Detecting the Long-Range Dependence in the Internet Traffic with Packet Trains

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In this paper we demonstrate a new method to measure one of the key state parameters of paths in the Internet, the background traffic arrival process. The traffic arrival process has been investigated in several studies, since the recognition of its self-similar nature ten years ago. The statistical properties of the traffic arrival process are very important since they are fundamental in modeling the dynamical properties. To determine that kind of statistical properties usually passively collected traces are used. However, these traces are not available in general. Here we demonstrate how the end-to-end packet train technique can be used to determine the main properties of the traffic arrival process. We show that the packet train dispersion is sensitive to the congestion on the network path. We introduce the packet train stretch as an order parameter to describe the phase transition between the congested and uncongested phases of the bottleneck links of the path. We find that the distribution of the background traffic arrival process can be determined from the average packet train dispersion at the critical point of the system.

Keywords: complex networks, Internet, long-range dependence, phase transition, Internet traffic

I. INTRODUCTION

In Internet measurements many authors detected the self-similar nature of the traffic time series [1–5]. Self-similarity is usually attributed to heavy-tailed distributions of objects at the traffic sources, e.g. sizes of transferred files [5, 6] or time delays in user interactions [3]. Recently the dynamical origins [7] of self-similarity also attract increasing attention. Chaotic maps are known to generate fractal properties [8], and it has been shown, that the exponential back-off algorithm of the TCP protocol can produce long range dependent traffic under some special circumstances [9]. Veres [10] emphasized the chaotic nature of the transport, and Fekete [11] gave an analytical explanation that this chaoticity is in close relation with the loss rate at highly utilized buffers due to packet drops.

Despite the large number of publications in this field, wide area estimates of the statistical properties of the background traffic are not available, except a limited number of real traffic traces collected at certain points of the network. In our study we present a new approach in the analysis of the well known packet train experiments, which is able to infer the background traffic arrival process with end-to-end methods. End-to-end methods are not collecting traces of a certain router, but uses a sender and a receiver node at the two end-points of the path and infers the properties of the bottleneck link. One of the main advantage of these methods is that they do not require the cooperative behavior of the network administrators, Internet Service Providers, since the probing is based on injecting standard Internet packets towards the receiver.

The rest of our paper is organized as follows. In Section II we give a brief introduction to the packet train measurement techniques. We describe the fluid model and also the observable packet train dispersion curve and their main properties in Section III. We introduce the stretch parameter as an order parameter to describe the phase transition between the congested and uncongested phases. In Section IV we demonstrate how the average stretch of the packet train converges to the fluid limit in the critical point. Our traffic arrival process inferring method is
based on the power law behavior of the convergence as we show it in several cases.

II. ACTIVE PROBING TECHNIQUES

Active probing is a class of measuring methods that are used to infer various characteristics of network paths [13, 14]. The common in these methods is that they involve probe packets that are injected into the network, while a receiver side analyzes the observed responses. This general framework admits the determination of the topology of a network [15, 16], the link-bandwidths on a path [17–20], and the statistics of packet size, packet-loss and delay along a route [22]. These properties are important for quality of service considerations, because together they determine the rate at which applications can send data on the route. In the modeling point of view there is an other important property namely the background traffic arrival process. Generally network models can not developed without certain assumptions on the background traffic arrival model. Our work aims to give an estimation method to determine the distribution of the background traffic arrival process of the bottleneck link with end-to-end active probing methods.

In general an active probing stream may contain \( n \) probe packets of different sizes \( p_i, i \in \{1 \ldots n\} \) sent with different inter-departure times (input spacing) \( \delta_i = t^d(i+1) - t^d(i), i \in \{1 \ldots n-1\} \). The actual choice of \( p(i) \) and \( \delta(i) \) determines the architecture of the probe stream that may vary according to the particular quantity under investigation (e.g. bandwidth, distribution or spectrum of end-to-end delays). Traversing the network the probe packets interact with the background traffic. Their initial spacing (e.g. the inter-departure time) changes due to these interactions. They can also suffer extra queueing delays, since the background traffic together with the probe traffic can be more than the physical capacity of the link. The analysis usually based on the arrived packets spacing (output spacing) \( \delta'_i = t^a(i+1) - t^a(i), i \in \{1 \ldots n-1\} \). In most of the applications it is customary to send constant sized packets regularly (\( p_i = p \) and \( \delta_i = \delta \)), this probe pattern is called packet train. Other probe patterns are also common in the networking practice. For instance to measure bottleneck bandwidth one can send packet-pairs with an inter-pair time chosen randomly from an exponential distribution, while the packets in a pair are sent in a back-to-back fashion [20]. Another example is the packet tailgating technique of [21], where pairs consisting of a packet with the highest possible size immediately followed by a packet with the smallest possible size are sent to measure the bandwidth of each link on a path. In this paper we only investigate packet trains (e.g. regularly sent uniform sized packets), that can be used for instance to measure the packet train dispersion.

III. PHASE TRANSITION IN PACKET TRAIN DISPERSION

In our study we use packet trains to explore the dispersion curve. We inject packet trains of constant sized packets with the same input spacing between them. The consecutive trains are separated with long idle periods since the trains have to be independent from each other. The interesting quantity in our case is the \( \delta' \) as a function of \( \delta \), where

\[
\delta = \frac{1}{n-1} \sum_{i=1}^{n} \delta_i, \tag{1}
\]

\[
\delta' = \frac{1}{n-1} \sum_{i=1}^{n} \delta'_i, \tag{2}
\]

the averaged input and output spacing for the packets in the trains.
The $\delta'$ vs. $\delta$ dispersion curve can be modeled by the simplistic fluid model. The fluid approximation is a simple limiting case, where the physical bandwidth $C$ and the average bandwidth of the background traffic $C_b$ are kept constant, while the average packet size of the background traffic goes to zero [23]. The real dispersion curves, observed in packet level simulations and wide area experiments, deviates from the result of the fluid approximation. The source of the deviation is that the assumption of infinitely small packets are not hold in wide area experiments. The fluid model describes correctly the small and large $\delta$ behavior of the dispersion curve, but it can not handle the transitional region between the congested and uncongested phases. The fluid model also serves as a lower bound of the real dispersion curves [23]. The theoretical model of the dispersion curve for a packet pair (where the train length $n = 2$) can be derived in closed form, based on diffusive approximation, which describes the observed packet pair dispersion curves correctly, also in the transitional region [18].

Since we study the convergence of the deviation of the observed dispersion curve from the fluid limit as a function of the packet train length we use the fluid equations. For the single bottleneck case the fluid curve is given by two linear segments

$$\delta' = \begin{cases} \frac{p}{C} + \frac{C_b}{C} \delta & \delta \leq \delta_c \\ \delta_c & \delta \geq \delta_c \end{cases}$$

(3)

where $\delta_c = p/(C - C_b)$, which separates the congested and uncongested phases of the bottleneck link.

Next, we show results coming from packet level simulations. Since the simulation considers both the probe and background traffic packet sizes, the observable dispersion correspond to the real wide area experiments and not argee with the fluid model. In Figure 1 the dispersion curves for different train lengths are shown. The physical bandwidth $C = 10$ Mbps, the average background traffic rate $C_b = 6$ Mbps, background traffic packet size $P = 12000$ bit and the size of the probe packets $p = 12000$ bit are the same for both sets of parameters. We plot the average output spacing $\delta'$ as a function of the input spacing $\delta$. The different symbols represent the results of the packet level simulation with train length from $n = 10$ to 1000. In these simulations we used a Poisson arrival process for the background traffic. Each data point represents an average for 600 packet train measurement events. As a limiting case and a lower bound we also show the curve in fluid approximation. The deviation of the observed curves from the fluid limit can be clearly seen, while this deviation decreasing with the increasing train length. The characteristic breakpoint is at the values of $p/(C - C_b) = 3$ msec.

![FIG. 1: The average output spacing curves for different train lengths.](image-url)
Now, we introduce a new parameter called \textit{stretch} to describe the average change of probe packet spacing the train traversing the network,

$$\Delta = \delta' - \delta.$$ \hspace{1cm} (4)

This quantity serves as an order parameter to describe the phase transition between the congested and uncongested phases. In Figure 2 the order parameter $\Delta$ can be seen as a function of the probing rate (probe traffic intensity) $p/\delta$. It can be clearly seen that below the critical point $(p/\delta_c = 4$ Mbps, which corresponds to $\delta_c = 3$ ms as above) the observed $\Delta$ order parameter is zero for the fluid limit and above the critical point the order parameter is increasing. The order parameter for the packet train measurements shows finite size scaling phenomena. As the train length grows the deviation from the fluid limit disappears.

In the next section we investigate this convergence at the critical point.

**IV. DETECTING THE ARRIVAL PROCESS IN THE CRITICAL POINT**

In this section first we investigate the deviation of the average output spacing from the fluid limit as a function of the train length in the critical point. This deviation can be written:

$$\eta(n) = \delta'(n) - \delta'_{fluid},$$ \hspace{1cm} (5)

where $\delta'(n)$ is the average output spacing for the $n$ length packet train and $\delta'_{fluid}$ is the output spacing calculated in the fluid approximation (Eq. 3). This quantity is closely related to the background traffic arrival process. Based on the central limit theorem, one can show that $\langle \eta \rangle \sim n^{\alpha}$. The $\alpha$ exponent is dependent on the arrival process of the background traffic. It can be also shown that

$$\alpha = \begin{cases} 
-0.5 & \text{for Poisson arrival process} \\
\frac{1}{\mu} - 1 & \text{for Pareto arrival process,} 
\end{cases}$$ \hspace{1cm} (6)

where $\mu$ is the shape parameter of the Pareto distribution. The Pareto distribution shows heavy-tailed properties in the case $1 < \mu < 2$. Otherwise, if $\mu > 2$ the observable behaviour is Poisson-like, with $\alpha = -0.5$.

The power law behavior makes it possible to infer the background traffic arrival process. As a next step we can investigate the exponents of the power law relation between the average stretch and the train length. Several simulated scenarios were performed with different kind of background...
traffic arrival processes. Besides the arrival process the other important parameters are set to be the same: \( C = 10 \text{ Mbps}, \ C_b = 6 \text{ Mbps}, \ P = 12000 \text{ bit} \) and \( p = 12000 \text{ bit} \). We used Poisson and Pareto arrival processes to model both short range and heavy-tailed distributions. The shape parameter of the Pareto distribution was varied in order to study the effect of the heavy-tailed behavior.

<table>
<thead>
<tr>
<th>Traffic Arrival Process</th>
<th>Calculated Exponent</th>
<th>Fitted Exponent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poisson process</td>
<td>-0.50</td>
<td>-0.51</td>
</tr>
<tr>
<td>Pareto, ( \mu = 2.1 )</td>
<td>-0.50</td>
<td>-0.50</td>
</tr>
<tr>
<td>Pareto, ( \mu = 1.7 )</td>
<td>-0.41</td>
<td>-0.40</td>
</tr>
<tr>
<td>Pareto, ( \mu = 1.5 )</td>
<td>-0.33</td>
<td>-0.33</td>
</tr>
<tr>
<td>Pareto, ( \mu = 1.3 )</td>
<td>-0.23</td>
<td>-0.22</td>
</tr>
</tbody>
</table>

TABLE I: Comparison of the fitted and calculated exponents for different traffic arrival processes. The fitted values match very well to the calculated ones, which allows us to infer the background traffic arrival process from these kind of experiments. The data sets and fitted lines are the same as in Figure 3.

In Figure 3 we present the average stretch as a function of the probe packet train length for different arrival processes. The axis have logarithmic scale to show the power law relation between the quantities. In this figure the system is studied in the critical point of the phase transition \( \delta_c = 3 \text{ ms} \) and \( p/\delta_c = 4 \text{ Mbps} \). From the slopes of the fitted lines it can be seen that different exponents belong to different arrival process. The fitted exponents are summarized in Table I to compare them with the calculated exponents. The calculation of the exponents are based on Eq 6. The fitted exponents match to the calculated theoretical values, which shows that with packet train measurements one can infer the arrival process of the background traffic in the bottleneck queue.

V. CONCLUSION

Based on the well known packet-train measurement technique we introduced a new approach to infer internal properties of the Internet traffic. We introduced the packet train stretch as an order parameter, which describes the phase transition between the congested and uncongested phases of the bottleneck link. We studied the scaling phenomena at the critical point and we found that the exponent of the power law function arising in the average stretch function is closely related to the
background traffic arrival process. We showed that the observed exponents can be calculated and the theoretical results match very well to the observed power law functions. It makes us possible to infer the qualitative and some of the quantitative parameters of the background traffic arrival process with end-to-end packet train technique.

As a future work we are planning to infer the traffic arrival process in wide geographic area in Europe with the Etomic infrastructure [13, 14]. With this measurement infrastructure we will be able to collect large number of estimates frequently, which will helps us in the study of the spatio-temporal structure of the background traffic arrival processes.

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[16] Cooperative Association for Internet Data Analysis (CAIDA) web page http://www.caida.org/Tools/