Efficient Distinct Heavy Hitters for DNS DDoS Attack Detection

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ABSTRACT
Motivated by a recent new type of randomized Distributed Denial of Service (DDoS) attacks on the Domain Name Service (DNS), we develop novel and efficient distinct heavy hitters algorithms and build an attack identification system that uses our algorithms.

Heavy hitter detection in streams is a fundamental problem with many applications, including detecting certain DDoS attacks and anomalies. A (classic) heavy hitter (HH) in a stream of elements is a key (e.g., the domain of a query) which appears in many elements (e.g., requests). When stream elements consist of a (key, subkey) pair, (domain, subdomain) a distinct heavy hitter (dhh) is a key that is paired with a large number of different subkeys. Our dHH algorithms are considerably more practical than previous algorithms. Specifically the new fixed-size algorithms are simple to code and with asymptotically optimal space accuracy tradeoffs.

In addition we introduce a new measure, a combined heavy hitter (cHH), which is a key with a large combination of distinct and classic weights. Efficient algorithms are also presented for cHH detection.

Finally, we perform extensive experimental evaluation on real DNS attack traces, demonstrating the effectiveness of both our algorithms and our DNS malicious queries identification system.

1. INTRODUCTION
The Domain Name System (DNS) service is one of the core services in the internet functionality. Distributed Denial of Service (DDoS) attacks on DNS service typically consist of many queries coming from a large botnet. These queries are sent to the root name server or an authoritative name server along the domain chain. The targeted name server receives a high volume of requests, which may degrade its performance or disable it completely. Such attacks may also contain spoofed source addresses resulting in a reflection of the attack or may send requests that generate large responses (such as an ANY request) to use the DNS for amplification attacks.

According to Akamai’s state of the internet report [3] nearly 20% of DDoS attacks in Q1 of 2016 involved the DNS service. Moreover, even some of the Internet’s DNS root name servers were targeted [22].

One type of particularly hard to mitigate DDoS attacks are randomized attacks on the DNS service. In these attacks, queries for many different non-existent subdomains (subkeys) of the same primary domain (key) are issued [16]. Since the result of a query to a new subdomain is not cached at the DNS resolver, these queries are propagated to the domain authoritative server, overloading both these servers and the open resolvers of the Internet Service Provider.

Motivated by this DNS attack vector we develop in this paper a new distinct heavy hitter algorithm which is more practical and accurate than previous algorithms, and build a system for the mitigation of this attack based on this algorithm.

Detecting heavy hitters in a stream of requests is a fundamental problem in data analysis, with applications that include monitoring for malicious activities and other anomalies. Consider a stream of DNS queries, with the top-level domain serving as the key. A key that appears a large number of times in the query stream constitutes a “classic” heavy hitter (e.g., google.com, cnn.com, etc.). In addition, each query’s sub-domain serves as the subkey (e.g., mail., home., game1., etc.), and a key with many different subkeys is then a distinct heavy hitters (dHH). As another example, in the case of a spoofed TCP SYN flood DDoS attack, the packets received consist of the same destination and many different sources, and therefore this attack may be represented as a dHH as opposed to a classic heavy hitter where most of the traffic could be due to a small number of different sources. Finally, a combined heavy hitter (cHH), a notion we present and motivate here, is a key with a large combination of distinct and classic weights. Intuitively, a cHH is a key that combines both a “classic” heavy hitter as well as a distinct heavy hitter, meaning it both appears a large number of times in the stream and has a high number of different sub-keys.

1.1 Contributions of this Paper

1.1.1 Algorithms
Our main contributions are novel practical sampling-based structures for distinct heavy hitter (dHH) and combined heavy hitter (cHH) detection whose size (memory requirements in number of cache entries) are only $O(\epsilon^{-1})$ keys, where every key with weight of at least $\epsilon$ fraction of the (respective) total weight is detected with...
high probability. The total weights for HH, dHH and cHH are respectively the total number of items, the total number of distinct (key:subkey) pairs, and a weighted sum of the two.

Our proposed fixed-size dHH algorithm, named Distinct Weighted Sampling (dwsHH), requires a constant amount of memory as opposed to the well known Superspreaders solution [21] which uses a linear, to the input stream length, amount of memory. Moreover, our use of sampling-based distinct counters is a significant practical improvement over Locher’s relatively new fixed-size solution [17] which utilizes linear-sketch based distinct counters, which are much less efficient in practice. In addition, our dHH algorithm produces a cardinality estimate for each key. This estimate is of much higher accuracy than the estimate produced by Locher, while the Superspreaders do not provide comparable estimates.

Our fixed-size cHH algorithm, named Combined Weighted Sampling (cwsHH) is, to the best of our knowledge, the first constant memory algorithm proposed which considers both the key volume as well as the distinctness of its subkeys.

Generally, approximate distinct heavy hitters algorithms exhibit a tradeoff between detection accuracy and the amount of space they require. Cardinality estimate accuracy is even more difficult to achieve with a fix-size structure since a key may be evicted from the cache and then re-enter the cache which presents some uncertainty with regards to cardinality. We provide a solution using a fix-size structure which outperforms known solutions both in terms of cardinality accuracy and practicality. A more detailed comparison of our results to previous work is shown in Section 3.

1.1.2 Applications

We design a system to detect randomized DNS request attacks. The design uses our dwsHH and cwsHH algorithms and is enhanced to be a complete system for this specific application. Additional applications of our dwsHH and cwsHH algorithms are given in Section 6.

1.1.3 Evaluation

We demonstrate, via experimental evaluations on both real internet traces and synthetically generated data, the effectiveness of our dwsHH and cwsHH algorithms as well as our system for detection of randomized DNS request attacks.

1.2 Paper Organization

Section 2 provides required definitions and background. In Section 3 we discuss our algorithms for distinct weighted sampling, followed by a discussion of our combined weighted sampling scheme in Section 4. Section 5 describes experimental evaluation of our algorithms. In Section 6 we describe the randomized DDoS attacks on DNS servers and our proposed system for mitigation of such attacks as well as an evaluation of our system. Section 7 summarizes related work, and Section 8 concludes the paper.

2. PRELIMINARIES AND NOTATIONS

2.1 Problem Definitions

Formally, our input is modeled as a stream of elements, where each element has a primary key $x$ from a domain $X$ and a subkey $y$ from domain $D_y$. For each key, the (classic) weight $h_x$ is the number of elements with key $x$, the distinct weight $w_x$ is the number of different subkeys in elements with key $x$, and, for a parameter $\rho \ll 1$, the combined weight is $b_x^{(\rho)} = \rho h_x + w_x$. In the particular example of a DNS resolver, $h_x$ is the total number of requests for a primary domain $x$ and $w_x \leq h_x$ is the number of distinct subdomains. Combined weights are interesting as they can be a more accurate measure of the load due to key $x$ than one of $h_x$ or $w_x$ in isolation: All $h_x$ requests are processed but the $w_x$ distinct ones are costlier. For DNS resolvers, the distinct requests are costlier because their responses aren’t in the cache.

A key $x$ with weight that is at least an $\epsilon$ fraction of the (respect) total is referred to as a heavy hitter: When $h_x \geq \epsilon \sum_y h_y, x$ is a (classic) heavy hitter (HH), when $w_x \geq \epsilon \sum_y w_y, x$ is a distinct heavy hitter (dHH) or superspreader [21], and when $b_x^{(\rho)} \geq \epsilon \sum_y b_y^{(\rho)}, x$ is a combined heavy hitter (cHH).

The notations used throughout the paper are summarized in Table 1.

| Symbol | Meaning |
|--------|---------|
| $x$    | key     |
| $y$    | subkey  |
| $h_x$  | number of elements with key $x$ |
| $w_x$  | number of different subkeys in elements with key $x$ |
| $m$    | $\max_x w_x$ |
| $\tau$ | detection threshold |
| $k$    | cache size |
| $\ell$ | number of buckets |
| $\rho$ | combined weight parameter |

Table 1: Notations

2.2 Background

2.2.1 Sample and Hold

The Sample and Hold (S&H) algorithm [14][11] is applied to a stream of elements, where each element has a key $x$. The weight $h_x$ of a key $x$ is the number of elements with this key.

The fixed threshold design is specified for a threshold $\tau$. The algorithm maintains a cache $S$ of keys, which is initially empty, and a counter $c_x$ for each cached key $x$. A new element with key $x$ is processed as follows: If $x \in S$ is in the cache, the counter $c_x$ is incremented. Otherwise, a counter $c_x \leftarrow 1$ is initialized with probability $\tau$. The fixed-size design is specified for a fixed sample (cache) size $k$ and works by effectively lowering the threshold $\tau$ to the value that would have resulted in $k$ cached keys.

An important property of S&H is that the set of sampled keys is a probability proportional to size without replacement (ppswor) sample of keys according to weights $h_x$ [29].

2.2.2 Approximate Distinct Counters

A distinct counter is an algorithm that maintains the number of different keys in a stream of elements. An exact distinct counter requires state that is proportional to the number of different keys in the stream. Fortunately, there are many existing designs and implementations of approximate distinct counters that have a small relative error but use state size that is only logarithmic or double logarithmic in the number of distinct elements [13][8][5][12][9]. The basic idea is elegant and simple: We apply a random hash function to each element, and retain the smallest hash value. We can see that this value, in expectation, would be smaller when there are more distinct elements, and thus can be used to estimate this number. The different proposed structures have different ways of enhancing this approach to control the error. The tradeoff of structure size and error are controlled by a parameter $\ell$: A structure of size proportional to $\ell$ has normalized root mean square error (NRMSE) of $1/\sqrt{\ell}$. In Section 3 we use distinct counters as a black box in
our dHH structures, abstracted as a class of objects that support the following operations:

- **Init:** Initializes a sketch of an empty set
- **Merge (x):** merge the string $x$ into the set ($x$ could already be a member of the set or a new string).
- **CardEst:** return an estimate on the cardinality of the set (with a confidence interval)

In Section 3.4, we also propose a design where a particular algorithm for approximate distinct counting is integrated in the dHH detection structure.

## 3. DISTINCT WEIGHTED SAMPLING

We now present our distinct weighted sampling schemes, which take as input elements that are key and subkey pairs. We build on the fixed-threshold and fixed-size classic S&H schemes but make some critical adjustments: First, we apply hashing so that we can sample the distinct stream instead of the classic stream. Second, instead of using simple counters $c_x$ for cached keys as in classic S&H, we use approximate distinct counters applied to subkeys. Third, we maintain state per key that is suitable for estimating the weight of heavy cached keys (whereas classic S&H was designed for unbiased domain queries).

Our algorithms, in essence, compute heavy hitters using weighted sampling. A sample set of the keys is maintained during the execution of each of the algorithms (HH, dHH, or CHH). The sample set constitutes a weighted sample according to the respective weights so that the heavier keys, in particular the heavy hitters, are much more likely to be included than other keys. The counts in each of the algorithms are different; number of repetitions, measure of distinctness, and a combined measure, respectively. The algorithms maintain counts with each cached key which allow to produce the cardinality estimate for each output key.

### 3.1 Fixed-threshold Distinct Heavy Hitters

Our fixed-threshold distinct heavy hitters algorithm is applied with respect to a specified threshold parameter $\tau$. We make use of a random hash function $h \sim U[0, 1]$. An element $(x,y)$ is processed as follows. If the key $x$ is not cached, then if $h(x,y)$ (applied to the key and subkey pair $(x,y)$) is below $\tau$, we initialize a $dCounters[x]$ object (say that now $x$ is cached) and insert the string $(x,y)$. If the key $x$ is already in the cache, we merge the string $(x,y)$ into the distinct counter $dCounters[x]$. The pseudo code is omitted due to lack of space and can be found in the technical report [2].

### 3.2 Fixed-size distinct weighted sampling

The fixed-size Distinct Weighted Sampling (dwsHH) algorithm is specified for a cache size $k$. Compared with the fixed-threshold algorithm, we keep some additional state for each cached key:

- The threshold $\tau_x$ when $x$ entered the cache (represented in the pseudocode as $dCounters[x].\tau$). The purpose of maintaining $\tau_x$ is deriving confidence intervals on $w_x$. Intuitively, $\tau_x$ captures a prefix of elements with key $x$ which were seen before the distinct structure for $x$ was initialized, and is used to estimate the number of distinct subkeys in this prefix.
- A value $seed(x) \triangleq \min_{(x,y) \in \text{stream}} Hash(x,y)$ which is the minimum $Hash(x,y)$ of all elements with key $x$. (In the pseudocode, $dCounters[x].seed$ represents $seed(x)$). Note that it suffices to track $seed(x)$ only after the key $x$ is inserted into the cache, since all elements that occurred before the key entered the cache necessarily had $Hash(x,y) > \tau_x$, as the entry threshold $\tau$ can only decrease over time.

The fixed-size dwsHH algorithm retains in the cache only the $k$ keys with lowest seeds. The effective threshold value $\tau$ that we work with is the seed of the most recently evicted key. The effective threshold has the same role as the fixed threshold since it determines the (conditional) probability on inclusion in the sample for a key with a certain $w_x$. A pseudo code is provided as Algorithm 1:

```plaintext
Algorithm 1: Fixed-size streaming Distinct Weighted Sampling (dwsHH)

Data: cache size $k$, stream of elements of the form (key, subkey), where keys are from domain $\mathcal{X}$
Output: set of $(c_x, \tau_x)$ where $x \in \mathcal{X}$

$dCounters \leftarrow \emptyset$; $\tau \leftarrow 1$ // Initialize a cache of distinct counters

foreach stream element with key $x$ and subkey $y$ do // Process a stream element
  if $x$ is in $dCounters$ then
    $dCounters[x].merge(x,y)$
    $dCounters[x].seed \leftarrow min\{dCounters[x].seed, Hash(x,y)\}$
  else
    if $Hash(x,y) < \tau$ then // Create $dCounters[x]$ in case $x$ is not already in $dCounters$
      $dCounters[x].Init$,
      $dCounters[x].merge(x,y)$
      $dCounters[x].seed \leftarrow Hash(x,y)$
      $dCounters[x].\tau \leftarrow \tau$
    if ($dCounters[x] > k$ then
      $x \leftarrow argmax_y \in dCounters[x].seed$
      $\tau \leftarrow dCounters[x].seed$
      Delete $dCounters[x]$

return (For $x$ in $dCounters$, $(x, dCounters[x].CardEst, dCounters[x].\tau)$)
```

### 3.3 Analysis and estimates

We first consider the sample distribution $S$ of dwsHH. As we mentioned (Section 2.2.1), it is known that classic S&H applied with weights $h_x$ has the property that the set of sampled keys is a pspsow sample according to $h_x$. [10] Surprisingly, the sample distribution properties of S&H carries over from being with respect to $h_x$ (classic S&H) to being with respect to $w_x$ (dwsHH). We obtain that key $x$ is very likely to be sampled when $w_x \gg \max_{y \notin \{k-1\} \cap \{top_i\}} \left(\min - \sum_{i \in \{top_i\}} w_{i}/(k - i)\right)$ where $top_i$ is the set of $i$ heaviest keys. A detailed explanation of this bound with relevant proofs is omitted due to lack of space and can be found in the technical report [2].

#### 3.3.1 Estimate quality and confidence interval

With the fixed-threshold scheme, we expect the sample size to include $\tau \sum w_x$ keys even when all keys have $w_x = 1$. With the fixed-size (dwsHH) scheme, we expect the cache to include keys with $w_x \gg \sum_i w_x/k$ but it may also include some keys with small weight.

For any applications, an estimate on the weight $w_x$ of the heavy hitters is needed. We compute an estimate with a confidence interval on $w_x$ for each cached key $x$, using the entry threshold $\tau$ (or $dCounters[x].\tau$ in the fixed-size scheme) and the approximate distinct count $dCounters[x].CardEst$.  


We obtain the confidence interval \[ \text{dCounters}[x].\text{CardEst} - a_3\sqrt{\sigma_1^2 + \sigma_2^2}, \text{dCounters}[x].\text{CardEst} + 1 + 1/\tau + a_3\sqrt{\sigma_1^2 + \sigma_2^2} \]
where \( a_3 = 2 \).

We note the confidence intervals are tighter (and thus better) for keys that are presented earlier and thus have \( \tau_x \ll \tau \).

Further explanations can be found in the technical report \[2\].

### 3.4 Integrated dwsHH design

We propose a seamless design (Integrated dwsHH) which integrates the hashing performed for the weighted sampling component with the hashing performed for the approximate distinct counters. We use a particular type of distinct counters based on stochastic averaging (\( \ell \)-partition) \[13\] \[12\] (see \[9\] for an overview). This design hashes strings to \( \ell \) buckets and maintains the minimum hash in each bucket. These counters are the industry’s choice as they use fewer hash computations. We estimate the distinct counts using the tighter HIP estimators \[9\]. Pseudocode for the fixed-size Integrated dwsHH is provided as Algorithm 2. The parameter \( k \) is the sample size and the parameter \( \ell \) is the number of buckets. Note, we use two independent random hash functions applied to strings: BucketOf returns an integer \( \sim U[0, \ell - 1] \) selected uniformly at random. Hash returns \( \sim U[0, 1] (O(\log m) \text{ bits suffice).} \)

As in the generic Algorithm 1, we maintain an object \( \text{dCounters}[x] \) for each cached key \( x \). The object includes the entry threshold \( \text{dCounters}[x].\tau \) and \( \text{dCounters}[x].\text{seed} \), which is the minimum \( \text{Hash}(x, y) \) of all elements \((x, y)\) with key \( x \). The object also maintains \( \ell \) values \( c[i] \) for \( i = 0, \ldots, \ell - 1 \) from the range of Hash, where \( c[i] \) is the minimum Hash over all elements \((x, y)\) such that the element was processed after \( x \) was cached and BucketOf\((x, y)\) is equal to \( i \) \( c[i] = 1 \) when this is empty. Note that \( \text{dCounters}[x].\text{seed} \equiv \min\{c[0], \ldots, c[\ell - 1]\} \).

The object also maintains a HIP estimate \( \text{CardEst} \) of the number of distinct subkeys since the counter was created.

For a sampled \( x \), we can obtain a confidence interval on \( w_x \) using the lower end point \( \text{dCounters}[x].\text{CardEst} - 1/\text{dCounters}[x].\tau \), with error controlled by both the distinct counter and the entry threshold. The errors are combined as explained in Section 3.3.1 using the HIP error of \( \sigma_2 \approx (2\ell)^{-\alpha} \cdot \text{dCounters}[x].\text{CardEst} \).

The size of our structure is \( O(k\ell \log m) \) and the representation of the \( k \) cached keys. Note that the parameter \( \ell \) can be a constant for DDoS applications: A choice of \( \ell = 50 \) gives NRMSE of 10%. Note, that this design can be further optimized according to resource constraints as explained in the technical report \[2\].

### 4. COMBINED WEIGHTED SAMPLING

We now present our cwsHH algorithm for combined heavy hitters detection. The pseudocode, which builds on our Integrated dwsHH design (Algorithm 2), is presented in Algorithm 3 and works with a specified parameter \( \rho \). For each cached key \( x \), the combined weighted sampling (cwsHH) algorithm also includes a classic counter \( \text{dCounters}[x].f \) of the number of elements with key \( x \) processed after \( x \) entered the cache.

Similarly to dwsHH, if we are only interested in the set of sampled keys (cHH candidates), it suffices to maintain the seed values of cached keys without the counting and distinct counting structures. The counters are useful for obtaining estimates and confidence intervals on the combined weights of cached keys: For a desired confidence level \( 1 - \delta \). The lower end of the interval is \( \text{dCounters}[x].\text{CardEst} + \rho \text{dCounters}[x].f - a_4\sigma_1, \) where \( \sigma_1 \)

\[
\text{Algorithm 2: Integrated dwsHH}
\]

| Data: cache size \( k \), distinct structure parameter \( \ell \), stream of (key, subkey) pairs
| Output: set of \((x, c_x, r_x)\) where \( x \in X \)
| \( \text{dCounters} \leftarrow \emptyset; \tau \leftarrow 1 // \text{Initialize a cache of distinct counters} \)
| foreach stream element with key \( x \) and subkey \( y \) do // Process a stream element
| if \( x \) is in \( \text{dCounters} \) then
| if Hash\((x,y)\) < \( \text{dCounters}[x].\ell/\text{BucketOf}(x,y) \) then
| \( \text{dCounters}[x].\text{CardEst} \leftarrow \ell/\sum\{0 \ldots \ell - 1\} \text{dCounters}[x][i] \)
| \( \text{dCounters}[x].\text{BucketOf}(x,y) \leftarrow \text{Hash}(x,y) \)
| \( \text{dCounters}[x].\text{seed} \leftarrow \min\{\text{dCounters}[x].\text{seed}, \text{Hash}(x,y)\} \)
| else
| if Hash\((x,y)\) < \( \tau \) then // Initialize \( \text{dCounters}[x] \)
| for \( i = 0, \ldots, \ell - 1 \) do \( \text{dCounters}[x][i] \leftarrow 1 \)
| \( \text{dCounters}[x].\text{CardEst} \leftarrow 0 \)
| \( \text{dCounters}[x].\text{BucketOf}(x,y) \leftarrow \text{Hash}(x,y) \)
| \( \text{dCounters}[x].\text{seed} \leftarrow \text{Hash}(x,y) \)
| \( \text{dCounters}[x].\tau \leftarrow \tau \)
| if \( \text{dCounters}[x] > k \) then
| \( x \leftarrow \text{arg max}_{x \in \text{dCounters}[x]} \cdot \text{dCounters}[x].\text{seed} \)
| \( \tau \leftarrow \text{dCounters}[x].\tau \)
| Delete \( \text{dCounters}[x] \)
| return (for \( x \in \text{dCounters}, (x, \text{dCounters}[x].\text{CardEst}, \text{dCounters}[x].\tau)) \)

is the standard error of the distinct count. For the higher end, we bound the contribution of the prefix, which has expectation bounded by \( 1/\tau - 1 \), and subject both to the \( \mathbb{S} \& \mathbb{H} \) error and the approximate distinct counter error, so we obtain

\[
\text{dCounters}[x].\text{CardEst} + \rho \text{dCounters}[x].f - a_4\sigma_1 - 1 + 1/\tau + a_3\sqrt{\sigma_1^2 + \sigma_2^2}.
\]

## 5. EVALUATION

### 5.1 Theoretical Comparison

In Table 2, we show a theoretical memory usage comparison of our algorithms, SuperSpreaders and Locher \[17\], assuming all algorithms use the same distinct count primitive. We are using the notations in Table 1 \( \delta \) as the probability that a given source becomes a false negative or a false positive, \( N \) as the number of distinct pairs, \( r \) as the number of estimates, \( s \) as the number of pairs of distinct counting primitives used to compute each estimate, and \( c \) (for a c-superspreader i.e. we want to find keys with more than \( c \) distinct elements) choosing \( c = \tau^{-1} \). As we can also see from the table, the cache size affects the distinct weight estimation error for the keys.

### 5.2 Fixed-size distinct weighted sampling (dwsHH)

We have done extensive testing of our algorithms both on real internet traffic traces and on synthetically generated data.

We begin our evaluation with the results of tests done on packets from a trace from The CAIDA UCSD Anonymized Internet Traces 2014 \[1\]. For each packet, the destination IP address is the key, and the source IP address is the value. In order to display the full ability of our algorithm, we added into this data synthetic packets which
form keys with many distinct values. Specifically, the synthetic packets all have unique subkeys and contain 4 keys, such that the keys have cardinalities 2000, 1000, 500, and 250. The entire data is made up of approximately 1M (993750) \{key, value\} pairs, containing 33977 keys and 52859 distinct pairs.

We evaluate the accuracy of our Fixed-Size dwsHH algorithm (see Section 5.2). The results presented are based on the implementation of Algorithm \(2\). We set the cache size \(k = 2000\) and distinct structure parameter \(t = 64\). We compare, both in terms of accuracy and space, our algorithm to a simple and highly inefficient algorithm which counts the number of distinct values associated with each key. Fig 1a shows the cardinality estimate (Cardest) calculated by the algorithm in this test, compared to the actual distinct count of each of these keys. We can see that the algorithm provides relatively accurate estimates, with the average error of the Cardest, measured by the average difference between the Cardest and the real distinct count was 1.5, with a median error of 1. In terms of memory usage, our algorithm consumes a constant amount of space, while the simple algorithm consumes space that is linear with the number of distinct pairs seen. The memory consumption of both algorithms is depicted in Fig 1c. While we chose to compare memory usage with the simplified Superspreaders algorithm - the one filter algorithm, its two filter variant algorithm reaches a better asymptotic memory usage model. However, the two filter variant is more complicated and its memory usage is more susceptible to implementation factors but in any event, its memory usage still grows linearly with the stream length. Fig 1d shows the injected Caida tests performed with cache size \(k = 500\). The confidence interval for the cardinality estimate is shown in Fig. 1d.

As explained in Section 3.3, our algorithm seeks to find keys with a cardinality over \(t = \sum_{y} w_{y}/k\). To evaluate the false positive (FP) and false negative (FN) rates of our algorithm, we set \(t\) to be the threshold and evaluate the keys’ deviation. Any key \(x\) with a cardinality \(w_{x} > t\) that is not reported by our algorithm (not in cache) and has a high deviation from \(t\) (normalized by the cardinality error), is a FN. FPs are defined respectively - a key \(x\) that is reported with a cardinality \(w_{x} < t\) and a high deviation from \(t\). Fig 1b shows the distinct count of keys that were reported (in cache) by the algorithm, and those that were not reported (not in cache - the red colored circles shown). Note that generally, the algorithm will also cache keys which have a distinct count much lower than \(t\). We use the Cardest to select only keys with a Cardest that is above \(t\). In the example shown, only 12 out of the 2000 cached keys had Cardest value higher than the real distinct count, all of these overestimates were within the confidence interval bounds - within error bounds. In the same example, we found 18 (9 depicted in graph) potential FN - unreported keys above the threshold set, but all of which are within one standard deviation shown by the dotted line. Note that we can tune parameters to obtain a near-zero FN rate instead of a near-zero FP since both the number of overall distinct pairs as well as the cache size affect this threshold.

5.3 Combined Weighted Sampling

We test our streaming cwsHH algorithm (see Section 2) on the data described above, with \(\rho = 0.1\). The cwsHH algorithm samples keys according to their combined weight. This is depicted in Fig 3 where for each key we compare the actual count, the distinct count and the combined weight of the key. We can see that the algorithm properly identifies the keys with highest combined weights and that those keys are different than when sampling by distinct weights. For example, item 28 which is unreported in Fig. 2b has a very high number of non-distinct queries and therefore is reported as item 18 in Fig. 3.

6. RANDOMIZED SUB-DOMAIN DDOS ATTACKS ON DNS

6.1 Attack Description

The DNS is a hierarchical distributed naming system for translating more readily domain names to the numerical IP addresses. The DNS distributes the responsibility by designating authoritative name servers for each domain. The Random Subdomain DDoS (RSDDoS) attack on DNS (also known as the Random QNAME attack or the Nonsense Name at-
Algorithm 3: Streaming cwsHH

Data: cache size k, distinct structure parameter ℓ, parameter ρ; stream 
(key, subkey) pairs

Output: set of (x, c, f, τ, y) where x ∈ X
dCounters ← 0; τ ← 1 // Initialize a cache of 
distinct counters

foreach stream element with key x and subkey y do // Process a 
stream element

   erand ← 1 − (1 − rand())¹/ρ // Randomization for 
   hυ count

   if x is in dCounters then
      dCounters[x].f ← f // Increment count
      if Hash(x, y) < dCounters[x].c[ BucketOf(x, y) ] then
         dCounters[x].CardEst ←
         (1 / ℓ) × Σℓ−1
         dCounters[x].c[i] ←
         dCounters[x].BucketOf(x, y) ← Hash(x, y)
         dCounters[x].seed ←
         min(dCounters[x].seed, Hash(x, y), erand)
      else
         if min{ erand, Hash(x, y) } < τ then // Initialize 
            dCounters[x]
            for i = 0, ..., ℓ − 1 do dCounters[x].c[i] ← 1
            dCounters[x].CardEst ← 0
            dCounters[x].f ← 1
            dCounters[x].BucketOf(x, y) ← Hash(x, y)
            dCounters[x].seed ← min{ Hash(x, y), erand }
            dCounters[x].τ ← τ
         if |dCounters[x]| > k then
            x ← argmaxy∈dCounters dCounters[y].seed
            τ ← dCounters[y].seed
            Delete dCounters[x]
      return (For x ∈ dCounters, 
            (x, dCounters[x].CardEst, dCounters[x].f, dCounters[x].τ))

6.2 Attack Query Identification System

We provide an overview for a system which identifies attack 
queries of the form VAR.vardomain.com. That is, queries that 
consist of a random (or automatically generated) string as a prefix 
of the domain (in the least significant domain sub-part), which have 
so far been the most common query form in these attacks. The sys-
tem detects RSDDoS attacks on DNS servers and creates signatures 
for subsequent mitigation. Queries are processed with the key be-
ing the vardomain.com and the subkey being the VAR part of the 
query. We are currently developing a system that expands mitiga-
tion capabilities to additional forms of these attacks. This advanced 
system is beyond the scope of this paper.

Traffic analysis is done in two stages. The first stage is a pre-

Table 2: Theoretic Comparison between methods

| Algorithm              | Memory usage        | Keys’ distinct weight estimation error |
|------------------------|---------------------|---------------------------------------|
| Fixed-threshold        | O(τ ∑ρ w y · ℓ log m) | τ⁻¹ + w y/√2t                          |
| Fixed-size dwsHH       | O(kℓ log m)          | (1/ℓ) ∑ρ w y/√2t                       |
| Superspreaders 1-Level | O(Δc)                | N.A                                   |
| Superspreaders 2-Level | O(Δc ln 1/2)         | N.A                                   |
| Locher [17]            | O((rs + 2t + |k|))    | N.A                                   |
processing of peacetime traffic, the second is an analysis of traffic during an attack. Our analysis makes use of both a Distinct Heavy Hitters module such as the combined sketch described in Section 4 and a Classic Heavy Hitters module such as that of Metwally et al. [18].

As can be seen in Fig. 4a during peacetime, queries are processed as follows:

1. Query parsing: (key, subkey) is extracted.
2. The (key, subkey) pair is inserted into our streaming combined weighted sampling module: This mechanism identifies zones (keys) that are heavily queried, and have a large number of distinct subdomains (subkeys). The output of this module is used to create a white-list of zones that are combined heavy hitters and most likely use disposable domains as part of their routine behaviour.
3. The subkey is inserted into a classic heavy hitters module: The output of this module generates a white-list of subdomains (subkeys) that appear frequently in the DNS queries. When mitigating an attack, the requests with a subkey from this list should not be blocked. The motivation for this is to identify strings which are commonly used as subdomains, and are therefore not likely to be randomly generated. Using this white-list minimizes the false positives when mitigating an attack with the signatures we generate.

As shown in Fig. 4b in the detection phase the system identifies the attacked domains as follows:

1. Query parsing: key and subkey are extracted.
2. The (key, subkey) pair is inserted into our streaming combined weighted sampling module: During an RSDDoS attack, the zones which are identified as having highly distinct subdomains and are heavy hitters, are suspected as being the victims. The output of this module is therefore used to create an initial set of attack signatures.
3. White-list filter: The white-lists created during the peacetime processing are used to filter out legitimate queries and therefore reduce the false positive rate of the system. Two types of filters are used:

- **Subkey white-list**: If the query subkey was identified as being frequent during peacetime, we assume that this is not an automatically generated subkey and therefore the query is considered to be legitimate. In this manner, legitimate queries of attacked domains may be serviced.

- **Key white-list**: the zones that have been identified as white-list domains in peacetime are filtered out since these are zones which have a large number of distinct sub-domains as part of their regular operation, e.g., disposable domains. We note however, that detection of attacks on disposable domains (which have been white-listed) is left for the full paper where the amounts of distinct values detected by the combined weighted sampling algorithm at attack time are compared with those of peacetime, and if a notable increase is observed then an attack is signaled and a corresponding mitigation is suggested. Note that bloom filters can be used to speed up whitelist search as described in [4].

The above system creates a list of domains which are likely under attack. Mitigation is thus proposed by filtering out DNS requests to these domains except if the VAR part appears in the subdomain white-list generated at peacetime. Therefore, the suggested mitigation would first allow the queries for domains with white-list subkeys, and then block the requests to the domains suspected to be under attack.

6.3 System Evaluation
The RSDDoS DNS attack query identification system presented above has been evaluated on traces of actual RSDDoS attacks captured by a large ISP.

We analyzed 5 captures which were sniffed during different RSDDoS attacks and contained both attack and legitimate DNS queries. All captures were taken within a single month in 2014. Note that most of the captures contain 5000 queries as that was the set amount that was sniffed for each attack spotted. The ISP identified the RSDDoS attacks as they were occurring. The victim was the authoritative name servers of the ISP (the victim domain belongs to one of the ISP’s clients) or the Open Resolvers of the ISP (the victim domain does not belong to the ISP). We compare our results to the analysis performed manually by the ISP. We use Cache size \( k = 50 \) and distinct structure parameter \( \ell = 256 \). Note that, some of the attacks analyzed had a very high percentage of distinct queries and others had lower rates. The repetitions are of randomly generated queries that were each repeated several times in the traffic. These different attack rates are an example for the usefulness of both the cHH and dHH algorithms. As we did not have access to a peacetime capture to obtain a whitelist, we generated a whitelist based on domains with a relatively high distinct subdomain count.

Consider attack 1 in Table 3. The capture consisted of 92469 DNS queries. Of these, 4133 are attack queries targeted at the same zone, with a randomly generated least significant domain sub-part, containing 2051 distinct queries, meaning that some of the queries were repeated. Of the 4133 queries, the system counted 4123. Meaning, that 10 queries for the attacked zone had gone through before the zone was placed in the structure (i.e., in the cache). Once inside, the zone was not evicted from the structure at any point, all subsequent queries were counted, hence 99.8% of the queries were identified.

| Source | Queries in capture | Attack queries | Distinct attack queries | Attack queries identified |
|--------|------------------|----------------|-------------------------|--------------------------|
| 1      | 92469            | 4133           | 2051                    | 99.8%                    |
| 2      | 5000             | 389            | 307                     | 99.7%                    |
| 3      | 5000             | 602            | 507                     | 100%                     |
| 4      | 5000             | 334            | 330                     | 100%                     |
| 5      | 5000             | 3364           | 631                     | 99.8%                    |

Table 3: Results on Real DNS Attack Captures

7. ADDITIONAL APPLICATIONS
Our algorithms are instrumentals in the detection and mitigation of various DDoS and other network attacks. In this section we provide several examples of such attacks.

7.1 SYN Attacks
A classic form of DDoS attacks still common in today’s networks is the TCP SYN Attack. In this form of attack, the attacker initiates many TCP connections, while never completing the TCP handshake. The connection queue of the target is therefore filled up with incomplete connections, preventing it from addressing new connection requests from legitimate parties. The attacker may make an attack more difficult to detect by utilizing a botnet or a large army of sources for carrying out the attack or even by simply using spoofed sources. In this case, the attacked destination receives connection requests from many different sources. Using our algorithm, we can identify destinations which have a large number of distinct sources,
and thus be able to identify the attack soon after the number of requested connections exceeds normal use.

### 7.2 Email Spam

Email spam is often characterized by having a single sender or a small number of senders which send emails to a large number of different recipients. By making the sender the key and the addressee as the subkey, our algorithm can easily detect spammers. Using peacetime along the lines suggested in Section 6 can improve the system accuracy and reducing false positives.

### 7.3 Flash Crowd Detection

Combined heavy hitters may be used, for example, when network load is a concern. Consider a flash event. A flash crowd or flash event, is a situation where a very large number of users simultaneously access some web site [15]. For example, a major developing news event may cause a flash crowd in major news web sites. Fast and automated detection and processing (mitigation or other responses) of such anomalies is important for maintaining robustness of the network service.

To identify the affects a flash crowd has on the entire network, it is not sufficient to solely identify the rise in the distinct number of users accessing a site. Instead, we would like to identify that there are both many accesses to this site causing a high load on the network as well as many different users who are accessing this site. For a network administrator to reallocate network resources to meet this demand, both of these measurements are significant. Our cwSHH algorithm can be used to identify the rise in both parameters.

### 8. RELATED WORK

The concept of distinct heavy hitters, together with the motivation for DDoS attack detection, was introduced in a seminal paper of Venkataraman et al. [21]. Their algorithm, aimed at detection of fixed-threshold heavy hitters, returns as candidate heavy hitters the keys with an (initialized) Bloom filter that is filled beyond some threshold. Keys with high count in the sample are likely to be heavy hitter and almost saturate their bloom filter. A related work adapts Bloom schemes to TCAMs [3]. Our fixed-threshold scheme is conceptually related to [21]. Some key differences are the better tradeoffs we obtain by using approximate distinct counters instead of Bloom filters, and our simpler structure with analysis that ties directly to classic analysis of weighted sampling, which also simplifies the use of parameters. More importantly, we provide a solution to the fixed-size problem and also address the estimation problem.

The estimates on the weight of the heavy keys that can be obtained from the Bloom filters in [21] are much weaker, since once the filter is saturated, it can not distinguish between heavy and very heavy keys.

Locher [17] recently presented two designs for dHH detection which makes use of approximate distinct counters. The first design is sampling-based and builds on the distinct pair sampling approach of [21]. This design also only applies to the fixed-threshold problem. The other design uses linear sketches and applies to the fixed-size problem. Locher’s designs are weaker than ours both in terms of practicality and in terms of theoretical bounds. The linear-sketch based design utilizes linear-sketch based distinct counters, which are much less efficient in practice that the sampling-based ones. The designs have a quadratically worse dependence of structure size on the detection threshold $\tau$, which is $\Omega(\tau^{-2})$ instead of our $O(\tau^{-1})$. Finally, multiple copies of the same structure are maintained to boost up confidence, which results in a large overhead, since heavy hitters are accounted for in most copies. Locher’s code was not available for a direct comparison.

Another conceivable approach is to convert to DHH classic fixed-size deterministic HH streaming algorithms, such as Misra Gries [19] or the space saving algorithm [18], by replacing counters with approximate distinct counters. The difficulty that arises is that the same distinct element may affect the structure multiple times when the same key re-enters the cache, resulting in much weaker guarantees on the quality of the results.

### 9. CONCLUSION AND FUTURE WORK

We have presented new and efficient algorithms for distinct Heavy Hitters and combined Heavy Hitters detection, as well as a system for detection of RSDDoS attacks on the DNS service.

We are currently working on a more robust DNS random attack detection and mitigation system for both non-existent domain attacks and other forms of random subdomain attacks.

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