

# The Changing Nature of Network Traffic: Scaling Phenomena

A. Feldmann, A.C. Gilbert\*, W. Willinger<sup>†</sup> and T.G. Kurtz

## Abstract

In this paper, we report on some preliminary results from an in-depth, wavelet-based analysis of a set of high-quality, packet-level traffic measurements, collected over the last 6-7 years from a number of different wide-area networks (WANs). We first validate and confirm an earlier finding, originally due to Paxson and Floyd [14], that actual WAN traffic is consistent with statistical self-similarity for sufficiently large time scales. We then relate this large-time scaling phenomenon to the empirically observed characteristics of WAN traffic at the level of individual connections or applications. In particular, we present here original results about a detailed statistical analysis of Web-session characteristics, and report on an intriguing scaling property of measured WAN traffic at the transport layer (i.e., number of TCP connection arrivals per time unit). This scaling property of WAN traffic at the TCP layer was absent in the pre-Web period but has become ubiquitous in today's WWW-dominated WANs and is a direct consequence of the ever-increasing popularity of the Web (WWW) and its emergence as the major contributor to WAN traffic. Moreover, we show that this changing nature of WAN traffic can be naturally accounted for by self-similar traffic models, primarily because of their ability to provide physical explanations for empirically observed traffic phenomena in a networking context. Finally, we provide empirical evidence that actual WAN traffic traces also exhibit scaling properties over small time scales, but that the small-time scaling phenomenon is distinctly different from the observed large-time scaling property. We relate this newly observed characteristic of WAN traffic to the effects that the dominant network protocols (e.g., TCP) and controls have on the flow of packets across the network and discuss the potential that *multifractals* have in this context for providing a structural modeling approach for WAN traffic and for capturing in a compact and parsimonious manner the observed scaling phenomena at large as well as small time scales.

## 1 Introduction

Self-similar traffic modeling has, from the beginning, emphasized the need for *physical-based* or *structural* approaches for understanding and describing actual network traffic dynamics. Structural models, as discussed in [19], attempt to implicitly take into account the complex hierarchical structure of modern computer communications networks and the intertwined networking mechanisms that determine the nature of the traffic which these networks carry. These structural models are different from the “black box” or “operational” traffic models which were popular in the past.

The main objective of this paper is to improve our current understanding of the dynamic nature of traffic carried over wide-area networks (WANs) such as the Internet and to outline new structural modeling approaches for WAN traffic that are consistent with actual measurements. In particular, we (i) identify

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distinct scaling regions in aggregate packet-level WAN traces, one for small time scales (a few hundreds of milliseconds and below) and one for large time scales (beyond a few hundreds of milliseconds); (ii) demonstrate the changing nature of WAN traffic characteristics at the transport (i.e., TCP/IP) level over time; (iii) provide empirical evidence for the presence of application-layer WAN traffic characteristics, which allows us to adopt a structural modeling approach that explains the empirically observed large-time scaling phenomenon in aggregate WAN traffic; and (iv) discuss the feasibility of a structural modeling approach for WAN traffic that is capable of capturing the large-time as well as small-time scaling properties in a compact and parsimonious manner. To accomplish these goals, we rely on a set of high-quality, packet-level WAN traffic measurements, collected over the past six to seven years from a number of different WANs and representing a reasonable cross-section of wide-area Internet behavior. Our in-depth analysis of these WAN traffic traces is based on a wavelet-based technique recently suggested and developed by Abry and Veitch [1]. This technique provides a natural and effective tool for investigating scaling properties that may be present in large data sets.

There have been significant advances in the recent past in structural modeling approaches for local area network (LAN) traffic as opposed to WAN traffic. In fact, the empirically observed self-similar or fractal nature of LAN traffic at the aggregate or macroscopic level (i.e., generated by all active hosts on the network; see for example [12]) has recently resulted in structural models that are based on self-similar processes, have a physical meaning in the LAN context, and provide fundamental and new insights into how individual network connections behave. Moreover, the proposed structural models are based on constructions that are mathematically rigorous, that highlight the predominance of heavy-tailed phenomena at the microscopic level (i.e., in the packet arrival patterns generated by the individual host-host pairs in a LAN), and that are fully consistent with measured LAN traffic at the macroscopic as well as microscopic level (for details, see [20]). However, WANs differ from LANs in a number of fundamental ways, which makes structural modeling of WAN traffic more challenging. On the one hand, WANs are generally more heterogeneous than LANs and, more importantly, they have to cope with the problem of latency (i.e., non-negligible delays associated with obtaining and adapting to feedback on current network conditions). They often do so by relying on sophisticated transport protocols (e.g., Internet uses predominantly TCP) which, in turn, are bound to introduce additional structure to the flow of packets over WANs that is absent in LAN environments where feedbacks are essentially instantaneous.

The first empirical evidence for large-time scaling phenomena in measured WAN traffic traces was reported by Paxson and Floyd [14], who relied on a set of 24 traces of WAN traffic traces, collected between 1993 and 1995, primarily at the Lawrence Berkeley National Laboratory and at Digital's Western Research Lab. They found typical scaling regions that extended over three to four orders of magnitudes with lower cutoffs that varied consistently around a few hundreds of milliseconds. Similar findings have been reported in other empirical traffic studies; e.g., see [20]. In Section 2 below, we use a collection of more recent WAN traces and a wavelet-based scaling analysis to validate this previously observed large-time scaling property of WAN traffic. We also identify a scaling phenomenon for small time scales (below a

few hundreds of milliseconds) that has been alluded to in previous studies; however, here we quantify this small-time scaling behavior and demonstrate that it is distinctly different from that for large time scales.

Focusing on their 1993 traces, Paxson and Floyd [14] also proposed a structural modeling approach for WAN traffic that attempts to explain the observed self-similar nature over large time scales of aggregate WAN traffic at the packet level in terms of the characteristics of the main applications (e.g., TELNET, FTP) which generated the overall traffic. Their structural model is based on a construction, originally due to Cox [3], known as  $M/G/\infty$  model or *birth-immigration process*: session arrivals are assumed to be Poisson or, more generally, of renewal-type; session duration (in seconds) or session size (in bytes) are required to be heavy-tailed (e.g., Pareto with finite mean and infinite variance) and packets are generated at a constant rate for the duration of a session. In Section 3, we provide new evidence that this structural modeling approach remains partly valid for today’s WAN traffic, even though over the last three to four years, WWW has become the main WAN application and typically makes up a major portion of modern WAN traffic. At the same time, we also demonstrate in Section 3 that with the increasing popularity and familiarity of the Web, the traffic characteristics at the transport layer have undergone significant changes between the pre-WWW days and now and that these changes clearly reveal the limitations of structural modeling a la Cox. To this end, we confirm here with our latest collection of WAN traffic traces a recent finding by Feldmann [6, 7] who observed self-similar features not only at the packet/bytes level (i.e., for the process representing the number of packets/bytes per time unit) but also at the TCP level (i.e., for the process representing the number of TCP connection arrivals per time unit). Clearly, Cox’s construction is not adequate enough to account either for this scaling property of WAN traffic at the transport level nor for the small-time scaling phenomenon at the packet level.

In light of the empirical evidence presented here, we revisit the question of structural modeling approaches for modern WAN traffic and discuss two alternatives. One approach which builds on Cox’s approach is based on a construction proposed by Kurtz [11] and allows for very flexible “within-session” traffic patterns that can, for example, mimic to some degree actual TCP dynamics, but cannot be accounted for by Cox’s construction. At this time, structural models based on Kurtz’s construction are capable of “explaining” the observed large-time scaling property of WAN traffic but fail to account for any additional structure that is present in today’s WAN traffic (e.g., small-time scaling features at the packet level, self-similarity at the TCP level). A second, more radical approach to understanding and describing the actual dynamics of modern WAN traffic is based on *multifractals*. Multifractals or self-similar measures, that is, measures with a nontrivial multifractal structure, have been applied in the past to such diverse fields as the statistical theory of turbulence, the study of strange attractors of certain dynamical systems, and more recently, to physically based rain and cloud modeling (see for example [8, 9] and references therein). In the networking context, multifractals have only very recently been considered; for example, Taqqu, Teverovsky and Willinger [17] discuss the question of whether or not network traffic is self-similar or multifractal, and they conclude that while self-similar models seem to suffice in a LAN setting, WAN environment may require more complex structures such as multifractals. In fact, the first

empirical evidence of multifractal features in wide area TCP traffic traces has recently been reported by Riedi and Levy-Vehel [15]. Multifractals are particularly appealing from a networking perspective because of their close connection to certain multiplicative processes or random cascade models which can be intuitively associated with the hierarchical structure present in modern communication networks. We conclude in Section 4 with an intuitive explanation for why multifractals might be an appropriate mathematical technique for gaining a better understanding of the dynamic nature of modern high-speed network traffic.

## 2 Scaling Properties of Measured WAN Traffic

Abry and Veitch [1] recently proposed a wavelet-based technique for analyzing long-range dependent data and for estimating the associated Hurst parameter. We briefly review their proposed method and illustrate that it has many attractive features including the ability to investigate scaling properties in large sets of traffic measurements from packet networks. The data sets analyzed below are summarized in Table 1 and represent a collection of high-quality WAN traffic traces, recorded in a number of different geographic locations, over a period of about seven years (1990–1997). In particular, note that this collection period covers the emergence of the Web (or WWW) as a “killer application” in the Internet and hence, the data sets in Table 1 allow for a systematic study of the changing nature of WAN traffic, from the pre-Web period (prior to 1993–1994) to today’s situation where WAN traffic is consistently and ubiquitously dominated by Web traffic.

### 2.1 MRA and a Wavelet-Based Scaling Analysis

Because the wavelet transform divides data into different frequency components and analyzes each component with a resolution matched to its scale, we can use the coefficients of a wavelet decomposition to directly study the scale (or frequency) dependent properties of the data. In particular, we can use wavelets to investigate the scaling structure in the spectra of self-similar processes which provide statistical models for many naturally occurring phenomena. Multiresolution analysis (MRA) gives us a natural framework for understanding wavelet bases and their transforms.

A *multiresolution analysis* is an approximation scheme in which a signal  $X$  is approximated successively by  $P_j X$ . Each approximation  $P_j X$  of  $X$  is a description of  $X$  at resolution  $2^j$ . In Figure 1  $X$  is approximated by  $P_j X$ , a piecewise constant function with stepwidth  $2^j$  (left side of the diagram) and by  $P_{j+1} X$ , a piecewise constant function with stepwidth  $2^{j+1}$  in the middle of the diagram. As  $j$  increases, we have coarser and coarser descriptions of  $X$ . We can express the information about  $X$  that is lost in going from  $P_j X$  to  $P_{j+1} X$  exactly in terms of the wavelets  $\psi_{j,k}(t) = 2^{-j/2} \psi(2^{-j}t - k)$ :

$$P_j X = P_{j+1} X + \sum_k \langle X, \psi_{j,k} \rangle \psi_{j,k}.$$

In Figure 1 the difference between the two approximations is the function on the right side of the diagram. In this case, the wavelet is the Haar wavelet, given by  $\psi(t) = 1/\sqrt{2}$  if  $t \in [0, 1/2)$ ,  $\psi(t) = -1/\sqrt{2}$  if

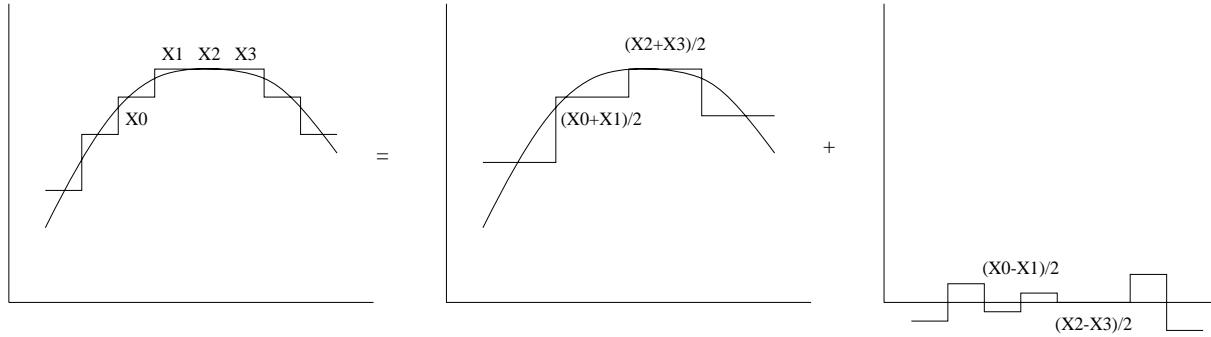


Figure 1: picture for wavelets

$t \in (1/2, 1]$ , and  $\psi(t) = 0$  otherwise. Thus, the wavelet basis is inherently linked to a multiresolution analysis. We can “iterate” the above equation, writing it for many scales  $j$  and using that  $P_j X$  tends to zero and that  $P_{-j} X$  tends to  $X$  as  $j$  tends to infinity to obtain the wavelet decomposition of  $X$

$$X = P_0 X + \sum_{j \leq 0} \sum_{k \in \mathbf{Z}} \langle X, \psi_{j,k} \rangle \psi_{j,k} = \sum_{j \in \mathbf{Z}} \sum_{k \in \mathbf{Z}} \langle X, \psi_{j,k} \rangle \psi_{j,k}.$$

We can implement this procedure using a hierarchical and fast algorithm, usually referred to as a subband filtering scheme. In the example in Figure 1, we start with a sequence of numbers  $X_k$  (the averages of  $X$  on intervals of size  $2^j$ ) that gives us the approximation  $P_j X$ , we compute the averages  $(X_{2k} + X_{2k+1})/2$  to obtain the approximation  $P_{j+1} X$  of  $X$  on intervals twice as wide, and we compute the differences  $(X_{2k} - X_{2k+1})/2$  to obtain the coefficients for  $\psi_{j+1,k}$ . In other words, given the approximation  $P_j X$ , we can compute the coarser approximation  $P_{j+1} X$  and the details  $\sum_{k \in \mathbf{Z}} \langle X, \psi_{j,k} \rangle \psi_{j,k}$  by convolving the sequence  $X_k$  with filters of length 2 (specifically, the filters  $\{1/2, 1/2\}$  and  $\{1/2, -1/2\}$ ). The reader is referred to [10] for a “friendly” introduction to wavelets and to [13, 4] for a more mathematical treatment of the subject.

We call the inner products  $\langle X, \psi_{j,k} \rangle$  of  $X$  with the rescaled and translated copies of the wavelet  $\psi$  the *wavelet coefficients*  $d_{j,k}$  of  $X$ . The set of all wavelet coefficients is generally referred to as the *discrete wavelet transform (DWT)* of the signal  $X$ . The coefficient  $|d_{j,k}|^2$  measures the amount of energy in a signal  $X$  about the time  $t_0 = 2^j k$  and about the frequency  $2^{-j} \lambda_0$ , where  $\lambda_0$  is a reference frequency which depends on the wavelet  $\psi$ . Abry and Veitch show that the time average of  $|d_{j,k}|^2$  at each scale  $j$  is a useful spectral estimator. In fact, if  $E_j$  denotes the average of  $|d_{j,k}|^2$  at each scale,

$$E_j = \frac{1}{N_j} \sum_k |d_{j,k}|^2$$

( $N_j$  is the number of wavelet coefficients at scale  $j$ ), then  $E_j$  is a measure of the energy that lies within a given bandwidth  $2^{-j}$  around frequency  $2^{-j} \lambda_0$ .

Consider now a signal  $X_t$  generated by a finite variance, wide-sense stationary, *long-range dependent* process with *Hurst parameter*  $H \in (1/2, 1)$ , that is, the autocorrelation function  $\rho(k)$  of  $X$  has the form

$$\rho(k) \sim c_\rho k^{-(2-2H)} \quad \text{as } k \rightarrow \infty$$

where  $c_\rho$  is a positive constant, and  $H$  measures the degree of long-range dependence; for short-range dependent processes,  $H = 1/2$ . In the frequency domain, long-range dependence is characterized by a spectral density  $f(\lambda)$  that exhibits a power-law near the origin; i.e.,  $f(\lambda)$  has the form

$$f(\lambda) \sim c_f |\lambda|^{1-2H} \quad \text{as } \lambda \rightarrow 0, \quad (1)$$

where  $c_f = 1/\pi\sigma^2 c_\rho$ ,  $(2H-1) \sin(\pi(1-H))$  and  $\sigma^2 = \text{Var}(X_t)$ . Long-range dependence plays an important role in the study of self-similar processes. Here, we call a wide-sense stationary process  $X$  *exactly self-similar* if for all integers  $m > 0$ ,

$$X = m^{1-H} X^{(m)}, \quad (2)$$

where the equality is understood in the sense of finite-dimensional distributions, and where the aggregated processes  $X^{(m)}$  with level of aggregation  $m$  are defined by  $X^{(m)}(k) = m^{-1} \sum_{i=(k-1)m+1}^{km} X_i$ ,  $k \geq 1$ . *Asymptotic self-similarity* is defined similarly but we only require that the above equality holds in the limit as  $m \rightarrow \infty$ . With this definition, a zero-mean  $X$  is long-range dependent if and only if  $X$  is (asymptotically) self-similar, and methods for studying the dependence structure of  $X$  can thus be exploited for investigating the scaling phenomenon expressed in Equation (2).

To illustrate, we return to the wavelet-based technique proposed by Abry and Veitch [1] and assume that the signal  $X$  is such that Equation (1) holds for all frequencies. Then the expectation of  $E_j$  is given by

$$\mathbf{E}[E_j] = \int f(\lambda) 2^j |\hat{\psi}(2^j \lambda)|^2 d\lambda = c_f |2^{-j} \lambda_0|^{1-2H} \int |\lambda|^{1-2H} |\hat{\psi}(\lambda)|^2 d\lambda,$$

where  $\hat{\psi}(\lambda)$  is the Fourier transform of  $\psi(t)$ . Observe that the multiplicative bias of  $E_j$  is simply a multiplicative constant which is independent of scale  $j$  and results in an effective scaling analysis of a given signal  $X$  by plotting  $\log_2 E_j$  against scale  $j$  and identifying scaling regions, breakpoints and non-scaling behavior. It also yields an asymptotically unbiased estimator for the Hurst parameter  $H$  by performing a simple linear regression of  $\log_2 \mathbf{E}[E_j]$  on the scale  $j$ ; that is,

$$\log_2 \mathbf{E}[E_j] = \log_2 \left( \frac{1}{N_j} \sum_k |d_{j,k}|^2 \right) = (1 - 2H)j + C.$$

The constant  $C$  estimates the value

$$\log_2(c_f |\lambda_0|^{1-2H} \int |\lambda|^{1-2H} |\hat{\psi}(\lambda)|^2 d\lambda)$$

provided the integral  $\int |\lambda|^{1-2H} |\hat{\psi}(\lambda)|^2 d\lambda$  exists. To insure that this integral is finite we must choose a wavelet  $\psi$  which has  $M > H - 1$  vanishing moments. In other words, the wavelet  $\psi$  must be orthogonal to all polynomials of degree less than  $M$ ;

$$\int t^l \psi(t) dt = 0 \quad \text{for } l = 0, \dots, M - 1.$$

The number of vanishing moments controls the order of the zero in the Fourier transform of  $\psi$  about  $\lambda = 0$ . If  $M$  is large enough, the behavior of  $|\hat{\psi}(\lambda)|^2$  will balance the singularity of the long-range

dependent spectrum. In addition, the estimation of the Hurst parameter is not affected by the presence of a deterministic polynomial trend if the degree of the polynomial is less than the number of vanishing moments.

As a technical note, we use the Daubechies wavelets (wavelets with compact support) which have the shortest support for a given number of vanishing moments (see [4] for details). We have not adapted these wavelets to a bounded interval to better account for possible border effects: To analyze the large data sets at hand requires a fast algorithm; so, for the sake of speed, we simply discard those coefficients which are polluted by border effects (the number of which is easily determined by the support width of the wavelet).

## 2.2 Measured WAN Traces Now and Then

In [1], Abry and Veitch use their wavelet-based technique to validate previously obtained results showing that measured Ethernet LAN traffic is consistent with long-range dependence, to estimate the corresponding values of the Hurst parameter, and to illustrate further interesting features of measured Ethernet LAN traffic. In this paper, we use their methodology primarily for investigating the scaling behavior of measured WAN traffic traces; that is, for identifying regions where the scaling property (2) holds, for detecting changes in scaling behavior, and for finding ranges of time scales with more complex scaling patterns than those captured by Equation (2). While we pay special attention to the scaling properties of the traffic traces at small time scales, we will comment on the observed large-time scaling features only in passing, mainly because our results simply confirm earlier findings about the long-range dependent or asymptotically self-similar nature of WAN traffic (e.g., see [14, 20]).

Packet Traces	Year	#Packets(Bytes)	% WWW (packets)
Bellcore	Jan.1990	87307(16533426)	0%
LBL (TCP only)	Jan.1994	677846(94124920)	3%
Bellcore	Dec.1994	1061966(546478200)	10%
MH (AT&T-Labs)	Feb.1997	458669(131906000)	27%
FP (AT&T-Labs)	Aug.1997	582538(218330000)	32%
TCP Connection Traces		#Connections	% WWW (connections)
lbl1 (ftp, telnet only)	Fall 1993	211	0%
lbl2	Fall 1993	2999	0%
cmu	Jun.1995	803	22%
mh (AT&T-Labs)	Feb.1997	5067	80%
fp (AT&T-Labs)	Aug.1997	7427	87%

Table 1: Packet-level and TCP connection-level WAN traces used in our study.

The five hour-long packet-level WAN traces used in our study are summarized in the top part of Table 1. The Bellcore'90 trace pre-dates WWW, and TELNET and FTP (as well as NNTP) comprised the main applications at that time. Also note that in 1990, the NSFNET backbone was T1-based; i.e., running at 1.5 Mbps. Both the LBL'94 and the Bellcore'94 WAN traces contain some Web traffic (close to 10% for the Bellcore trace) and represent measurements of Internet traffic as the Internet is going through

drastic changes (e.g., emergence of WWW, transition to a 45 Mbps backbone). WWW is the main WAN application and makes up a major portion of the traffic in both the Murray Hill (MH) AT&T-Labs'97 and Florham Park (FP) AT&T-Labs'97 traces and by that time, the privatization of the Internet is well on its way. Note that for both the MH'97 and FP'97 traces, the given percentage of WWW traffic only consists of packets associated with port number 80 (WWW). More than half of all the recorded packets are associated with non-standard port numbers, and about 20% of the total traffic is due to some site specific applications. Finally, the time stamp accuracy varies from a few microseconds for the Bellcore and LBL traces to milliseconds for the other traces.

Selecting three representative traces which span seven years of WAN traffic, with 0%, 10%, and 30% or more Web traffic, respectively, Figure 2 (left column) shows the scaling analyses for the signals  $X$  representing the number of packets per ten milliseconds for the Bellcore'90, Bellcore'94, and FP'97 WAN traces; the corresponding analysis for the number of bytes per 10 milliseconds time series is given in the right column in Figure 2. We have plotted the energy  $E_j$  as a function of the resolution level  $2^j$ , on a  $\log_2 - \log_2$ -scale; i.e.,  $\log_2 E_j$  as a function of scale  $j$ . To clarify the time scales which correspond to scales  $j$ , we have included the time (in seconds) on the top axis of each graph.

The scaling analysis of a traffic trace which is asymptotically self-similar (or, equivalently, exhibits long-range dependence) will, for large times/scales, result in a linear relationship between  $\log_2 E_j$  and the scale  $j$ . If the trace is exactly self-similar (i.e., the spectral density characterization of long-range dependence in Equation (1) holds for all frequencies), a plot of  $\log_2 E_j$  vs.  $j$  will show a linear relationship for all scales. As can be seen, all plots show an approximate linear relationship between  $\log_2 E_j$  and scale  $j$  for sufficiently large time scales; i.e., the corresponding WAN traces are fully consistent with asymptotic self-similarity or long-range dependence, irrespective of where the traces were collected and whether or not they contained no, some or mostly Web traffic. Note that while pre-Web traffic (i.e., Figure 2, top row) seems to exhibit some indications for departure from exact self-similarity (i.e., a linear relationship appears to hold throughout the range of observed time scales, with some obvious "bumps" around scales 3-6), the more recently collected WAN traces show this departure much clearer: a non-trivial scaling behavior for small time scales (typically below a few hundreds of milliseconds) and a distinctly different large-time scaling behavior, with a "change-point" that shows up very clearly as a pronounced "knee" in the graphs in the middle and bottom rows in Figure 2, approximately at scale  $j = 5$  corresponding to about 500 milliseconds, irrespective of whether we consider the packet counts or byte counts.

These observations are not restricted to the three representative traces shown in Figure 2, but we found a very similar scaling behavior when analyzing the remaining packet-level traffic traces contained in Table 1 (top part): Before the predominance of WWW (i.e., in the Bellcore'90 traffic trace and, to some extent, in the LBL'94 trace), we observe indications of deviations from a single scaling region (e.g., as in Figure 2, top plots), with some clearly visible "bumps" at the small time scales (i.e., on the order of hundreds of milliseconds); after the rise in popularity of the Web (i.e., in the MH'97 and FP'97 traces), we can easily and consistently identify two distinct scaling regions, irrespective of the length of the traces, time



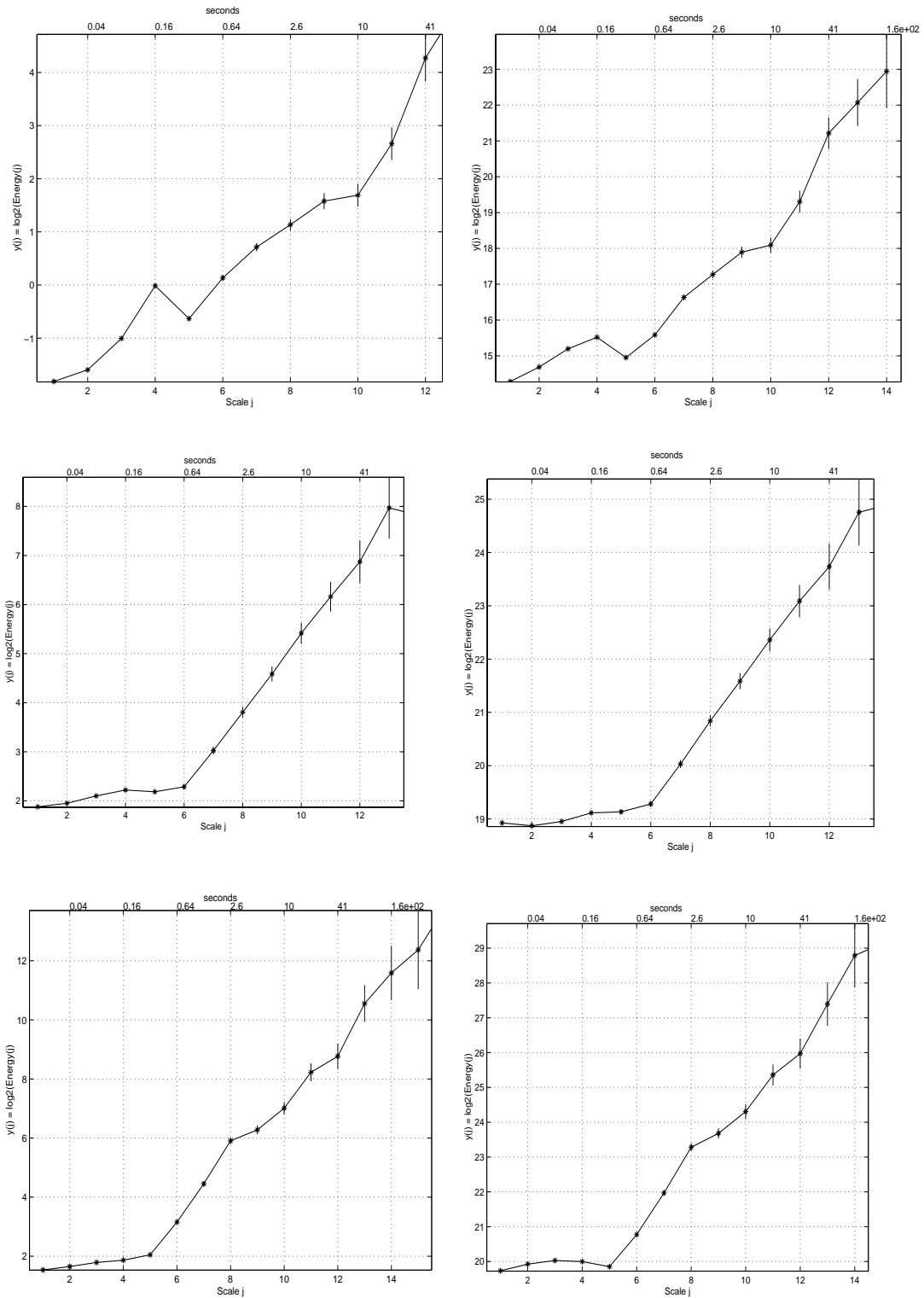


Figure 2: Scaling analysis of packet-level WAN traces (left column: packets/10 msec; right column: bytes/10 msec): Bellcore'90 (top), Bellcore'94 (middle), FP'97 (bottom).

of day the traces were collected and geographic location of the traffic collection. For the Web-dominated traffic traces, we also separated the data into Web-only and non-Web traffic. Performing the same scaling analysis for the Web-only traces (not shown here), we noticed the same non-trivial scaling behavior as for the combined traffic. Moreover, if we aggregate each of our traces and perform scaling analyses for the time series representing the number of packets (or bytes) per one second, small-time scaling structures are no longer visible and all we observe is a simple linear relationship between  $\log_2 E_j$  and the scale  $j$  that holds now for all scales. Thus, at time scales larger than about one second, WAN traffic is statistically self-similar, and this characteristic has remained unchanged throughout the years, regardless of whether WAN traffic has been dominated by TELNET, FTP, NNTP or WWW, independent of how fast the Internet backbone has been running, and despite all the other drastic changes the Internet has experienced over the past 7 years. Finally, concerning the ever-present question of non-stationarity vs. long-range dependence, we note that as part of the wavelet-based scaling analysis, a systematic search for the presence of certain non-trivial deterministic trends is possible through a judicious choice of the number of vanishing moments,  $M$ , for the wavelet used in the analysis. For the traces at hand, this part of the scaling analysis (not shown here) provided no indications for the presence of certain deterministic trends that might adversely effect our conclusions about scaling laws in measured WAN traffic.

While our finding of the large-time scaling is not new and simply confirms earlier studies by Paxson and Floyd [14] (see also Willinger et al. [20]) who first observed the asymptotically self-similar or long-range dependent nature of measured WAN traffic, our empirical observation of the existence of a pronounced small-time scaling behavior is new in the sense that it clearly differentiates between small-time and large-time scaling properties. While earlier empirical studies of measured WAN traffic have also pointed out apparent deviations from exact self-similarity at small time scales, their exclusive reliance on analysis techniques such as variance-time plots, the  $R/S$  method, or periodogram-based approaches made it difficult to focus in more detail on the nature of these deviations over small time scales. Subsequently, the results of our wavelet-based scaling analysis of a historical collection of WAN traces imply that to fully understand and accurately describe modern WAN traffic, exactly self-similar processes are not sufficient and need to be replaced by traffic models that allow for a richer scaling behavior. To this end, gaining a physical understanding of the origins of the observed small-time scaling phenomenon is of crucial importance as it will lead to structural modeling approaches for WAN traffic that capture the full range of observed scaling phenomena in a compact and parsimonious manner.

### 3 Physical Explanations for Scaling in WAN Traffic

To gain a physical understanding of the empirically observed scaling phenomena in actual WAN traffic collected over the last 7 years, we provide in this section a plausible, application-level phenomenological explanation for the large-time scaling behavior of WAN traffic at the packet level, identify (and provide a physical explanation for) an intriguing feature of the changing nature of WAN traffic at the TCP connection

level as WANs experienced more and more Web traffic over the past couple of years, and illustrate with further examples the difficulties associated with answering the question of the origins of the observed small-time scaling behavior in today’s WAN traffic.

### 3.1 Large-Time Scaling Phenomenon: Application Layer

The main applications that generated WAN traffic in the pre-Web days were TELNET, FTP, SMTP and NNTP. Among those, FTP played a particularly important role because FTP sessions created the bulk of data bytes sent over WANs in the pre-Web days. In an attempt to provide a physical explanation for the observed asymptotically self-similar nature (i.e., large-time scaling phenomenon) of measured WAN traffic, Paxson and Floyd [14] focused in part on the application layer trying to understand the characteristics of such measurable quantities as FTP session size (in bytes), FTP session duration (in seconds) and FTP session arrival times. Their extensive analysis of FTP traffic traces shows two key characteristics: (i) Over one hour intervals, FTP session arrivals are well modeled by a Poisson process; and (ii) the distributions of FTP session sizes or durations are heavy-tailed, with upper tails that are consistent with Pareto-type tails and entail finite mean but infinite variance, i.e., high variability. Similar observations are made in [14] about TELNET sessions, even though TELNET is an application qualitatively quite different from FTP, with much less demand for bandwidth, but generating a high volume of (generally small) packets. Paxson and Floyd also investigated the “within-session” structure of TELNET and FTP connections, and while their approach seems adequate for describing pre-Web WAN traffic dynamics within individual connections, the findings reported in this paper point out the need for new approaches to understanding WAN traffic at the level of individual applications and connections.

In view of these empirically observed application-layer traffic characteristics, a construction due to Cox [3], also known as an *immigration death process* or *M/G/∞ queueing model*, provides a structural modeling approach for pre-Web WAN traffic that is (i) mathematically rigorous, (ii) consistent with measured packet-level WAN traffic at the macroscopic (i.e., aggregated over all individual connections) as well as microscopic (i.e., for individual connections) level, and (iii) highlights the intimate connection between high variability (i.e., heavy-tailed phenomenon) at the microscopic level and (asymptotic) self-similarity (i.e., large-time scaling phenomenon) at the macroscopic level. In short, in the context of WAN traffic modeling, Cox’s construction assumes that sessions arrive according to a Poisson process (or, more generally, a renewal process), that the distribution of session lengths/sizes is heavy-tailed, and that packets/bytes are transmitted at a constant rate for the duration of the session. Working in discrete time and letting  $X_n$  denote the number of packets/bytes generated during the n-th time period by all the sessions active at that time, it can be shown that Cox’s construction results in a traffic model that exhibits large-time scaling features (i.e., is long-range dependent or asymptotically self-similar) if and only if the distribution of the session lengths/sizes has infinite variance; for details, see [19].

With the advent and popularity of the Web, WWW-related traffic makes up a significant portion of the overall traffic on today’s WANs (see Table 1). Despite the drastic changes that WANs have undergone

in the past 7 years, we have seen in Section 2 that the large-time scaling property is a robust characteristic of WAN traffic, irrespective of how much of the traffic is due to WWW. Naturally, this gives rise to the question of the appropriateness of Cox's construction not only for pre-Web but also for today's WWW-dominated WAN traffic, and begs for a clear understanding of Web traffic at the level of individual user sessions, each of which consists in general of several TCP connections. To this end, it is important to note that to date, Web session characteristics have not been studied in detail, mainly because of the difficulties in determining, from a packet-level WAN link trace, the instants when a Web session begins and ends. Due to the details in how the different WAN applications are structured, this determination is easy for FTP and TELNET (and other applications).

Here, we partially avoid these difficulties by relying on an indirect, somewhat inexact, but intuitively reasonable method that provides novel insights into Web sessions and their statistical characteristics. Our method makes use of a data base that provides information about every single modem call made to a certain commercial ISP (Internet Service Provider); for our purposes, the important items collected for each modem call are time of arrival of call (accurate to 1 second), duration (in seconds) and size (i.e., for each direction, number of bytes transmitted during the length of the call; below, we consider the total number of bytes transmitted). Although there is no one-to-one correspondence between modem calls and Web sessions (e.g., a single modem call can consist of a Web session, followed by email, followed by a TELNET session, followed by another Web session etc.), substituting one for the other seems justified and appears to be reasonably accurate if we focus mainly on arrival time and size information; after all, web-browsing is the main activity of a typical ISP customer, and compared to email or TELNET or other non-WWW related applications, Web sessions create currently the bulk of data bytes. In the following, we will therefore use the notions of Web session and modem calls in an interchangeable fashion, and the context in which these notions appear will typically resolve any potential confusion.

Given these caveats, Figure 3 shows the results of our analysis of an hour worth of calls into a large modem pool (other data sets show similar characteristics). The top left plot in Figure 3 gives the empirical complementary cumulative distribution function (CCDF) of the interarrival times of modem calls, on log-linear scale; the plot illustrates that the interarrival time distribution is light-tailed and, moreover, that it is consistent with the tail-behavior of an exponential distribution (note that we are here not concerned with the shape of the main body of the distribution). The top right plot shows the autocorrelation function of the number of modem call arrivals during successive one-second intervals. As can be seen, the autocorrelations are essentially zero for all positive lags (i.e., lag 1 and beyond), implying that the arrivals are consistent with a renewal-type process, i.e., independent and identically distributed. Finally, in the two bottom plots in Figure 3, we plot the CCDF of the sizes (on the left) and durations (on the right) of modem calls, respectively, on log-log scale; the plots demonstrate the heavy-tailed or Pareto-type nature of the corresponding distributions, and a crude estimate of the slope of the corresponding linear regions indicates consistency with infinite variance behavior. In summary, using the modem call data as substitute for Web session information, we find that Cox's construction remains valid as a structural modeling approach for

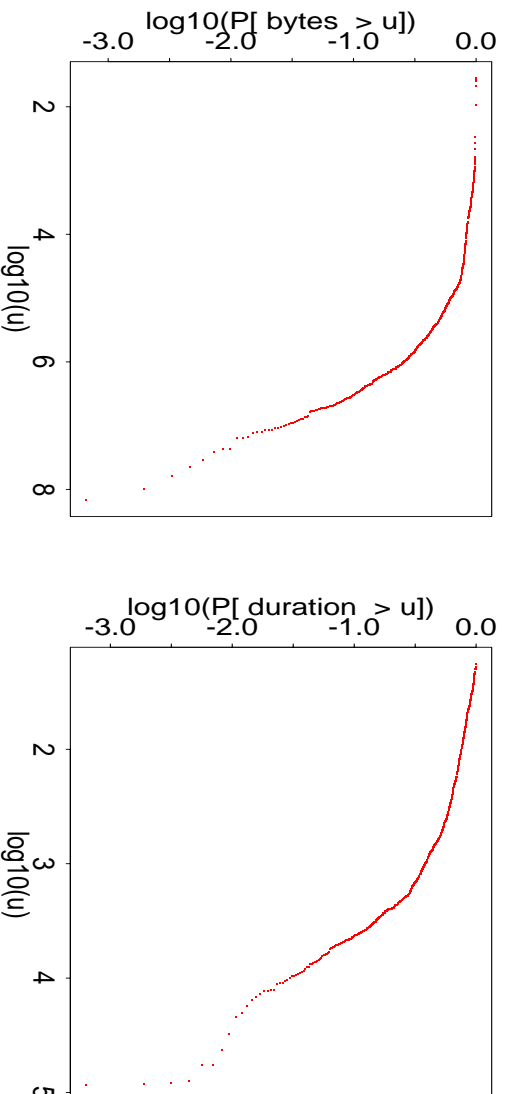
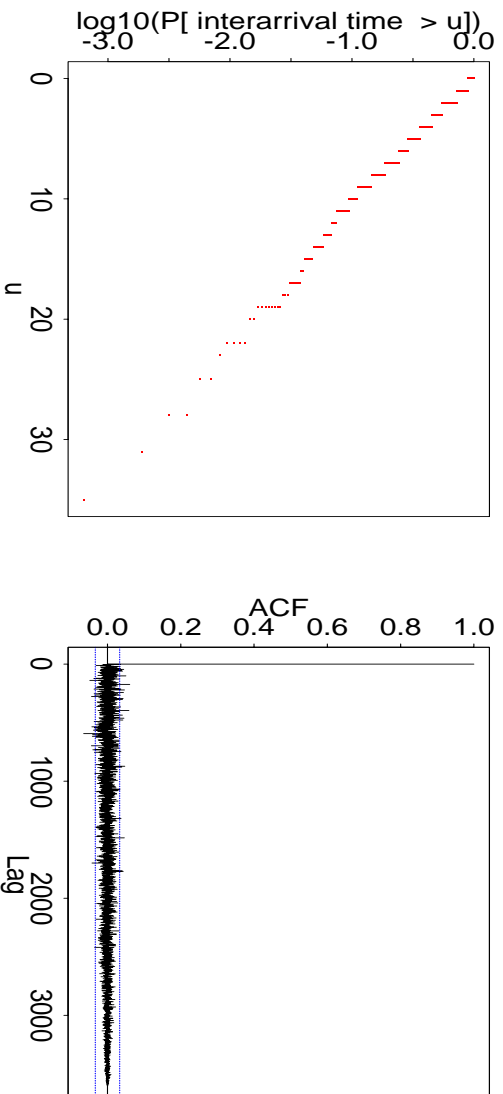


Figure 3: Analysis of modem call data: Complementary cumulative distribution function (CCDF) for modem call interarrival times (top left, log-linear scale); autocorrelation function of modem call arrivals per second (top right); CCDF for modem call size in bytes (bottom left, log-log scale); CCDF for modem call duration in seconds (bottom right, log-log scale).

WAN traffic, even when the latter is dominated by the Web – as long as we are only concerned with application and packet level information and ignore other layers in the networking hierarchy, for example TCP layer or IP layer (see Section 3.2 below).

### 3.2 Large-Time Scaling Phenomenon: TCP Layer

To date, structural modeling approaches for WAN traffic (e.g., Cox’s construction) have focused almost exclusively on explaining the observed large-time scaling phenomenon in packet-level WAN traffic in terms of the phenomenon of high variability or infinite variance at the application level. They have done so successfully (see Section 3.1), despite the constantly changing nature of modern-day WANs and of the traffic they carry. However, these approaches reflect a source-centered view of traffic modeling, where sources are assumed to simply inject (at a constant rate) as many packets into the network as is required by a user session, and they essentially ignore the impact that the applications (e.g., downloading several Web pages) and networks (e.g., TCP dynamics) have on the flow of packets that individual sources attempt to transmit over the network. On the one hand, such a modeling view is justified for LAN environments where the feedback from the network to the hosts about the current state of the network is essentially instantaneous. On the other hand, because WANs are generally used for sending packets over long distances, the speed-of-light limitations have a practical impact upon the transmission time of packets. In fact, latency or non-negligible delays associated between obtaining and adapting to feedback on current network conditions is one of the most difficult problems that WANs have to cope with, and they often do so by relying on sophisticated “transport” protocols and/or end-to-end flow control schemes. In the Internet, the dominant transport protocol continues to be the *Transmission Control Protocol (TCP)* that ensures reliable transfer of data across the network (e.g., see Stevens [16]).

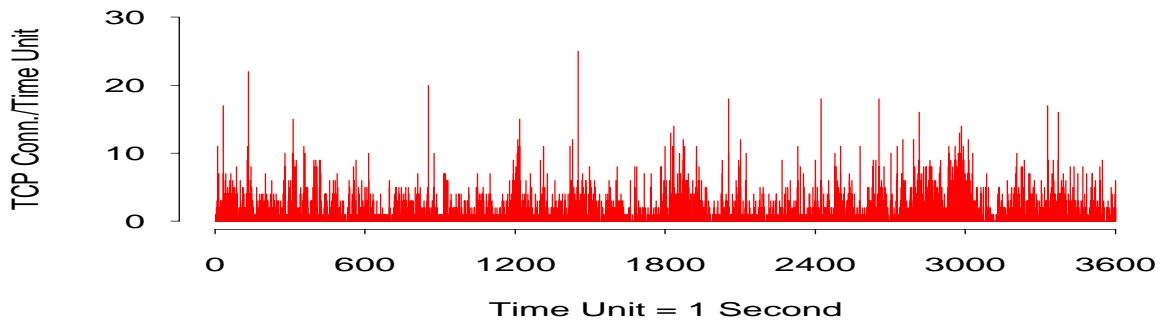


Figure 4: Time series plot of the number of TCP connection arrivals per second (for the hour-long trace fp’97).

In this subsection, we focus exclusively on the transport layer which resides directly underneath the application layer in the hierarchical structure of modern-day networks, but a few layers above the link layer with its mechanisms and protocols controlling how the individual packets are sent over the media and where

our WAN traces were recorded. In today’s Internet, application-layer protocols such as TELNET, FTP and HTTP (Hyper Text Transport Protocol) are responsible for the details in how the major applications are structured and segmented into lower-layer units (so-called TCP connections) that can be given off to and are recognized by TCP, the protocol running at the transport layer. For example, a TELNET session always corresponds to one TCP connection, while FTP or Web sessions can result in one or more and often many individual TCP connections. Given a packet-level WAN link trace, it is easy to determine TCP connection information (e.g., time of arrival of a TCP connection, its size in bytes and its duration in seconds) by inspecting the header of every TCP packet seen on the monitored link. Our interest here is in studying the characteristics of measured WAN traffic at the TCP connection level; that is, investigating the statistical properties of the process representing the number of TCP connection arrivals per time unit. A time series plot of such a process (i.e., number of TCP connection arrivals per second, for the fp’97 data set in Table 1) is depicted in Figure 4.

We illustrate our analysis of WAN traffic at the TCP connection level with four hour-long traces whose pertinent statistics are summarized in the lower part of Table 1. Note that lbl2’93 contains an hour worth of all TCP connections from LBL 7 in [14], while lbl1’93 consists of only those TCP connections in lbl1’93 that correspond to successful TELNET or FTP control sessions. As is the case with the packet-level data shown in the upper part of the table, the connection-level WAN traces also cover the period from the pre-Web days to now – with no, some, or a significant portion of Web traffic, depending on whether we consider lbl1’93 (or lbl2’93), cmu’95, or mh’1997 and fp’1997, respectively. Note that the reason for the difference in the 1997 traces between the 30% portion of WWW traffic (in terms of packets) versus the 80% portion of WWW traffic (in terms of TCP connections) is that the average Web-related TCP connection is much smaller (about 8 KB) than the average non-Web related TCP connection. As in Section 2.2, we can again study the changing nature of WAN traffic, this time at the level of TCP connection arrivals, over a period where WANs have undergone drastic changes.

Performing the same wavelet-based scaling analysis as in Section 3.1, Figure 5 shows the scaling properties for the time series representing the number of TCP connection arrivals per second, for all five connection-level WAN traces. Starting with the top left plot in Figure 5, we observe a trivial (i.e., a value of the Hurst parameter of about 0.5) scaling behavior for the lbl1’93 data set across all scales; upon further analysis (not shown here), we find that in this case, the arrival instances of TCP connections are consistent with a Poisson (or, more generally, a renewal-type) behavior. Since the majority of observations in this data set correspond to successful TELNET connections (plus some FTP control connections), this finding is in agreement with the results reported in [14]. However, when moving from the lbl1’93 to the lbl2’93 data set, i.e., when considering all TCP-connections arrivals (including those spawned by FTP control connections and SMTP or email), we see in Figure 5 (top right plot) a drastic change, namely the appearance of a non-trivial scaling region for the large time scales. The difference between the two plots in the top row of Figure 5 can be intuitively explained by (i) SMTP-triggered TCP connections dominate and reflect a user behavior for email sessions that is different from TELNET, for example; and (ii) FTP-control con-

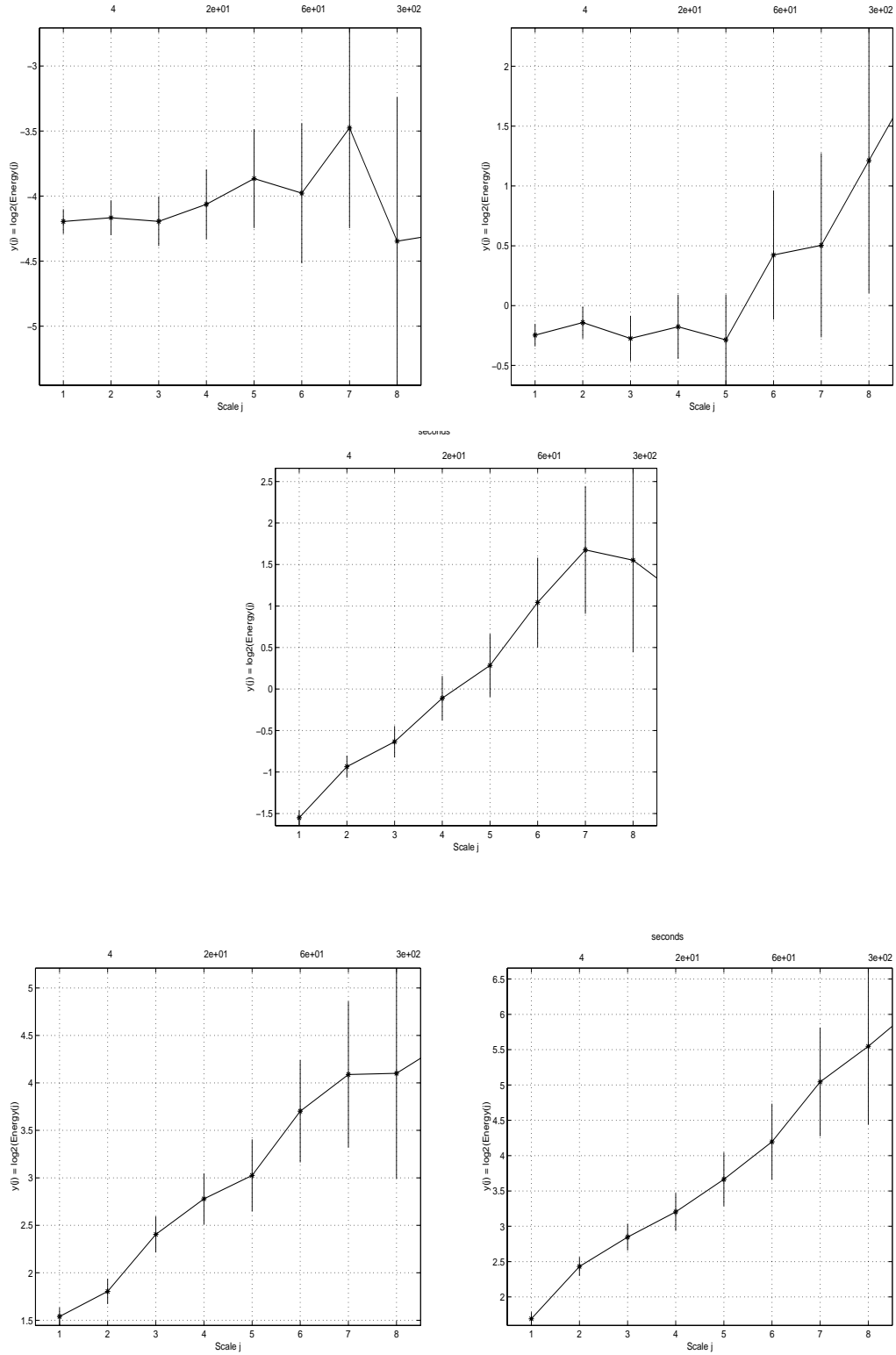


Figure 5: Scaling analysis of TCP connection-level WAN traces (number of TCP connection arrivals per second): lbl1'93 (top left); lbl2'93 (top right); cmu'95 (middle row); mh'97 (bottom left), fp'97 (bottom right).



nections typically spawn a number of TCP connections within the FTP session, and it is not unreasonable to expect that there is an increasingly high variability in the number of spawned connections as the use of FTP becomes more sophisticated. Moving on to the cmu'1995 trace and analyzing only the HTTP-related portion of the TCP connections, Figure 5 (middle row) shows yet another change in the scaling behavior; Web traffic at the level of TCP connection arrivals no longer exhibits trivial scaling at the small scales but shows across all scales the same non-trivial scaling that we have seen in the pre-Web lbl2'93 trace for large time scales; that is, the traffic representing the number of HTTP-related TCP connection arrivals per second is (exactly) self-similar for time scales of one second and beyond. As can be seen from the remaining two plots in Figure 5 (i.e., bottom row), this observation is confirmed and becomes even more pronounced as we move to the latest connection-level WAN traces and perform the same scaling analysis for the HTTP-related portion of TCP connections.

The finding of self-similarity of measured WAN traffic at the TCP connection level is not new, but has been pointed out earlier by Feldmann [6, 7], and our analysis here simply confirms this previously observed feature of TCP connection arrivals. What is new here is the observed gradual appearance of non-trivial scaling in WAN traffic at the transport layer, from trivial scaling to non-trivial large-time scaling to non-trivial scaling for all scales, as WANs see the traffic mix at the application level change from mostly TELNET and simple use of email and FTP, to all-of-the-above plus more sophisticated use of FTP, to all-of-the-above plus some Web usage, to predominantly Web-based. It will be interesting to see, how this empirically observed scaling phenomenon at the transport layer will be affected as a growing portion of Internet traffic will be “multicast”, where a single sender transmits to multiple receivers, as other new transport protocols come along, or as the current characteristics of a “typical” Web-page (i.e., median of about 3K bytes, average around 8K bytes) change.

### 3.3 TCP Connection Arrival Dynamics Within Web Sessions

Naturally, the gradual appearance over time of self-similarity in measured WAN traffic at the transport layer gives rise to the question about the origins of this phenomenon, especially in view of its distinct presence in today's WWW-dominated WAN traffic. To provide a plausible and empirically verifiable answer to this question, we make again use of the information contained in the ISP's modem call data base (see Section 3.1) and correlate it with the packet-level WAN trace collected from the same ISP's wide-area network. To illustrate, Figure 6 shows the dynamics of a single Web session (i.e., modem call) at the level of individual TCP connections. We use the textured plotting technique to indicate in the top plot the bursty nature of TCP connection arrivals. Recall that the idea of textured plots is to display one-dimensional data points in a strip in an attempt to show all data points individually. If necessary, the points are displaced vertically by small amounts that are partly random, partly constrained. The resulting textured dot strip facilitates a visual assessment of changing patterns of data intensities in a way other better-known techniques (e.g., histogram plots) are unable to provide. Note that the plot in Figure 6 contains about 480 points, each of which represent the arrival time of a TCP connection within one

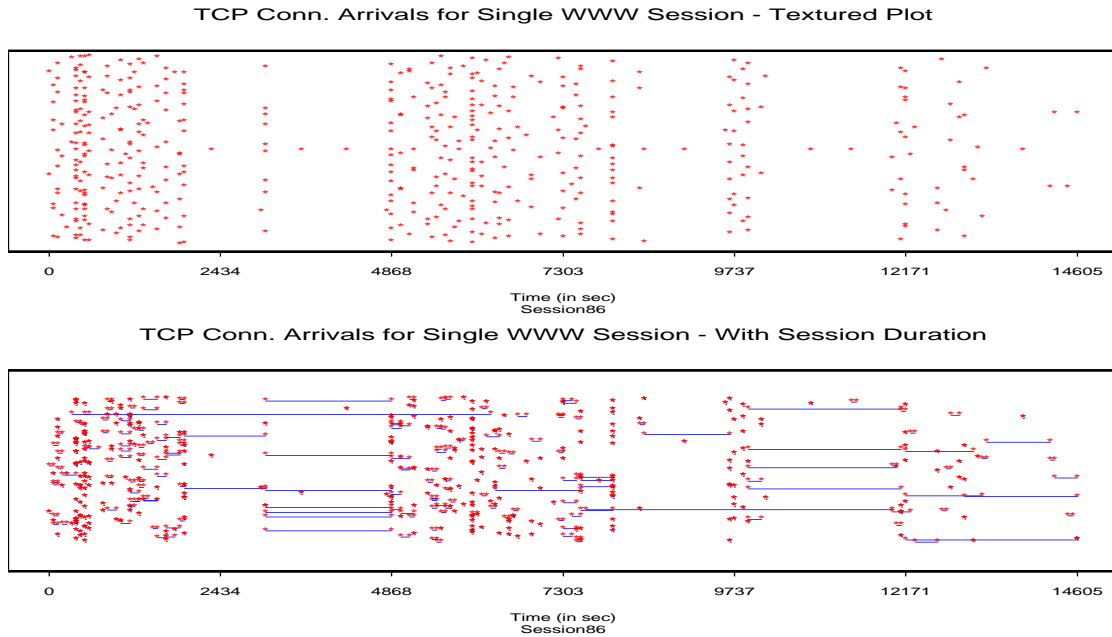


Figure 6: Textured plot of TCP connection arrivals within a single Web-session (top) and augmented with their corresponding durations (bottom).

and the same Web session. In addition, for each arriving TCP connection, the bottom plot in Figure 6 shows a horizontal line, representing the length or duration of the corresponding TCP connection. Thus, in addition to the bursty nature of TCP connection arrivals, this plot also demonstrates the high variability associated with the TCP connection durations; many of the connections are too short to show up in plot, and those that can be recognized range in duration from seconds to minutes and hours. The plot also shows a number of other characteristics that are typical for today’s Web and its “typical” users: opening multiple simultaneous connections (a characteristics of popular Web browsers such as Netscape 3.0), running more than one Web-browser at the same time, and multiple connections stopping all at once (e.g., the result of hitting the stop bottom). Note that while this particular Web session is somewhat atypical with respect to its duration (it lasts for about 4 hours!), we found it, in fact, to be very typical with respect to the “within-session” dynamics of TCP connection arrivals for sessions – with the exception of the very short ones.

Next, we consider all Web-sessions that were active during the packet-level traffic collection period (i.e., 3.5 days, totaling 39620 sessions) and extract from the measured WAN trace the number of TCP connections per Web session. Not counting the unsuccessful connections, the mean connection size is about 2Kbytes and the median is 14 Kbytes. Figure 7 shows the complementary cumulative distribution function of the number of TCP connections per Web session, on log-log scale. In view of Figure 6, it should come as no big surprise that the number of TCP connections per Web session is highly variable (extending over more than 4 orders of magnitude, see x-axis); in fact, the apparent linear region in the tail of the plot suggests that the number of TCP connections per Web session is heavy-tailed, and “eyeballing” the slope

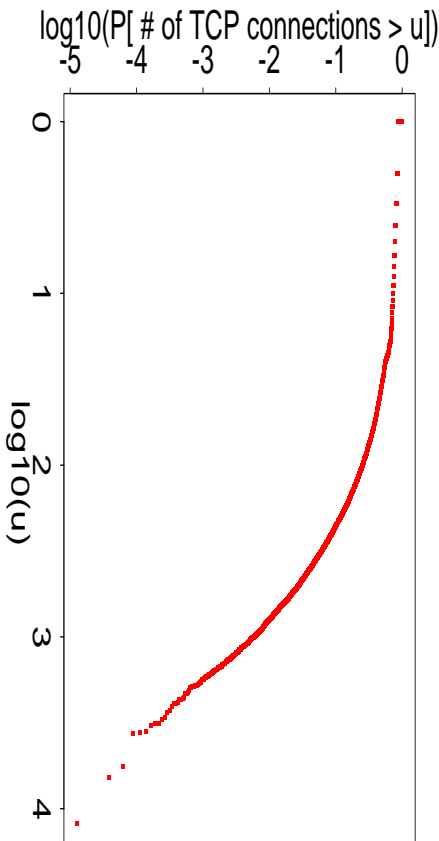


Figure 7: Complementary cumulative distribution function of the number of TCP connections per Web sessions.

of the linear region indicates that the observations are consistent with finite mean but are on the border between having finite variance and exhibiting infinite variance (i.e., the “Noah Effect” or infinite variance syndrome). This heuristic approach can be made more rigorous using, for example, Hill’s method for assessing the heavy-tailed nature of a distribution (e.g., see [20]).

Together with the Poisson nature of Web session arrivals (see Section 3.1), the empirically observed property that the number of TCP connections per Web session are heavy-tailed with indications of infinite variance behavior provides a mathematical explanation for the self-similar nature of WAN traffic at the TCP level via a separate Cox’s construction, where in this case, the “service times” are measured in terms of the number of TCP connections. As far as *overall* structural modeling of WAN traffic is concerned, the observed self-similar nature of WAN traffic at the TCP connection level clearly demonstrates the limitations of Cox-like constructions; they are restricted to two layers (i.e., sessions and packets, or sessions and TCP connections) and are therefore too inflexible to account for multi-layer (i.e., more than two) structures. In particular, they allow for no other “within-session” structure than emitting units (e.g., packets or connections) at a constant rate. Thus, they are unable to account at the same time for the observed packet-level as well as TCP-layer dynamics.

In general, these constructions are also inadequate to capture the small-time scaling phenomena observed in measured WAN traffic and reported in Section 2.2. However, recent work by Kurtz [11] provides new insights into the problem of allowing for a more flexible “within-session” structure. Briefly, Kurtz considers a large number of sessions, each of which arrives at a random point in time (i.e., session arrivals are assumed to follow a Poisson process), is active for a random duration  $\tau$ , and then leaves the system. Associated with each active session is a stochastic process  $Y = (Y(t), 0 \leq t \leq \tau)$  such that  $Y(t)$  represents the cumulative number of packets/bytes generated during the first  $t$  time units during the active session. The only condition on  $Y$  is that since it describes the cumulative work generated during a session, it is required to be non-decreasing. For example,  $Y(t) = t$  for the duration of the session means constant rate

and we recover Cox’s construction; however, a  $Y$ -process that is piecewise linear with different non-negative slopes (including slope 0, i.e., no traffic is generated) is an obvious candidate for capturing the fragmentation of an application-layer session into one or more transport-layer connections (e.g., a Web-session being segmented into a number of TCP connection, interspersed with “idle periods” representing periods of user inactivity or “think time”; see [2]). Kurtz’s main results show that the same limiting regime (i.e., fractional Brownian motion) holds for an appropriately normalized version (for details, see Kurtz [11]) of the total traffic generated by all active sessions, under a number of different scenarios for the particular “within-session” structure defined by the process  $Y$ ; the only condition needed to obtain the limiting regime is that the session duration  $\tau$  is heavy-tailed with infinite variance. From the perspective of structural modeling approaches for WAN traffic, Kurtz’s construction is an improvement over Cox’s construction because it can accommodate a number of relatively complex “within-session” structures. However, at this time, it remains unclear how one would account for the observed self-similar nature of the “within-session” TCP connection arrival counts or how such a structure (if it exists) would impact the limiting result. In its current version, Kurtz’s construction has two properties in common with Cox’s construction: they both provide a (the same) physical explanation for the observed large-time scaling phenomenon in measured packet-level WAN traces, but they both cannot parsimoniously account for the small-time scaling phenomenon that is present in measured packet-level WAN traces and is distinctly different from the large-time scaling property. In fact, the observed pronounced small-time scaling behavior strongly suggests the presence of local irregularities in measured WAN traces that, in turn, can only be accounted for by relying on mathematical models that allow for scaling laws (e.g., multifractals - see below) that are more complex than the ones exhibited by self-similar processes.

### 3.4 Small-Time Scaling Properties: Preliminary Observations

We have seen in Section 2.2 that modern-day packet-level WAN traffic exhibits small-time scaling features that are distinctly different from the observed large-time scaling phenomenon. Phenomenological or structural modeling approaches for WAN traffic, such as Cox’s or Kurtz’s constructions, successfully explain the latter phenomenon in terms of the observed high variability of WAN traffic at the application level, but have failed so far to capture the former. Clearly, the difficulties are with the small-time scaling features which have generally been ignored by the mathematical modeling community and the networking researchers alike. One problem that contributes to this neglect continues to be the difficulty to routinely capturing WAN packet traces at a fine enough time resolution that makes fine-time scale analysis credible and does not require expensive, custom-made traffic recorders. As an illustration of the insights gained from measuring and analyzing high-time resolution WAN packet traces and the ensuing difficulties in trying to understand and describe in a compact manner the small-time scaling behavior in packet-level WAN traffic, we show in Figure 8 the results of a wavelet-based scaling analysis for a WAN trace collected in July’97 from a commercial network. For this WAN traffic trace, the time stamp accuracy is estimated at about 10 microseconds and allows for a scaling analysis down to the millisecond scale, without being

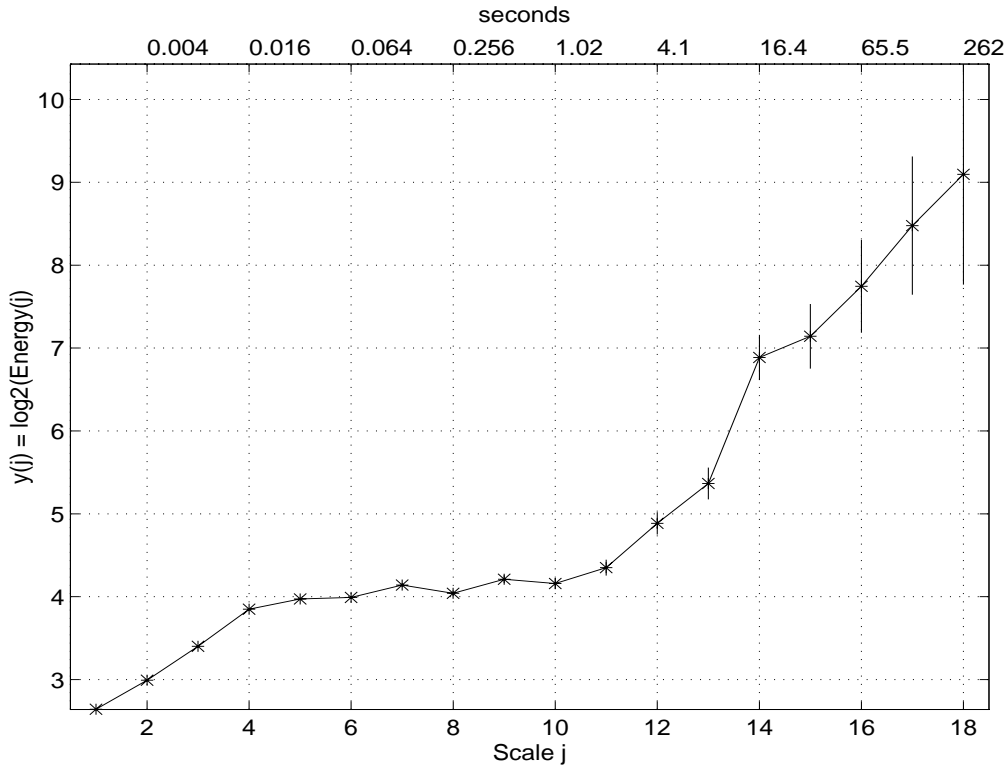


Figure 8: Scaling analysis for a high-time resolution WAN trace.

impaired by binning effects (i.e., we are not dealing with time scales where either one or no packet is present). Somewhat surprisingly, the plot shows yet further scaling structure on the very fine time scales, distinctly different from the observed scaling properties over intermediate time scales (see Figure 2), and still different from the well understood large-time scaling feature. This observation should serve as a reminder that even though “black box” models such as fractional ARIMA( $p, d, q$ ) processes can often be tweaked so as to reproduce a certain prescribed scaling behavior, they do so without providing any insights into the origins of the fitted scaling behavior. Moreover, if a more detailed scaling analysis reveals yet further scaling features (as in the case in Figure 8), these “operational” modeling approaches (i.e., data fitting exercises) simply result in replacing one black box by another.

From a networking perspective, the presence of non-trivial scaling behavior at small time scales comes as no surprise and is intimately related to the intricacies of the different protocols that rule the flow of traffic at each layer in the networking hierarchy. These protocols interact in non-trivial ways with one another, and are responsible for creating complex interactions between the network on the one side and the sources on the other side. While we used Figure 6 to demonstrate the presence of a rich structure in the arrival pattern of TCP connections within a single Web session, Figure 9 illustrates the richness in structure that exists within a single TCP connection. Using the same textured plotting technique, the figure depicts very clearly the high variability of “within-TCP-connection” activity levels and behaviors. The challenge for structural modeling approaches for WAN traffic is to (i) understand the underlying mechanisms that

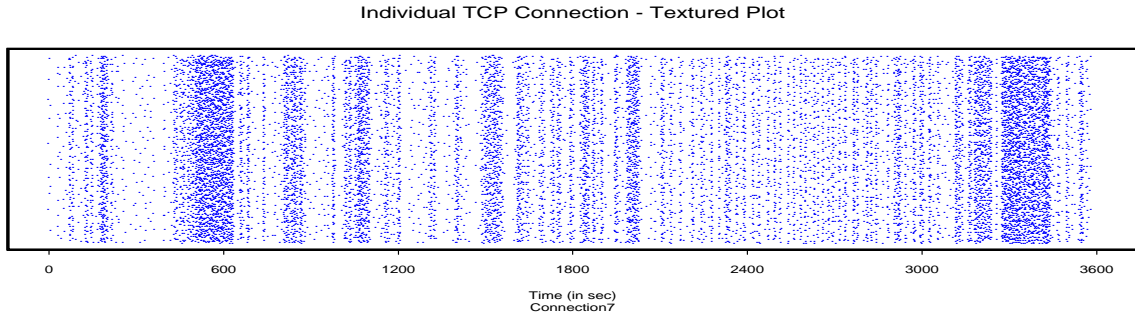


Figure 9: Textured plot for an individual TCP connection. The connection lasted for an entire hour, and consists of 14,305 packets.

give rise to such rich structures at the transport layer and possibly at the other layers in the networking hierarchy as well, (ii) describe the relevant aspects of the observed structure in a compact and parsimonious manner, and (iii) provide mathematical constructions that reflect the underlying mechanisms and, at the same time, continue to capture the well-understood large-time scaling behavior.

## 4 Conclusions and Outlook

Based on a wavelet-based scaling analysis of a historical collection of WAN traces at the packet-level as well as at the TCP connection-level, we show in this paper that packet-level WAN traffic has remained asymptotically self-similar (i.e., is long-range dependent; i.e., exhibits non-trivial large-time scaling properties) during the last 7 years. In view of earlier studies involving TELNET and FTP and of the new evidence reported in this paper on Web session characteristics, the origins of the large-time scaling phenomenon in measured WAN traffic are now well understood and are directly related to well known features of WAN traffic at the application layer. As a result, we fully expect future WAN traffic to exhibit this same feature – unless we are in for dramatic changes (such as extreme schemes for pricing Internet traffic, or radically different transport protocols). We also identify and quantify here a small-time scaling property of modern-day WAN traffic which is distinctly different from the large-time scaling behavior and is less pronounced in pre-Web WAN traffic. On an intuitive level, there is agreement that much of this small-time scaling phenomenon must be due to “real life” TCP dynamics; however, we currently do not have a good understanding of the physics behind this phenomenon, which, in turn, makes it difficult to predict whether or not future WAN traffic will have these same (or similar) small-time scaling properties. As a third result of our study of measured WAN traffic, we confirm a recently observed new scaling phenomenon of WAN traffic at the TCP level where the process in question are TCP connections. In particular, we find the process representing the number of TCP connection arrival per seconds to be self-similar (i.e., to have non-trivial scaling across all scales larger than 1 second), and we observe that this scaling phenomenon has appeared gradually as the amount of Web traffic has increased over the past 3–4 years. Combining

information that is generally hard to get access to, we also provide a plausible physical explanation of the observed TCP-layer self-similarity (i.e., an  $M/G/\infty$ -construction at the TCP layer, where every session brings with it a heavy-tailed number of TCP connections) and validate it against measured WAN traffic.

Currently considered structural modeling approaches for WAN traffic, especially two constructions due to Cox and Kurtz, respectively, are well-suited to explain the large-time scaling features in terms of the well-understood application layer traffic characteristic. However, in their current form, neither of these approaches are capable of explaining the small-time scaling properties, nor are they able to reproduce the self-similar nature of traffic at the TCP layer in an intrinsic and natural manner. The most promising of the current approaches appears to be Kurtz’s construction, mainly because in its general form, it allows for the possibility of very general “within-session” packet arrival patterns, and because to date, the limiting regime (i.e., aggregation over many sessions) is only known for a very special cases, all of which can only account for large-time scaling properties. The challenge is to incorporate a more “network-centered” view of traffic modeling into Kurtz’s construction (as opposed to further pursuing the traditional “source-centered” approach; see Section 3.2), so as to better account for the impact that the network has on the sources.

One plausible way of making Kurtz’s construction more network-oriented – without getting into the details of how the different protocol at the different layers in the networking hierarchy work and interact with one another – is to view WANs or other networks, together with their protocols and controls, as defining the deterministic mechanisms and rules of a process that fragments units of information at one layer into smaller units at the next layer etc. That is, networks act as *cascades* by fragmenting, for example, a Web session into a number of TCP connections (determined by the HTTP protocol) which, in turn, are further fragmented into several HTTP requests (the mechanism for this is provided by the HTTP protocol) which, in turn, are fragmented into IP flows, and so on. Note that during this fragmentation process, the total number of information units (in our example, this would be the total number of bytes transmitted during the Web-session) remains essentially preserved and hence, the cascade analogy is appropriate.

Cascades are an important paradigm in the theory of *multifractals* as they can account for many multifractal or self-similar measures; that is, measures with a nontrivial multifractal structure (for an overview, definitions and properties of multifractals, see for example Holley and Waymire [9] and Evertsz and Mandelbrot [5]). Although the multifractal approach to understanding and describing network traffic appears to be a radical departure from the more conventional structural traffic modeling approaches pursued to date, there exists a close link between Kurtz’s construction and random cascade models: simply allow the  $Y$ -process that defines the “within-session” traffic patterns (see Section 1 or consult [11]) to be a multifractal measure, generated via an appropriately defined random cascade model. Moreover, there already exists empirical evidence in favor of non-trivial multifractal properties of measured WAN TCP traffic – see the recent work by Riedi and Levy-Vehel [15]. Although multifractals and random cascade models are new traffic modeling paradigms, the motivation for studying them in the network context comes directly from the desire for physically meaningful descriptions of empirically observed phenomena in measured network traffic. In view of the already existing empirical evidence, these new modeling paradigms

are more than speculation and offer unique opportunities for studying challenging new mathematical and statistical problems. At the same time they point towards new ways of understanding and describing real-world network traffic, resulting in new engineering insights that can be expected to be of practical relevance for a wide range of network engineering tasks.

## Acknowledgments

Many of the traces considered in this paper were collected using the *tcpdump* packet capture tool developed by V. Jacobson, C. Leres and S. McCanne and available via anonymous ftp to [ftp. ee. lbl. gov](ftp://ee.lbl.gov). To extract TCP connection information from the traces, we relied on V. Paxson's *tcp-conn* and/or *tcp-reduce* tools, both of which are available from <http://ita. ee. lbl. gov/ index. html>.

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Anja Feldmann, Anna C. Gilbert, Walter Willinger  
 AT&T Labs-Research  
 Florham Park, NJ 07932-0971, USA  
*Email:* {anja, agilbert, walter}@research.att.com

Thomas G. Kurtz  
 Center for the Mathematical Sciences  
 University of Wisconsin at Madison  
 Madison, WI 53717  
*Email:* kurtz@math.wisc.edu