Counting Data Stream Based on Double Hash Algorithm

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Abstract: In order to solve the problem of high false positives probability of Bloom Filter (BF), this paper proposed a novel mechanism based on double hash algorithm for counting data stream in high speed network. The algorithm improves the performance by using Time Bloom Filter to sample the packets of flows, and using Hierarchy Bloom Filter to identify flows. In this way, the algorithm can separate the process of filtration from the recognition. The mechanism could not only record more flows, but also adapt dynamically when the number of flows rapidly rising. The experimental simulation results shown that compared with Bloom Filter, the algorithm can significantly improve the accuracy of recording flows information.

Keywords: Traffic measurement, Network flow, Hash, Bloom filter

INTRODUCTION

With the development of high-speed network technology, In particular gigabit and higher rate network technology appearance, traditional statistical techniques for recording flow information become no longer useful gradually[Cheng et al., 2013]. At present, the research on statistical flows information mainly concentrated in the packet sampling techniques and packet filtering technology aspects. Packet sampling technique is to sample packets from all elements. It can effectively reduce the storage space required during the process of statistical flows information. But it can also cause some loss of information, even though some studies reduce this loss by using inference methods such as EM algorithm and so on, however, the calculation of those methods is too big, and is not suitable for online processing[Domenico et al., 2008]. Packet filtering technology is starting from the application of Bloom Filter in the network [Estan et al., 2001]. As a kind of simple information representation scheme, Bloom Filter can meet the demand of high interaction and search requirement in the development of high speed network. It not only supports the collection element query, but filtrates out the elements which does not belong to this collection. Because of the cost of time and storage space is few the BF algorithm has been widely used in network technology appearance, traditional statistical flows information. However, when more elements need to be handled, BF will generate false positive, which means an element is considered in a collection even though it is not. This will result in a significant impact for network traffic statistics. In this paper we proposed a novel mechanism based on double hash strategy for counting network flows statistic.

STANDARD BLOOM FILTER

A Bloom filter is a data structure which is described by an array of \( m \) bits for representing a set \( S = \{ x_1, x_2, \ldots, x_n \} \) with \( n \) elements, initially set all of \( m \) bits to 0 [Kun et al., 2009]. It uses \( k \) independent hash functions \( H_1, H_2, \ldots, H_k \) with range \( \{ 1, \ldots, m \} \). Bloom Filter will use the functions to map all of the elements of the set into \( \{ 1, \ldots, m \} \) vector space [Andrei et al., 2003]. For each element \( x \in S \), the bits \( H_i(x) \) are set to 1 for \( 1 \leq i \leq m \). A location can be set to 1 multiple times, but only the first change has an effect. To check if an item \( y \) is in \( S \), we check whether all \( H_i(y) \) are set to 1. If not, then clearly \( y \) is not a member of \( S \). Figure 1 shows an example of BF with 3 functions.

As shown above, the filter begins as an array of all 0. Each item of set is hashed 3 times, with each hash yielding a bit location; those bits are set to 1. To check if an element \( y \) is in the set, hash it 3 times and check the corresponding bits. The element \( y_1 \) cannot be in the set, since a 0 is found at one of the bits. Even though the corresponding bits of \( y_2 \) is 1, but it is either in the set or it has yielded a false positive. A...
false positive means that an element is considered in a collection even though it is not.

**DOUBLE HASH ALGORITHM**

**Time Bloom Filter**

Time Bloom Filter (TBF) is similar to BF except that it does not have \( m \) bits, but \( m \) buckets instead, each of which contains a timestamp. The \( m \) timestamps are denoted as \( t[0], t[1], ..., t[m-1] \). Besides, it has a bucket time-out value \( t_0 \). TBF compare the difference between two packets timestamp which hash to the corresponding \( k \) buckets in order whether is greater than a pre-set timeout \( t_0 \), then will update the timestamp of \( k \) buckets to the current timestamp of arriving packet. If any of the \( k \) timestamps, the \( ith \) for example, \( t[h_i(c_j)] - t[h_i(c_{j-1})] > t_0 \), the packet is discarded [Shao et al., 2006].

Small flows have different 5-tuple identity (source/destination IP addresses, source/destination port numbers, and protocol identifier), will hash into different position of TBF. If any of the position timeout, the packets will be discarded. Packets belong to a large flow have less interarrival time and will hash into same position, then will be recorded. Extremely, when \( t_0 = N_{max} \), TBF algorithm will become invalid.

![Figure 2. A TBF with 3 hash function](image)

**HIERARCHY BLOOM FILTER**

A Hierarchy Bloom Filter aims at the problem of having big false positive rate when the set elements arbitrary growth in single Bloom Filter. A HBF is composed of a series of Bloom Filters that increase the length gradually. Each Bloom Filter in HBF is created with a predefined false positives probability. When the element of some Bloom Filter exceeds limited number, the HBF will increase a new BF which length multiplied. For example, when the number of elements of some BF \( \cdot N \), HBF will create a new BF with 2 times the length of the original BF.

![Figure 3. An example of the process of HBF with 3 BF](image)

**The Procedure Of Counting Flows By Double Hash Algorithm**

According to the analysis result shown in the previous subsection, the procedure for recording flows by double hash algorithm is described as follows.

1. First, when a packet arrives, \( k \) independent hash functions will map a given key to one of the buckets according to the 5-tuple identity (source/destination IP addresses, source/destination port numbers, and protocol identifier).

2. Secondly, TBF compare the difference between two packets timestamp which hash to the corresponding buckets in order whether is greater than a pre-set timeout \( t_0 \), and update the timestamp of buckets to the current timestamp of arriving packet. If any of the timestamp is greater than \( t_0 \), the packet will be sampled. Then, the sampled packet will handled by HBF.

3. HBF will lookup whether the packet has presented before, If can find, then discard, else record the corresponding information of the flows, and add this packet to HBF.

4. This process is continued until to the end of the measurement period. At last, output the flows which we recorded.

Figure 4 illustrate the whole process.

![Figure 4. Flow chat of our algorithm record flows](image)
Performance Evaluation

Just as BF, our algorithm also will bring a false positive error probability which is caused by TBF and HBF. Giving a set $S=\{x_1, x_2, \ldots, x_n\}$ of $n$ elements, the probability of hash position is empty in TBF is $p = (1 - \frac{1}{m})^t \approx e^{-\frac{t}{m}}$, let $p = e^{-\frac{t}{m}}$, then $f_{TBF} = (1 - p)^k \approx (1 - p)^k = (1 - e^{-\frac{t}{m}})^k$.

At a given times, we will have $l$ filters in HBF with false positive error probabilities $P_0, P_1, P_2, \ldots, P_{l-1}$ for every BF the probabilities $P_i = (1 - e^{-\frac{m_i n}{m}})^k$, $m_i$ is the capacity of $i$th BF. Let $P_i = P_0 r^{i-1}$, $r$ is a ratio with $0 < r < 1$, then $P = 1 - \prod_{i=0}^{l-1} (1 - P_i r^i)$, now that $1 - \prod_{i=0}^{l-1} (1 - P_i) \leq \sum_{i=0}^{l-1} P_i$, so $P \leq \lim_{l \to \infty} \sum_{i=0}^{l-1} P_i r^i$, and therefore $P \leq P_0 \frac{1}{1 - r}$.

Now that, double hash algorithm handle the packets by using hash functions, so the cost of computing once time by hash algorithm is $O(n)$.

Because the packets belonged to the same flow have the same flow identity, and the flow identity is unique, so will always map to the same position. Furthermore, the hash result is associate with store address, we can find the location of the flow in $O(n + \frac{n}{cm})$, $C$ is a constant.

EXPERIMENTAL SIMULATE

We simulate and verify our algorithm validity by actual experimental data, and compare the measurement accuracy between the standard Bloom Filter and our algorithm. The experimental data we used is come from The Cooperative Association for Internet Data Analysis (CAIDA) [Zhang et al., 2013]. There are a total of 6187376 packets and 68367 original flows. Figure 5 displays the distribution of original flows.

As shown in Figure 5, the flows distribution of network traffic meet the heavy-tailed distribution which means that most flows only have a small number of packets, while a very few flows have a large number of packets.

Figure 6 displays TBF sample rate when timeout interval $t_0$ changed. When $t_0 = 0$, all packets will be sampled, $t_0 \to +\infty$, none packet will be sampled. So the value of the threshold $t_0$ can determine the number of packets sampled.

Figure 6. TBF sample rate when $t_0$ changed

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Sample rate</th>
<th>statistical error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our algorithm</td>
<td>2.484</td>
<td>0.427</td>
</tr>
<tr>
<td>BF</td>
<td>0.962</td>
<td>12.976</td>
</tr>
</tbody>
</table>

As upwards table showed, the sample rate of our algorithm is slightly higher than the BF, but the statistical error is much smaller than the BF. For the reason of increasing the number of packets, BF will be full filled, and the error probability grows exponentially. For our algorithm, by using TBF to sample mice flows and using HBF which restricted by dynamic multilayer scalable mechanism, can reduce the measurement error significantly, and record more flows information statistic.

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REFERENCES


