Measuring Congestion States of Paths With Delay Entropy

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Abstract. With knowing the congestion states of end-to-end paths, network Boolean tomography is able to identify congestion links without direct monitoring. Most of existing work on network Boolean tomography uses the loss-based metric to determine congestion states of paths. However, such metric often needs to inject lots of probing traffic into the intervening network in order to obtain a better loss measurement. In this paper, we employ the entropy of the delays to characterize their congestion states instead. As simulation results demonstrate, the delay entropy exhibits better convergence rate than the loss rate with respect to the number of probing packets.

1 Introduction

Identifying congestion links is a significant issue in the context of network monitoring and troubleshooting. It is important in practice because congestion links would greatly decrease user experience and introduce blame on the Internet Service Providers (ISPs), particularly when the Service Level Agreements (SLAs) are violated. Network Boolean tomography [1] is an appealing method to identify congestion links as it only deploys end-to-end measurements at the edge of the networks of interest, and thus it works even when the access to the network-internal elements is not available [2].

Network Boolean Tomography [1] classifies whether the end-to-end paths' performance is "good" versus "congested" (or "bad"), and infers the performance status of the links under Boolean algebra. Loss rate is one of the most important metrics that are used to measure the performance of some network services and applications. Most existing (network) Boolean tomography methods exploit loss rate to classify the Boolean status of links and paths [3-7]. However, in order to ensure measurement accuracy, those loss-based methods require a relatively larger number of probing packets [8, 9], which means a long measurement period as well as a high chance of introducing more serious congestion. Moreover, loss-based methods will not work for many online network applications, as their services (e.g., the Internet phone service) often more heavily rely on delays rather than losses.

We attempt to identify the congestion states of paths with their delay distribution instead of their loss rate. Based on a discrete delay model [9], we can compute the delay entropy from the end-to-end delay measurement. Since the delay measurement has a better convergence performance than loss, our delay-entropy based metric also shows to get a better convergence rate than the conventional loss-based metric.

2 Network Delay Model and the Entropy Based Metric

Network Delay Model. Network congestion not only results in great losses to paths or links, but also poses significant impacts on their delays. To obtain the discrete delay distribution of a path, we first discretize its delay measurements: Given a delay bin width b_t, we quantize a delay measurement d_t with a state of $s = d_t / b_t \leqslant N$. When a loss observed or $d_t > (N-1)b_t$, we get a maximum delay state

N. Let ς_j for l_j and ξ_k for p_k be the random variables of the quantized delay state, where $\varsigma_j, \xi_k \subset \mathbb{N}$ (the set of natural numbers). We let $P_r(\varsigma_j = s)$ represent the probability for $\varsigma_j = s$.

Delay Entropy Model. When a packet traverses a router queue, it will suffer a (queuing) delay. Due to the existence of the cross traffic, the length of the router queue would vary all the time and thus give rise to the randomness of the delays. The delays will vary within a small scope when the cross traffic is light. However, when the cross traffic becomes more intensive (e.g., more underlying traffic flows are on the link or the path,), it will cause the delays to distribute in a larger range and will make them less predictable.

I.e., the delays evolve to be more dispersive as the cross traffic becomes more intensive, indicating the link or the path suffers a performance decrease.

Therefore, if we could find a metric which can take advantage of such changing patterns shown by the delay distributions, we will be able to use it to evaluate the link or path performance.

Fortunately, such a metric could be the Shannon entropy, which is widely used to measure the uncertainty as well as the dispersion degree. The the entropy is defined as following,

$$H(\varsigma_j) = -\sum_{s=0}^{N} P_r(\varsigma_j = s)\log_2 P_r(\varsigma_j = s), \tag{1}$$

where $H(\varsigma_j)$ denotes the delay entropy for link l_j. Accordingly, $H(\xi_k)$ for path p_k is defined in the same way above.

Characterize Delay Entropy. As in most existing work, we also assume all the network links $\mathcal{L}$ are independent with each other. According to [10], we get the following inequality,

$$H(\varsigma_i), H(\varsigma_j) \leqslant H(\varsigma_i + \varsigma_j) \leqslant H(\varsigma_i) + H(\varsigma_j). \tag{2}$$

The inequality (2) above describes the relationships of entropy between two independent links l_i and path l_j. For any one link l_a on p_k, we can derive from (2) another entropic inequality (3), where $\xi_k = \sum_{j \succeq k} \varsigma_j$ and $j \succeq k$ denotes that j is a successive node of k. The following inequality (3) generally describes the relationship between the entropy between the partial links and the entire path:

$$H\Big(\sum_{j \succeq k, j \neq a} \varsigma_j\Big), H(\varsigma_a) \leqslant H(\xi_k) \leqslant \sum_{j \succeq k} H(\varsigma_j), \tag{3}$$

Here we further present a brief proof to inequality (3).

Proof: For the path p_k, we select l_a from $\{l_j \mid j \succeq k\}$. Since all the links are independent from each other, then $Pr(\sum_{j \succeq k, j \neq a} \varsigma_j)$ and $Pr(\varsigma_a)$ are also independent. Therefore, we get $H(\sum_{j \succeq k, j \neq a} \varsigma_j), H(\varsigma_a)$ $\leqslant H(\xi_k) \leqslant H(\sum_{j \succeq k, j \neq a} \varsigma_j) + H(\varsigma_a)$, according to (2).

We select another l_b from $\{l_j \mid j \succeq k, j \neq a\}$. As in the same way above, we get $H(\sum_{j \succeq k, j \neq a, j \neq b} \varsigma_j + \varsigma_b) + H(\varsigma_a) \leqslant H(\sum_{j \succeq k, j \neq a, j \neq b} \varsigma_j) + H(\varsigma_a) + H(\varsigma_b)$. And so on and so forth, we select all the remained links one by one and finally we can get $H(\sum_{j \succeq k, j \neq a} \varsigma_j) + H(\varsigma_a) \leqslant H(\sum_{j \succeq k, j \neq a, j \neq b} \varsigma_j) +$ $H(\varsigma_a) + H(\varsigma_b) \leqslant \ldots \leqslant \sum_{j \succeq k} H(\varsigma_j)$. Since we have $H(\sum_{j \succeq k, j \neq a} \varsigma_j), H(\varsigma_a) \leqslant H(\xi_k) \leqslant H(\sum_{j \succeq k, j \neq a} \varsigma_j) + H(\varsigma_a)$, we then obtain $H(\sum_{j \succeq k, j \neq a} \varsigma_j), H(\varsigma_a) \leqslant H(\xi_k) \leqslant \sum_{j \succeq k} H(\varsigma_j)$. Hence, the inequality (3) holds. □

In practical networks, the cross traffic will somewhat introduce variations to the delays. Then it is barely for the delays of a path or a link to remain constant over time. Therefore, it is reasonable to believe that the equality in (2), (3) could not hold in practice. And as you see, the entropic inequality of (5) generally enables us to choose an entropic threshold for a path, e.g., a possible entropic threshold can be set either as $\max\{H(\sum_{j \succeq k, j \neq a} \varsigma_j), H(\varsigma_a)\}$ or $\sum_{j \succeq k} H(\varsigma_j)$. Here, we set the empirical entropic thresholds for each path with $H(\sum_{j \succeq k, j \neq a} \varsigma_j)$.

3 Simulation and Evaluation

Simulation Setup. We conduct simulations in NS-2 [11] to evaluate our scheme with the logical tree topology depicted in Fig. 1. We simulate the cross traffic with the FTP flows and the UDP-based Pareto flows. The loss rates of the good links (congestion links resp.) are set to be less than 0.005 (between [0.01, 0.03] resp.), and the bandwidth utilization rates of the good links (congestion links resp.) are set to be between [0.30, 0.65] (greater than 0.85 resp.). As shown in Fig. 1, the link bandwidths for the edge links and the internal links are 5Mb and 15Mb, respectively.

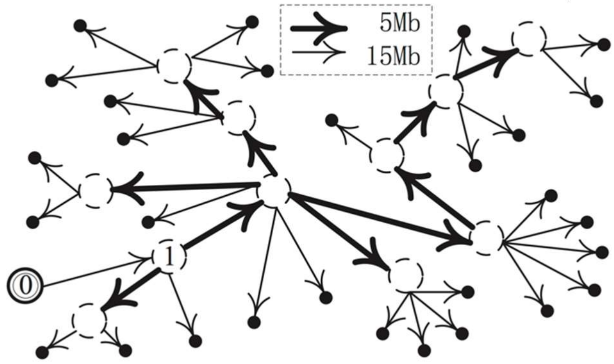

Figure 1. The logical topology is composed of 30 end-hosts and 11 interior nodes. In the NS-2 simulation, the interior links have a bandwidth of 15Mb while 5Mb for the edge links.

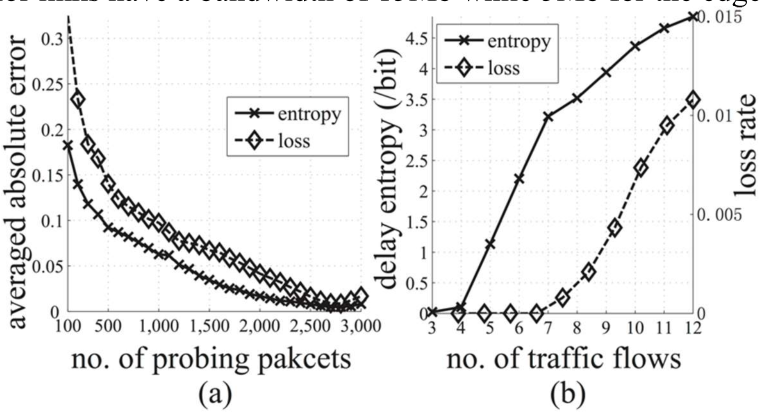

Figure 2. The delay entropy vs. the loss rate. In (a), the no. of probing packets increases by 100. And for each setup, the simulations are repeated for 100 times and then we average the absolute errors of the entropy and the loss rate for all the 29 paths, respectively. In (b), we increase the no. of the traffic flows on the link that has a bandwidth of 10Mb.

Performance Evaluation. In Fig. 2(a), the solid line and the dashed line represent the averaged absolute errors of the delay entropy and the loss rate of the 29 paths, respectively. The averaged errors of the delay entropy and the loss rate both decrease as the number of the probing packets increase. This is because more probing packets will lead more accurately empirical delay distribution and loss measurements. In Fig. 2(a), it also demonstrates that the delay entropy has a better convergence rate against the loss rate. For an absolute error of 0.1, entropy needs about only 500 probing packets while the loss rate requires about nearly 1000 probing packets, which is almost twice as what entropy needs. A similar proportion could still be found when the absolute error comes to 0.05. These rely on the better accuracy of the delay distribution, which is known to require much less probes than the loss rate. In Fig. 2(b), we find both of the entropy and the loss rate become large as the number of the traffic flows on a link increases. However, it will result in a failure for the loss-based performance evaluation when the link has fewer traffic on it. It is because that the loss rate generally goes zero for a light traffic load.

4 Conclusions

In this paper, we deal with the issue of obtaining path congestion states, which are the fundamental inputs required by network Boolean tomography to identify congestion links in the intervening network. We propose the delay entropy metric to characterize the path state, which as shown in simulations can be identified accurately with nearly half less the probes required by the conventional loss based metric.

In the future, further research efforts will first be paid on introducing noise model to the delay measurements. And then we will develop a scheme to detect whether a congestion path passes through multiple congestion links.

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