

## Advanced Topics in Communication Networks (Fall 2019)

Group Project Report

# Hearding the Elephants: Detecting Network-Wide Heavy Hitters with Limited Resources

Authors:

Yannick Merkli

Tim Bohren

Felix Rüssli

Advisor: Albert Gran Alcoz

Supervisor: Prof. Dr. Laurent Vanbever

Submitted: Dec 16, 2019

9 Pages

## Abstract

Detecting heavy hitters (e.g. flows whose packet counts exceed a certain threshold) is an important task for Denial of Service detection, load balancing and traffic routing. Past work has shown how to detect heavy hitters on a single network switch. However, nowadays heavy hitter flows are often *network-wide*, thus detecting them on a single switch is not enough. A flow can enter a network over multiple ingress switches and from each switch's local view, the flow might look like normal. However, from a global view, the flow would be classified as a heavy hitter. A detection protocol should *quickly* detect flows from a *global view*. Further, detecting heavy-hitter flows inherently poses a trade-off between limitations in network-wide communication and memory resources on the ingress switches and accuracy in detecting heavy hitters.

In this work, we have implemented Herd [1]. Herd is a distributed algorithm that identifies network-wide heavy hitters in real time and under constraints on communication and switch memory. The algorithm uses a sample-and-hold technique for flow measurements on ingress switches and probabilistic sampling and reporting of flows. Reporting is done to a central coordinator, which allows for a global view on the network.

# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
<b>2</b>	<b>Background and related work</b>	<b>1</b>
<b>3</b>	<b>Implementation</b>	<b>2</b>
3.1	Herd algorithm . . . . .	2
3.2	Locality . . . . .	3
3.3	Switch logic . . . . .	3
3.4	Herd Controller . . . . .	4
3.5	Herd controller - coordinator communication . . . . .	5
3.6	Coordinator . . . . .	5
3.7	Tuning the parameters . . . . .	5
3.8	Full hash tables . . . . .	6
3.9	Challenges . . . . .	6
3.10	Assessment of the original paper . . . . .	7
<b>4</b>	<b>Evaluation</b>	<b>7</b>
4.1	Topology . . . . .	7
4.2	Detection accuracy . . . . .	8
4.3	Herd performance over different sampling probabilities . . . . .	8
<b>5</b>	<b>Conclusion</b>	<b>9</b>
	<b>References</b>	<b>10</b>
<b>A</b>	<b>Group organization</b>	<b>I</b>

# 1 Introduction

Heavy hitters are a minority of flows that are responsible for a majority of packets inside a network. Network operators are interested in spotting them in order to detect and prevent Denial of Service attacks and to maximize the throughput by detecting congestion and failures. Further, heavy hitter detection can also be used for network management such as usage-based pricing or load balancing. To effectively manage and protect networks, heavy hitter detection needs to be quick and efficient. For the following sections, we assume a network to consist of multiple ingress switches through which traffic enters a network. The topology of the inner network is ignored and not important for this work.

Detection of heavy hitters faces several challenges. First of all, heavy hitters don't necessarily enter a network through a single ingress switch and they don't always originate from a single source. As an example, a single host inside a network might be the target of a denial-of-service attack, but traffic targeted towards the host may enter over multiple ingress switches. Local detection on ingress switches will not capture the network-wide view of a flow and will inherently fail at detecting network-wide heavy hitters. Second, network devices are usually limited in their resources, especially when it comes to memory and processing power. This often results in network operators having to choose between high detection accuracy and low processing overhead (i.e. low delay).

The problem of a missing network-wide view can be solved by introducing a centralized instance that receives and aggregates partial information from network devices. The burden of heavy hitter detection thus no longer lies on ingress switches but on this centralized instance; usually a general-purpose CPU. The ingress switches only observe and report flows.

With unlimited memory and processing power on switches and unlimited communication, detecting network-wide heavy hitters would be easy. Each switch could keep track of every single flow, communicate as much as needed with the centralized instance, which can immediately detect based on aggregated information. In reality, switches are highly limited in their memory and processing power. Sending a subset of flow information to a central, general-purpose CPU lifts parts of the limitations on processing power and memory, however new limitations are introduced by the resulting network-wide communication and the fact that a general-purpose CPU is not able to process data at line rate.

Herd [1] solves these problems by sampling traffic probabilistically, which saves memory on the switches, and reporting to a central coordinator once an observed flow exceeds a certain threshold. This allows for high accuracy in flow detection while operating under the constraints imposed by network devices. The coordinator sees all flows that entered the network and that were reported by an ingress switch. The coordinator is thus able to combine partial information reported by various ingress switches. This system makes it possible to not only detect local heavy hitters, but also distributed ones, potentially even detecting distributed Denial of Service attacks (DDoS) before they grow to their full potential.

## 2 Background and related work

The basic problem to solve is the following: various flows enter a network and we want to classify them based on a measure that captures each flow's strain on the network (e.g. the packet count). We then want to distinguish *mice flows* (flows without local or global significance) from *elephant flows* (flows with local and global significance).

There already exist a number of protocols with different approaches to detect elephants. Some existing algorithms, such as NetFlow [2], sample incoming packets and export them to a central collector. This addresses the constrained switch resources and the flow locality, however these algorithms suffer from temporal 'blind spots' due to low sampling rates and the resulting long delays. Other approaches to heavy hitter detection run streaming algorithms, combined

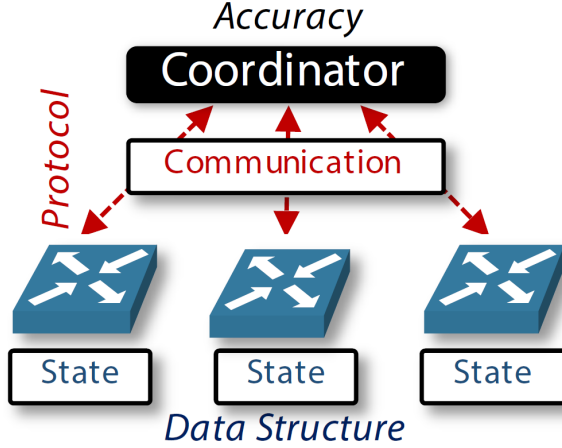


Figure 1: The Herd switches communicate with the coordinator. [1]

with a compact data structure like a count-min sketch [4] or a bloom filter.

These algorithms address the resource constraints of switches, however they fail to capture network-wide heavy hitters since detection is done on each switch individually.

### 3 Implementation

We have implemented Herd, as proposed by [1]. The Herd architecture consists of local ingress switches and a central coordinator that achieves a global view. Ingress switches probabilistically sample and report incoming flows to the coordinator. Each flow can be of local and global significance. Additionally to mice and elephants, Herd thus introduces two more flow categories to describe all four types of significance: mice, moles, mules and elephants.

#### 3.1 Herd algorithm

All flows that enter a network are first classified as mice (a flow is defined by the five-tuple  $(srcIP, dstIP, srcPort, dstPort, protocol)$ ). Mice are the most common but also the smallest flow type. When a packet arrives, Herd uses the sample-and-hold algorithm: if the flow to which the packet belongs is already tracked, then its counter is simply increased. Otherwise, we start tracking the flow with sampling probability  $s$ . With an increasing number of packets belonging to the same flow, the flow's packet count is more likely to be tracked.

Once a flow is captured by an ingress switch it advances to the next higher tier: the mole. A mole flow is simply a flow whose packet count is tracked by an ingress switch. As such, a mole flow exhibits local significance but no global significance.

As soon as the packet count of a mole flow on a single ingress switch exceeds the mule threshold  $\tau$ , the mole flow is reported to the coordinator with report probability  $r$ . The packet count threshold  $\tau$  is introduced for two reasons: First, the coordinator should not waste its precious memory on every mouse flow that happened to be sampled by the switch. By making sure that each reported flow's packet count exceeds a certain threshold, we ensure to only report globally significant flows that have the potential to become an elephant, especially when combining reports for the same flow from multiple ingress switches. The other reason is that the network does not have infinite bandwidth, so the switches have to be careful not to congest the links with coordinator communication. A flow that has been reported to the coordinator at least once advances from mole flow to mule flow, which means that the flow now has global significance.

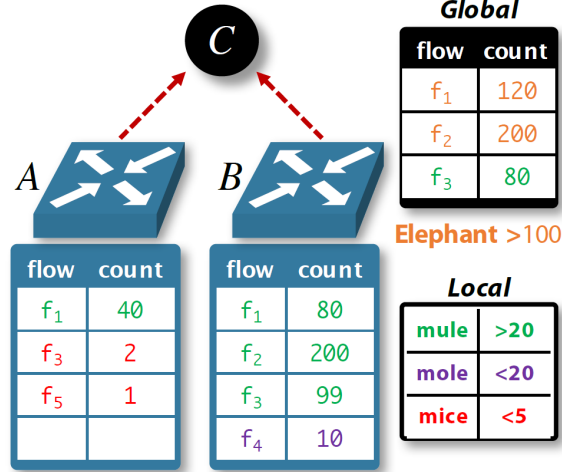


Figure 2: Zoology in the Herd protocol.

The coordinator has a global view over all mule flows reported by the ingress switches running Herd. In contrast, the ingress switches only have a local view since they do not know what other switches observe. Thus the actual classification of elephant flow is solely done by the coordinator. It counts how many reports for a specific flow were received, independently from which switch the report originated from, and as soon as the number of reports for a mule flow exceeds  $R$  the coordinator classifies the flow as an elephant flow, which is synonymous to being a heavy hitter.

### 3.2 Locality

So far it was assumed that all ingress switches have the same probability to observe a flow. However, in real networks flows often exhibit preference for certain ingress switches. So, certain switches are more likely to observe certain flows. Considering this, we need to increase the mule threshold  $\tau$  since every ingress switch observes more packets for fewer flows. A too low mule threshold  $\tau$  would result in too many flows being reported to the coordinator, which increases the network-wide communication and increases the number of false positives.

Herd thus introduces the notion of a *locality parameter*  $l_f$ , which denotes the number of ingress switches that observed flow  $f$ . However, tracking the locality on a per-flow level introduces significant overhead. That's why Herd only tracks the locality on a per-group level. A group is defined as

$$g_{src,dst} = \{f | f.srcIP \in src, f.dstIP \in dst\}$$

where  $src$  and  $dst$  are  $/8$  IP subnets.

The new locality parameter  $l_g$  now tracks how many ingress switches observe a flow  $f \in g$ . Using the per-group locality parameter  $l_g$ , the mule threshold  $\tau_g$  and the report probability  $r_g$  can now be dynamically adapted on a per-group level. Since tracking  $l_g$  requires a global view of the network, this is done at the coordinator. For the coordinator to know which ingress switch observes which flows, the ingress switches need to send a message to the coordinator when observing an unexpected (i.e. never before seen) flow. These messages are called *hellos* in Herd.

### 3.3 Switch logic

Herd uses randomness for packet sampling and reporting to the global coordinator. Since P4 doesn't have a random library, hashes are used to 'flip' coins and simulate randomness. A 32bit

hash  $h$  is calculated from timestamps, the destination IP and the last hash; if

$$h < int32_{MAX} * probability$$

the probability is hit. However, the right part of this inequation requires floating point arithmetic, which P4 does not have. For this reason, the calculation  $int32_{MAX} * probability$  is done by the local controller at startup and the resulting  $int32$  number is then written into a register which can be read by the data plane.

As described in section 3.2, the mule threshold  $\tau_g$  and the report probability  $r_g$  vary on a per-group level. We thus use a match-action table that maps a group  $g_{src,dst}$  to its respective values  $\tau_g$  and  $r_g$ . A second match-action table is used for packet forwarding. As of now, ingress switches simply forward all traffic to an internal aggregator switch, thus this table only has one rule.

The life of a packet when entering an ingress switch looks as follows: the switch first extracts the group  $g_{src,dst}$  to which the flow belongs and applies the group values match-action table. In case of a table miss the switch sends a hello message to the local controller, which will then send the hello to the coordinator. The coordinator answers with the locality parameter  $l_g$  to the local controller, which will then add a rule to the group values table. For known groups the switch applies the sample-and-hold algorithm. In case the flow is not yet being sampled, we start sampling it with sampling probability  $s$ . If the flow is already being sampled, its counter is increased. In case the counter reaches the group-based mule threshold  $\tau_g$ , the switch resets the counter and reports the flow with report probability  $r_g$ . Again, the report will first be sent to the local controller, which will then send it to the coordinator. The communication between data plane and control plane (hellos and reports) is done via copy-to-cpu, where a cloned packet has a CPU header which has six fields: ( $srcIP, dstIP, srcPort, dstPort, protocol, flow\_count$ ).

The counters counting the number of seen packets per flow are stored in a multi-stage hash table with three stages. The index of the flow counter in the hash table is determined by hashing the flow five-tuple ( $srcIP, dstIP, srcPort, dstPort, protocol$ ). Register entries are 64 bit wide. The lower 32 bit store the flow count. The upper 32 bit store a hash (with a different hash function) of the flow five-tuple (hash key) which is used to detect hash collision. In case of a hash collision, the next hash table is considered. Note that the width of the registers can be chosen smaller than 64 bit. In case of few flows, hash collision become less likely and a smaller hash space for the flow key is acceptable. Further, the flow counter will never become larger than  $\tau_g$  since at that point it will be reset to zero and a report will be sent. We decided to use 64 bit wide registers to make sure that hash collisions are unlikely, even for large numbers of flows.

### 3.4 Herd Controller

A Herd controller is running on each ingress switch. The controller's main task is to communicate with the coordinator and write rules into the group values match-action table.

During the startup phase, the controller cleans all hash tables, writes the sampling probability to the data plane, fills the forwarding table and connects to the coordinator RPC server. To handle communication between data plane and control plane, the controller sniffs on the copy-to-cpu interface and unpacks each received cloned packet. Each clone packet includes a CPU header, stating the flow five-tuple and the packet count for the flow (flow count). The controller determines, based on the flow count, whether the received message is a hello or report: hellos have a flow count of zero whereas reports have a flow count larger than zero. The controller then sends the hello or report to the coordinator by initiating a remote procedure call, including the flow and the switch name as arguments.

When a flow belonging to a never before seen group  $g$  arrives at an ingress switch, it is possible that the data plane sends multiple hellos due to delayed writes into the group values table. In

order to avoid overloading the network with hellos, we adapted the Herd controllers to keep track of the flows for which a hello was already sent. This way, each controller only sends one hello per flow to the coordinator and we don't overload the network or the coordinator with unnecessary hello messages.

Additionally to a sending, the Herd Controller also needs to receive messages from the coordinator. Upon receipt of  $l_g$ , the controller calculates the mule threshold as  $\tau_g = \frac{\epsilon T}{l_g}$  and the reporting probability as  $r_g = \frac{1}{l_g}$ , where  $r_g$  is then transformed into an '*int32-probability*' (see section 3.3). The controller then writes  $\tau_g$  and  $r_g$  into the group values table with the group  $g$  ( $f \in g$ ) as match key and  $\tau_g, r_g$

### 3.5 Herd controller - coordinator communication

The communication model specified by Herd has the following three important characteristics: First, the coordinator needs to provide a service to one or many Herd controllers, which request the service. Second, communication should be asynchronous since hellos and reports can be generated anytime. Waiting for synchronous communication rounds would introduce additional delay, which would worsen accuracy. Last but not least, the communication needs to be two-way, since the coordinator needs to respond to hellos.

We decided to use a remote procedure call (RPC) protocol, since it fulfills all three mentioned characteristics. The coordinator server runs an RPC service that implements two exposed methods, *send\_hello* and *send\_report*, which can be invoked by Herd controllers. The communication from coordinator to Herd controller is implemented through a callback. When invoking *send\_hello*, a Herd controller passes the name of the switch and a callback function, which will be registered at the coordinator and called once the locality parameter  $l_g$  is sent back.

### 3.6 Coordinator

The central coordinator receives and handles hellos and reports sent by Herd controllers and sends back the locality parameter  $l_g$ . The coordinator further keeps track of the number of sent reports and classifies flows as heavy hitters.

When a hello arrives, the coordinator first registers the callback for the sending switch. It then extracts the group  $g$  from the flow five-tuple and looks up the locality parameter  $l_g$ . The coordinator further keeps track of which switches observe at least one flow belonging to group  $g$ . In case the number of switches that see a group doubled,  $l_g$  is updated and sent to each switch that observes  $g$ . Otherwise,  $l_g$  is only sent to the switch sending the hello.

Handling reports is rather simple. The coordinator simply counts the number of received reports for each flow. As soon as the number of reports reaches the reporting threshold  $R$ , the flow is put into a heavy hitter set and thus promoted to an elephant flow.

### 3.7 Tuning the parameters

Until now it was assumed that the approximation parameter  $\epsilon$ , the sampling probability  $s$  and the report threshold  $R$  were given.

Now we try to find those parameters in order to maximize the detection accuracy of Herd under communication and switch memory constraints. We do this by simulating the whole protocol for one Herd switch and the coordinator. In *tuningparameters.py* one can specify the packets needed to promote a flow into a heavy hitter and a set of training data in form of a pcap-file, but also the limited switch memory and communication budget. The program then iterates through the possible approximation factors  $\epsilon$  and returns the parameters which maximize the accuracy.

First, we try to configure the sampling probability  $s$  of the sample-and-hold algorithm. With unlimited switch memory  $S$  the sampling probability could simply be set to  $s = 1$  and



the switches would memorize all flows going through them. Let  $M$  be the set of observed moles on the switch. Thus the switch has to store  $|M|$  different flows. From this we conclude that we need  $|M| \leq S$  in order to be able to store all the observed flows. To be sure that the real  $M$  has enough space in  $S$  we even want  $|M| < S$ . In order to have this in expectation  $s$  is set to  $1/\tau$ . For that an estimation of  $\tau$  is needed. At the beginning  $\tau$  is set to the global threshold  $T$ .  $T$  is the size a flow needs to have in order to be recognized as a heavy hitter. Then we look in our training data  $D$  how many moles are found and check whether the found moles  $M$  use up all the memory  $S$ . Afterwards  $\tau$  is made smaller to increase the chance to categorize a flow as mole. This is done iteratively as long as there is still space in  $S$ .

If unlimited bandwidth was available  $r$  could be set to 1, since there would be more than enough bandwidth to send all the mule reports to the global coordinator. Further, the coordinator would need at least  $R = T/\tau$  reports to classify a flow as elephant. However, under the communication budget  $C$  the parameters  $r$ , as well as  $\tau$  and  $R$  need to be adjusted. This is done with the help of the approximation factor  $\epsilon$ . We approximate global threshold with  $\epsilon$  and expect to see at least  $\tau$  packets of that flow on every local switch with that flow, so in  $l$  switches. This brings us to the equality  $\tau l = \epsilon T$ , from which we get  $\tau = \frac{\epsilon T}{l}$ . Now that we have again a  $\tau$ . We calculate now first the set of moles  $M$  from our training data, and then from that the set of mules  $U$  since the necessary  $\tau$  is now available for that. The total number of sent reports can be bound with  $\frac{T|U|r}{\tau}$  which leads to  $r = \frac{T|U|C}{\tau}$ . The coordinator needs to see at least  $R = \frac{lr}{T}$  reports. We can now finally adjust  $\epsilon$  in steps of  $\sigma = \frac{l}{T}$  since  $\tau$  is an integer. Every time we change the value of  $\tau$  we calculate  $\tau$ ,  $r$  and  $R$  anew as well. This is done until the accuracy decreases for the first time. Afterwards the program returns the optimal parameters and terminates.

### 3.8 Full hash tables

Flow counters are stored on each ingress switch in a multi-stage hash table. In case of full hash tables, Herd proposes to just send all packets of the flow to the coordinator which introduces significant delay and communication cost. In our implementation, we handle full hash tables differently. Instead of sending all packets to the coordinator, the data plane sends an error message to the controller, indicating full hash tables. The controller will subsequently reset the hash tables. We argue that due to the fact that counters of large flows are reset back to zero anyways in case of a report, this leads to a minor decrease in accuracy. In the worst case, we reset the hash table when the packet count of flow  $f \in g$  is  $n_f = \tau_g - 1$ . The flow needs to be resampled in order for it to be counted. Thus, in expectation, the number of missed packet counts is  $\tau_g - 1 + \frac{1}{s}$ .

### 3.9 Challenges

We faced several challenges during the implementation and evaluation of Herd. The main challenge was limitations imposed by running Herd in a simulated environment and not in hardware. An important part of classification accuracy is how fast we can write or update an entry in the group values table. Whenever an incoming packet on the switch creates a table miss in the group values table, the switch will send a hello in order to fill the table. The total delay between the switch sending a hello and the controller writing the table rule is

$$\Delta t_{hello} = t_{DC} + 2 * t_{CC} + t_{table.write} + \epsilon$$

where  $t_{DC}$  is the delay introduced by the data plane to control plane communication (digests or copy-to-cpu),  $t_{CC}$  is the delay introduced by the controller-coordinator communication,  $t_{table.write}$  is the time it takes to write into a match-action table and  $\epsilon$  are negligible processing delays. Every packet belonging to a flow  $f \in g$  that arrives during  $\Delta t_{hello}$  will not be sampled

and the higher the sending speed, the more packets will arrive during  $\Delta t_{hello}$ . Further, we observed that the mininet starts dropping digest/copy-to-cpu messages at packet sending rates exceeding 400 packets per second (pps). We were thus limited to sending rates of 300 pps, which made evaluation over large pcap files take a long time. For a sending rate of 300 pps, a packet trace consisting of five million packets would take 4.6 hours. When running multiple evaluation runs, the total evaluation would easily take days. We thus limited our evaluation to packet trace with 100'000 and 400'000 packets. Note that these limitations only apply to simulations; in real hardware, the data plane to control plane communication would work over a direct link, which would remove that bottleneck. In that case, the main delay would come from the controller to coordinator communication.

Another challenge we faced was that the Herd paper [1] was often times very unspecific and omitted crucial details (see section 3.10).

### 3.10 Assessment of the original paper

Unfortunately, the Herd paper [1] has several weaknesses which made implementing it rather challenging. The paper is often extremely vague and omits crucial details. The authors stress the importance of tuning parameters such as the sampling probability  $s$ , the report probability  $r$  or the approximation factor  $\epsilon$ , to that end they propose a tuning parameters algorithm which intends to simulate Herd and find an ideal parameter set, given a packet trace as training data. Although providing part of the algorithm in pseudo code, many details are neglected, which required assumptions from our side. In the end, we were not able to reproduce a meaningful set of parameters using their tuning algorithm.

Considering the importance the paper puts on finding the right parameters, the authors blatantly omit mentioning which parameters were used for their evaluation. Since we were not able to reproduce the paper's tuning parameter algorithm, we thus had to find an optimal set of parameters by evaluating Herd in a mininet over multiple parameters, which eventually allowed us to at least find a locally optimal parameter set.

## 4 Evaluation

### 4.1 Topology

For the evaluation, we used the topology displayed in figure 3, as proposed by the Herd paper [1]. The topology is composed of  $k = 10$  edge (ingress) switches  $s_1 - s_{10}$ , representative of a wide-area network. Each ingress switch is running Herd with its Herd controller communicating with the coordinator. The host  $h_1$  represents an external host which sends traffic towards an internal host  $h_2$ , crossing the ingress switches  $s_1 - s_{10}$ . As outlined in section 3.2, flows usually show affinity for a limited number of ingress switches. As proposed by the paper, each flow will enter the network over  $l = 2$  ingress switches  $s_{primary}$ ,  $s_{secondary}$ , where  $P[s_{primary}] = p = 0.95$  and  $P[s_{secondary}] = 1 - p = 0.05$ . The two ingress switches are selected based on the hash of the source IP address. In order to distribute flows over ingress switches, we added a load balancer switch, which simply extracts the source IP of each packet, calculates a hash and sends the packet to  $s_{primary}$  with 0.95 probability and to  $s_{secondary}$  with 0.05 probability. Probabilistic coin flips are again implemented as explained in section 3.3. Additionally, we added an aggregating switch to the topology, which basically just collects all traffic that the ingress switches forward and then sends it to the internal host  $h_2$ .

Both, the load balancing switch and the aggregating switch have their own controllers that run at initialization time and write forwarding rules into match-action tables.

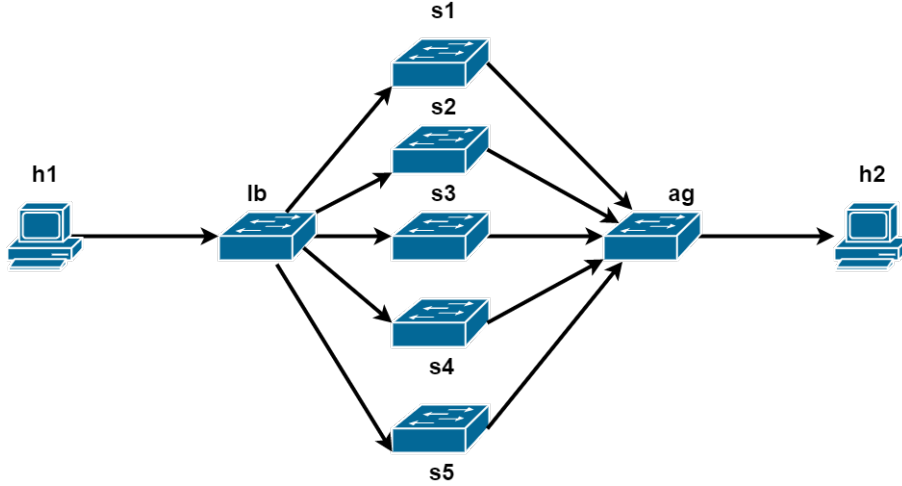


Figure 3: Evaluation topology:  $h_1$  sends traffic towards  $h_2$ , crossing the ingress switches  $s_1 - s_{10}$ , which all run Herd

To generate a sizable amount of traffic on the sending host  $h_1$  we use CAIDA’s anonymized internet packet traces from 2016, the same packet traces the Herd paper used. Due to the problems specified in 3.9, we sized down the packet traces to pcap files with 100’000 or 400’000 packets. Instead of Python’s scapy library, which only achieves very low sending rates, we used *tcpreplay* to send packets on host  $h_1$ . *tcprewrite* was used in order to add the correct source and destination MAC addresses (i.e. the MAC address of the sending interface on  $h_1$  and the MAC address of the receiving interface on the load balancer  $lb_1$ ) to the packets in the pcap file.

## 4.2 Detection accuracy

In the following evaluations, we look at detection accuracy, meaning out of all flows that actually are heavy hitters, how many do we classify correctly (true positive), how many do we mistakenly classify as heavy hitters (false positive) and how many actual heavy hitters don’t we classify as such (false negative). Note that by *positive* we always mean *heavy hitter*. We look at the following accuracy measures

$$Precision = \frac{tp}{tp + fp} \quad recall = \frac{tp}{tp + fn} \quad F1score = \frac{2 \cdot tp}{2 \cdot tp + fp + fn}$$

In order to calculate these accuracy measures, we need to know the actual heavy hitters of a packet trace. This is done by parsing all packets of a pcap file and calculating the flow count for each flow. The heavy hitter set is the set of flow whose flow count exceeds a global threshold  $T$ . Setting  $T$  is a design choice that depends on the network and traffic specifics. The Herd paper used the 99.99<sup>th</sup> percentile flow count in the packet trace. We decide to use the 99<sup>th</sup> percentile since we use smaller packet traces and a smaller global threshold will result in more heavy hitter flows. Accuracy is then simply calculated by evaluating all ‘real’ heavy hitter flows and comparing them with the ‘found’ heavy hitter flows, which are returned by the coordinator.

## 4.3 Herd performance over different sampling probabilities

One of the main ideas behind Herd is to probabilistically sample flows such that network devices don’t need to keep track of every flow they observe, which would be infeasible for large number of flows due to the limited memory on network devices. The sampling probability  $s$  dictates how many states a switch eventually will have to track, i.e. the lower the sampling probability, the lower the number of required states.

Figure 4: some graph about the evaluation

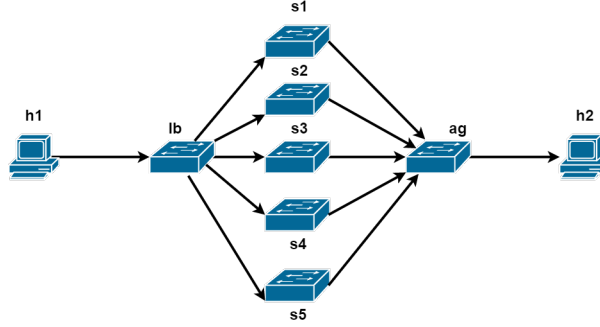


Figure 5: some other graph

## 5 Conclusion

We reimplemented Herd, a distributed heavy hitter protocol. Compared to the original paper we changed when to reset the flow/count tables. Further we had to implement a load balancing switch in front of the Herd switches for the evaluation. Additionally, we had severe speed issues in the implementation in software compared to a implementation in hardware.

Further research could go towards improving the selection of the parameters. How it is implemented at the moment, the tuning has to be done ahead of the protocol with training data. An improved protocol could maybe adjust the parameters according to captured data, and not prerecorded data. Even a dynamically changing tuning can be imagined. Another research topic would be, in case a single coordinator reaches its limit in processing power and speed, to have multiple coordinators, each responsible for a subnet, transferring data between each other.

## References

- [1] AUTHOR(S), A. Herding the elephants: Detecting network-wide heavy hitters with limited resources. Tech. rep., 2019.
- [2] B. CLAISE, E. Cisco systems netflow services export version 9. Tech. rep., 2004.
- [3] BOSSHART, P., DALY, D., GIBB, G., IZZARD, M., McKEOWN, N., REXFORD, J., SCHLESINGER, C., TALAYCO, D., VAHDAT, A., VARGHESE, G., ET AL. P4: Programming protocol-independent packet processors. *ACM SIGCOMM Computer Communication Review* 44, 3 (2014), 87–95.
- [4] CORMODE, G., AND MUTHUKRISHNAN, S. An improved data stream summary: The count-min sketch and its applications. Tech. rep., 2003.
- [5] ESTAN, C., AND VARGHESE, G. New directions in traffic measurement and accounting: Focusing on the elephants, ignoring the mice. Tech. rep., 2003.
- [6] MISRA, J., AND GRIES, D. Finding repeated elements. Tech. rep., 1982.
- [7] WU, H., HSIAO, H.-C., AND HU, Y.-C. Efficient large flow detection over arbitrary windows: An algorithm exact outside an ambiguity region. Tech. rep., 2014.

## A Group organization

*Briefly describe what each team member was contributing to the project*

### **Yannick Merkli**

- Coordinator
- Controllers
- Load balancer, aggregator

### **Tim Bohren**

- Ingress switch (P4 part of Herd)
- Data plane - control plane communication
- Automated evaluation

### **Felix Rüssli**

- Tuning Parameters
- Report
- Presentation