Research paper

ActiveGuardian: An accurate and efficient algorithm for identifying active elephant flows in network traffic

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A B S T R A C T

Active elephant flows, which indicate the real-time data transmission status, are of primary interest in network management and various applications. However, existing network measurement efforts mainly focus on finding elephant flows, and limited works on identifying active elephant flows suffer from low accuracy and heavy overheads. To address this issue, this paper proposes ActiveGuardian to identify active elephant flows with high accuracy, low memory, and high throughput. The key idea is to intelligently separate potential elephant flows from mice flows, and guard and report the information of active elephant flows in every time window. To obtain high accuracy, we devise a filtering module that adaptively filters unnecessary flows with low arrival rates, by applying an Adaptive Counter Update strategy. To achieve high memory utilization, we design a Leapfrog Hashing algorithm for the guarding module to effectively solve hash collisions. Lastly, we perform theoretical derivation on the false positive and the error bound of ActiveGuardian, and experimental evaluations on its performance with real network traffic traces. The experimental results show that ActiveGuardian achieves higher accuracy (99.65%) with identical memory sizes, and higher throughput (26.53Mps) than the state-of-the-art solutions.

1. Introduction

Network traffic measurement is indispensable to efficiently understand and manage network performance. Until now, extensive efforts have been carried out in this area to accurately identify elephant flows, where a flow’s ID is usually defined as a combination of certain protocol header fields, and flow size is defined as the number of transmitted packets. Elephant flows contribute a large portion of network traffic, and have a great impact on network performance. Hence, it is significant to identify elephant flows, whose flow size exceeds a predefined threshold. Accurate identification of elephant flows plays a significant role in areas such as traffic engineering (Burnett et al., 2020), network security (Wang et al., 2011; Curtis et al., 2011), data mining (Mirylenka et al., 2015; Chang and Lee, 2003) and information retrieval (Davenport, 2012). For instance in network management, administrators can accurately estimate the demand for equipment and bandwidth based on the situation of elephant flows, allowing for rational capacity planning (Feldmann et al., 2001). In traffic engineering, traffic allocation and scheduling policies can be optimized by analyzing elephant flows to ensure priority and performance of critical applications or services and improve Quality of Service (QoS) (Sivaraman et al., 2016). In data mining, the analysis of elephant flows can identify the most influential features and attributes to optimize feature selection and dimensionality reduction, thereby improving the efficiency of model training and predictive accuracy (Cheung and Fu, 2004).

Elephant flow identification strives to collect historical statistical information of packet flows from the beginning of traffic measurement. Nevertheless, many applications primarily focus on the real-time state of packet flows, especially with a mass of packets arrived recently. For example in intrusion detection (Garcia-Teodoro et al., 2009), Intrusion Detection Systems (IDS) rely on real-time packet flow information to promptly spot suspicious activity and rapidly respond to threats before they can cause significant damage (Zhuang et al., 2021). In congestion control (Zhu et al., 2020; Liao et al., 2020), by identifying recently active elephant flows, network administrators can promptly detect congestion situations and quickly pinpoint the source of the problem.

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to implement congestion control measures. Additionally, bandwidth management and optimization of these active elephant flows can effectively predict and avoid potential congestion, enhancing network performance and stability. As for task offloading in network scenarios (Sarrar et al., 2012), it can alleviate the load on main processor to improve overall network performance, by offloading network tasks associated with recently active elephant flows to specialized hardware accelerators or dedicated network devices. Active elephant flows, which have a large number of packets frequently arrived within a certain time window, greatly influence the performance of network applications. Therefore, there is a pressing need to identify and report active elephant flows by time window.

Existing solutions for identifying active elephant flows, inspired by traditional elephant flow identification methods, usually employ sketch-based algorithms for efficient memory utilization. However, due to hash collisions in sketches and highly skewed flow size distribution, mice flows are probably mistreated as elephant flows, leading to low identification accuracy. To overcome this issue, several strategies have been proposed, including the majority vote algorithm (Boyer and Moore, 1991), exponential-weakening decay (Yang et al., 2018a, 2019), and pre-filtering stages (Garcia-Teodoro et al., 2009). While these solutions have made progress in separating elephant flows from mice flows, they still cannot support real-time queries and detect active elephant flows. More recent works, such as Clock-Sketch (Chen et al., 2021) and FastKeeper (Wang et al., 2021), have attempted to address these two challenges by employing sliding-window-based algorithms to accurately estimate flow rates of active elephant flows. However, it will incur significant memory overhead to record flow ID. In summary, existing solutions cannot simultaneously achieve high accuracy, low overhead, and high throughput in identifying active elephant flows.

In this paper, we propose a novel algorithm, named ActiveGuardian, to accurately identify active elephant flows. The key idea of Active-Guardian is called separate-mice-and-guard-active. Specifically, ActiveGuardian consists of a filtering module intelligently separating suspected elephant flows from mice flows, and a guarding module guarding and reporting the information of active elephant flows in every time window. To ensure the persistent effectiveness of the filtering module, we propose an Adaptive Counter Update strategy that consistently filters unnecessary flows. To enhance the accuracy of the guarding module, we utilize a replacement policy evicting inactive flows that are wrongly treated as active elephant flows. To optimize the memory efficiency of the guarding module, we design a novel hashing algorithm called Leapfrog Hashing that provides storage locations for each incoming flow at all possible. Our main contributions can be summarized as follows:

- A novel algorithm called ActiveGuardian is designed for identifying active elephant flows, which constantly filters unnecessary flows and smartly guards elephant flows by time window, to simultaneously achieve high accuracy, low overhead, and high throughput.
- An Adaptive Counter Update strategy is proposed for the filtering module of ActiveGuardian, which persistently filters numerous mice flows and low-arrival-rate flows even under network traffic fluctuation, to improve the precision of subsequent elephant flow identification.
- A Leapfrog Hashing algorithm is devised for the guarding module of ActiveGuardian, which smartly find storage locations for all potential elephants via multiple mapping and kicking operations, to greatly reduce hash collision rates, enhancing accuracy and memory efficiency.
- We prove that ActiveGuardian can provide the precise estimation of active elephant flows, by theoretically deriving the false positive error rate of its filtering module and the error bound of its guarding module.
- We conduct extensive experiments with real network traffic traces, which indicates that ActiveGuardian achieves higher accuracy and throughput than the state-of-the-art.

The rest of the paper is organized as follows. Section 2 discusses related work regarding the identification of active elephant flows. In Section 3, we provide a detailed description of the ActiveGuardian algorithm. Section 4 presents the theoretical analysis of our algorithm’s error bounds. In Section 5, we present our experimental setup and results, followed by a comparison with existing solutions. Finally, Section 6 concludes the paper.

2. Related work

Early works regarding elephant flow identification mainly focus on applying sketch-based algorithms to estimate the frequency of each flow in network traffic. Sketches, a kind of probabilistic data structure, have been widely employed for data stream summarization, achieving high memory efficiency at the expense of slightly less accuracy. A sketch is commonly manifested as a two-dimensional array, where each array contains multiple counters and an associated hash function that randomly maps incoming packets to the counters. The well-known CM Sketch (Cormode and Muthukrishnan, 2005) increases all mapped counters by 1 for an arrived packet, and returns the minimum value among these counters as the estimated size of its belonging flow. On this basis, CU Sketch (Estan and Varghese, 2003) only increases the smallest mapped counter by 1, which further improves the estimation accuracy of flow size. To achieve unbiased estimation, Count Sketch (Charikar et al., 2004) implements an additional hash function to determine whether the mapped counters are incremented or decremented, and returns their median as the query value. CMM Sketch (Deng and Rafiei, 2007) inserts packets to the counters in the same way as CM Sketch, but minuses noises during query operation. However, due to hash collisions, a mice flow is probably mistreated as an elephant flow when they share an identical counter. Moreover, it is challenging to allocate adequate memory for sketches ahead of time, due to unpredictable flow sizes in network traffic.

To adapt to highly skewed flow size distribution, there are several approaches to separate elephant flows from mice flows. CountMax (Yu et al., 2018) and MV-Sketch (Tang et al., 2019) apply the majority vote algorithm (MJRTY) (Boyer and Moore, 1991) to track the candidate elephant flow in each bucket. HeavyGuardian (Yang et al., 2018a) and HeavyKeeper (Yang et al., 2019) leverage a novel strategy, named exponential-weakening decay, to actively remove mice flows through decaying. Augmented Sketch (Roy et al., 2016) proposes a pre-filtering stage to identify the elephants and only permits the mice to sketch. Elastic Sketch (Yang et al., 2018b) monitors the elephants in the heavy and evicts the mice to the light part by voting. Pyramid Sketch (Yang et al., 2017) develops a sketch framework to prevent counters from overflowing by automatically enlarging their sizes, which significantly improves the speed and accuracy of identifying elephant flows. Cold Filter (Zhou et al., 2018) designs a two-layer sketch, which captures mice flows in the first stage and elephant flows in the second stage, to accurately estimate both mice flows and elephant flows. Unfortunately, these solutions only support queries on the overall traffic from the beginning of the measurement, unable to provide real-time information of elephant flows by time window.

Closely related to our work, several notable studies have explored the identification of the most recent elephant flows (i.e., active elephant flows) by sliding window models. WCSS (Ben-Basat et al., 2016) extends Space Saving (Metwally et al., 2005) to keep track of the most recent elephant flows in a sliding window and supports constant time point queries. Sliding Sketch (Gou et al., 2020) presents a generic sketch framework and utilizes a scanning pointer to delete outdated flows. More recently, Clock-Sketch (Chen et al., 2021) adopts multiple counters to preserve information about all flows within a time window, and cleans information of inactive flows as quickly as possible. FastKeeper (Wang et al., 2021) applies a sliding-window-based algorithm to accurately estimate the flow rates of active elephants, and timely replace flows that have become small through bitmap-voting. However,
these sliding window schemes still need to process a large number of mice flows, resulting in low memory efficiency and poor accuracy of estimation. Further, BurstSketch (Zhong et al., 2021) first employs the running track technique to efficiently select potential burst flows, and then detects active elephant flows at the end of every time window by the snapshotting technique. Yet, this algorithm requires recording all flow IDs in the first stage with heavy memory overhead.

To provide a visualized overall comparison, Table 1 summarizes the aforementioned works on the identification of active elephant flows. As summarized from Table 1, Sketch-based algorithms suffer from potential mistreatment of mice flows as elephant flows. Existing solutions by separating elephant flows from mice flows are unable to effectively identify active elephant flows. Sliding window schemes still face the challenge of high memory overhead and low precision. In a nutshell, existing solutions cannot accurately identify active elephant flows while simultaneously achieving high throughput and memory utilization. To solve the above problem, we are motivated to propose a novel algorithm named ActiveGuardian, which achieves comprehensive performance promotion by intelligently separating mice flows and guarding active elephant flows.

### 3. The design of ActiveGuardian

In this section, we provide an identification scheme of active elephant flows, design the data structure and algorithm of ActiveGuardian, and present two optimization techniques to further improve the precision and memory efficiency of ActiveGuardian.

#### 3.1. Scheme

To provide a comprehensive understanding on the operation of ActiveGuardian, we design an identification scheme of active elephant flows depicted in Fig. 1. The scheme consists of the following components: (a) Network devices such as routers and Software-Defined Networking (SDN) switches, typically performing packet forwarding in the network domain; (b) Data collector, responsible for capturing packet traffic from network devices and preprocessing data before being transmitted to subsequent processing and analysis components; (c) Flow identification component, namely ActiveGuardian, designed for identifying active elephant flows from the collected packet traffic; (d) Controller such as a central management host or SDN controller, which learns about active elephant flows, conducts further analysis and optimizes network management for better network application performance.

In Fig. 1, we deploy the data collector on SDN switches to capture incoming packet traffic. Subsequently, we run the ActiveGuardian to aggregate statistics on active elephant flows based on predefined parameters. The identification results are then sent to the SDN controller. The controller performs tasks such as traffic monitoring, performance management, and network optimization through data analysis. Additionally, ActiveGuardian can be deployed on the controller, where it identifies active elephant flows by receiving network traffic information from data collector. In practical deployments, it is crucial to appropriately configure devices, components, and algorithms, in accordance with specific network environment and requirements. By this way, the scheme is expected to process large-scale network traffic.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Core idea</th>
<th>Shortcoming</th>
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<tbody>
<tr>
<td>Sketch-based algorithms</td>
<td>Increasing the smallest mapped counter by 1</td>
<td>Potential mistreatment of mice flows as elephant flows due to hash collisions</td>
</tr>
<tr>
<td>Count Sketch (Charikar et al., 2004)</td>
<td>Incrementing or decrementing the mapped counters by an additional hash function</td>
<td></td>
</tr>
<tr>
<td>CMM Sketch (Deng and Rafiei, 2007)</td>
<td>Subtracting noises during query operation</td>
<td></td>
</tr>
<tr>
<td>CountMax (Yu et al., 2018)</td>
<td>Utilizing the majority vote algorithm for identifying elephant flows</td>
<td></td>
</tr>
<tr>
<td>MV-Sketch (Tang et al., 2019)</td>
<td>Adapting the exponential-decay strategy to actively remove mice flows</td>
<td></td>
</tr>
<tr>
<td>HeavyGuardian (Yang et al., 2018a)</td>
<td>Designing pre-filtering stage to identify elephant flows</td>
<td></td>
</tr>
<tr>
<td>HeavyKeeper (Yang et al., 2019)</td>
<td>Monitoring elephants in the heavy part and evicting mice to the light part by voting</td>
<td></td>
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<tr>
<td>Augmented Sketch (Roy et al., 2016)</td>
<td>Automatically enlarging the size of counters</td>
<td></td>
</tr>
<tr>
<td>Elastic Sketch (Yang et al., 2018)</td>
<td>Employing pre-filtering stage to filter mice flows</td>
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<tr>
<td>Pyramid Sketch (Yang et al., 2017)</td>
<td>Employing the running track technique to efficiently select potential burst flows</td>
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<tr>
<td>Cold Filter (Zhou et al., 2018)</td>
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</table>

| Sliding window schemes | Extending Space Saving (Metwally et al., 2005) in a sliding window | Requiring to process a large number of mice flows, leading to low memory efficiency and poor estimation accuracy. |
| WCSS (Ben-Basat et al., 2016) | Utilizing a scanning pointer to delete outdated flows. | |
| Sliding Sketch (Gou et al., 2020) | Introducing CLOCK algorithm into item batch measurement | |
| Clock-Sketch (Chen et al., 2021) | Applying a sliding-window-based algorithm to estimate flow rates of active elephants | |
| FastKeeper (Wang et al., 2021) | Employing the running track technique to efficiently select potential burst flows | |
| BurstSketch (Zhong et al., 2021) | | |
The flag indicates hashing offsets from the directly mapped bucket of the flow. Specifically, if the flag is equal to 0, the flow is preserved rightly in its hashed bucket. Otherwise, we can calculate its mapped position by adding its current position and hashing offset. Similarly, we leverage a guarding threshold \( \beta \) for all recorded flows to determine whether they are active elephant flows.

**Algorithm 1: FilteringModuleInsert(Flow ID)**

**Input:** The flow ID \( F_i \) of an incoming packet \( e \); the filtering threshold \( \alpha \); the updating threshold \( \theta \); the packet counter \( C_{pkt} \); the weight \( \omega \)

1. If \( F_i \) is in \( B[|F_i|] \) then
   2. Increment the frequency of \( F_i \) by 1;
   3. Else
      4. For each \( i \in [1, k] \) do
         5. \( A[h_i(F_i)].C_{avg} = A[h_i(F_i)].C_{avg} + 1; \)
         6. \( C_{avg} = \min(C_{avg}, A[h_i(F_i)].C_{avg}); \)
         7. \( C_{avg} = \min(C_{avg}, A[h_i(F_i)].C_{avg}); \)
      8. End
      9. If \( C_{avg} \geq \alpha \) or \( C_{avg} \geq \theta \) then
         10. GuardingModuleInsert(\( F_i \));
      11. End
      12. \( C_{pkt} = C_{pkt} + 1; \)
      13. If \( C_{pkt} \geq \theta \) then
         14. For each \( i \in [1, M] \) do
            15. \( A[|F_i|].C_{avg} = A[|F_i|].C_{avg} + \omega A[|F_i|].C_{avg} + 1; \)
            16. Reset \( A[|F_i|].C_{avg} \) to 0;
         17. End
      18. End
   19. End

**Insertion:** Initially, all fields in the two modules of ActiveGuardian are 0 or null. Given an incoming packet within the flow \( f \), we first check whether \( f \) is already in the guarding module. If so, we increment the frequency of flow \( f \) by 1. Otherwise, we insert it into the filtering module. Below we show the details of our solution.

**1) Insertion of the filtering module:** When inserting a packet within the flow \( f \) into the filtering module, ActiveGuardian first computes k hash functions to map \( f \) to \( k \) buckets \( A[h_i(f)] \) (1 ≤ \( i \) ≤ \( k \)). Then \( A[h_i(f)].C_{avg} \), \( A[h_i(f)].C_{avg} \), ..., \( A[h_i(f)].C_{avg} \) are respectively incremented by 1, and applies different strategies for the following three cases:

**Case 1:** When \( \min(A[h_i(f)].C_{avg}) \geq \alpha \). In this case, the flow \( f \) is a potential elephant flow in current time window, and then we insert the packet into the guarding module, which corresponds to lines 9–10 in Algorithm 1.

**Case 2:** When \( \min(A[h_i(f)].C_{avg}) \geq \alpha \). In this case, the flow \( f \) is a potential elephant flow in the latest few time windows, and we also let the packet enter into the guarding module, manifested as lines 9–10 in Algorithm 1.

**Case 3:** When \( \min(A[h_i(f)].C_{avg}) < \alpha \) and \( \min(A[h_i(f)].C_{avg}) < \alpha \). In this case, the flow \( f \) is not a potential elephant flow by far, and then we discard the packet directly.

**2) Insertion of the guarding module:** When inserting a packet within the flow \( f \) into the guarding module, we first maps \( f \) to the bucket \( B[g(f)] \) by the hash function \( g(f) \) (1 ≤ \( g(f) \) ≤ \( N \)). For the mapped bucket, there are three cases as follows.

**Data Structure:** As shown in Fig. 2, ActiveGuardian consists of a filtering module evicting mice flows as well as low-arrival-rate flows and a guarding module identifying active elephant flows. The filtering module is a counter array with \( M \) buckets. There are \( k \) independent hash functions \( h_1(\cdot), h_2(\cdot), \ldots, h_k(\cdot) \) mapping each flow to \( k \) buckets randomly. Each bucket has two counters: a current counter \( (C_{curr}) \) and a weighted average counter \( (C_{avg}) \). \( C_{curr} \) is used to estimate the number of packets within a flow in current time window, while \( C_{avg} \) is utilized to preserve the weighted average flow size from the start of traffic measurement. Note that we leverage a filtering threshold \( \alpha \) for incoming flows to check whether they are potential elephant flows.

The guarding module is a bucket array \( B[1], B[2], \ldots, B[N] \) associated with one hash function \( g(\cdot) \). Each bucket consists of \( m \) cells. Each cell keeps the information of a flow: flow ID, count, and flag. The key is the flow ID, which consists of five-tuples: source IP address, destination IP address, source port, destination port, and protocol type. The count value is its estimated frequency in network traffic, i.e., the number of arrived packets within the flow. The flag indicates hashing offsets from the directly mapped bucket of the flow. Specifically, if the flag is equal to 0, the flow is preserved rightly in its hashed bucket. Otherwise, we can calculate its mapped position by adding its current position and hashing offset. Similarly, we leverage a guarding threshold \( \beta \) for all recorded flows to determine whether they are active elephant flows.

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**Table 2** Symbols in ActiveGuardian.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
</tr>
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<tbody>
<tr>
<td>( A_i )</td>
<td>The ( i )-th bucket in the filtering module</td>
</tr>
<tr>
<td>( B_i )</td>
<td>The ( i )-th bucket in the guarding module</td>
</tr>
<tr>
<td>( C_{curr} )</td>
<td>The number of packets within a flow in current time window</td>
</tr>
<tr>
<td>( C_{avg} )</td>
<td>The weighted average flow size from the start of traffic measurement</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>The filtering threshold</td>
</tr>
<tr>
<td>( \beta )</td>
<td>The guarding threshold</td>
</tr>
<tr>
<td>( \theta )</td>
<td>The updating threshold of the filtering module</td>
</tr>
<tr>
<td>( M )</td>
<td>The number of buckets in the filtering module</td>
</tr>
<tr>
<td>( N )</td>
<td>The number of buckets in the guarding module</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>The number of cells in a bucket in the guarding module</td>
</tr>
<tr>
<td>( \omega )</td>
<td>The updating threshold in adaptive counter update strategy</td>
</tr>
</tbody>
</table>

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**Fig. 1.** Identification scheme of active elephant flows.

**Fig. 2.** The data structure of ActiveGuardian.
Algorithm 3: IdentifyAndUpdate()

| Input: the last report time \( T_{last} \), the current time \( T_{curr} \); the guarding threshold \( \beta \); the time window size \( W \); |
| 1 if \( T_{curr} - T_{last} \geq W \) then |
| 2 for each \( i \in [1, N] \) do |
| 3 if \( B[i].Count \geq \beta \) then |
| 4 return \( B[i].ID \) and \( B[i].Count \) + 1; |
| 5 end |
| 6 clear \( B[i] \) to empty; |
| 7 end |
| 8 end |
| 9 \( T_{last} \leftarrow T_{curr} \); |

The identification of active elephant flows: ActiveGuardian constantly monitors potential elephant flows, and reports active elephant flows illustrated in Algorithm 3. We define time window as a fixed quantity of measured data packets, and denote the size of time window as \( W \). At the end of every time window, we first examine the frequencies of guarded elephant flows in each bucket of the guardian module. If their frequencies are higher than the guarding threshold \( \beta \), ActiveGuardian identifies them as active elephant flows, and reports their flow sizes. Finally, in preparation for next time window, we empty all buckets of the guarding module and set current time to the last report time.

A running example: Fig. 2 shows a running example of flow processing by ActiveGuardian. In this example, in the filtering module, given a bucket with (2, 15), where 2 represents the counter \( C_{avg} \), and 15 is the threshold counter \( C_{cyw} \). In the guarding module, given a cell in a bucket with \( (F_2, 12) \), where \( F_2 \) is the flow ID, and 12 represents \( F_2 \)'s frequency. Suppose the threshold \( a = 10 \), and the guarding threshold \( \beta = 50 \). (1) To insert \( P_1 \) within the flow \( F_2 \), we find it in the guarding module, so we just increment \( F_2.Count \) by 1. (2) To insert \( P_2 \) within the flow \( F_2 \), we do not find it in the guarding module, so we insert it into the filtering module and increment \( A[\text{ID}(F_2)].C_{avg} \) by 1. (3) To insert \( P_3 \) within the flow \( F_2 \), we do not find it in the guarding module, so we insert it into the filtering module similarly to \( P_1 \). After the increment, we find that the \( \min(A[\text{ID}(F_2)].C_{avg}) \) reaches the filtering threshold \( a \) and there is an empty cell in the guarding module. Then we insert \( F_1 \) with the frequency of 1. (4) To insert \( P_4 \) within the flow \( F_0 \), which passes through the filtering module, we observe that the mapped bucket of the guarding module is full, so we try to find an empty cell in its two logical adjacent buckets. Then we insert \( F_1 \) into the logical adjacent bucket with the frequency of 1 and set its flag to +1. (5) To insert \( P_5 \) within the flow \( F_2 \), we do not find any empty cell in the mapped bucket as well as its two adjacent buckets in the guarding module, so we replace the minimum flow \( F_{min} \) with \( F_2 \), and set the frequency \( F_{min}.Count \) to 1. Meanwhile, we set the frequency to 19 and the flag to –1; Therefore, we report \( F_1, F_2, F_3 \), and \( F_4 \) as active elephant flows, since their frequencies reach the guarding threshold \( \beta \) at the end of time window. Eventually, we clean all the buckets in the guarding module.

3.3. Optimization 1: Adaptive Counter Update strategy

In filtering module, we update all counters after inserting a fixed number of packets, irrespective of packet arrival rates. This leads to the steady operation of the filtering module even under network traffic fluctuations. However, it is challenging to determine an appropriate filtering threshold for a given number of packets in each updating period, due to variable flow size distributions even in a specific network scenario. In particular, a low filtering threshold may result in misidentifying potential elephant flows, while a high one probably leads to the omission of real elephant flows. The filtering threshold is typically configured based on average flow size varying with network traffic fluctuations. It is worth noting that the filtering threshold determines the size of each counter in the filtering module. Precisely, the counter size generally rounds up to the logarithm base two of the filtering threshold (Corrado and Muthukrishnan, 2005; Estan and Varghese, 2003; Charikar et al., 2004). Consequently, the counter size has to be set by the maximum of possible filtering thresholds under different states of network traffic, which incurs unnecessary memory overhead.

To address the above issue, we propose a novel strategy named Adaptive Counter Update, which supports arbitrary configurations of the counter size, and adapts to network traffic fluctuations. In this strategy, we set the filtering threshold as the maximum of each counter with an arbitrary size, to ensure optimal memory utilization. Then we update all counters when the proportion of overflowed counters reaches a predetermined threshold, to steadily filter mice flows with lower-ranking number of packets in flow size distribution. By this way, the counter size barely influences the accuracy of filtering mice flows, and can be flexibly configured in accordance with the constraints of network applications on the memory space of traffic measurement. In addition, the threshold limits the number of packets entering the filtering module, resulting in that the filtering accuracy is independent of packet arrival rates.

Fig. 3 presents a typical instance of the proposed Adaptive Counter Update strategy. Suppose the counter size is 4 bits with the filtering threshold \( a = 15 \), the weight \( \omega = 1 \), and the updating threshold \( \gamma \) is 60%. When inserting an incoming packet, we increment each current counter \( C_{cyw} \) in its mapped buckets by 1, and monitor the proportion of
overflown counters to decide if an update is necessary. In this instance, 4 out of 6 current counters have overflowed, already surpassing the updating threshold $\gamma$. Therefore, we update each average weighted counter $C_{avg}$ by average weighted accumulation, and reset all current counters to 0. Taking the first bucket for example, the $C_{cur}$ is 10, and the $C_{avg}$ is 12. We update the $C_{avg}$ through computing the weighted average of 10 and 12 with the weight $\omega$. Thus, we set $C_{avg}$ to 11 and subsequently empty $C_{cur}$.

3.4. Optimization 2: Leapfrog Hashing algorithm

In guarding module, we guard and track potential elephant flows in each bucket, so as to accurately identify and report active elephant flows at the end of each time window. However, a large number of flows passing through the filtering module will result in high hash collision rates when network traffic surges. This is likely to further cause the omission of real active elephant flows, thereby degrading identification accuracy. To alleviate this problem, we propose a novel hashing algorithm called Leapfrog to promote memory utilization. The algorithm makes room for each incoming flow via iterative kicking operations, striving to evict an inactive flow while retaining active elephant flows. Specifically, if all candidate positions for an incoming flow are occupied, we select a flow with minimum packets from the two logical adjacent buckets of its mapped position, and kick it into its adjacent bucket away from the mapped position. Subsequently, we repeatedly kick the minimum flow in current bucket into its adjacent bucket in same direction, until we find an empty location for it or an inactive flow for replacement.

**Query:** For an incoming packet within the flow $f$, we query the guarding module to check whether $f$ has already been recorded. In particular, we initially map $f$ into a bucket in the guardian module by hashing, and look up the mapped bucket along with its two logical adjacent buckets. If the lookup succeeds to match the flow $f$, we increment its frequency by 1.

**Insertion:** Given a new flow $f$ passing through the filtering module, we insert $f$ into the guarding module. Specifically, we first locate its mapped bucket and two logical adjacent buckets. Then we insert the flow $f$ into these buckets with three cases:

1. **Case 1:** There exists an empty cell in the mapped bucket. We insert $f$ into the empty cell, and set its frequency to 1.
2. **Case 2:** There exists an empty cell in the two logical adjacent buckets. We insert $f$ into the empty cell with the frequency of 1, and set its flag with its hashing offset.
3. **Case 3:** There exists no empty cell in the three buckets. We choose the minimum flow with the frequency below the guarding threshold $\beta$ in the three buckets for replacement. If no flow can be replaced, we select a flow from a logical adjacent bucket to be kicked out, and insert $f$. For the kicked flow, we continue to look for an empty bucket to insert, or select the minimum flow with the frequency below the guarding threshold $\beta$ to replace, in the adjacent bucket in the kicking direction. After the insertion or replacement, we update its flag with its new hashing offset. If there are no empty cell and no flow can be replaced, we iteratively perform the above operations until the number of kicking operations reaches a preset threshold.

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**4. Mathematical analysis**

In this section, we present the theoretical analysis of ActiveG-guardian, including false positive error rate of the filtering module and error bound of the guarding module. The symbols frequently used in mathematical analysis are summarized in Table 3.

### Table 3

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L$</td>
<td>The $i$th bucket of the filtering module</td>
</tr>
<tr>
<td>$M$</td>
<td>The $i$th bucket of the guarding module</td>
</tr>
<tr>
<td>$g/f$</td>
<td>The average number of packets in mice flows</td>
</tr>
<tr>
<td>$G$</td>
<td>The number of flows inserted into the guarding module</td>
</tr>
<tr>
<td>$a$</td>
<td>The average number of packets per flow of $G$</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>The number of flows carrying more than $\beta$ packets</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>The number of packets in the flow $f$</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>The estimated number of packets in the flow $f$</td>
</tr>
</tbody>
</table>

**4.1. False positive error rate of filtering module**

**Theorem 1.** Suppose there are $L$ elephant flows and $S$ mice flows in network traffic. The filtering module consists of $M$ buckets, with $k$ independent hash functions. Given a flow entering the filtering module, the false positive error rate $P_{FPR}$ can be estimated as follows:

$$P_{FPR} = \frac{1}{1 - \left(1 - \frac{1}{M}\right)^L} + 1 - \sum_{i=0}^{L-1} \left(\frac{1}{M}\right)^i \left(1 - \frac{1}{M}\right)^{S-i}$$  

(1)
where $\lambda = \left[ \frac{\alpha}{MN} \right]$, $\alpha$ is the filtering threshold and $\|f\|$ represents the average number of packets in mice flows.

**Proof.** For an incoming mice flow $f$, it is first mapped to $k$ buckets in the filtering module through $k$ hash functions. If all $k$ buckets reach the filtering threshold $\alpha$, this mice flow will be erroneously classified as an elephant flow, which constitutes a false positive error. There are two cases for each bucket to reach the filtering threshold: (1) with at least one mapped elephant flow, or (2) with at least $\lambda$ mapped mice flows. We will proceed to respectively determine the probabilities of these two cases.

Suppose that all flows randomly map into $M$ buckets, the probability of any bucket not mapped by an elephant flow is $1-1/M$. Since there are $L$ elephant flows in total, the probability of any bucket mapped by at least one elephant flow can be derived as:

$$P_L = 1 - \left( 1 - \frac{1}{M} \right)^L$$  \hspace{1cm} (2)

Similarly, the probability of any bucket not mapped by a mice flow is $1-1/M$. Since there are a total of $S$ mice flows, the probability of any bucket mapped by $i$ mice flows can be deduced as:

$$P_i = \left( \frac{1}{M} \right)^i \left( 1 - \frac{1}{M} \right)^{S-i}$$  \hspace{1cm} (3)

Therefore, we can compute the probability that any bucket is mapped by at least $\lambda$ mice flows as:

$$P_{\lambda} = 1 - \sum_{i=0}^{\lambda-1} P_i = 1 - \sum_{i=0}^{\lambda-1} \left( \frac{1}{M} \right)^i \left( 1 - \frac{1}{M} \right)^{S-i}$$  \hspace{1cm} (4)

In summary, the probability that any bucket reaches the filtering threshold can be expressed as $P_L + P_{\lambda}$. Consequently, we can obtain the probability that all $k$ buckets mapped by a mice flow reach the threshold, that is, the false positive error rate as:

$$P_{FPK} = (P_L + P_{\lambda})^k = \left[ 1 - \left( 1 - \frac{1}{M} \right)^L \right]^k + 1 - \sum_{i=0}^{\lambda-1} \left( \frac{1}{M} \right)^i \left( 1 - \frac{1}{M} \right)^{S-i}$$  \hspace{1cm} (5)

Theorem holds.  \hspace{1cm} $\Box$

### 4.2. Error bound of the guarding module

**Theorem 2.** Assume that there are $G$ flows passing through the filtering module and inserted into the guarding module, and the average number of packets per flow is $\sigma$. Let $N$ be the total number of buckets in the guarding module, $m$ be the number of cells in each bucket, $\beta$ be the packet number threshold of the guarding module. Suppose there are $g$ flows each of which carries more than $\beta$ packets. For a flow $f$ with the number of packets $g$, let $\hat{f}$ be its estimated frequency, we can bound the error expectation of its frequency estimation in the guarding module as:

$$E(\hat{f} - f) \leq \frac{\beta}{\sigma - \alpha} \left( \frac{e^{\beta m}}{m!} \right)^3 \frac{G - g}{GNm}$$  \hspace{1cm} (6)

where $\lambda = G/N$.

**Proof.** To determine the error in estimating the frequency of any flow $f$, we first analyze all cases that have an impact on the flow for an arrived packet entering the guarding module as follows.

**Case 1:** The packet resides in the flow $f$. In this case, we locate the flow in the guarding module, and increment its count value by 1. Thus, there is no error in estimating the frequency of $f$, i.e., $|\hat{f} - f| = 0$.

**Case 2:** The packet belongs to a new flow $f'$, and there is no empty cell in its mapped bucket and adjacent buckets, where $f$ is the minimum flow with a frequency lower than the guarding threshold $\beta$. In this case, the flow $f$ will be replaced by $f'$ and its estimated frequency will become zero. Hence, the estimation error of its frequency equals to its count value, i.e., $|\hat{f} - f| = f'.Count$.

**Case 3:** The packet is affiliated to a new flow $f'$, and there is no vacancy in its mapped bucket and adjacent buckets, where all flows have higher frequencies than the guarding threshold $\beta$ and $f$ is the minimum flow among them. In this case, the flow $f$ will be kicked out to a new cell in one of its adjacent buckets for preserving $f'$. Therefore, there is also no error in estimating the frequency of $f$, i.e., $|\hat{f} - f| = 0$.

According to the above analysis, we can conclude that the estimation error of flow frequency primarily stems from flow replacements in case 2. Then, we analyze the probability of case 2 with the following conditions: (1) A new flow $f'$ is arrived; (2) There is no empty cell in its mapped and adjacent buckets; (3) The flow $f$ is preserved in these buckets $B(g(f'))$, $B((g(f')) + 1)%N$, and $B((g(f')) + 1)%N$; (4) The flow $f$ is the minimum one in the buckets. (5) The count value of the flow $f$ is lower than the guarding threshold $\beta$.

For a flow $f'$, it is classified as a new flow only when its first packet comes into the guarding module. Since the average number of packets per flow is $\sigma$, and a flow must first reach the filtering threshold $\alpha$ before getting into the guarding module. Therefore, we can derive the probability of the condition 1 as the ratio of the number of flows to the total number of packets entering the guarding module in (7).

$$P_1 = \frac{G}{G(\sigma - \alpha)} = \frac{1}{\sigma - \alpha}$$  \hspace{1cm} (7)

Given that each bucket operates independently, the probability of all three buckets having no empty cells can be considered as a classic bin packing problem. Then, we model this problem with the Poisson stream, where the parameter $\lambda = G/N$ represents the average number of flows in each bucket. Accordingly, the probability that a bucket is full can be expressed as:

$$P_{full} = e^{-\frac{\lambda^m}{m!}}$$  \hspace{1cm} (8)

Consequently, we can calculate the probability of the condition 2 that all three buckets are full in (9).

$$P_2 = P_{full}^3 = \left( e^{-\frac{\lambda^m}{m!}} \right)^3$$  \hspace{1cm} (9)

Owing to that each flow is randomly mapped across $N$ buckets by hashing, all buckets have the equal probability $1/N$ to accommodate the flow $f$. Therefore, we can get the probability of the condition 3 that the flow $f$ is preserved in the three buckets $B(g(f'))$, $B((g(f')) + 1)%N$, and $B((g(f')) + 1)%N$ in (10).

$$P_3 = \frac{3}{N}$$  \hspace{1cm} (10)

Since each bucket contains $m$ cells, we can obtain the probability of the condition 4 that the flow $f$ is the minimum one in the three buckets in (11).

$$P_4 = \frac{1}{3m}$$  \hspace{1cm} (11)

Due to that there are $G$ flows entering into the guarding module and $g$ flows each of which carries more than $\beta$ packets, we can compute the number of flows with a frequency lower than $\beta$ as $G-g$, and the probability of the condition 5 that the count value of flow $f$ is lower than the guarding threshold $\beta$ in (12).

$$P_5 = \frac{G - g}{G}$$  \hspace{1cm} (12)

By integrating the above probabilities of 5 conditions in (7), (9), (10), (11) and (12), we can infer the probability of flow replacements in (13).

$$P_{replace} = P_1P_2P_3P_4P_5 = \frac{1}{\sigma - \alpha} \left( e^{\beta m} \right)^3 \frac{G - g}{GNm}$$  \hspace{1cm} (13)

Since the frequency of a replaced flow is lower than the guarding threshold $\beta$, we can conclude that the error in estimating the frequency
of f satisfies $|\hat{f} - \tilde{f}| < \beta$. By combining with (13), we can eventually bound the error expectation of flow frequency estimation in the guarding module as:

$$E(|\hat{f} - \tilde{f}|) \leq \beta P_{\text{replace}} = \frac{\beta}{\alpha - \delta} \left( \frac{e^{x} \chi_{m}}{m!} \right)^{1} G - g$$

(14)

Theorem holds. \qed

5. Experiments

In this section, we introduce our experimental setup, metrics, and parameter settings, and validate the superiority of ActiveGuardian by comparative experiments with existing solutions.

5.1. Experimental setup

Platform: Our testbed is comprised of 2 servers connected directly to each other. Each server is an HP ProLiant DL380 Gen10, equipped with two 10-core Intel(R) Xeon(R) Gold 5218 CPU @ 2.30 GHz and 128 GB RAM. One server assumes the role of the sender, while the other functions as the receiver. ActiveGuardian is implemented on the receiver side. Each server is outfitted with one Broadcom NetXtreme E-Series dual-port 100GbE NIC.

Dataset:

MAWI Dataset: The MAWI dataset was collected from daily traces at the transit link of WIDE to the upstream ISP (MAWILab, 2019). As for each packet in the dataset, we extract its packet size, timestamp, and a standard 5-tuple (IP address and port number for source and destination, and protocol type) utilized to construct flow ID. We select 20M packets in total, belonging to 4.6M flows with 6579 active elephants at the transit link of WIDE to the upstream ISP (MAWILab, 2019). As for BurstSketch, the size of Stage 1 and Stage 2 are determined by the memory size. For HeavyKeeper, the number of arrays is 3, and the width of each array is determined by the memory size. For ASketch, the size of the filter is set from 0.1 kB to 12 kB, the sketch occupies the rest memory size. For WCSS, the size is also determined by the memory size. In our algorithm, we set the number of hash functions $k$ to 3, the updating threshold $\gamma$ to 0.85, the filtering threshold $\nu$ to 15, the guarding threshold $\beta$ to 500, and the size of ActiveGuardian depends on the memory size. The counter field and the guarding field are 4 bits and 16 bits respectively. In particular, some of the parameters mentioned above are based on experimental evaluations to obtain the best performance.

For each dataset, we read 20M packets. We set the length of the window $W = 100K$, and vary the memory size between 10 kB and 50 kB. When the frequency of a flow in the present time window is more than 500, we consider it as an active elephant flow. We compare the precision rate, recall rate, AER, AAE, and throughput of the above solutions under the same memory size.

5.2. Metrics

(1) Precision Rate (PR): The ratio of the number of correctly reported to the number of reported instances.

(2) Recall Rate (RR): The ratio of the number of correctly reported to the number of true instances.

(3) ARE (Average Relative Error): $\frac{1}{|Z|} \sum_{f \in Z} \frac{|\tilde{n}_{f} - n_{f}|}{n_{f}}$, where $Z$ is the estimated set of active flows, $\tilde{n}_{f}$ is the estimated size of flow $f$, and $n_{f}$ is the real size of flow $f$. We use ARE to evaluate the accuracy of flow size estimation and the identification of active elephant flows.

(4) AAE (Absolute Average Error): $\text{AAE} = \frac{1}{|Z|} \sum_{f \in Z} |\tilde{n}_{f} - n_{f}|$, similarly to ARE.

(5) Throughput: $\frac{T}{N}$, where $N$ is the total number of packets, and $T$ is the total measurement time. We use Million of insertions per second (Mps) to measure the throughput.

5.3. Parameter settings

In this subsection, we measure the effects of key parameters in ActiveGuardian on its performance, including the filtering threshold $\alpha$, the guarding threshold $\beta$, the update threshold $\gamma$, and the window size $W$. In the following experiments, we set memory to 50 kB and conduct experiments on the MAWI dataset. Fig. 5 illustrates the valuing of performance metrics PR, RR, AAE, and ARE, under different parameter settings.

Effects of $\alpha$: We obtain the performance metrics of ActiveGuardian in Fig. 5(a), by incrementally increasing the filtering threshold $\alpha$ from $2^{3} - 1$ to $2^{4} - 1$, with the constancy of other parameters. As shown in Fig. 5(a), the optimal value for $\alpha$ is 7 or 15. With the filtering threshold continues to rise, there is a slight increase in RR, while PR decreases, and AAE and ARE increase. This phenomenon is attributed to the fact that the update cycle of the filter becomes longer with a higher filtering threshold. This further lets mice flows easily pass into the Guardian module due to hash collisions, and leads to misjudgments and overestimation of active elephant flows. We also observe that ActiveGuardian achieves superior overall performance, with RR exceeding 99%, PR over 98%, and the lowest AAE and ARE, when $\alpha$ is set to 15. Therefore, $\alpha$ defaults to $2^{3} - 1 = 15$.

Effects of $\beta$: We incrementally increase the guarding threshold $\beta$ from 300 to 700, while keeping the remaining parameters constant. With these settings, we gain the performance metrics of ActiveGuardian in Fig. 5(b). We can see from Fig. 5(b) that PR shows an increasing trend, and AAE and ARE gradually decrease with the increase in the guarding threshold. When $\beta = 500$, RR exceeds 99%, PR goes beyond 98%, and AAE and ARE reach relatively low levels. As $\beta$ continues...
to rise, the performance tends to become stable and is hard to be further optimized. Since our goal is to find out flows that potentially impact network performance, it is unsuitable to set too high guarding threshold. In summary, $\beta$ is set as 500 by default.

**Effects of $W$:** We incrementally increase the window size $W$ from 10K to 200K, while keeping the rest parameters constant. With these settings, we get the performance metrics of ActiveGuardian in Fig. 5(d). We can observe from Fig. 5(d) that, RR keeps above 99%, PR initially rises, then slightly decreases and finally stabilizes at around 98%, while AAE and ARE gradually decrease, for the increasing window size. This suggests that ActiveGuardian consistently maintains excellent performance even as packet traffic grows. In order to report active elephant flows in short periods, $W$ is configured as 100K by default.

### 5.4. Precision and recall

**Precision vs. memory size:** As shown in Fig. 6(a) with the MAWI dataset, the precision of ActiveGuardian, BurstSketch, FastKeeper, HeavyKeeper, ASketch, and WCSS is respectively 92.96%, 87.62%, 84.64%, 93.32%, 88.08%, and 71.62% at the memory size of 10 kB. With the increase in memory, the precision of ActiveGuardian gradually increases from approximately 92.96% to around 98.65%. As seen from Fig. 6(b) with the WebDocs dataset, the precision rates for ActiveGuardian, BurstSketch, FastKeeper, HeavyKeeper, ASketch, and WCSS are respectively 90.12%, 83.62%, 78.64%, 94.00%, 86.08%, and 70.62% when the memory size is 10 kB. In addition, ActiveGuardian provides higher accuracy in memory sizes between 20 kB and 50 kB, while AAE and ARE gradually decrease, for the increasing window size. This suggests that ActiveGuardian consistently maintains excellent performance even as packet traffic grows. In order to report active elephant flows in short periods, $W$ is configured as 100K by default.

**Recall vs. memory size:** As shown in Fig. 7(a) with the MAWI dataset, the recall rates for ActiveGuardian, BurstSketch, FastKeeper, HeavyKeeper, ASketch, and WCSS are respectively 99.77%, 88.62%, 76.64%, 42.89%, 98.55%, and 66.56% at a memory size of 10 kB. As the memory size increases, the recall rate of ActiveGuardian shows a gradual improvement from approximately 99.77% to around 99.96%. As displayed in Fig. 7(b) with the WebDocs dataset, the recall rates for ActiveGuardian, BurstSketch, FastKeeper, HeavyKeeper, ASketch, and WCSS are respectively 99.67%, 87.62%, 74.64%, 51.89%, 90.55%, and 70.56% when the memory size is 10 kB. ActiveGuardian also maintains relatively high recall rates in memory sizes from 20 kB to 50 kB, ranging from approximately 99.96% to 99.89%. In conclusion, ActiveGuardian consistently achieves high recall rates with the same memory size, and exhibits a pronounced advantage in low-memory scenarios. This indicates that ActiveGuardian is more suitable for resource-constrained measurement environments. This is primarily due to that ActiveGuardian utilizes an Adaptive Counter Update strategy to filter out mice flows continuously and effectively even at significantly variable flow rates and with limited memory resources.

### 5.5. ARE and AAE

**ARE vs. memory size:** As depicted in Fig. 8(a) with the MAWI dataset, the $\log_{10}$ ARE of ActiveGuardian, BurstSketch, FastKeeper, HeavyKeeper, ASketch, and WCSS are respectively 2.48, 2.90, 3.41, 1.85, 3.75, and 2.90 at a memory size of 10 kB. As the memory size varies, the $\log_{10}$ ARE of ActiveGuardian exhibits relatively low $\log_{10}$ ARE across all memory conditions, ranging from 2.53 to 2.18. Conversely, other solutions like BurstSketch, FastKeeper, ASketch, and WCSS consistently exhibit higher $\log_{10}$ ARE, with ASketch reaching a peak $\log_{10}$ ARE of 3.75 at 10 kB memory. As seen from Fig. 8(b) with the WebDocs dataset, the $\log_{10}$ ARE of ActiveGuardian, BurstSketch, FastKeeper, HeavyKeeper, ASketch, and WCSS are respectively 2.38, 2.50, 2.81, 1.75, 3.45, and 2.60 when the memory size is 10 kB. On top of that, ActiveGuardian also maintains relatively low $\log_{10}$ ARE in memory sizes varying from 20 kB to 50 kB, with $\log_{10}$ ARE ranging from approximately 2.96 to 2.71. In brief, ActiveGuardian maintains a relatively low ARE compared with other algorithms. This is primarily because that ActiveGuardian reports active elephant flows and cleans expired information at the end of each time window, significantly enhancing memory utilization.

**AAE vs. memory size:** As shown in Fig. 9(a) with the MAWI dataset, ActiveGuardian achieves $\log_{10}$ AAE between 2.11 and 2.38, while the $\log_{10}$ AAE of BurstSketch ranges from 2.49 to 2.96, FastKeeper changes from 2.24 to 2.91, HeavyKeeper varies from 2.44 to 2.66, ASketch goes from 2.75 to 2.85, and WCSS varies from 3.15 to
allowing for simultaneous insertion and query operations. This is mainly owing to that ActiveGuardian utilizes efficient data identification of active elephant flows in high-speed network environments. This is because we apply Leapfrog hashing algorithm to provide multiple storage locations for active elephant flows, and timely replace mice flows and low-arrival-rate flows.

5.6. Throughput

Throughput vs. memory size: According to the testbed described in Section 5.1, we allocate 6 CPU cores for packet generation in the sender server, and its throughput can reach 30 Mps. In the receiver server, two dedicated cores are assigned to packet reception, with each core achieving a maximum throughput of 15 Mps. Various flow identification algorithms are deployed on an additional CPU core, tasked with obtaining packet traffic from the receiving cores.

As illustrated in Fig. 10, ActiveGuardian and HeavyKeeper exhibit higher throughput performance compared to ASketch and WCSS for the MAWI dataset. Specifically, ActiveGuardian achieves a throughput of 26.53 Mps and HeavyKeeper achieves 25.34 Mps, while ASketch and WCSS respectively exhibit lower throughput performance, achieving 24.98 Mps and 24.96 Mps. As for the WebDocs dataset, ActiveGuardian maintains the highest throughput performance of 25.34 Mps, followed by HeavyKeeper with 24.98 Mps. Conversely, ASketch and WCSS respectively exhibit lower throughput performance, measuring at 22.87 Mps and 22.85 Mps. Overall, ActiveGuardian maintains the highest throughput performance of 25.34 Mps, which is followed by ASketch and WCSS respectively exhibiting lower throughput performance, achieving 24.98 Mps and 24.96 Mps. As a result, ActiveGuardian has higher throughput performance compared to ASketch and WCSS for the MAWI dataset. Additionally, ActiveGuardian achieves a higher throughput of 25.34 Mps compared to the state-of-the-art algorithms. This suggests that it has better adaptability to high-speed network environments.

In our future work, we will extend ActiveGuardian to report continuous time windows of active elephant flows. Simultaneously, we will explore robust update strategies and adaptive capacity expansion mechanisms for filtering module and guarding module, for better adaptivity to network traffic jitters or even malicious attacks. In the future, we also plan to deploy ActiveGuardian into various network applications such as intrusion detection systems, network management platforms and online network devices.

6. Conclusion

Accurate and efficient identification of active elephant flows is an essential task in network traffic measurement. Due to the unbalanced flow size distribution and changeable flow rates, existing works in real-time measurement suffer from limited precision and high error rates with restricted space memory. In this paper, we propose an algorithm for accurately and efficiently identifying active elephant flows, named ActiveGuardian. We design an Adaptive Counter Update strategy to adaptively guarantee the persistent separation of unnecessary flows, and a Leapfrog Hashing algorithm to greatly reduce hash collision rates, therefore improving accuracy and efficiency.

Experimental evaluation confirms that ActiveGuardian achieves up to 99.65% precision for identifying active elephant flows, and also maintains around 90% precision even in low-memory scenarios. The recall rate consistently remains above 99%, significantly outperforming existing methods. In summary, ActiveGuardian can achieve accurate identification of active elephant flows with low memory usage. This implies that ActiveGuardian is more suitable for network devices with limited memory resources than other methods. Additionally, ActiveGuardian achieves a higher throughput of 26.53 Mps compared to the state-of-the-art algorithms. This suggests that it has better adaptability to high-speed network environments.

In our future work, we will extend ActiveGuardian to report continuous time windows of active elephant flows. Simultaneously, we will explore robust update strategies and adaptive capacity expansion mechanisms for filtering module and guarding module, for better adaptivity to network traffic jitters or even malicious attacks. In the future, we also plan to deploy ActiveGuardian into various network applications such as intrusion detection systems, network management platforms and online network devices.

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Bing Xiong: Funding acquisition, Methodology, Writing – original draft, Review – review & editing. Yongjing Liu: Formal analysis, Visualization, Writing – review & editing. Rui Liu: Formal analysis, Software, Writing – original draft. Jinyuan Zhao: Funding acquisition, Investigation, Project administration. Shiming He: Funding acquisition, Validation. Baokang Zhao: Funding acquisition, Supervision. Kun Yang: Conceptualization, Methodology. Keqin Li: Conceptualization, Resources.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Shiming He reports financial support was provided by National Natural Science Foundation of China. Baokang Zhao reports financial support was provided by National Natural Science Foundation of China. Bing Xiong reports financial support was provided by Hunan Provincial Natural Science Foundation of China. Bing Xiong reports financial support was provided by Scientific Research Foundation of Hunan Provincial Education Department. Jinyuan Zhao reports financial support was provided by Scientific Research Foundation of Hunan Provincial Education Department. Bing Xiong has patent pending to Changsha University of Science and Technology.

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References


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