Network Traffic Modeling using Connection-Level Information

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ABSTRACT

Aggregate network traffic exhibits strong burstiness and non-Gaussian distributions, which popular models such as fractional Gaussian noise (fGn) fail to capture. To better understand the cause of traffic burstiness, we investigate the connection-level information of traffic traces. A careful study reveals that traffic burstiness is directly related to the heterogeneity in connection bandwidths and round-trip times and that a small number of high-bandwidth connections are solely responsible for bursts. This separation of connections has far-reaching implications on network control and leads to a new model for network traffic which we call the alpha/beta model. In this model, the network traffic is composed of two components: a bursty, non-Gaussian alpha component (stable Lévy noise) and a Gaussian, long range dependent beta component (fGn). We present a fast scheme to separate the alpha and beta components of traffic using wavelet denoising.

1. INTRODUCTION

Network traffic analysis and modeling play a major role in characterizing network performance. Models that accurately capture the salient characteristics of traffic are useful for analysis and simulation, and they further our understanding of network dynamics and so aid design and control.

Most traffic analysis and modeling studies to date have attempted to understand *aggregate traffic*, in which all simultaneously active connections are lumped together into a single flow. Typical aggregate time series include the number of packets or bytes per time unit over some interval. Numerous studies have found that aggregate traffic exhibits *fractal* or *self-similar* scaling behavior, that is, the traffic "looks statistically similar" on all time scales.[1] Self similarity endows traffic with *long-range-dependence* (LRD).[2] Numerous studies have also shown that traffic can be extremely bursty, resulting in a non-Gaussian marginal distribution.[3] These findings are in sharp contrast to classical traffic models such as Markov or homogeneous Poisson. LRD and non-Gaussianity can lead to much higher packet losses than predicted by classical Markov/Poisson queueing analyses.[2,4]

The discovery of self-similar behavior in traffic led immediately to new fractal aggregate traffic models (see[5,6] for example). *Fractional Gaussian noise* (fGn), the most widely applied fractal model, is a Gaussian process with strong scaling behavior. Due to its Gaussianity, it lends itself to rigorous analytical studies of queueing behavior. Also, approximate fGn can be synthesized rapidly by a variety of different techniques, including wavelets. A strong argument for fGn in networks is that often aggregate traffic can be viewed as a superposition of a large number of independent individual ON/OFF sources that transmit at the same rate but with heavy-tailed ON durations.[7,8] In the limit of infinitely many sources, the ON/OFF model converges to fGn. The LRD in the resulting process stems from the heavy-tailed nature of the ON durations.

Unfortunately, fGn is unrealistic for bursty non-Gaussian traffic. For instance, when the standard deviation of the traffic exceeds its mean, a considerable portion of an fGn traffic synthesis is negative. These failings have motivated more complicated models for aggregate traffic such as multifractals and infinitely divisible cascades.[3,9] However, while more statistically accurate, these models lack network relevance in their parameterizations. In particular, they do not account for *why* bursts occur in network traffic.

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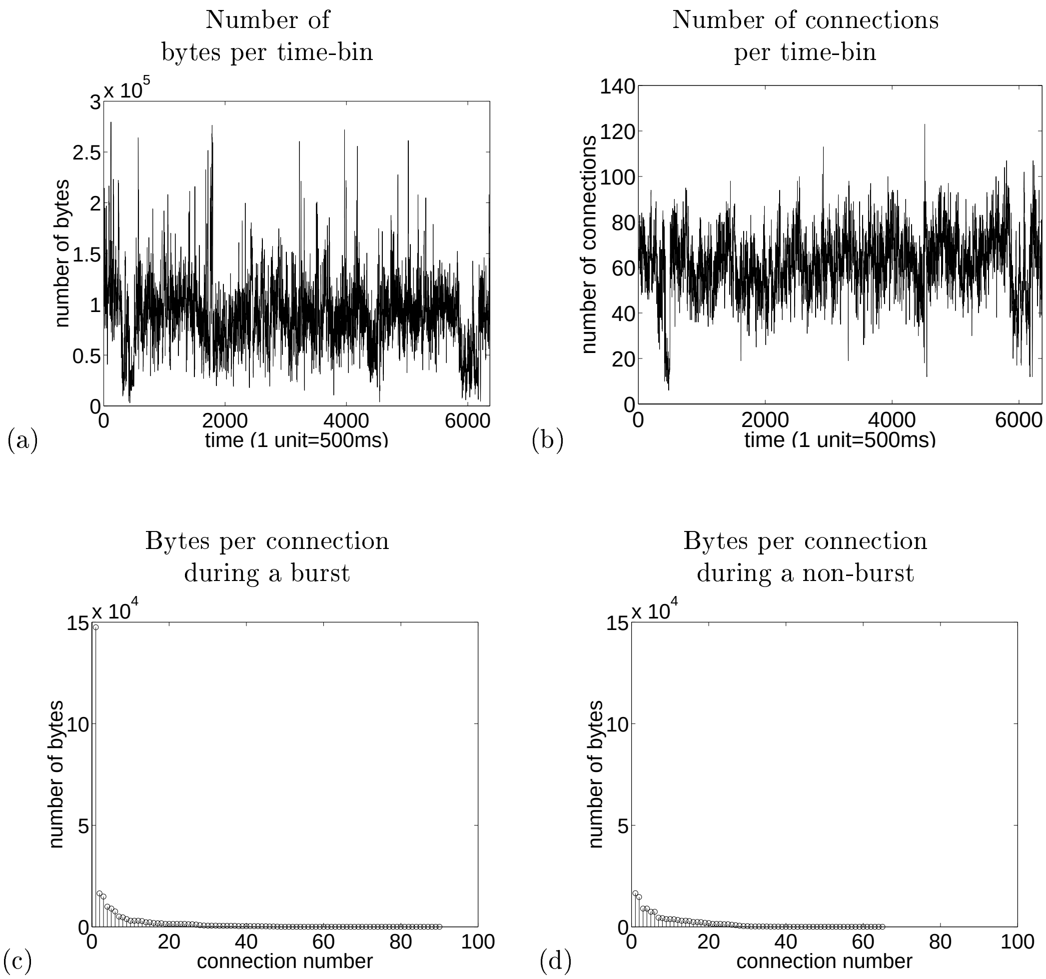


Figure 1. (a) Bytes-per-time and (b) number of connections-per-time of an aggregate traffic trace collected in Auckland, NZ[12] . (c) Number of bytes per connection (sorted in decreasing order) during a typical burst. Clearly one connection dominates all others. (d) Number of bytes per connection (sorted in decreasing order) during a non-burst. There is no dominant connection.

The aggregated total load in the ON/OFF model converges to fBm as the number of sources go to infinity first, followed by letting the time interval for aggregation of load go to infinity. However, if we reverse the order and consider the limit where the time interval tends to infinity first and then the number of sources, we get a Lévy stable motion[10] , a process with independent and stationary increments but with infinite variance. Roughly speaking, the Gaussian limit is obtained for very large numbers of sources (more precisely, when the number of sources is kept larger than a certain power of the time scale when both going to infinity), and the Lévy limit is obtained for very large time scales (see[11] for an overview). We argue through a careful analysis of several real world traces that network traffic is a mixture of both limits.

In this paper, we propose a model — the alpha/beta model — in which the fGn part of traffic constitutes the *beta* component, and the Lévy part of traffic constitutes the *alpha* component. We show that the alpha and beta components are linked to the connection level information and hence have networking relevance. Alpha component comes from connections that have large files to send and have high available bandwidth. Beta component comes from connections that have small available bandwidth and/or small files to transfer. We explain the alpha/beta model through the heterogeneity of connection bandwidths and round-trip times (RTT). Finally, we suggest a fast scheme using wavelets to separate the alpha and beta components.

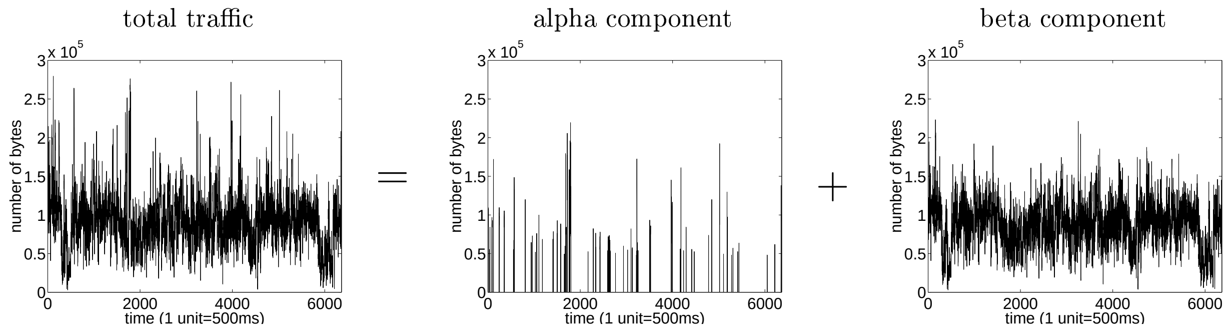


Figure 2. Decomposition of the traffic trace into the sum of a bursty alpha component (Lévy) and a Gaussian beta component (fGn).

2. SEPARATION OF TRAFFIC

2.1. Alpha and beta components of traffic

Connection-level information enables us to conduct a refined analysis of traffic bursts. In Gaussian aggregate traffic models (such as the classical ON/OFF model[8]), traffic bursts arise from a large number of connections transmitting bytes or packets simultaneously. That is, bursts stem from a kind of "constructive interference" of many connections. With connection-level information, we can test this hypothesis. If it were true, then we should observe in real traffic traces a large number of active connections during bursts. However, Figure. 1(a) and (b) demonstrate that this is not the case. Bursts in bytes-per-time generally do not coincide with large values connections-per-time.

Quite to the contrary, a careful analysis of many real traces[13] reveals that generally *very few high-rate connections dominate during a burst*. In fact in most cases only *one* connection dominates. This surprising finding has far-reaching implications for traffic analysis and modeling. To explore further, we propose a new analysis technique that exploits connection-level information to separate a measured traffic trace into two distinct components at a time-scale T of interest:[†]

1. In each T-second time bin, identify the connection(s) that transmits the largest number of bytes.
2. If the strength of the identified connection(s) is greater than a threshold, then label it as a *dominant connection*. The (large) threshold is chosen based on the mean of the aggregate traffic at time-scale T plus a few standard deviations.

We call the traffic corresponding to the dominant connections the *alpha* component. The residual traffic is called the *beta* component.[‡] Our procedure thus decomposes an aggregate traffic trace into

$$\text{total traffic} \ = \ \text{alpha traffic} \ + \ \text{beta traffic}. \tag{1}$$

See Figure 2 for real data example.

We have applied the alpha/beta traffic decomposition to many real-world traffic traces, from Auck[12] to LBL[14] and found tremendous consistency in our results.[13] The statistical properties of the components can be summarized as follows.

Beta traffic: At time-scales coarser than the RTT, the beta component is very nearly Gaussian and strongly LRD (i.e., approximately fGn), provided a sufficiently large number of connections are present. Moreover, the beta component carries the same fractal scaling (LRD) exponent as the aggregate traffic[13] .

[†]While we set $T = 500$ ms for the analyses in this paper, our results hold for a wide range of T.

[‡]By analogy to the dominating *alpha males* and submissive *beta males* observed in the animal kingdom.

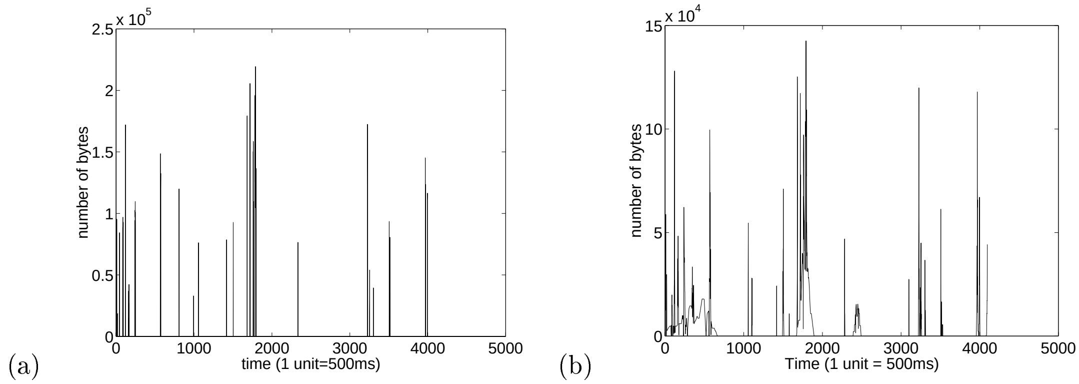


Figure 3. *(a) Isolated bursts in the real trace. (b) Bursts isolated using the wavelet separation scheme.*

Alpha traffic: The alpha component constitutes a small fraction of the total workload but is entirely responsible for the bursty behavior. Alpha traffic is highly non-Gaussian.

It is notable that this decomposition in networking terms (based on connection-level information) achieves a separation in statistical terms.

2.2. Fast alpha/beta separation using Wavelets

The computationally intense connection-level separation of alpha and beta traffic does not lend itself to massive data processing or on-line monitoring.[13] Fortunately, approximate separation of alpha and beta traffic can be done using a wavelet-based thresholding scheme that does not require explicit connection information. This scheme is based on the fact that we can treat the beta component as "noise" and the alpha component as the "signal", and use well-known denoising techniques to separate the two. We use wavelet based denoising techniques, with coefficient thresholding. For colored denoising (since beta traffic is colored noise, fGn), we use different thresholds for wavelet coefficients at different scales. Kaplan and Kuo[15] have shown that for Haar wavelet, the variance progression of the wavelet transform of fGn with Hurst parameter H satisfies a power-law decay:

$$\mathrm{var}(W_{j,k}) = \sigma^2 \ 2^{(2H-1)(j-1)} \ (2 - 2^{2H-1}). \tag{2}$$

In a colored denoising scheme, the threshold at each scale is made proportional to the expected standard deviation of the wavelet coefficients at that scale. Thus, knowing the Hurst parameter, we can fix the threshold at each scale using equation (2). Johnstone *et al*[16] have shown that this thresholding scheme is optimal for colored denoising. For more details, see[13] .

3. ORIGINS OF ALPHA AND BETA TRAFFIC

We have seen that bursts are not caused by a "conspiracy" of many moderate flows, but rather by individual alpha connections. Here we study the origins of this behavior. To begin, we list four possible reasons for connections to dominate and cause bursts. The first three are based on the predominant network protocol, TCP, while the last one blames the heterogeneity in bottleneck bandwidths.

3.1. Potential causes of bursts

Burst-causing connections can arise due to several reasons. An exhaustive list of such reasons is given below:

- Transient response to re-routing: This could occur if packets from a connection are re-routed from a high-bandwidth end-to-end path to a low-bandwidth one. TCP, which probes for the available bandwidth by adjusting its window size, will find that the optimal window size to use in the new route is far less than the current window size, which was suitable for the old route. Since feedback to TCP takes at least one RTT, we could expect a transient bursty behavior for such connections.

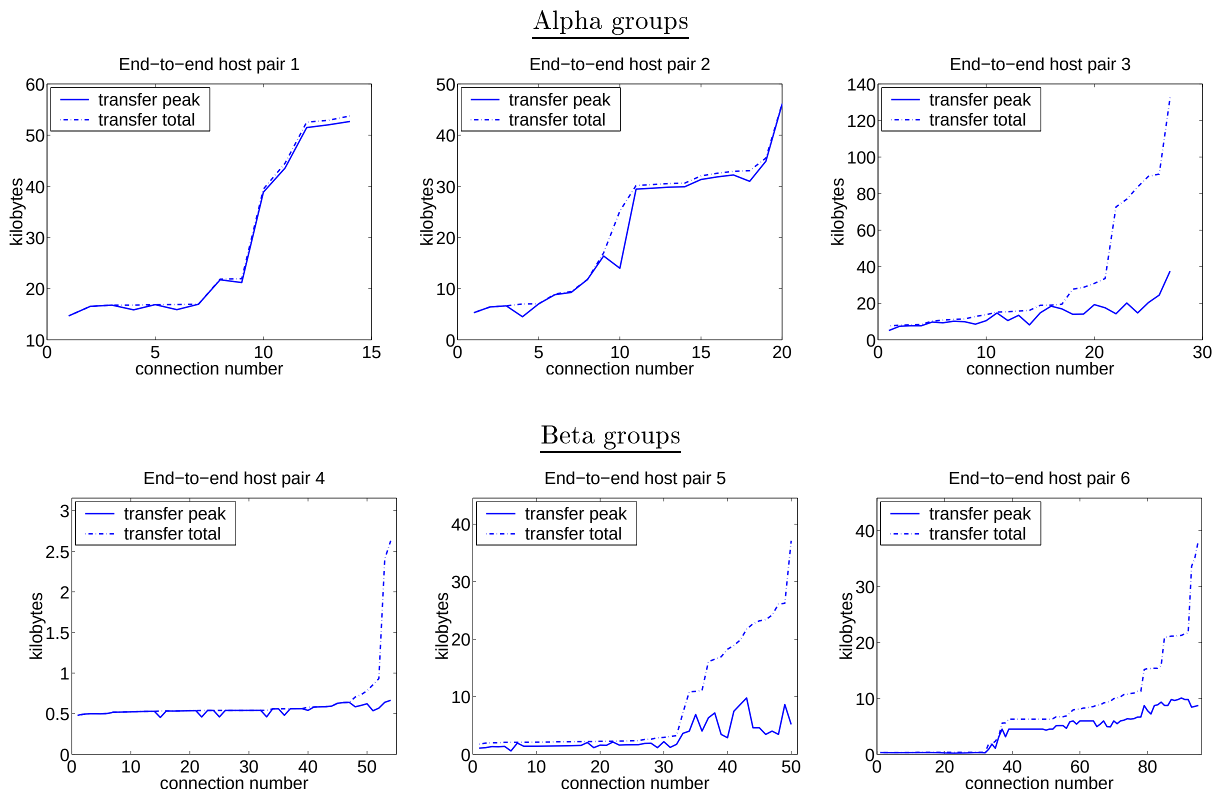


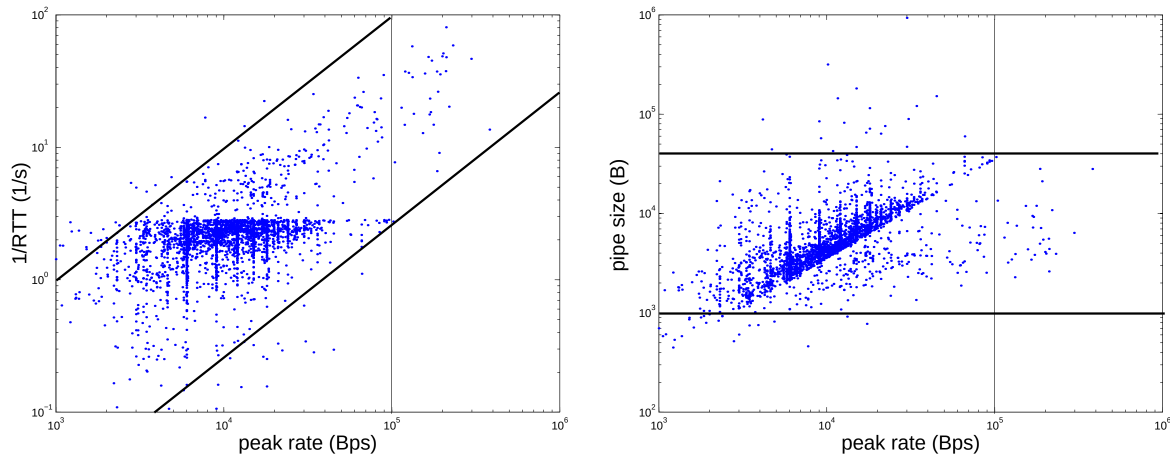
Figure 4. Plot of peak rate and total transfer for all connections which share the same pair of source and destination hosts. Note the high peak rates in the top row (alpha connections). Notice the starvation of connections in the groups of the bottom row and the overall low peak rate (beta connections).

- Transient response to start/stop of connections: When a connection sharing a link terminates, it frees up available bandwidth for other competing connections. TCP will sense the increase in available bandwidth and try to grab its share. This could potentially lead to bursty connections, especially for those connections in TCP slow-start, for example.
- TCP slow-start peculiarities: In this case, some connections could get "lucky" during slow start in that they encounter no packet drops for an unusually long time. This could happen when packet drops at congested routers happen only for competing connections, albeit with very low probability.
- Heterogeneity in bottleneck bandwidths: This scenario acknowledges the fact that connections are limited in their transmission rates by bottlenecks somewhere in the network, which may or may not be at the measured link. Bottlenecks can occur through limited capacity at a router, through shaping, or through a thin client, to give a partial list. We can imagine, for example, a wide range of link speeds, ranging from slow modem lines to fast ones such as DSL and Ethernet. When we have a large pool of connections, we would expect that the high bottleneck connections should dominate over the low-bottleneck connections and could potentially cause bursts. This scenario assumes that there are only a few connections that have high bottleneck bandwidth.

We now argue that the last scenario, i.e., *heterogeneity in bottleneck bandwidths*, is solely responsible for the bursts observed in our analyses.

3.2. Dominance and bursts as an end-to-end property

Our reasoning is simple: If indeed the end-to-end bandwidth is the crucial indicator of whether or not connections are able to cause bursts, then we would expect dominating connections to group naturally according to their



(a) (b)

Figure 5. (a) 1/RTT vs. peak rate for connections; (b) Connection pipe size vs. peak rate.

source-receiver host pairings. Thus, we collect all connections with the same source and destination hosts into an *end-to-end group*. If the peculiarities of the networking protocols are at work, then we should find both dominating and non-dominating connections mixing in the end-to-end groups.

We define *alpha groups* as those end-to-end groups which contain at least one alpha connection. Let us focus for a moment on the top row of Figure 4, which shows three *alpha* groups. For each connection in a group, we determine the *peak rate*, i.e., its maximum sending rate for the time period T under study, by sliding a moving window along the connection duration. We observed that typically *all* connections of an alpha group with a *sufficiently large* transfer load are alpha connections. Thus, we verified that alpha connections naturally group according to their end-to-end host pairs. This leads us to exclude effects of the transfer protocol as causes for bursts and conclude that bursts emerge indeed from end-to-end properties.

It is also instructive to compare the peak rate to the total number of bytes transferred for each connection. The fact that host pairs 1 and 2 in Figure 4 have peak rates as high as the total bytes transferred suggests that many of the alpha-group connections did not utilize the full available bandwidth. Also, in each of those connections most of the file transfer was over within a single time period of $T = 500$ms. The peak rates for host pair 3, on the other hand, does not increase beyond 40kbps, and is very likely due to a bottleneck link in the end-to-end path.

For the beta-groups (see bottom row of Figure 4) the connections with large loads are obviously not getting as much bandwidth as they could consume. This provides further confirmation to our claim that heterogeneity in bottleneck bandwidths is the cause of burstiness in traffic.

In summary, we conclude that all burst causing connections are due to *large file transfers with a large bottleneck bandwidth in its end-to-end path.*

Connection bandwidth is determined by the connection pipe size and RTT through

$$\text{bandwidth} \;=\; \text{pipe size} \;/\; \text{RTT}. \tag{3}$$

To see whether the heterogeneity in connection bandwidths is primarily due to heterogeneity in pipe size or RTT, we look at several network measurements. Consistent results show that RTT plays a major role.

Figure 5 shows the relation between RTT, pipe size and connection peak rate for all TCP connections in 300,000 packets of Auckland-2 trace. We can see that most connections fall between the two parallel lines shown. The connections to the right of the vertical line are alpha connections. The connection RTTs are estimated from the initial three-way handshake packets. In the 1/RTT vs. peak rate loglog plot (Figure 5(a)), the 45

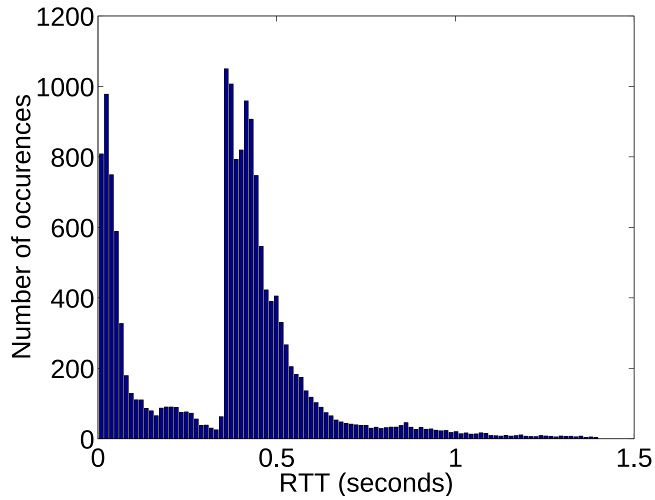


Figure 6. RTT histogram for the Auck-2 trace; connections in the first 300,000 packets.

degree linear relation is observed, while in pipe vs. rate plot (Figure 5(a)), the correlation between the two is much smaller than that of the RTT-rate pair. In fact, the pipe sizes of alpha and beta connections are not very different. We find that the correlation coefficient between 1/RTT and peak rate is 0.75, and the correlation coefficient between pipe size and peak rate is 0.10.

Consider a scenario where a relatively small number of hosts locate close to the measured link while the majority of hosts are far away. As a consequence, the distribution of RTT is bimodal: a small number of connections with small RTTs and the remaining with large RTTs. See Figure 6 for a real trace example. Let us further assume that the TCP congestion windows of all connections are equal. The latter is certainly a rough approximation but draws some validity from our observations (see Figure 5).

Applying the superposition ON/OFF model or the infinite source Poisson model[11] to the scenario above, we obtain the following results. The alpha traffic is composed of the few connections with small RTTs and, therefore, high sending rates. The TCP clock ticks faster for these sources, therefore we approximate this component as the ON/OFF limit at infinite time, i.e., by i.i.d. Lévy stable noise. So the alpha traffic brings in burstiness but not LRD.

The beta traffic is made up from the bulk of remaining connections with large RTTs and low rates and is well approximated by the ON/OFF limit at infinite source number, i.e., by fGn. It inflicts LRD on the overall traffic but is not as bursty as the alpha traffic.

We conclude that both connection RTT and pipe size are behind the heterogeneity in connection bandwidths, and RTT plays a much bigger role. Therefore, network traffic burstiness is due to a small number of high-bandwidth connections (alpha connections) which transmit large files and have small RTTs.

There has been a great deal of research recently based on a separation termed *elephants* and *mice*.[17] Elephants are defined as the small fraction of connections that carry most (e.g., 80%) of the network traffic, and mice are the remaining connections that contribute little to the total load. The relationship between the alpha/beta separation and the elephants/mice separation is as follows. First, alpha connections also represent a small percentage of total number of connections, but in contrast with elephants, they typically take only a small fraction of total traffic load. Moreover, the percentage of alpha connections depends on network conditions such as network utilization, while the percentage of elephants does not. Finally, elephants/mice is purely a source property, while alpha/beta is also a property of bandwidth and RTT, which relates to network topology and network conditions. As a result, we feel that the alpha/beta separation is more network-relevant and thus more useful for applications such as network control, performance monitoring, network design and simulations, etc.

4. CONCLUSIONS

We have proposed a framework for analyzing and modeling network traffic that takes into account the crucial connection-level information that aggregate analysis ignores. The topological variability of the network enters through the distribution of RTTs and bottlenecks link speeds. In a real world situation these distributions will depend on the particular location where the measurements are taken. Client behavior will determine both the LRD component as well as how often large files are transferred over large bottlenecks.

While empirical evidence for consistency of measured network traffic with stable noise or fGn is not convincing at present, this paper claims that a closer match is obtained by an appropriate mixture of the two processes. The approach sketched in this paper explains the relevance of the two components in terms of an LRD background traffic produced by the "big crowd" and a bursty but light weight component due to a few "alpha connections". This has implications not only for modeling, but also for simulation, synthesis, estimation, prediction, performance evaluation and understanding of traffic dynamics. This approach also opens a clear alley towards studying the influence of RTT distributions on network traffic dynamics which is currently under way.

As future work, we intend to study the impact of alpha and beta components in queueing behavior. We have shown that the alpha component contributes to large build-up of queues. This suggests scope for AQM[18] techniques that treat alpha and beta packets differently. Another area of future work is to link the alpha/beta model to the network topology.

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