Characteristic of Internet Traffic with Respect to Long-Range Dependence

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Abstract

Nowadays network traffic has been modeled as self-similar process and identified as long-range dependence (LRD) in large time scales compared with the Poisson process around ten years ago. In our project, we employ the WIDE backbone traces and try to demonstrate the existence of LRD in large time scales. The data we use here include two-day trace files, as well as the aggregated traffic over the last four years. We examine various statistics characteristics of the original network traces, including auto-correlation function, cross-correlation function, as well as the evaluation of differrent Hurst estimators. In order to eliminate the effect of short-range dependence, we also apply to the trace files with internal shuffling buckets. After numerous statistical data analysis of the result from the experiments, we show that LRD does exist in WIDE daily traces at large time scales. Since the non-consistent estimations for Hurst exponent from different methods have been shown in our results, we believe that it is unreliable to use only one or several estimators to verify the existence of long-range memory. At the end of the report, we propose some future work.

1 Introduction

When modeling the network traffic, the commonly assumed model for packet and connection arrivals has been Poisson process for a long time in community. Its theoretical properties have been widely accepted [1]. Poisson process states that the packet arrival process is memory-less and interarrival times follow the exponential distribution [2].

Following the Poisson process, the traffic would have a characteristics burst length, which would tend to be smoothed by averaging over a long enough time scale. However, in [3], measurements of Ethernet network traffic indicate that significant traffic burstiness is present on a wide range of time scales. The authors demonstrate that the network traffic is statistically self-similar and the burstiness of traffic typically intensifies as the number of active traffic sources increases using the degree of self-similarity (measured in *Hurst estimator* H to denote the overall utilization of the Ethernet).

One year after the self-similarity characteristics of network traffic have been established, [4] shows the wide-area traffic is much burstier than Poisson models predicting over many time scales.

Thus, its correlation function persists across large time scales, which is called *long-range dependence* (LRD). The simplest models with LRD are self-similar process, which are characterized by hyperbolically decaying *autocorrelation functions* (ACF). From the experiment, author also states that even if the finite arrival process derived from a particular packet trace does not appear self-similar, if it exhibits large-scale correlations suggestive of long-range dependence, that process is almost certainly better approximated using a self-similar process than using Poisson processes.

The reason why self-similar process is a particular attractive model is because a single estimator can characterize the long-range dependence, as I mentioned above, Hurst exponent (H). We can infer that LRD characterizes a time series of network traffic if $0.5 < H < 1$. As $H \rightarrow 1$, the dependence is stronger [3]. However, identifying LRD is far from straightforward. Firstly, the Hurst exponent can't be calculated in a definitive systematic way, it can only be estimated as a scalar. Second, although there are several different methods to estimate it, they often produce conflicting and misleading estimates [2].

Despite the overwhelming evidence of LRD's presence in network traffic, a few findings indicate that Poisson models and independence could still be applicable as the number of sources increases in fast backbone links that carry vast numbers of distinct flows, leading to large volumes of traffic multiplexing [5]. In addition, other studies [6] point out that several end-to-end network properties seem to agree with the independence assumptions in the presence of nonstationarity (that is, statistical properties vary with time).

Due to the tremendous growth of the Internet backbone in recent years, in [7] author reexamines the Poisson traffic assumption and shows the coexistence of Poisson distributions and long-range dependence in traces from WIDE backbones. Internet arrivals show three different situations as below: 1) they appear Poisson at sub-second time scales. Packet sizes and interarrival times appear uncorrelated. 2) They appear nonstationary at multi-second time scales. The traffic oscillates around a global mean, in a piecewise linear manner. 3) They appear long-range dependence at scales of seconds and above. Here, author challenges the trend of abandoning Poisson process completely and draws the community's attention back to the different traffic modeling according to different time scales.

In our project, we use network WIDE backbone trace to demonstrate whether LRD exists in large time scale. We particularly adopt the traces on Nov. 04 and Nov.05, 2004, as well as the aggregated traffic from Jan. 01, 2001 to Nov. 19, 2004. Here, we use the software package SELFIS (publicly distributed at www.cs.ucr.edu/ tkarag) [8] to do the experiments below.

In order to demonstrate the existence of LRD for the independence of packet sizes and interarrival times of the traffic trace, we apply various experiments including auto-correlation function (ACF), cross-correlation function (XCF), as well as the evaluation of Hurst estimator. While computing the ACF, we employ the normal trace files for two days, the aggregated traffic for four years, as well as the trace files with internal shuffling buckets (bucket size = 10, 50, 100) to eliminate the effect of short-range dependence. During the evaluation of Hurst estimator, we divide the traffic series by 20ms time intervals from 20ms to 500 ms and apply seven different estimators for those divided series to estimate the value of H. We also employ randomized series with internal shuffling buckets (bucket size = 10, 30, 50, 70, 100) for the evaluation of H. From the experiments above, we demonstrate that the LRD do exist in our daily trace.

The rest of this report is structured as follows: Section 2 gives a brief description of self-similarity and long-range dependence. Section 3 describes the data for experiments. Section 4

presents the detailed experimental procedure as well as the result analysis. Section 5 concludes the paper and expresses the future work.

2 Definition

Before deducting our analysis on daily network trace files from the WIDE backbone archives, we first briefly describe the concept on *self-similarity* and *long-range dependence* in the context of time-series analysis. Please refer to [9] and [10] for detailed discussion of self-similarity, long-range dependence and the corresponding statistical tests. In a more vigorous sense, self-similarity and long-range dependence are not equivalent to each other though they are often used interchangeably in the literature.

2.1 Self-Similarity in Internet Traffic

Self-similarity describes the phenomenon where certain properties are preserved irrespective of scaling in space or time. Let $X(t)$ be a stochastic process. In some cases, X can take the form of a discrete time series $\{X_t\}$, $t = 0, 1, ..., N$, either by periodic sampling or averaging its value across a series, which is of fixed length intervals. We say that $X(t)$ is stationary if its joint distribution across a collection of times $t_1, ..., t_N$ is invariant to time shifting. We may give the definition of self-similarity over the mathematically more convenient definition of a self-similar continuous-time stochastic process $X = (X_t : t \geq 0)$ with stationary increments, namely, for all $a > 0$, $X(at) = a^H X(t)$, where equality is understood in the sense of equality of the finite-dimensional distributions, and the exponent H is the self-similarity parameter, namely the *Hurst Exponent*.

Of interest to network traffic processes is second-order self-similarity. Second-order self-similarity describes the property that the correlation structure of a time-series is preserved irrespective of time aggregation. This correlation is captured by the *autocorrelation function* (ACF), which is $\rho(k)$. The ACF measures the similarity between a series X_t and a shifted version of itself X_{t+k}.

$$\rho(k) = \frac{E[(X_t - \mu)(X_{t+k} - \mu)]}{\sigma^2}$$

where μ, σ are the sample mean and standard deviation respectively.

Simply put, a second-order self-similar time series ACF is the same for either coarse or fine time scales. A stationary process X_t is second-order self-similar if

$$\rho(k) = \frac{1}{2}[(k+1)^{2H} - 2k^{2H} + (k-1)^{2H})$$

$$(0.5 < H < 1)$$

and asymptotically exactly self-similar if

$$\lim_{k \to \infty} \rho(k) = \frac{1}{2}[(k+1)^{2H} - 2k^{2H} + (k-1)^{2H})$$

$$(0.5 < H < 1)$$

2.2 Long-range dependence

Long-range dependence (LRD)measures the memory of a process. Intuitively, distant events in time are correlated. If the ACF decays hyperbolically to zero, that is , then we say the process is long-range dependent. The strength of the long-range dependence is quantified by the Hurst exponent (H). A series exhibits LRD when $0.5 < H < 1$. Furthermore, the closer H is to 1, the stronger the dependence of the process is.

Another way to characterize long-range dependence is to study the properties of the aggregated process $X_{(m)}(k)$ which is defined as follows:

$$X^{(m)} = \frac{1}{m} \sum_{i=(k-1)m+1}^{km} X_i$$

$$k = 1, \cdots, [\frac{N}{M}]$$

Intuitively, $\{X^{(m)}(k)\}$ describes the average value of the time series across windows of m consecutive values from the original time series. If $\{X^{(m)}(k)\}$ were independent and identically distributed, then $Var(X^{(m)}) = \frac{\sigma^2}{m}$. However, if the sequence exhibits long memory, then the aggregated process s variance converges to zero at a much slower rate than $\frac{1}{m^2}$.

Second-order self-similarity usually implies long-range dependence (i.e., nonsummable ACF), but the reverse is not necessarily true. In addition, not all self-similar processes are long-range dependent (e.g., Brownian motion).

3 Data description

The data in our study comes from the WIDE (*Widely Integrated Distributed Environment*) project, which monitors Internet traffic between USA and Japan. The daily network trace is taken for several consecutive years from the WIDE backbone maintained by the MAWI Working Group Traffic Archive and the WIDE project.

Traffic traces are captured in a trans-Pacific line (18Mbps CAR on 100Mbps link). They are 15-minute traces taken daily at 14:00 local time (JST). We use the daily network traces from Dec. 2000 to Nov. 2004 to analyze the aggregated behavior of the traffic. Specifically, we also examine the backbone traces captured on 11/04/2004 and 11/05/2004. Table 1 shows some specific details about the data on these days, such as Total Packets, Total Bytes, AvgRate, NO. of flows per second, TCP bytes (packets) and UDP bytes (packets) in 15 minutes every day.

The traces are in the *tcpdump* raw format so that all header information is available and can be used for detailed analysis. *Tcpdump* [11] is the most popular packet-capturing tool in the UNIX community. It is based on a powerful filtering mechanism called BSD packet filter (BPF) [12]. The packet capturing and filtering facilities of *tcpdump* are implemented in separate library, *pcap* [13]. In the tcpdump file, user private data is removed from traces. Traffic traces have only protocol headers. Protocol payload which contains user data should be removed. Besides, IP address, which is unique and can be used to identify a user, is scrambled to provide anonymity to users. We use tcpdump to obtain traffic traces because tcpdump is widely used, and installed as part of the

Table 1: Summary of the WIDE backbone traces used in section 4

	11-04-2004 (14:00-14:15, JST)	11-05-2004 (14:00-14:15)
Bytes	2774.33MB	2293.26MB
Packets	6892509	5590762
Bytes/packet	422.07	430.11
AvgRate	25.86Mbps	21.38Mbps
TCP bytes/packets(%)	92.35 (84.56)	93.02 (86.41)
UDP bytes/packets(%)	7.08 (11.43)	6.43 (10.03)

default tools on many systems. In addition, there are many tools that integrate the pcap library and be able to read tcpdump output files. Those tools include tcptrace, tcpslice, tcpdstat and ttt.

In the protocol breakdown, we can see that the TCP is dominant in the traffic trace, about 93% of the total packets and 85% of the total bytes. While UDP accounts for approximately 11% in packets and 7% in bytes.

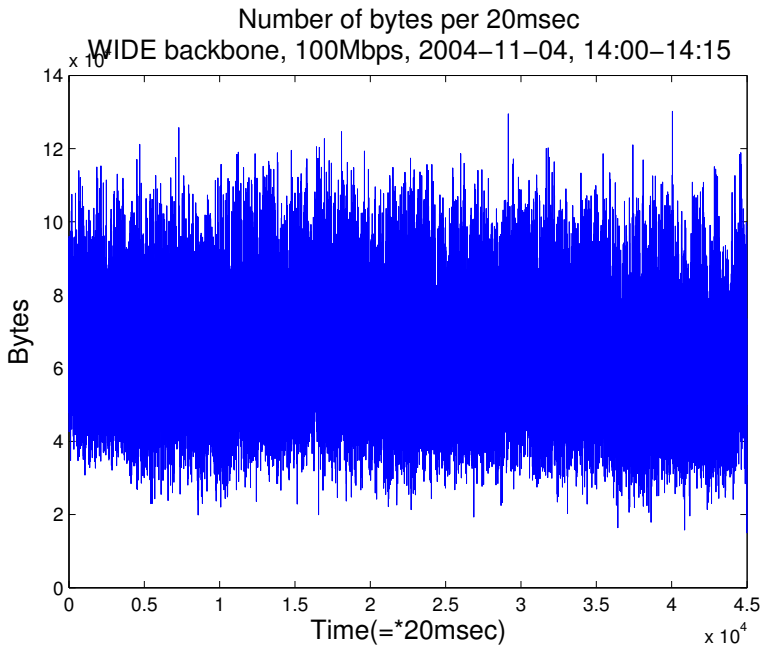
4 Analysis

In order to examine the independence of the packet sizes and interarrival times of the WIDE traffic trace, we use various tests as following. First, we calculate the auto-correlation (ACF) of the traffic traces for 11/04/2004 and 11/05/2004 respectively, and observe how they decay. Next, we compare these two traffic trace files by using the cross-correlation (XCF) functions to detect their possible similarity. In order to quantify the self-similarity property, the Hurst exponent value is estimated in several ways. Finally, to further ensure the existence of long-range dependence, we employ the original traffic traces with internal shuffling of different bucket sizes. With the randomized data, we repeat the same analysis methods and compare these results with those done before.

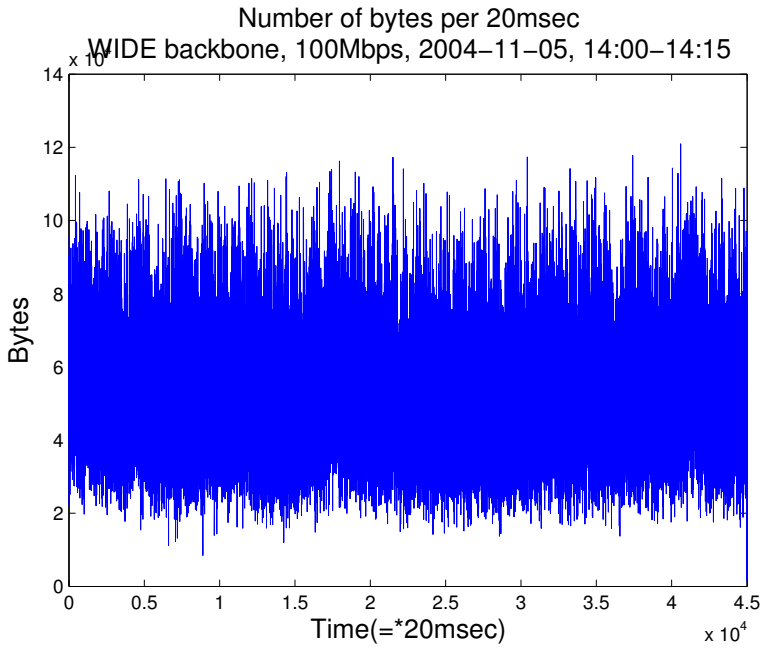
4.1 Autocorrelation Function and Cross-correlation Function

For the 15-minute network trace on 11/04/2004 and 11/05/2004, we calculate the accumulative traffic by counting the total bytes arrived during every 20ms interval. Figure 1 (a), (b) represents a sequence of simple plots of the byte count for 45,000 consecutive samples over a 15-minute window for two days respectively. In order to eliminate the difference between the busy hour and the low hour, we analyze the data which is in the same fifteen minutes during the daytime over 4 years. We calculate the total traffic during 15-minute interval (14:00-14:15 JST) daily, from 01/01/2001 to 11/19/2004. Figure 2(a) depicts the sequence of plots of the total byte counts for 1383 samples during this 15-minute interval over 4-year period. From the three per-interval graphs which show the original traffic data, we can only see that the byte count during consecutive intervals varies chaotically.

In order to examine the existence of long-range dependence in our sampled traces, first we calculate auto-correlation (ACF) for the two 15-min traces and aggregate traffic trace. As shown in Figure 3, plot (a), (b) presents the autocorrelation functions calculated for the byte counts per

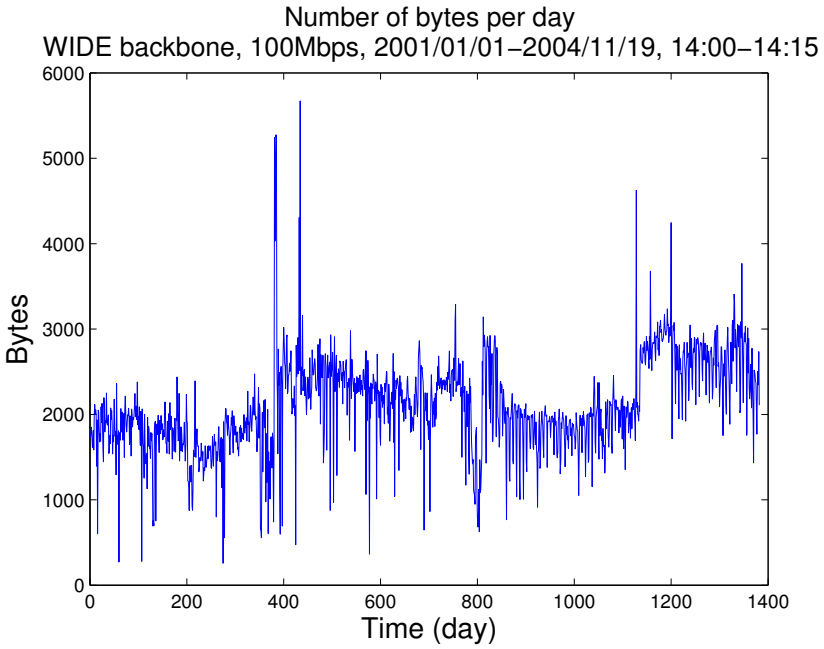


(a) 2004-11-04

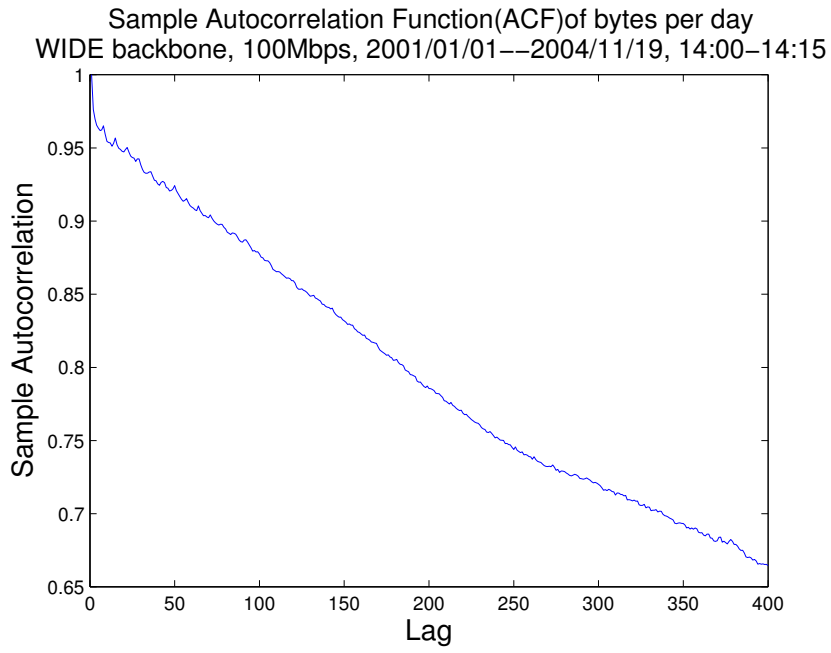


(b) 2004-11-05

Figure 1: **Traffic byte count per time unit (20msec) from the 15-minute network trace.**



(a) Aggregated Traffic



(b) Autocorrelation Function

Figure 2: **Aggregated Traffic : (a) shows the daily byte count for the total traffic arrived in 15 minutes over a four-year period (1383 samples). (b) The ACF calculated for aggregated traffic, which also shows the power-law behavior.**

20mec from 14:00-14:15 on 11/04/2004 and 11/05/2004, respectively. Similarly, in Figure 2, plot (b) represents the autocorrelation function calculated for aggregated traffic, which are byte counts of total packet arrival in 15 minutes every day from 01/01/2000 to 11/19/2004. There is a 24-hour difference between two adjacent intervals.

The correlation structure of a time-series is preserved irrespective of time aggregation. This correlation is captured by the autocorrelation function (ACF), which measures the similarity between a series X_t, and a shifted version of itself, X_{t+k}. Both of two ACF curves in Figure 3 have a heavy-tail shape: as time lags increase, the normalized ACF value stay above 0.9 and does not converge to zero. The ACF curve in 2 (b) also shows power-law like behavior. Besides, we can see that their power-law behavior is similar to each other, both in small lags and in large lags. The figures show that the autocorrelation function (ACF) of the series decays hyperbolically to zero and implies long-range dependence.

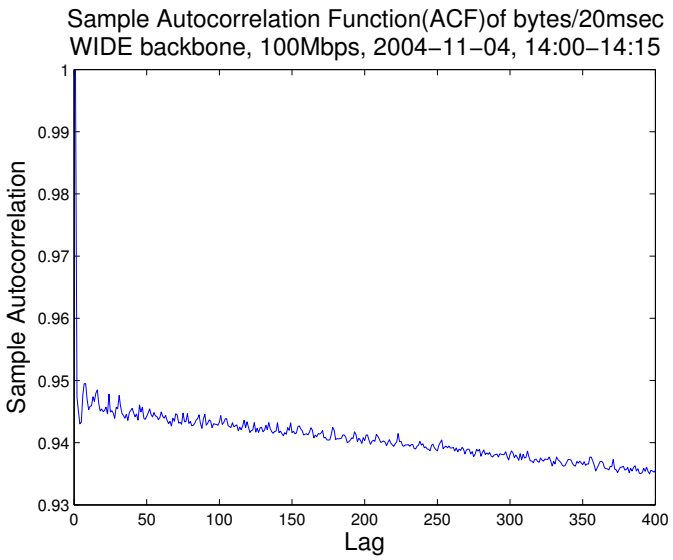
To determine the similarity between the traffic traces taken on different days, we also calculate the cross-correlation function using these traces from 11/04/2004 and 11/05/2004 as inputs. In Figure 4, the cross-correlation value is always above 0.99 over the 400 lags, which further indicates that the traffic flow in the 15 minutes of the two days correlate to each other and the self-similarity property of the network traffic.

We apply internal shuffling mechanism to our original data with random buckets. The idea behind randomized buckets is to decouple the short-range from long-range correlations in a series to facilitate the study of the effects of long range dependence [14]. This is achieved through partitioning the time series into a set of buckets of length b. Thus, we define the contents of the uth bucket to be items $X_{ub}, \cdots, X_{(u+1)b-1}$ from the series, and the home of item X_i to be bucket . Also, we say that two items (X_i, X_j) form an inbucket pair if $H(i) = H(j)$; otherwise, they form an outbucket pair with an offset of $\mid H(i) - H(j) \mid$ buckets. For the network trace taken on 11/04/2004, we randomize it with different bucket sizes (10, 30, 50, 70, 100). As shown in Figure 5 we also draw the ACF curves for each randomized series with bucket size 10, 50, 100 respectively. Compared with the ACF curve for original series in Figure 3, we find internal randomization almost has no effect on the behavior of ACF: these four curves are almost the same with each other. The ACF curves show the same power-law behavior as the original series. Since the effect of equalizing the inbucket correlations on ACF is minimal, we can further verify that long-range dependence dominates the original series.

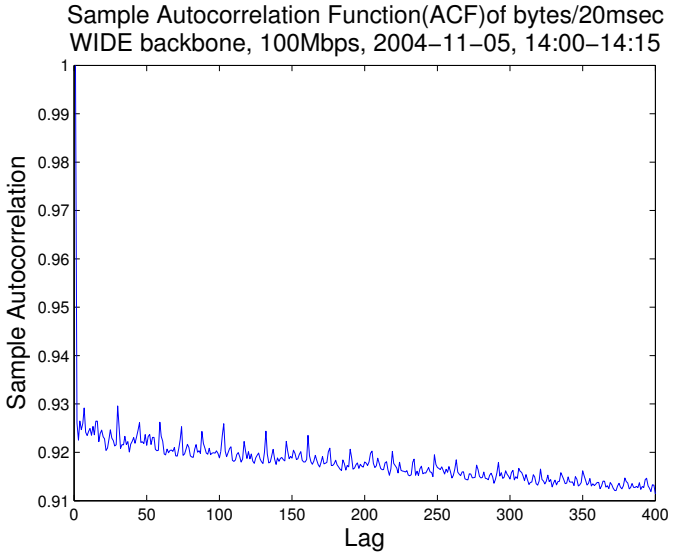
4.2 Hurst Exponent Estimators

As we have described in Section 2, the Hurst exponent can be used to quantify the strength of the long-range dependence. But there is no definitive way to calculate the value of H exponent, they can only be estimated. These estimators can be classified into two main categories: time-domain based and frequency-domain based [14]. Time-domain methodology are based on examining the power-law relationship between a specific statistic of the time-series and the aggregation block m, which includes *Absolute method*, *Aggregate Variance method*, *R/S method* and *Variance of Residual*. Other estimators, such as *Periodogram method*, *Whittle estimator* and *Abry-Veitch*, operate in the frequency or the wavelet domain. [9] provides a general overview of Hurst exponent estimation methods.

It is not suggested that relying on single estimator to justify the long-range dependence [14].



(a) ACF: 2004-11-04



(b) ACF: 2004-11-05

Figure 3: **Autocorrelation Function: (a) The ACF calculated for the byte count per 20mec from 14:00-14:15 on 11/04/2004. (b) The ACF calculated for the byte counts per 20mec from 14:00-14:15 on 11/05/2004. Both (a) and (b) show the similar power-law behavior and both decay to zero hyperbolically.**

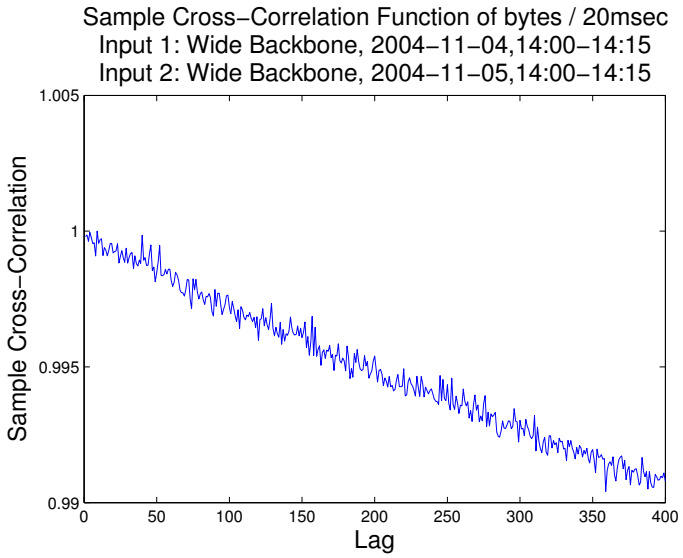


Figure 4: **Cross-Correlation Function, using the traces from 11/04/2004 and 11/05/2004 as inputs. It shows the similarity between the network traffic taken on two differrent days.**

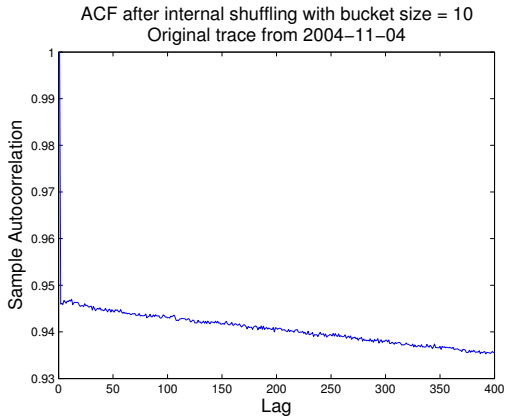
Table 2: H estimators for aggregated traffic(from 01/01/2001 to 11/19/2004)

AV	R/S	Periodogram	Absolute	Variance of Residual	Abry Veitch	Whittle
0.807	0.446	0.774	0.299	1.011	0.901	0.812

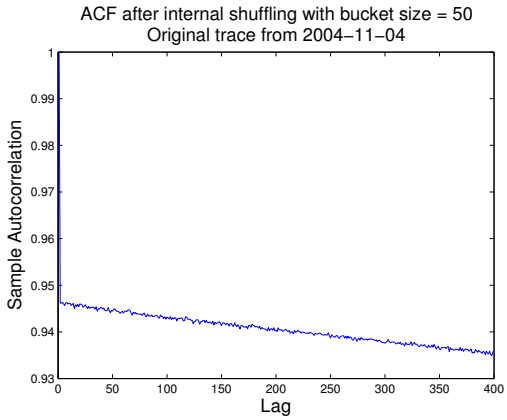
In this project, we use SELFIS tool to estimate the value of Hurst exponent of network trace series. To obtain a higher accuracy in verifying the possible existence of long-range dependence, we apply all the estimators implemented in SELFIS.

For each day's traffic trace, we produce sample series at different time intervals, from 20ms to 500ms. In fig 6 a) and fig 6 b), we calculate the value of H estimator at different time scales for each sample series, using the methodologies described above. The X axis represents time scales and the Y axis shows the value of H estimator. We also calculate the H estimator values for the aggregated traffic, as shown in table 2. By comparing the H estimator values for two different series taken on 11/04/2004 and 11/05/2004 respectively, we find the all the estimators have quite similar trend on different day, and they are compatible with the value calculated for the aggregated traffic as shown in table 2.

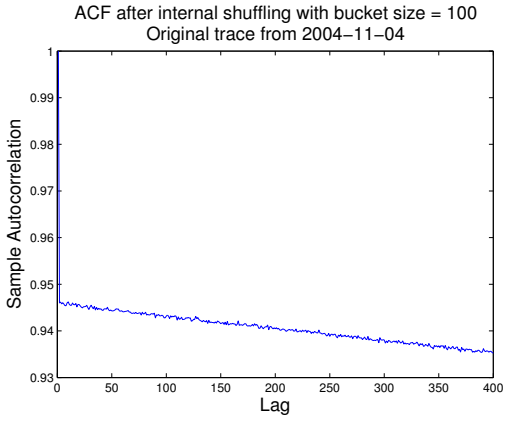
Clearly we can also see non-consistent estimations from different methodologies: some of the H estimators show the long-range dependence and others not. We find that the scaling behavior of *Periodogram method*, *Whittle estimator*, *Variance of Residual* and *Abry-Veitch* follow the similar pattern: start from 0.6 at smaller time scales and smoothly increase to 0.8 at larger time scales, and we conclude that these four H estimators can provide sufficient estimations in our case. The value of *Aggregate Variance* estimator fluctuates a little, but it's always above 0.5. As for *Absolute* and *R/S* estimators, their behavior are quite different from others: *R/S* estimator begins at approximately 0.6 and decreases as time scales become larger, and the *Absolute* estimator is generally



(a) ACF: bucket size $b = 10$



(b) ACF: bucket size $b = 50$



(c) ACF: bucket size $b = 100$

Figure 5: **Internal randomization with different bucket sizes = 10, 50, 100 : we can see that internal shuffling almost has no effect on the behavior of ACF: the three curves are almost the same as the original ACF curve of the same day(11/04/2004). It further verifies that long-range dependece dominates the original series.**

below 0.4 and even decrease to zero at some points. To this point, we can not deny the accuracy and robustness of the last three estimators, because each estimator relies on different statistics (e.g. power spectrum, variance) of the signal to detect the existence of long-range dependence [15]. The other possible reason for this inconsistence is that the number of samples decrease as time scale becomes larger, thus resulting in loss of statistics certainties.

Because most estimators can report the H exponent value to be greater than 0.5, we can defer the existence of long-range dependence in these two day-pair's traces. Try to eliminate the effect of short-range dependence on these estimators, we randomize the original series with internal shuffling buckets. Intuitively, internal bucket randomization can break the short-range correlation, while preserve the long-range dependence character. So, if the original signal do show long-range memory, the estimator values should not be affected even after applying internal randomizations which destroy only the short-rangecorrelations. We apply to the original series of 2004-11-04 with buckets of various sizes ($b = 10, 30, 50, 70, 100$). As we can see in fig 7, the X axis presents different bucket size b, and the Y axis shows the estimated H value. In this graph, we only choose five estimators whose values for original series are above 0.5, because only When $b = 1$, that is, no shuffling at all, the estimated H values for initial series are revealed. Generally speaking, all the five estimation of H exponent look stable as expected. In particular, Variance of Residual, Abry Veitch and Whittle estimators do not seem to be affected by the internal randomization irrespective of the different bucket size. However, Periodogram estimator drops 0.07 as the bucket size increases. At this point, based on the behavior of all the estimators, we can tell that long-range dependence exists in our daily trace taken from WIDE backbone trace.

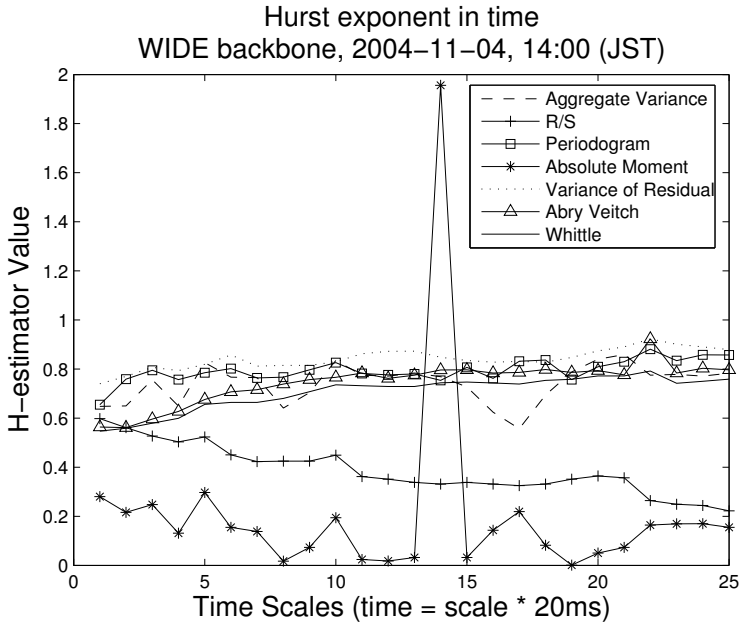
5 Conclusion and future work

The main purpose of this project is to demonstrate the existence of long-range dependence in the large time scales. Using the SELFIS tool, we analyze recent two-day trace files from WIDE backbone as well as the aggregated traffic in the past four years. We apply multiple experiments including auto-correlation function curves of two days' traffic, cross-correlation function between those two, as well as the evaluation of Hurst estimator by seven different methods. Besides the normal interval series, we also employ the trace files with internal shuffling buckets mechanisms to eliminate the effect of short-range dependence of traffic.

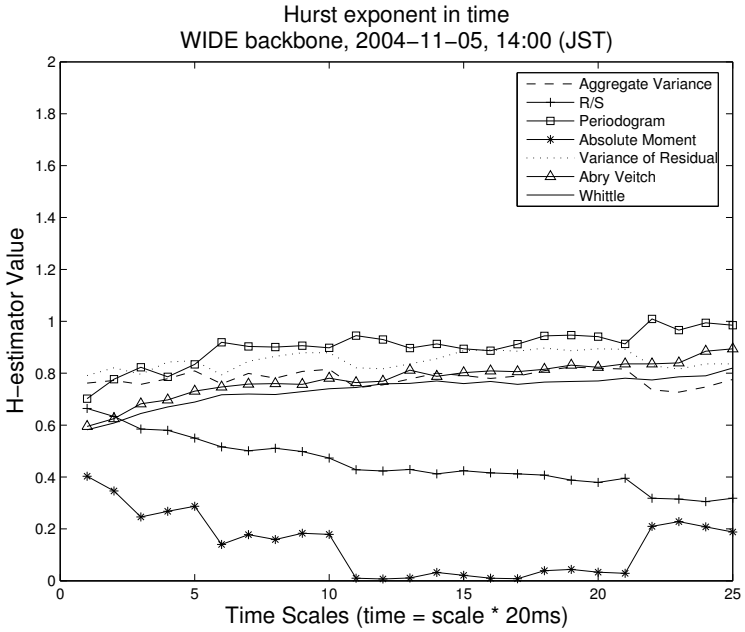
From our experiments of tremendous statistical data analysis, we draw the conclusion for the following points: (1) WIDE backbone trace is statistically self-similar and long range dependent in large time intervals. (2) The self-similarity characteristics of network traffic can be scaled in Hurst estimator. Due to the non-consistent estimators for different methods shown in our experiments, however, we can't reply on one or several methods to decide the existence of LRD. Some of estimators are optimistic but some of them are deceived by trend and periodicity.

Since we have observed the non-consistent estimators for different methodologies here, we realize that different estimators reveal distinctive statisctical characteristics. Therefore, they can predict H vulue correctly only under certain circumstances. In the future, we can explore the most suitable scenarios they can be applied.

In our project, we have applied the internal shuffling buckets mechanism to eliminate the impact of short-range dependence. We can try to find some other adoptable methods to better evidence



(a) 2004-11-04



(b) 2004-11-05

Figure 6: **Scaling behavior of Hurst exponent estimators: The Hurst values estimated by various estimators at different time scales (20ms, 40ms,...,500ms). The estimators have quite similar trend for traces taken on two differrent days. Most of the H estimators have values greater than 0.5, which verify the existence of long-range dependence, but some others (Aggregate Variance, Absolute and R/S estimators) don't.**

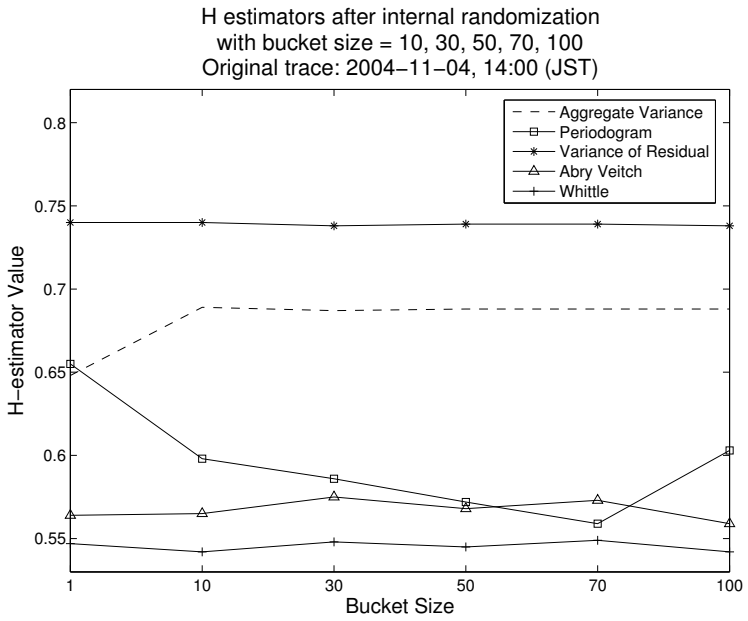


Figure 7: **H estimators after internal bucket shuffling with various buckets sizes (10, 30, 50, 70, 100). All the five estimations of H exponent look stable as expected. In particular, Variance of Residual, Abry Veitch and Whittle estimators do not seem to be affected by the internal randomization irrespective of the differrent bucket size. However, Periodogram estimator drops 0.07 as the bucket size increases. As a special case, bucket size $b = 1$ represent the original trace.**

the existence of LRD afterwards.

Due to the limited time, we only use WIDE backbone traces in our study, in which all the daily traces are of 15-min length. It is far from enough to further reveal the statistics properties of traffic. In the future, we can observe different kinds of backbone traffic and examine a much longer network trace intervals (maybe 24 hours) to discover the characteristics of the network traffic. Moreover, we are interested in extending our analysis to network traces on access links, more specifically, on mobile and wireless networks later.

6 Acknowledgments

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