

# Estimating Logarithmic and Exponential Functions to Track Network Traffic Entropy in P4

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Figure source: Kreutz, Diego, et al. "Software-defined networking: A comprehensive survey." Proceedings of the IEEE 103.1 (2015): 14-76. and https://n0where.net/real-time-network-monitoring-cyberprobe





- 1. Significant communication overhead
  - 2. The latency caused by interaction



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- **>** Shannon entropy  $H = -\sum_{i=1}^{n} \frac{f_i}{|S|_{tot}} \log_2 \frac{f_i}{|S|_{tot}}$ 
  - $f_i$ : the packet count of the incoming flow i
  - $\triangleright$   $|S|_{tot}$ : the total number of processed packets by the switch during time interval
  - ▶ *n*: the overall number of flows



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#### Is it implementable in P4-enabled programmable switches?



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Loops (For/While )

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Logarithmic function



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Enable logarithmic and exponential-function estimation as the building blocks for network traffic entropy estimation entirely in P4





#### Why logarithmic and exponential-function estimations?

Network traffic entropy estimation

$$\begin{split} H &= -\sum_{i=1}^{n} \frac{f_i}{|S|_{tot}} \log_2 \frac{f_i}{|S|_{tot}} = \log_2 |S|_{tot} - \frac{1}{|S|_{tot}} \sum_{i=1}^{n} f_i \log_2 f_i \\ &= \log_2(|S|_{tot}) - 2^{(\sum_{i=1}^{n} f_i \log_2 f_i - \log_2 |S|_{tot})} \end{split}$$

 ${\bf 3}$  times of logarithmic computation and  ${\bf 1}$  time of exponential-function computation



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 ${f 3}$  times of logarithmic computation and  ${f 1}$  time of exponential-function computation

- SOTA <sup>1</sup> needs thousands of table entries in TCAM for the logarithmic and exponential-function estimations to assure the relative error is under 1%
  - TCAM is expensive and power-hungry
  - SOTA needs a controller to populate the TCAM lookup tables in the switch



<sup>&</sup>lt;sup>1</sup>Sharma, N. K., Kaufmann et al. "Evaluating the power of flexible packet processing for network resource allocation" Symposium on Networked Systems Design and Implementation (NSDI 17) (pp. 67-82).

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# Network traffic entropy estimation should avoid using TCAM to work entirely in programmable data planes



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- 1. P4Log: An algorithm for the estimation of logarithmic function
- 2. **P4Exp:** An algorithm for the estimation of exponential function
- 3. **P4Entropy:** A novel strategy allowing the estimation of network traffic entropy without relying on TCAM
- 4. We implemented the prototypes of the proposed algorithms and strategy in the P4 behavioral model <sup>2</sup>, proving that they can be **entirely** executed in the programmable data plane.

<sup>2</sup>https://github.com/p4lang/behavioral-model



- **INPUT:** An L-bit integer x (L  $\in$  {16, 32, 64}) and a given logarithmic base d
- ▶ **OUTPUT:** Estimation of  $\log_d x \ll 10$  (i.e.,  $\log_d x \cdot 2^{10}$ )



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- **INPUT:** An integer base x and a real number exponent d
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• Binomial series expansion:  $2^y = 1 + y + \frac{y(y-1)}{2!} + \frac{y(y-1)(y-2)}{3!} + \cdots$ 



- **INPUT:** An integer base x and a real number exponent d
- **OUTPUT:** Estimation of  $x^d$



#### So it holds that:

$$2^{(d\log_2 x)_{dec}} = \underbrace{1 + (d\log_2 x)_{dec} + \frac{(d\log_2 x)_{dec}((d\log_2 x)_{dec} - 1)}{2!} + \cdots}_{N_{terms}}$$













#### A new time interval starts





The packets are identified by flow key  $\{srcIP, dstIP\}$ The flow key can be any subset of 5 tuple without any loss of generality





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- The accuracy of estimated packet count increases as  $N_h$  or  $N_s$  increases









 $Sum(|S|) = Sum(|S|-1) + \bar{f}_i(|S|) \log_2 \bar{f}_i(|S|) - (\bar{f}_i(|S|) - 1) \log_2 (\bar{f}_i(|S|) - 1)$ 





$$\begin{split} Sum(|S|) &= Sum(|S|-1) + \bar{f}_i(|S|) \log_2 \bar{f}_i(|S|) - (\bar{f}_i(|S|)-1) \log_2 (\bar{f}_i(|S|)-1) \\ \text{Applying L'Hopital's rule }^3: \ Sum(|S|) &= Sum(|S|-1) + \log_2 \bar{f}_i(|S|) + \frac{1}{\ln 2} \end{split}$$



<sup>&</sup>lt;sup>3</sup>D. J. Struik, "The origin of L'Hopital's rule," The Mathematics Teacher, vol. 56, no. 4, pp. 257–260, 1963.

## P4Entropy strategy









## P4Entropy strategy





## P4Entropy strategy



#### P4Entropy can estimate network traffic entropy entirely in the switch



# **Evaluation settings**

Metric: Relative error

▶ **P4Log** Given an input value x, relative error is defined as  $\frac{|P4Log(x,2)-\log_2 x|}{\log_2 x} \cdot 100\%$ , where  $\log_2 x$  is the exact value.

▶ **P4Exp** Given an input base x and an exponent d, the relative error is defined as  $\frac{|P4Exp(x,d)-x^d|}{x^d} \cdot 100\%.$ 

▶ **P4Entropy** We call  $\hat{H}$  the estimated traffic entropy in an observation window and H its exact value. The relative error is defined as the average value of  $\frac{|H-\hat{H}|}{H} \cdot 100\%$  in the 10 observation windows each composed by  $2^{21}$  packets captured from a real flow trace <sup>3</sup>



<sup>&</sup>lt;sup>3</sup>CAIDA UCSD Anonymized Internet Traces Dataset http://www.caida.org/data/passive/passive\_dataset.xml







(a) Sensitivity to  $N_{bits}$  ( $N_{digits} = 3$ ) (b) Sensitivity to  $N_{digits}$  ( $N_{bits} = 4$ ) Figure: Sensitivity of P4Log to  $N_{bits}$  (a) and  $N_{digits}$  (b)

All the bits after  $N_{bits}$  are ignored and considered as 0. The algorithm leads to worst-case estimations when most significant bits after  $N_{bits}$  are 1s.





(a) Sensitivity to  $N_{bits}$  ( $N_{digits} = 3$ ) (b) Sensitivity to  $N_{digits}$  ( $N_{bits} = 4$ ) Figure: Sensitivity of P4Log to  $N_{bits}$  (a) and  $N_{digits}$  (b) **AVG** is the average relative error in logarithm estimations among randomly-selected  $5 \cdot 10^6$ integer numbers such that  $x \in \{1, 2^{64} - 1\}$ 





(a) Sensitivity to  $N_{bits}$  ( $N_{digits} = 3$ ) (b) Sensitivity to  $N_{digits}$  ( $N_{bits} = 4$ ) Figure: Sensitivity of P4Log to  $N_{bits}$  (a) and  $N_{digits}$  (b)

Relative error < 1% when  $\mathit{N_{bits}}$  = 4 and  $\mathit{N_{digits}}$  = 3









We fix the integer exponent d to a chosen value, then we find the largest 64-bit integer base x that maximizes the output  $x^d$  within 64 bits







(a)  $N_{bits}$  (b)  $N_{digits}$  (c)  $N_{terms}$ Figure: Sensitivity analysis of P4Exp ( $N_{bits} = 7, N_{digits} = 3$  and  $N_{terms} = 7$ )

AVG is the average relative error in exponential function estimation among  $5 \cdot 10^6$  integer numbers with base  $x \in \{1, 2^{32} - 1\}$  and exponent  $d \in \{2, 32\}$  both randomly chosen



# P4Exp



(a)  $N_{bits}$  (b)  $N_{digits}$  (c)  $N_{terms}$ Figure: Sensitivity analysis of P4Exp ( $N_{bits} = 7, N_{digits} = 3$  and  $N_{terms} = 7$ )

$$2^{(d\log_2 x)_{dec}} = \underbrace{1 + (d\log_2 x)_{dec} + \frac{(d\log_2 x)_{dec}((d\log_2 x)_{dec} - 1)}{2!} + \cdots}_{N_{terms}}$$







Relative error 
$$< 1\%$$
 when  $N_{bits} =$  7,  $N_{digits} =$  3 and  $N_{terms} =$  7





Figure: Sensitivity of P4Entropy to sketch size ( $N_{bits} = 4$ ,  $N_{digits} = 3$  and  $N_{terms} = 7$ )

Network traffic entropy estimation is more sensitive to the overestimation caused by Count-min Sketch with respect to Count Sketch

SOTA\_entropy: Lapolli, Ângelo Cardoso, Jonatas Adilson Marques, and Luciano Paschoal Gaspary. "Offloading real-time ddos attack detection to programmable data planes." 2019 IFIP/IEEE Symposium on Integrated Network and Service Management (IM). IEEE, 2019.



# P4Entropy



(a) Sensitivity to  $N_h$  ( $N_s = 1000$ ) (b) Sensitivity to  $N_s$  ( $N_h = 10$ ) Figure: Sensitivity of P4Entropy to sketch size ( $N_{bits} = 4$ ,  $N_{digits} = 3$  and  $N_{terms} = 7$ ) 3% is the maximum possible relative error ensuring that accuracy of practical monitoring applications is not affected <sup>4</sup>



<sup>&</sup>lt;sup>4</sup>Ashwin Lall et al. "Data streaming algorithms for estimating entropy of network traffic". In: ACM SIGMETRICS Performance Evaluation Review. Vol. 34. 1. pp. 145-156, 2006.

# Conclusion and future work

- 1. We presented two new algorithms, **P4Log** and **P4Exp**, providing the estimation of logarithm and exponential function in P4.
- 2. Based on these two algorithms, we also proposed **P4Entropy** strategy to estimate the network traffic entropy.
- 3. The algorithms have the similar accuracy to the state-of-the-art solutions but do not rely on expensive and energy-hungry TCAMs while working entirely in the switch.
- 4. P4Entropy adopts a time-interval-based observation window that may allow the controller to synchronize the entropy collected from all switches

#### Future work:

- 1. Implement network traffic entropy-based DDoS detection entirely in programmable data planes
- 2. Test proposed algorithms and strategy on a real testbed

