides a key property that if there is no large flow, its counter values follow a Gaussian distribution (see Theorem 1 in §4.2). Based on this property, SketchLearn extracts large flows from the multi-level sketch and leaves the residual counters for small flows to form Gaussian distributions. Such separation enables SketchLearn to resolve hash collisions for various traffic statistics (R4). For example, SketchLearn considers the extracted large flows only for heavy hitter detection, but includes the residual counters when estimating cardinality. Note that some measurement

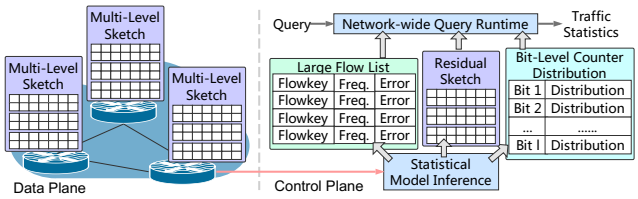


Figure 3: SketchLearn architecture.

works also separate large and small flows, but they are designed for different contexts (e.g., traffic matrix [14, 69] or top-k counting [32]).

Parameter-free model inference (§4.3). SketchLearn automatically digs the information hidden in a multi-level sketch to distinguish between large and small flows without relying on expected errors, threshold parameters, or configuration tuning (L1, L2, and L3 addressed). It iteratively learns the statistical distribution inside a multi-level sketch and leverages the distribution to guide large flow extraction.

Note that parameter-free model inference does not imply that SketchLearn itself is configuration-free. SketchLearn still requires administrators to configure the multi-level sketch. Also, it cannot eliminate the parameters induced by queries (e.g., heavy hitter threshold). Nevertheless, SketchLearn minimizes configuration efforts as its configuration can now be easily parameterized via self-adaptive modeling.

Attachment of error measures with individual flows (§5.2). During the model inference, SketchLearn further associates each flow with an error measure corresponding to a given type of traffic statistics. Thus, we do not need to specify any error (L1 addressed); instead, we use the attached error to quantify the correctness of flows (L5 addressed).

Network-wide inference (§5.3). SketchLearn facilitates the coordination of results of one or multiple multi-level sketches deployed at multiple measurement points to form parameter-free model inference for the entire network.

3.2 Architectural Design

Architecture. SketchLearn is composed of a distributed data plane and a centralized control plane, similar to existing software-defined measurement architectures [32, 40–42, 47–49, 67]. Figure 3 depicts SketchLearn's architecture. The data plane comprises multiple measurement points (e.g., software/hardware switches or end-hosts) spanning across the network. It deploys a multi-level sketch at each measurement point, which processes incoming packets, records packet statistics into the multi-level sketch, and reports the multi-level sketch to the control plane for analysis.

The control plane analyzes and decomposes each collected multi-level sketch into three components: (i) the *large flow list*, which identifies a set of large flows and includes the estimated frequency and the corresponding error measure

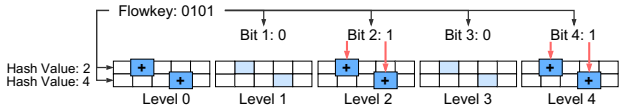


Figure 4: Multi-level sketch updates.

for each identified large flow, (ii) the *residual multi-level sketch*, which stores the traffic statistics of the remaining small flows after filtering the identified large flows, and (iii) the *bit-level counter distributions*, each of which models the distribution of counter values for each bit of a flowkey in the residual multi-level sketch. The control plane has a *query runtime*, which takes either regular or ad-hoc measurement queries and reports the relevant statistics from one or more multiple multi-level sketches (depending on the queries) for specific measurement tasks of interest.

Multi-level sketch. Before showing the model learning, we describe the multi-level sketch. Let l be the number of bits of a flowkey. The multi-level sketch comprises $l + 1$ levels from level 0 to level l, and each level corresponds to a sketch formed by a counter matrix with r rows and c columns. The level-0 sketch records the statistics of all packets, while the level-k sketch for $1 \le k \le l$ records the statistics for the k-th bit of the flowkey. Let $V_{i,j}[k]$ be the counter value of the level-k sketch at the i-th row and the j-th column, where $1 \le i \le r$, $1 \le j \le c$, and $0 \le k \le l$. Also, let $h_1, h_2, \cdots, h_r$ be r pairwise independent hash functions, where h_i maps a flowkey to one of the c columns in the i-th row for each level, where $1 \le i \le r$. We use the same r hash functions for all levels. Note that the use of pairwise independent hash functions is also assumed by most sketch-based approaches [17, 18, 58].

SketchLearn updates the multi-level sketch for each incoming packet. Let (f, v) be the tuple denoting the packet, where f is the flowkey and v is the frequency. Let $f[k]$ denote the k-th bit of f, where $1 \le k \le l$. To update the sketch, SketchLearn first computes the r hash values to select the r counters (one per row) from each level. It updates all r counters in the level-0 sketch, and selectively updates the counters at the level-k sketch if and only if $f[k]$ equals one.

Figure 4 shows an example how SketchLearn updates a packet into a multi-level sketch, in which $l = 4$ and each level has a sketch with $r = 2$ rows and $c = 5$ columns. Suppose that $f = 0101$. SketchLearn first updates the two rows (say the 2nd and 4th counters, respectively) in the level-0 sketch (i.e., $V_{1,2}[0]$ and $V_{2,4}[0]$). It then updates $V_{1,2}[2]$, $V_{2,4}[2]$, $V_{1,2}[4]$, and $V_{2,4}[4]$, since both bits 2 and 4 are one.

4 MODEL LEARNING

4.1 Motivation and Notation

Our primary goal is to build a statistical model that utilizes only the information embedded inside a multi-level sketch to mitigate errors, without taking any extra information. Our model components take into account two factors.

Hash collisions. Errors in sketch-based measurement are mainly caused by hash collisions of multiple flows mapped to the same counter. To quantify the impact of hash collisions, we first model the number of flows that each counter holds.

Notation: Counters in the same row and column across all $l + 1$ levels share the same set of colliding flows. We collectively call the $l + 1$ counters a *stack*, and let (i, j) denote the stack in row i and column j. Thus, there are a total of $r \times c$ stacks with $l + 1$ counters each. Also, let $n_{i,j}$ be the number of flows hashed to stack (i, j), and n be the total number of flows observed (i.e., $n = \sum_{j=1}^{c} n_{i,j}$ for any $1 \le i \le r$).

Bit-level flowkey distributions. Flowkeys often exhibit non-uniform probabilistic distribution in their bit patterns. For example, IP addresses in a data center tend to share the same prefix; the protocol field is likely equal to six since TCP traffic dominates. We characterize the flowkey distribution at the granularity of bits.

Notation: Let $p[k]$ be the probability that the k-th bit of a flowkey (call it *k-bit* for short) is equal to one, where $1 \le k \le l$. Also, to relate $p[k]$ with hash collisions, let $p_{i,j}[k]$ be the probability that the k-bit in stack (i, j) is equal to one.

Analysis approach. Our analysis addresses the two factors collectively rather than individually. In particular, we focus on characterizing $R_{i,j}[k] = \frac{V_{i,j}[k]}{V_{i,j}[0]}$, which denotes the ratio of the counter value $V_{i,j}[k]$ to the overall frequency $V_{i,j}[0]$ of all flows hashed to stack (i, j). Also, let s_f be the true frequency of a flow f, so $V_{i,j}[k] = \sum_{h_i(f)=j} f[k] \cdot s_f$.

We emphasize that the notation defined above is only introduced to facilitate our analysis. As we show later, the notation can either be canceled or inferred. There is no manual effort to parameterize their values in advance.

4.2 Theory

Assumptions. Our model builds on two assumptions.

- *Assumption 1*: Each hash function maps flows to columns uniformly, so $n_{i,j} \approx \frac{n}{c}$ for $1 \le j \le c$.
- *Assumption 2*: Both $h_i(f)$ and $p[k]$ are (nearly) independent for all $1 \le i \le r$ and $1 \le k \le l$, so $p_{i,j}[k] = p[k]$.

Justification. Assumption 1 is straightforward provided that SketchLearn employs good hash functions. For Assumption 2, the intuition is that if we fix the value of any bit of all flows, the hash values derived from the remaining bits still follow a nearly identical distribution. We further validate Assumption 2 in our technical report [34].

Theorem. With the two assumptions, we can derive the distribution for $R_{i,j}[k]$. Intuitively, in each stack, the number of flows at level k follows a Bernoulli distribution by Assumption 2. With sufficient flows (Assumption 1), we can

approximate the Bernoulli distribution as a Gaussian distribution. We can map the distribution for number of flows into the distribution for $R_{i,j}[k]$ if stack (i, j) has no large flows based on the following theorem (see the proof in [34]).

Theorem 1. *For any stack (i, j) and level k, if stack (i, j) has no large flows whose frequencies are significantly larger than others, $R_{i,j}[k]$ follows a Gaussian distribution $N(p[k], \sigma^2[k])$ with the mean $p[k]$ and the variance $\sigma^2[k] = p[k](1-p[k])c/n$.*

4.3 Model Inference

Theorem 1 requires that no large flows exist in a multi-level sketch. This motivates us to extract large flows from the multi-level sketch and draw Gaussian distributions for remaining flows at different levels. We build our statistical model with the following three components:

- *Large flow list F*: It contains all identified large flows, each of which is described by its flowkey, estimated frequency, and error measure.
- *Residual sketch S*: It is the multi-level sketch with the frequencies of large flows removed.
- *List of l bit-level counter distributions $\{N(p[k], \sigma^2[k])\}$*: The distribution of $R_{i,j}[k]$ for the k-bit, where $1 \le k \le l$, is characterized by the mean $p[k]$ and the variance $\sigma^2[k]$.

Algorithm. To decompose the three components from a multi-level sketch, SketchLearn learns a statistical model in a self-adaptive manner as there is no accurate model to directly characterize and separate a mix of large and small flows. Algorithm 1 details our close-loop model inference algorithm. It takes the whole multi-level sketch $S = \{V_{i,j}[k]\}$ as input. Initially, it sets the large flow list F as empty and a control parameter $\theta = 1/2$ (lines 1-2) (see details about θ in §4.4). It also computes the l bit-level counter distributions $\{N(p[k], \sigma^2[k])\}$ (line 3); even though there may exist large flows that compromise Theorem 1, we let SketchLearn start with such inaccurate estimates for the l bit-level distributions. To eliminate the interference from large flows, SketchLearn iteratively extracts large flows based on the (inaccurate) distributions (lines 5-8). In each iteration, it removes the extracted flows in set F' from S (line 9), and recomputes the distributions $\{N(p[k], \sigma^2[k])\}$ (line 10). The iterations terminate until all l bit-level counter distributions fit Gaussian distributions well (lines 11-12). If no large flows are extracted in this iteration, the algorithm halves θ (lines 13-14).

The algorithm calls four subroutines: (i) computing bit-level counter distributions (lines 2 and 10), (ii) extracting large flows (line 7), (iii) removing extracted flows from S (line 9) and (iv) checking the termination condition (line 11). We elaborate them below.

Computing distributions. We compute the bit-level counter distribution $N(p[k], \sigma^2[k])$ for the k-bit, where $1 \le k \le l$, by estimating its mean $p[k]$ and variance $\sigma^2[k]$. By Theorem 1,

Algorithm 1 Model Inference

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Input: Multi-level sketch S = {V_{i,j}[k] | 0 ≤ k ≤ l, 1 ≤ i ≤ r, 1 ≤ j ≤ c}
 1: Large flow list F = ∅
 2: θ = 1/2
 3: Bit-level counter distributions {N(p[k], σ²[k])} = ComputeDist(S)
 4: while true do
 5:     Set of extracted large flows F' = ∅
 6:     for all stack (i, j), 1 ≤ i ≤ r, 1 ≤ j ≤ c do
 7:         F' = F' ∪ ExtractLargeFlows(θ, (i, j), S, {N(p[k], σ²[k])})
 8:     F = F ∪ F'
 9:     RemoveFlows(S, F')
10:     {N(p[k], σ²[k])} = ComputeDist(S)
11:     if Terminate({N(p[k], σ²[k])}) then
12:         break
13:     if F' == ∅ then
14:         θ = θ/2
```

$R_{i,j}[k]$'s from all stacks follow an identical distribution. Thus, each stack provides one sample for $N(p[k], \sigma^2[k])$. We estimate $p[k]$ and $\sigma^2[k]$ from the $r \times c$ samples in the level-k sketch, by computing $p[k]$ and $\sigma^2[k]$ as the sample mean and sample variance of $R_{i,j}[k]$ across for all (i, j), respectively. For Gaussian distributions, such estimates are unbiased and have minimum variance [10]. If all large flows are extracted, the estimates converge to the true values (see Theorem 1).

Large flow extraction. It is the core subroutine in model inference. It works on a per-stack basis. Recall that $V_{i,j}[0]$ is the overall frequency of flows in stack (i, j). The subroutine takes a parameter θ (where $0 \le \theta \le 1$), multi-level sketch S, the estimated distributions $\{N(p[k], \sigma^2[k])\}$ as input (see §4.4 for how θ is set), and compares $R_{i,j}[k]$ with θ and $p[k]$. The intuition is that a large flow significantly influences the counter values in S. When other flows in stack (i, j) have limited sizes, a large flow dominates the stack and often leaves $R_{i,j}[k]$ either very large (if its k-bit is one) or very small (if its k-bit is zero). Even though the large flow is not significantly dominant, it should at least alter the counter distributions, making $R_{i,j}[k]$ deviate much from its expectation $p[k]$. Thus, by checking $R_{i,j}[k]$ and its difference from $p[k]$, we can determine the existence of large flows. Specifically, the subroutine performs the following five steps to extract flows exceeding $\theta V_{i,j}[0]$.

Step (i) Estimating bit-level probabilities. We estimate a probability $\hat{p}[k]$ to quantify the likelihood that the k-bit is equal to one, where $1 \le k \le l$. We first check whether $R_{i,j}$ is dominated by a potentially large flow. If $R_{i,j}[k] < \theta$, a large flow must not be included in $V_{i,j}[k]$, so we estimate $\hat{p}[k] = 0$; similarly, if $1 - R_{i,j}[k] < \theta$, we estimate $\hat{p}[k] = 1$. If neither of them holds (e.g., $R_{i,j}[k] = 0.5$ and $\theta = 0.3$), we check whether the counter distribution is altered by a large flow. Specifically, we estimate $\hat{p}[k]$ by assuming the existence of a large flow with the k-bit equal to one. We calculate the residual $R_{i,j}[k]$ after removing the large flow and examine

the difference between the residual $R_{i,j}[k]$ and its expectation $p[k]$. In particular, the difference can be converted to the likelihood $\hat{p}[k]$ via Bayes' Theorem. Our technical report [34] presents the detailed calculation.

Step (ii) Finding candidate flowkeys. If $\hat{p}[k]$ or $1-\hat{p}[k]$ is close to one (> 0.99 in our paper), the subroutine sets the k-bit as one or zero, respectively; otherwise, if neither of them is close to one, the k-bit is assigned a wildcard bit $*$, meaning that it can be either zero or one. We then obtain a template flowkey composed of zero, one, and $*$. We enumerate all candidate flows matching the template and check whether they can be hashed to stack (i, j).

Step (iii) Estimating frequencies. We estimate the frequency for each candidate flowkey. We first produce a frequency estimate for each k-bit using the idea of maximum likelihood estimation. Our goal is that after excluding the contribution of some candidate flow f, the residual $R_{i,j}[k]$ is equal to its expectation $p[k]$. Specifically, if we remove f, the residual overall frequency is reduced to $V_{i,j}[0] - s_f$. If the k-bit is one, $V_{i,j}[k]$ is also reduced to $V_{i,j}[k] - s_f$; however, if the k-bit is zero, $V_{i,j}[k]$ remains unchanged after f is removed (as we do not update the counter). Thus, by setting the residual $R_{i,j}[k]$ (i.e., the ratio of the residual $V_{i,j}[k]$ to the residual $V_{i,j}[0]$) equal to $p[k]$, we can estimate s_f as

$$s_f = \begin{cases} \frac{R_{i,j}[k]-p[k]}{1-p[k]} V_{i,j}[0], & \text{if } k\text{-bit is one,} \\ (1 - \frac{R_{i,j}[k]}{p[k]}) V_{i,j}[0], & \text{if } k\text{-bit is zero.} \end{cases}$$

The final frequency estimate is taken as the median of the estimates for all l levels of sketches to avoid outliers.

Step (iv) Associating flowkeys with bit-level probabilities. If the k-bit is equal to one (resp. zero), we associate it with a bit-level probability $\hat{p}[k]$ (resp. $1-\hat{p}[k]$). Each candidate flowkey is accordingly associated with a vector of l bit-level probabilities to quantify the correctness of the flowkey. Intuitively, if most of the bits have high bit-level probabilities, the candidate flowkey is more likely to correspond to a true flowkey. In §5.2, we also show how to leverage this vector to attach an error measure to a given flow.

Step (v) Verifying candidate flows. The subroutine may produce false positives since there are multiple flows being constructed by matching $*$. We filter out false positives with the aid of other stacks. Specifically, we hash an extracted flow with other hash functions except h_i to some other stack (i', j'), where $i' \neq i$. We compare the current frequency estimate using the counters in other stacks, and take the smallest value as the final frequency estimate. Finally, we check the final frequency estimate and remove any extracted flow if the final frequency estimate is below $\theta V_{i,j}[0]$.

Example. Figure 5 depicts the large flow extraction subroutine with an example, in which we extract four-bit flows with $\theta = \frac{1}{3}$ from a stack (i, j) whose overall frequency is

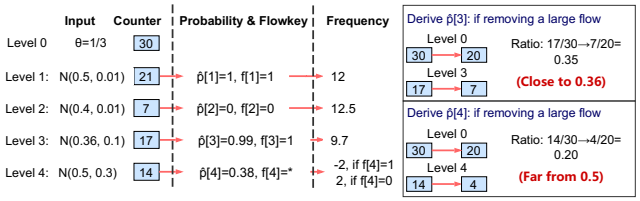


Figure 5: Example: large flow extraction.

$V_{i,j}[0] = 30$. For level 1, since $1 - R_{i,j}[1] = 1 - \frac{21}{30} = 0.3 < \theta$, we estimate $\hat{p}[1] = 1$ and hence $f[1] = 1$; the estimated frequency for level 1 is $\frac{21/30-0.5}{1-0.5} \cdot 30 = 12$. For level 2, since $R_{i,j}[2] = \frac{7}{30} < \theta$, we estimate $\hat{p}[2] = 0$ and hence $f[2] = 0$; the estimated frequency is $(1 - \frac{7/30}{0.4}) \cdot 30 = 12.5$. For level 3, since both $R_{i,j}[3]$ and $1 - R_{i,j}[3]$ exceed θ, we compute $\hat{p}[3]$ by assuming a large flow $f[3] = 1$ and $s_f \geq \theta \times 30 = 10$. After removing the flow, the residual $R_{i,j}[3]$ is at most 0.35 (both $V_{i,j}[0]$ and $V_{i,j}[3]$ decrease by at least 10), which is close to its expectation 0.36. By Bayes' Theorem, we estimate $\hat{p}[3] > 0.99$, so we estimate $f[3] = 1$ and the estimated frequency is $\frac{17/30-0.36}{1-0.36} \cdot 30 = 9.7$. Similarly, for level 4, after assuming $f[4] = 1$ and $s_f \geq \theta \times 30 = 10$, the residual $R_{i,j}[4]$ is 0.2, which is far from its expectation 0.5. We assign a $*$ to $f[4]$ and produce two frequency estimates. Finally, we have two candidate flowkeys 1011 and 1010, both of which have the same frequency estimate if we take the median across the four levels. We check whether the two candidate flowkeys are actually hashed into the stack, and compare their frequency estimates using the counter values in other stacks to filter out wrong flows.

Removing large flows from S. Removing a flow f is inverse to the update (see §3.2). It hashes f to the corresponding columns and subtracts the counter in level k by the estimated flow frequency if $f[k] = 1$. Recall that our large flow extraction subroutine verifies each extracted flow and its frequency by rehashing it to multiple stacks, so as to remove any wrong flow. The probability that a false positive flow remains is actually small under independent hash functions. Thus, the estimation error is also small has very limited impact on the final inference results.

Termination. The large flow extraction depends on the existence of large flows; otherwise, the observed $R_{i,j}[k]$ already fits a Gaussian distribution well by Theorem 1. We check by fitting $R_{i,j}[k]$ across all stacks to $N(p[k], \sigma^2[k])$. By the Gaussian distribution, when more than 68.26%, 95.44%, and 99.73% of the observed values of $R_{i,j}[k]$ (for all (i, j)) deviate $p[k]$ within one, two, and three standard deviations, respectively, we terminate the algorithm.

4.4 Analysis

The effectiveness of our model learning depends on what the minimum frequency would be in order that all flows above

the minimum frequency are guaranteed to be extracted. A smaller minimum frequency not only implies more flows to be extracted, but also leaves smaller remaining flows in the residual sketch and makes the residual sketch fit better Gaussian distributions according to Theorem 1. Note that when there are only a handful of flows, there are few hash collisions in each stack. In this case, each flow is likely to dominate its own hashed stacks and can be easily extracted. Thus, our analysis only focuses on the case where there are numerous small flows.

Guaranteed extraction frequency. SketchLearn provides guarantees for a certain frequency above which all large flows are extracted. First, we consider a single stack (i, j). We argue that if a flow f has $s_f > \frac{1}{2}V_{i,j}[0]$, it is guaranteed to be extracted from stack (i, j). The reason is that when we set $\theta = \frac{1}{2}$, either $R_{i,j}[k] < \theta$ (if the k-bit of f is one) or $1 - R_{i,j}[k] < \theta$ (if the k-bit of f is zero) must hold. In this case, the flow extraction can deterministically reconstruct each bit of f. Theorem 2 extends this single stack case for the entire sketch (see the proof in [34]).

Theorem 2. *For a multi-level sketch with c columns, flows with more than $\frac{1}{c}$ of the total frequency must be extracted.*

Intuitively, since large flows are iteratively extracted, the total residual frequency contributed by the remaining small flows in one stack will be no larger than $\frac{1}{c}$ of the overall frequency, provided that a hash function uniformly distributes flows across c columns (Assumption 1). Thus, if a flow has frequency exceeding $\frac{1}{c}$ of the total frequency, it will contribute at least $\frac{1}{2}$ of the frequency to the stack it is hashed to, after other large flows in the stack are extracted.

Recommended configurations. Administrators need to configure the number of rows and columns for a multi-level sketch. For the number of rows, our evaluation suggests that one row suffices to work well (see §7). For the number of columns, it can be configured based on the memory budget, or by specifying a guaranteed frequency and translating it to the number of columns using Theorem 2.

Internal parameters. The model inference introduces two internal parameters. Note that administrators need not be concerned about their actual values; in fact, their current settings work well for various types of traffic statistics based on our evaluation (see §7).

The first parameter is θ. Currently, we start with $\frac{1}{2}$. The initial value is motivated by Theorem 2 to provide guarantees on how large flows are extracted and make the residual sketch converge quickly. The subsequent values of θ are halved iteratively to control the extraction procedure. Our experience is that our large flow extraction procedure works for any decreasing sequence of θ.

The second parameter is the probability threshold to assign the k-bit for a candidate flowkey in large flow extraction, in which we now employ a sufficiently large value 0.99. The rationale behind is that we will assign a $*$ for the k-bit whose probability is below the value. A large value results in more $*$ and eventually reduces the errors of wrong bit assignments.

Discussion. Our model addresses Limitations L1 to L3. First, Theorems 1 and 2 collectively guarantee the correctness of model inference, so that we do not need to configure any expected error probabilities as input (L1 addressed). While SketchLearn still employs two user-specified parameters, both parameters are straightforward to configure since administrators can easily tell the minimum flow size of interest or the memory budget in their devices. Second, for flows smaller than $\frac{1}{c}$ of the total frequency, SketchLearn also strives to extract them although they are not theoretically guaranteed. Our experience is that even for 50% of the guaranteed frequency (i.e., $\frac{1}{2c}$), more than 99% of flows are still extracted (see Experiment 7 in §7.3). Thus, SketchLearn is robust to very small thresholds (L2 addressed). Finally, our model inference is iterative until the results fit both theorems. Thus, administrators can simply follow the theorems and do not need further tuning (L3 addressed).

5 QUERY RUNTIME

Administrators can query for various traffic statistics through SketchLearn's query runtime, which extracts the required information through the learned model. We now show how SketchLearn supports standard traffic statistics (§5.1) and more sophisticated queries (§5.2). We further discuss how SketchLearn realizes network-wide measurement (§5.3).

5.1 Traffic Statistics

Per-flow frequency. To query for the frequency of a given flow, SketchLearn first looks up the large flow list and returns the frequency estimate if found. Otherwise, it queries the residual sketch to estimate the frequency and bit-level probabilities, as in Steps (iii) and (iv) in §4.3.

Heavy hitters. SketchLearn compares all extracted flows in the large flow list for a given heavy hitter detection threshold (recall that the threshold is not used for resource configurations). Note that SketchLearn can extract flows with relatively small frequencies (see §4.4). For example, with 256KB memory, almost all flows whose frequencies are above 0.01% of the overall frequency are extracted (Experiment 8 in §7.3). Thus, it suffices to only consider the extracted flows in the large flow list for some practical detection threshold.

Heavy changers. Detecting heavy changers across two consecutive epochs combines the queries for per-flow frequencies and heavy hitters. Specifically, SketchLearn first identifies heavy hitters exceeding the threshold used in heavy changer detection in either one of the two consecutive epochs. It then queries for the per-flow frequency of

each identified heavy hitter in the other epoch. It calculates the frequency change and returns the flows with change exceeding the threshold.

Cardinality. SketchLearn computes the flow cardinality based on Theorem 1, which relates the number of flows n remaining in the residual sketch to probability $p[k]$ and its variance $\sigma^2[k]$. Since our model has learned $p[k]$ and $\sigma^2[k]$ for each k, SketchLearn estimates n as $n = \frac{p[k](1-p[k])c}{\sigma^2[k]}$ with every k. In addition, it adds the number of extracted flows in the large flow list. To avoid outliers, SketchLearn returns the median over all k.

Frequency distribution and entropy. The residual sketch compresses the information of flow frequency distributions in its counters. SketchLearn restores the distribution with the MRAC technique [38], which employs Expectation Maximization to fit the observed counter values. With the frequency distribution, many other statistics, such as entropy, can also be computed. Administrators can also employ other estimation approaches (e.g., [11]).

5.2 Extended Queries

SketchLearn proposes two extensions: (i) attaching error measures to measurement results; and (ii) enabling arbitrary flowkey definitions.

Attaching error measures. The estimated statistics are derived from both the residual sketch and the extracted large flows. We address the errors in both parts.

First, the errors from the residual sketch depend on the correctness of Gaussian distributions, including the goodness of fitting and the quality of the estimated $p[k]$ and $\sigma^2[k]$. In §4.4, we show that SketchLearn is guaranteed to extract large flows, so the residual sketch fits Gaussian distributions well. In addition, the estimates of both $p[k]$ and $\sigma^2[k]$ are derived from a large number (hundreds or even thousands) of counters in the level-k residual sketch, and they are unbiased and have minimum variance (see §4.3). Thus, the errors caused by the residual sketch are negligible and can be discarded.

Second, the errors of the extracted large flows are due to the presence of false positives. SketchLearn associates the vector of l bit-level probabilities as the error measure for each extracted large flow. Administrators can use the bit-level probabilities to decide if any flow should be excluded. For example, we can employ a simple *error filter* that discards the flows whose 50% of bits have a bit-level probability lower than 90%. Our evaluation shows that this error filter effectively eliminates almost all false positives (Experiment 10 in §7.3). Administrators can also apply other filters as needed. We argue that proposing such an error filter is much easier than specifying errors in resource configurations prior to measurement (see Limitation L1) since administrators can tune the error filter *after* collecting the measurement results.

Arbitrary flowkey definitions. SketchLearn can measure traffic statistics for any combination of bits in the original flowkey definition (e.g., any subsets of the 104 bits in 5-tuple flows) from both the large flow list and the residual sketch. For the former, SketchLearn simply sums up the flows based on the specified flowkey definition; for the latter, SketchLearn only examines the levels for the bits of interest.

One important issue is that when flows are grouped into *hyperflows* based on some specified flowkey definition (e.g., source-destination address pairs), a hyperflow may appear in multiple stacks, since the flows derived from the original flowkey definition (e.g., 5-tuples) are hashed to multiple columns. Thus, a hyperflow may have an inaccurate frequency if we miss its associated 5-tuple flows in some stacks. Fortunately, we observe that flows belonging to the same hyperflow exhibit some skewness distribution [5], so each hyperflow often has some large flows extracted. Thus, SketchLearn queries all stacks for every hyperflow grouped by existing large flows. It extracts a hyperflow from a stack and adds its frequency if its bit-level probabilities pass our error filter. After the extraction, SketchLearn recomputes the mean and variance of the residual sketch to preserve Gaussian distributions before estimating traffic statistics. After the estimation, the newly extracted hyperflows are inserted back to the residual sketch.

5.3 Network-wide Coordination

SketchLearn allows administrators to access part of or all measurement points to compute network-wide measurement statistics. In particular, it conveniently supports network-wide deployment and network-wide integration.

Network-wide deployment. SketchLearn can be deployed in any hardware/software switch or server host. By varying the hash functions across measurement points, we essentially provide more rows for a multi-level sketch. Thus, in practice, it suffices to allocate one row per multi-level sketch in each measurement point. Furthermore, we do not restrict deployment decisions (e.g., task placement), making SketchLearn orthogonal to previous deployment approaches for network-wide measurement (e.g., [47, 48, 59]).

Network-wide integration. Since a flow typically traverses multiple measurement points, we can improve our model learning for a particular measurement point by leveraging the results from others. Specifically, we examine the bit-level probabilities of each extracted flow along its traversed path. If a flow fails to pass our error filter in a majority of measurement points in the path, we drop it. On the other hand, if a flow is missed in only one measurement point yet its bit-level probabilities are high in other measurement points along the path, we query for its frequency and bit-level probabilities in the missing measurement point. If the results

are consistent with those of other measurement points, we extract this flow from the missing measurement point. How to aggregate results from multiple measurement points depends on measurement tasks and network topologies, and we leave the decision to administrators. We show some case studies in our evaluation (see §7.4).

6 IMPLEMENTATION

We implement a prototype of SketchLearn, including its software data plane, hardware data plane, and control plane.

Software data plane. We build the software data plane atop OpenVSwitch (OVS) [52], which intercepts and processes packets in its datapath. OVS has two alternatives: the original OVS implements its datapath as a kernel module, while an extension, OVS-DPDK, puts the datapath in user space and leverages the DPDK library [22] to bypass the kernel.

We propose a unified implementation for both OVS and OVS-DPDK. We connect the datapath and the SketchLearn program with shared memory, which is realized as a lock-free ring buffer [39]. When the data plane intercepts a packet, it inserts the packet header into the ring buffer. The SketchLearn program continuously reads packet headers from the ring buffer and updates its multi-level sketch.

The major challenge for the software data plane is to mitigate the per-packet processing overhead, as each packet incurs at most $r \times (l+1)$ updates. We address this using *single instruction multiple data (SIMD)* to perform the same operation on multiple data units with a single instruction. To fully utilize SIMD, we allocate counters of the same stack as one contiguous array. Currently, we employ 32-bit counters, and note that the latest `avx512` instruction set can manipulate 512 bits (i.e., 16 32-bit counters) in parallel. For 5-tuple flows with 104 bits (i.e., 105 levels), we divide the array into $\lceil \frac{105}{16} \rceil = 7$ portions. For each portion, we execute four SIMD instructions: (i) `_mm512_load_epi32`, which loads 16 counters from memory to a register array; (ii) `_mm512_maskz_set1_epi32`, which sets another register array whose element is set to the packet frequency if the k-bit is one, or zero if the k-bit is zero; (iii) `_mm512_add_epi32`, which calculates the element-wise sum of the two arrays; and (iv) `_mm512_store_epi32`, which stores the first register array back to memory.

P4 data plane. We use P4 [53] to demonstrate that SketchLearn can be implemented in hardware. P4 is a language that specifies how switches process packets. In P4, one fundamental building block is a set of user-defined *actions* that describe specific processing logic. Actions are installed in *match-action tables*, in which each action is associated with a user-defined matching rule. Each table matches packets to its rules and executes the matched actions. Our current implementation realizes each level of SketchLearn counters as an array of registers, which can be directly updated in the data plane. We implement a hash computation action in a dedicated table, and employs subsequent tables to accommodate counter update actions for different levels of sketches. Each counter update action encapsulates a stateful ALU to update the corresponding register array based on the bit value in the flowkey.

Measurement tasks	Approximate solutions
Heavy hitter (HH) detection Heavy hitter (HC) detection	Misra-Gries (MG) [46]
	Lossy Count (Lossy) [43]
	Space Saving (SS) [44]
	Fast Path (FP) [32]
	Deltoid (Del) [17]
	RevSketch (Rev) [58]
	SeqHash (Seq) [7]
	LD-Sketch (LD) [33]
Per-flow Frequency	CountMin (CM) [18]
	CountSketch (CS) [12]
Cardinality estimation	PCSA [25]
	kMin (KM) [3]
	Linear Counting (LC) [66]
	HyperLoglog (HLL) [24]
Flow size distribution	MRAC [38]
Entropy estimation	MRAC [38]
General-purpose	FlowRadar (FR) [40]
	UnivMon (UM) [42]

Table 1: Measurement tasks and approx. solutions.

Control plane. We implement a multi-threaded control plane that runs model learning and query runtime. A dedicated thread receives results from the data plane. It dispatches stacks to multiple computing threads as flows can be extracted from each stack independently. Finally, a merging thread integrates results to form the final model and computes traffic statistics accordingly.

Limitations. SketchLearn consumes many architecture-specific hardware resources to boost the performance because updating $l+1$ levels of counters is time consuming. For example, the software implementation occupies the AVX registers, which can be used by other high-performance applications. In P4, actions are executed in physical stages. The number of stages and number of stateful actions per stage are both limited. We will address such limitations by simplifying the multi-level design in future work.

7 EVALUATION

We conduct experiments to show that SketchLearn (i) incurs limited resource usage; (ii) supports general traffic statistics; (iii) completely addresses limitations of state-of-the-arts; and (iv) supports network-wide coordination.

7.1 Methodology

Testbed. We deploy the OVS-based data plane (including standard OVS and OVS-DPDK) in eight physical hosts, each of which has two 8-core Intel Xeno 2.93GHz CPUs, 64GB

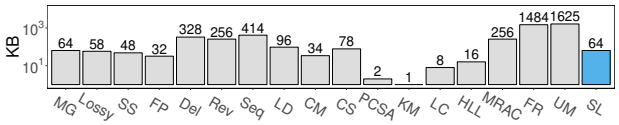


Figure 6: (Exp#1) Memory usage.

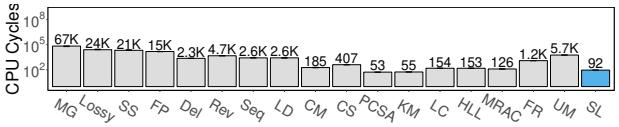


Figure 7: (Exp#2) Peak per-packet overhead.

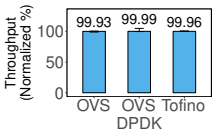


Figure 8: (Exp#3) Testbed throughput.

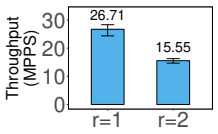


Figure 9: (Exp#4) Simulator throughput.

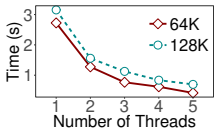


Figure 10: (Exp#5) Inference time.

RAM, a 1Gb NIC, and a 10Gb NIC. Each host in the data plane runs a single-threaded process that sends traffic via the 10Gb NIC and reports its sketch via the 1Gb NIC to the control plane, which runs in a dedicated host. For the P4 data plane, we deploy it in a Tofino hardware switch [4].

Simulator. Our OVS-based and P4-based testbeds are limited by the number of devices and the NIC speed. Thus, we implement a simulator that runs both the data plane and control plane in a single machine and connects them via loopback interfaces, without forwarding traffic via NIC. It eliminates network transfer overhead to stress-test SketchLearn.

Traces. We generate workloads with two real-world traces: a CAIDA backbone trace [8] and a data center trace (UN2) [6]. Each host emits traffic as fast as possible to maximize its processing load. The data plane reports multi-level sketches to the control plane every 1-second epoch. In the busiest epoch, each host emits 75K flows, 700K packets, and 700MB traffic for the CAIDA trace, and 3.1K flows, 35K packets, and 30MB traffic for the data center trace.

Parameters. By default, we allocate a 64KB multi-level sketch and set $r = 1$ per level (see §4.4). We consider 5-tuple flowkeys (with 104 bits), so a 64KB sketch implies $c = 156$.

7.2 Fulfilling Design Requirements

We first evaluate how SketchLearn addresses the requirements in §2.1. We consider various measurement tasks and compare SketchLearn with existing approximate measurement approaches (see Table 1). We fix the expected errors and manually tune each existing approximate measurement approach to achieve the errors. For heavy hitter and heavy changer detection, we set the threshold as 1% of the overall frequency and the error probability as 5%. For remaining statistics, we set the expected relative error as 10%.

(Experiment 1) Memory usage. As per R1, Figure 6 shows that 64KB memory suffices for SketchLearn (SL) to achieve the desired errors. This is comparable and even much less than many existing approaches. The only exception is that cardinality estimation approaches require much less memory as they do not need flow frequency and flowkey information, yet they are only designed for cardinality estimation.

(Experiment 2) Per-packet processing. As per R2, Figure 7 shows the peak per-packet processing overhead in CPU cycles. SketchLearn incurs only 92 cycles with SIMD, much lower than the 200-cycle budget for 10Gbps links (a non-SIMD version incurs 600 CPU cycles, not shown in the figure). For comparisons, top-k approaches consume an order of 10^4 CPU cycles as they traverse the whole data structure in the worst case. Some sketch-based approaches (e.g., CM) also fulfill the requirements, but they are specialized. Other sketch-based solutions (e.g., FR and UM) employ complicated structures to be general-purpose but incur high overhead.

(Experiment 3) Testbed throughput. We measure the throughput of SketchLearn in both OVS-based and P4 platforms. Figure 8 shows the normalized throughput to the line-rate speed without measurement. The processing speed is preserved and the variance is very small. The high performance comes from the fact that counters in different levels have no dependencies, providing opportunities for parallelization in both software and hardware platforms (see §6). In particular, for P4, counter update actions are distributed in different physical stages and executed in parallel.

(Experiment 4) Simulator throughput. Figure 9 presents the throughput of SketchLearn for $r = 1$ and $r = 2$ per level in our stress-test simulator. The throughput is above the 14.88Mpps requirement for 64-byte packets in a 10Gbps link.

(Experiment 5) Inference time. As per R3, we measure the model inference time (see §4.3). Figure 10 shows that the model inference time decreases as the number of threads grows. With five threads, the inference time takes less than 0.5 seconds. Doubling the sketch size only slightly increases the inference time, as the large flow extraction converges faster with more stacks and preserves the total time.

(Experiment 6) Generality. As per R4, we evaluate the accuracy of SketchLearn for various measurement tasks (see Table 1). We configure two memory sizes 32KB and 64KB, and set the number of rows per sketch as $r = 1$ or $r = 2$. We have four configurations for SketchLearn and call them S32-1, S32-2, S64-1, and S64-2. Other approaches being compared are allocated 64KB memory each.

Figure 11 shows that SketchLearn achieves high accuracy for all cases. Its accuracy remains fairly stable across

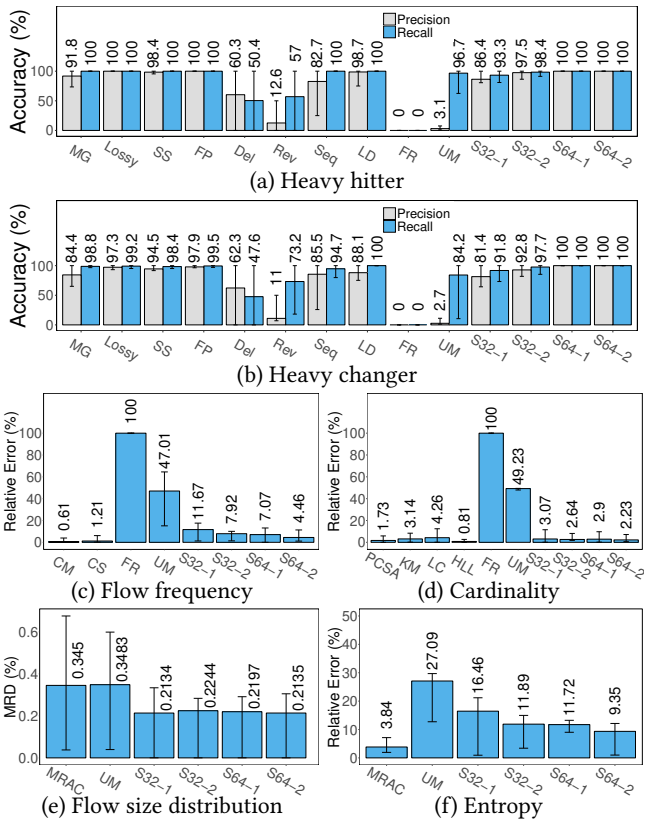
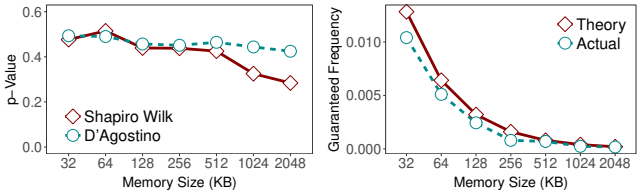


Figure 11: (Exp#6) Generality.

all four configurations as it can extract very small flows to produce accurate results. Although its error is higher than the best state-of-the-art for some cases (e.g., HLL for cardinality), those state-of-the-arts are specialized. In particular, SketchLearn outperforms the two general-purpose approaches FlowRadar and UnivMon, as they need excessive memory (see Figure 6) to mitigate errors. With only 64KB of memory, they suffer from serious hash collisions. In particular, FlowRadar fails to extract flows as it requires that some counters contain exactly one flow in order for the flow to be extracted; UnivMon has significant overestimates (see Figure 11(c)) and hence high false positives (see Figure 11(a)).

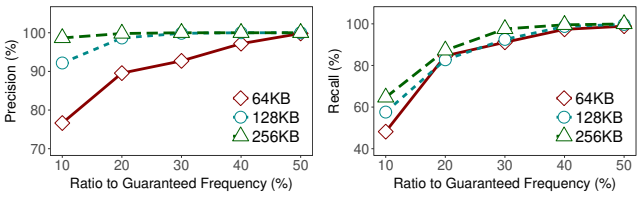
7.3 Addressing Limitations

(Experiment 7) Fitting theorems (L1 and L3). We verify Theorems 1 and 2, which address L1 and L3 (see §4.4). For Theorem 1, the experiment tests the null hypothesis that $R_{i,j}[k]$ follows a Gaussian distribution. It performs two statistical tests: Shapiro-Wilk Test [61] and D'Agostino's K^2 Test [21]. Figure 12(a) shows that the p-values are above 0.4 for most cases, so Theorem 1 holds (with a high probability). Note that the p-value of Shapiro-Wilk Test falls below 0.4 when the memory exceeds 1024KB as its accuracy drops



(a) Theorem 1 (b) Theorem 2

Figure 12: (Exp#7) Fitting theorems.



(a) Precision (b) Recall

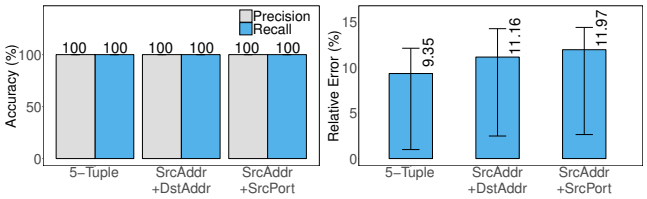
Figure 13: (Exp#8) Robust to small thresholds.

when the number of stacks exceeds 2000. For Theorem 2, the experiment compares its theoretical guaranteed frequency with the actual value. Figure 12(b) shows that actual guaranteed frequencies are slightly below the theoretical ones across all epochs and memory sizes, so Theorem 2 follows. Also, the small gap between the theoretical and actual values implies that Theorem 2 already achieves near-optimal configurations and administrators do not need manual tuning.

(Experiment 8) Robust to small thresholds (L2). This experiment shows that flows smaller than the guaranteed frequency are also extracted (see §4.4). We measure the accuracy for frequencies from 10% to 50% of the guaranteed ones. Figure 13 shows that for 50% of the guaranteed frequency, the precision and recall remain around 99%. Also, our default configuration with 64KB implies a guaranteed frequency of 0.5% of the total frequency (see Figure 12(b)). For 20% of the guaranteed frequency (i.e., 0.1% of the total frequency), SketchLearn still achieves 90% precision and 80% recall, much higher than those in Figure 1. Even for 10% of the guaranteed frequency, the precision and recall are above 75% and 50%, respectively. The accuracy can be further improved via network-wide coordination (see Experiment 11).

(Experiment 9) Arbitrary field combinations (L4). Figure 14 presents the accuracy for three flowkey definitions: 5-tuples (our default), source/destination IP addresses, and source IP address and port. We focus on heavy changer detection and entropy estimation. Although the relative errors of entropy estimation slightly increase for the latter two definitions, the results are still comparable to 5-tuples.

(Experiment 10) Attaching error measures (L5). We show the effectiveness of attaching error measures by comparing the accuracy with and without error filtering (see §5.2). We focus on heavy hitter detection, heavy changer



(a) Heavy changer (b) Entropy

Figure 14: (Exp#9) Arbitrary flowkey definitions.

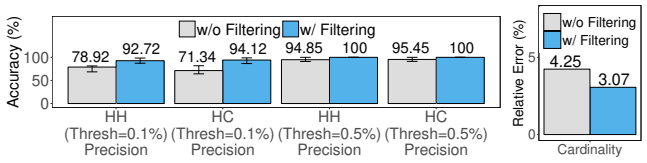
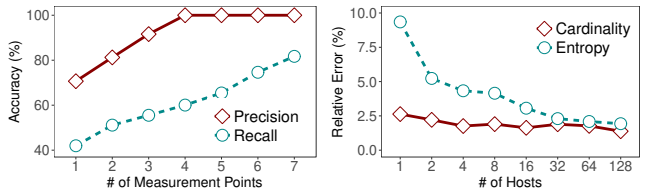


Figure 15: (Exp#10) Attaching error measures.



(a) Heavy hitter (b) Cardinality and entropy

Figure 16: (Exp#11) Network-wide coordination.

detection, and cardinality estimation. We use 64KB memory and set the detection threshold 0.1% and 0.5%. Figure 15 shows that for heavy hitter and heavy changer detection, error filtering improves the precision to above 90% for threshold 0.1%, and to 100% for threshold 0.5%. It also decreases the error for cardinality from 4.25% to 3.07%.

7.4 Network-wide Coordination

We evaluate network-wide coordination of SketchLearn using our simulator, in which we build an 8-ary Fat-Tree with 128 hosts and 80 switches. We evaluate three network-wide statistics: heavy hitters, cardinality, and entropy.

(Experiment 11) Network-wide coordination. Figure 16(a) shows network-wide heavy hitters. In our 8-ary Fat-Tree topology, a flow traverses at most seven devices (two software switches in hosts and five hardware switches). We vary the number of measurement points x from one to seven; for each x ($1 \leq x \leq 7$), we analyze all flows that traverse x devices, on which we deploy measurement points. We use an extremely small threshold, 0.01% of the total frequency, to show the improvement of network-wide coordination. Initially, when the number of measurement points is one, the precision and recall are only around 70% and 40%, respectively. However, the accuracy significantly improves as the number of measurement points increases. When the number is four, the precision is 100%, and the recall reaches 80% when the number is seven. Figure 16(b) shows the network-wide cardinality and entropy. To avoid duplicate measurement, we collect results from end hosts so that each flow is measured exactly twice. We vary the number of participating hosts here. The cardinality is stable for different numbers of hosts. The error of network-wide entropy decreases from 9% to 2% as the number of hosts increases, since more hosts provide more hash rows to improve learning accuracy.

8 RELATED WORK

Hash tables. Some studies [1, 41, 49, 63] advocate hash tables for per-flow tracking. However, hash tables inevitably consume substantial resources. Trumpet [49] uses rule-matching to monitor only the important events and optimizes cache locality to limit tracking overhead. However, it requires domain knowledge to configure appropriate rules, and hence incurs user burdens in some scenarios. Also, cache optimizations only work for software and how to apply them in hardware switches remains an open issue.

Rule matching and query languages. PacketHistroy [29] and Planck [55] mirror traffic for further analysis, while incurring high bandwidth consumption for mirroring. EverFlow [70] selectively processes flows to reduce overhead with pre-defined rules. Recent studies on query languages [26, 28, 65] allow expressions of sophisticated measurement requirements. These approaches build on existing switch techniques and are restricted by the resources in switches. SketchLearn is orthogonal and can be deployed with them.

Hardware enhancement. Some measurement systems leverage hardware support, such as using TCAM to boost performance [36, 47, 50]. TPP [35] and Marple [51] retrieve switch states to build measurement systems. Enhancing SketchLearn with hardware assistance is a future work.

9 CONCLUSION

SketchLearn provides a novel perspective for approximate measurement by decoupling the binding between resource configurations and accuracy parameters. Its idea is to leverage automated statistical inference to extract traffic statistics. Experiments show that SketchLearn is resource-efficient, accurate, and general, with minimum user burdens on configurations. The source code of SketchLearn is available at: **https://github.com/huangqundl/SketchLearn**.

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APPENDIX: ARTIFACTS

Source Code and Executables

The source code of the SketchLearn prototype is available at:

https://github.com/huangqundl/SketchLearn

Requirements: Existing prototype depends on *two* libraries: `libpcap` and `iniparser`.

In Ubuntu, `libpcap` can be installed with command:

```
sudo apt-get install libpcap libpcap-dev
```

`iniparser` can be downloaded at:

```
http://github.com/ndevilla/iniparser.git
```

After **make**, we should manually copy the library files and header files to system directory with **sudo cp lib* /usr/lib/** and **sudo cp src/*.h /usr/include**.

Files: after compiling with `make` command (no extra options needed), there will be five executable files generated:

- `dp_simulate`
- `dp_ovs`
- `controller`
- `trace_preprocess`
- `true_flows`

The source code also includes a configuration file called `config.ini`, which specifies the setup of SketchLearn. Each executable takes the configuration file as the only argument. Table 2 lists the fields in the configuration file.

1. `trace_preprocess`: Packet Preprocessing

We provide a tool `trace_preprocess` to convert a list of pcap files into a compact binary trace file. It reads packets from pcap files, extracts the 5-tuple key and byte count of each packet to form a record, and writes all records into a file.

[How to]

Step 1: Put all pcap files in a directory `$DIR` (e.g., `/data/caida`).
Step 2: Create a file `$FILE` (e.g., `pcap_list.txt`) in `$DIR`. Each line in `$FILE` contains one pcap file.
Step 3: Specify the input pcap file in `config.ini`:

Field	Meaning
trace_dir	directory in which SketchLearn works
trace_pcap_list	file listing all raw pcap files
trace_record_file	trace file after preprocessing
trace_bufsize	buffer size (in bytes) for trace pre-loading
key_len	number of bits in flowkey (104 for 5-tuple)
is_output	whether dump results into file
interval_len	length of a time interval (in ms)
num_interval	number of time interval considered in one experiment
depth	number of rows in SketchLearn multi-level structure
width	number of columns in SketchLearn multi-level structure

Table 2: Fields in `config.ini`.

- `trace_dir` = `$DIR`
- `trace_pcap_list` = `$FILE`

Also, specify the output file name `$RECORD_FILE` for extracted records. For example:

- `trace_record_file` = `records.bin`

Step 4: Execute the program:

```
./trace_preprocess config.ini
```

After the execution, a new file `$RECORD_FILE` is created in `$DIR`.

2. `true_flows`: Computing True Flows

Another tool `true_flows` extracts the true flows in each time interval as the ground truth of our evaluation.

[How to]

Step 1: Setup the configuration file. Here we show an example for required fields in `config.ini`.

- `trace_dir` = `/data/caida`
- `trace_record_file` = `records.bin`
- `trace_bufsize` = `2000000000`
- `key_len` = `104`
- `is_output` = `1`
- `interval_len` = `1000`
- `depth` = `2`
- `width` = `2500`

Step 2: Execute the program:

```
./true_flows config.ini
```

After the execution, a new directory `$DIR/true_flows` will be created. Each file in this directory contains all flows (including flowkey and true byte count) in one interval.

3. `dp_simulate`: Data Plane Simulator

The data plane simulator `dp_simulate` first loads the extracted (key, byte count) records into a memory buffer. Then it updates SketchLearn's multi-level structure with the loaded records. It periodically dumps the sketch into a file if `is_output` is set to 1.

[How to]

Step 1: Setup the configuration file as `true_flows`.

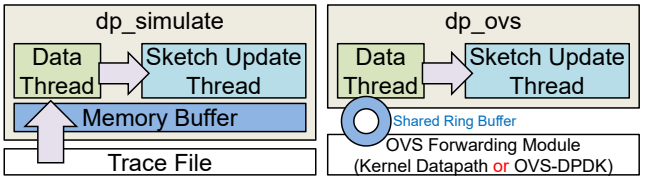
Step 2: Execute the program:

```
./dp_simulate config.ini
```

After the execution, a new directory `$DIR/sketches` will be created. Each file in this directory is a sketch file for one interval.

4. `dp_ovs`: Data Plane for OpenVSwitch (OVS)

The usage of `dp_ovs` is the same as `dp_simulate`. The only difference is that `dp_ovs` reads packets from the OVS forwarding module (which can be either the kernel-based datapath module or the user-space DPDK module), while `dp_simulate` reads extracted records from a trace file. Figure 17 depicts the difference.



(a) Data Plane for Simulation (b) Data Plane for OVS

Figure 17: Internals of `dp_simulate` and `dp_ovs`.

To enable packet extraction, we need to extend the OVS forwarding module with a hook to extract incoming packets.

[How to]

Step 1: Copy all files in the `openvswitch` directory to the correspond source tree of OVS. In particular, the directory `openvswitch/datapath` includes the kernel-based datapath extension; the directory `openvswitch/lib` includes the DPDK extension.

Step 2: Re-compile the OVS source code and install OVS by following the official documents.

Step 3: Configure `config.ini` and execute the command to start measurement:

```
./dp_ovs config.ini
```

5. Data Plane for P4

SketchLearn's P4 data plane is independent of the above components. All P4 files are in the `p4` directory. These files can be compiled and executed in the `bmv2` target by following the official documents.

6. `controller`: Control Plane Functionality

The program `controller` includes the control plane functionality of SketchLearn. In this artifact, `controller` not

only performs model inference, but also examines the correctness of the inference results with the ground truth generated by `true_flows`.

[How to]

Step 1: Ensure all sketch files are in `$DIR/sketches` and true flow files are in `$DIR/true_flows`.

Step 2: Configure `config.ini`. In addition to the fields in previous programs, `controller` requires an additional field:

- `num_interval`

Step 3: Execute the program:

```
./controller config.ini
```

After the execution, a new directory `$DIR/controller` will be created. We will illustrate the results in the following example.

Example

We show an example using `dp_simulate` as the data plane to stress-test SketchLearn. This example employs one PCAP file from CAIDA. We have uploaded the PCAP file and all experiment results in this example in

https://goo.gl/UKuQis

Anyone can download and reproduce the results.

```
config.ini
1 [Common]
2
3 trace_dir = /data/caida/
4 trace_pcap_list = pcap_list.txt
5 trace_record_file = records.bin
6 trace_bufsize = 20000000000
7
8 key_len = 104
9 is_output = 1
10 interval_len = 1000
11 num_interval = 58
12
13 [SketchLearn]
14
15 depth = 2
16 width = 2500
```

Figure 18: Example of `config.ini`.

Figure 18 shows the configuration file. We consider 5-tuple flows and one-second time intervals in this example. There are 58 such one-second intervals in our trace.

Figure 19 shows the procedure of `./trace_preprocess`. Note that `/data/caida/pcap_list.txt` contains only one line because we have only one PCAP file.

Figure 20 lists the results after executing `true_flows`, `dp_simulate`, and `controller`. The three programs produce results in `true_flows`, `sketches`, and `controller` directories, respectively.

```
→  SketchLearn git:(master) ✗ ls /data/caida
equinix-chicago.dirB.20150219-140000.UTC.anon.pcap
pcap_list.txt
→  SketchLearn git:(master) ✗ cat /data/caida/pcap_list.txt
equinix-chicago.dirB.20150219-140000.UTC.anon.pcap
→  SketchLearn git:(master) ✗ ./trace_preprocess config.ini
/data/caida/equinix-chicago.dirB.20150219-140000.UTC.anon.pcap complete
→  SketchLearn git:(master) ✗ ls /data/caida
equinix-chicago.dirB.20150219-140000.UTC.anon.pcap
pcap_list.txt
records.bin
→  SketchLearn git:(master) ✗
```

Figure 19: Example of trace pre-processing.

```
→  SketchLearn git:(master) ✗ ls /data/caida
equinix-chicago.dirB.20150219-140000.UTC.anon.pcap
pcap_list.txt
records.bin
→  SketchLearn git:(master) ✗ ./true_flows config.ini
→  SketchLearn git:(master) ✗ ./dp_simulate config.ini
→  SketchLearn git:(master) ✗ ./controller config.ini
→  SketchLearn git:(master) ✗ ls /data/caida
controller
equinix-chicago.dirB.20150219-140000.UTC.anon.pcap
pcap_list.txt
records.bin
sketches
true_flows
→  SketchLearn git:(master) ✗
```

Figure 20: Processing results.

In the `controller` directory, there are four types of files. First, each interval k has a `large_flow_`k file, containing all extracted large flows. Each flow occupies 105 lines: the first line is the flowkey and estimated byte count, while the remaining 104 lines specifies its bit-level flow confidence (one line for each bit). Second, `res_sketch_`k is the residual sketch after large flow extraction for interval k. Third, `quality_`k details the extraction accuracy for each interval k. It contains the estimated error of each large flow, as well as lists all false positive and false negative flows at the end of the file (not shown in the figure).

```
→  controller head -n 22 stat
time interval: 0
4351 flows extracted
        1 are false positives, fp rate (0.022983%)
Theory:
        flows >0.040000% of total traffic are guaranteed to be extraced
Experiment:
        flows >0.019289% of total traffic are all extraced
        flows >0.01% of total traffic are extraced with probability 99.946183%
decode_time: 1.862798

====================

time interval: 1
4255 flows extracted
        0 are false positives, fp rate (0.000000%)
Theory:
        flows >0.040000% of total traffic are guaranteed to be extraced
Experiment:
        flows >0.023610% of total traffic are all extraced
        flows >0.01% of total traffic are extraced with probability 99.964243%
decode_time: 2.215025
```

Figure 21: Controller result statistics.

Finally, a file `stat` summarizes the overall accuracy of all intervals. In particular, SketchLearn theoretically guarantees

to extract large flows above a boundary. `stat` prints this theoretical boundary, the actual boundary in this example, as well as the extraction probability for flows much below the boundary (see Figure 21). The results are consistent with our paper.