NORTHWESTERN
UNIVERSITY

Computer Science Department

Technical Report
NWU-CS-02-13
October 15, 2002

Multiscale Predictability of Network Traffic

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Abstract

Distributed applications use predictions of network traffic to sustain their performance by adapting their behavior. The timescale of interest is application-dependent and thus it is natural to ask how predictability depends on the resolution, or degree of smoothing, of the network traffic signal. To help answer this question we empirically study the one-step-ahead predictability, measured by the ratio of mean squared error to signal variance, of network traffic at different resolutions. A one-step-ahead prediction at a low resolution is a prediction of the average behavior over a long interval. We apply a wide range of linear time series models to a large number of packet traces, generating different resolution views of the traces through two methods: the simple binning approach used by several extant network measurement tools, and by wavelet-based approximations. The wavelet-based approach is a natural way to provide multiscale prediction to applications. We find that predictability seems to be highly situational in practice---it varies widely from trace to trace. Unexpectedly, predictability does not always increase as the signal is smoothed. Half of the time there is a "sweet spot" at which the ratio is minimized and predictability is clearly best. We conclude by describing plans for an online wavelet-based prediction system.

Effort sponsored by the National Science Foundation under Grants ANI-0093221, ACI-0112891, and EIA-0130869. The NLANR PMA traces are provided to the community by the National Laboratory for Applied Network Research under NSF Cooperative Agreement ANI-9807479. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation (NSF).}

Keywords: network traffic characterization, network traffic prediction, wavelet methods, multiscale methods

Multiscale Predictability of Network Traffic

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I. INTRODUCTION

The predictability of network traffic is of significant interest in many domains, including adaptive applications [6], [33], congestion control [22], [8], admission control [23], [11], [10], wireless [24], and network management [9]. Our own focus is on providing application-level performance queries to adaptive applications. For example, an application can ask the Running Time Advisor (RTA) system to predict, as a confidence interval, the running time of a given size task on a particular host [14]. We are trying to develop an analogous Message Transfer Time Advisor (MTTA) that, given two endpoints on an IP network, a message size, and a transport protocol, will return a confidence interval for the transfer time of the message. A key component of such a system is predicting the aggregate background traffic with which the message will have to compete. We model this traffic as a discrete-time *resource signal* representing bandwidth utilization. For example, a router might periodically announce the bandwidth utilization on a link.

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The timescale for prediction that a tool like the MTTA is interested in depends on the query posed to it. If the application wants to send a small message, the MTTA requires a short-range prediction of the signal, while for a large message the prediction must be long-range. However, the appropriate resolution of the signal varies with the query. A short-range query demands high resolution while a long-range query can make due with low resolution. Note that a one-step-ahead prediction of a low resolution signal corresponds to a long-range prediction in time.

To easily support this need for multi-resolution views of resource signals, we have proposed disseminating them using a wavelet domain representation [32]. A sensor would capture a one-dimensional signal at high resolution and apply an N-level streaming wavelet transform to it, generating N signals with exponentially decreasing resolutions and sample rates. Tools like the MTTA would then reconstruct the signal at the resolution they require by using a subset of the signals, consuming a minimal amount of network bandwidth to get an appropriate resolution view of the resource signal. We call this view a *wavelet approximation signal*.

In our scheme, the final signal an application receives is in effect an appropriately low-pass filtered version of the original signal. How close the filter is to an ideal low-pass depends on the nature of the wavelet basis function that is used. Interestingly, in currently available network monitoring systems like Remos [13] and the Network Weather Service [36] an analogous filtering step occurs in the form of binning. The signal is smoothed by reducing it to averages over non-overlapping bins, producing what we refer to as a *binning approximation signal*. For example, Remos's SNMP collector periodically queries a router about the number of bytes transfered on an interface and uses the difference between consecutive queries divided by the period as a measurement of the consumed bandwidth.

Given the context of the MTTA and these two methods, binning and wavelets, for producing approximations to resource signals that represent network traffic, what is the nature of the predictability of the signals and how does it depend on the degree of approximation? This paper reports on an empirical study that provides answers to these questions. The study is based on 180 short (90 second) and 34 long (one day) packet traces collected by the NLANR PMA system on WANs, and the well known Bellcore packet traces (2 hour-long LAN traces and 2 day-long WAN traces). In our presentation, we focus primarily on the 34 long NLANR traces, which we refer to as the AUCKLAND traces. Generally, the short NLANR traces tend to be difficult to predict, and, because they are short, the range of approximations we can make using binning and wavelets is very limited. The Bellcore traces, especially for the WAN, show a fair bit of predictability at different approximations.

Our methodology is simple. We generate a very high resolution view of a trace by binning the packets into very small bins. Then we produce an approximation using either the binning approach or the wavelet approach. We fit a linear time series model to the first half of the approximated trace and use it to produce one-step-ahead predictions for the second half. As we noted earlier, one-step-ahead predictions are sufficient in the context of the MTTA because as the timescale of prediction increases, the resolution can decrease. Our measure of predictability is the ratio of the mean squared error for the predictions to the variance of the second half of the signal. This is basically the "noise to signal" ratio of the predictor. The smaller the ratio, the better the predictability. We use a wide range of models, including the classical AR, MA, ARMA, and ARIMA models [7], fractional ARIMAs [20], [18] and simple models such as LAST and a windowed average. Our prediction tools are currently available as part of our RPS Toolbox [15]. [1]. Our Tsunami wavelet toolbox, which we describe further in Sections IV and V, will also soon be released.

The earliest work in predicting network traffic of which we are aware is that of Groschwitz and Polyzos who applied ARIMA models to predict the long-term (years) growth of traffic on the NSFNET backbone [19]. Basu, et al produced the first in-depth study of modeling FDDI, Ethernet LAN, and NSFNET entry/exit point traffic using ARIMA models [4]. As in our binning study, they binned packet traces into non-overlapping bins in order to produce a periodic time series to study. Our trace sets overlap slightly in that they also studied the Bellcore LAN traces. Leland, et al demonstrated that Ethernet traffic is self-similar [25], while Willinger, et al suggested a mechanism for this phenomenon [34]. The long-range dependence suggested by self-similarity suggests that fractional ARIMA models might be appropriate. On the other hand, You and Chandra found that traffic collected from a campus sight exhibited non-stationary and non-linear properties and studied modeling it using threshold autoregressive (TAR) models [37]. Wolski developed the first network measurement system that integrated prediction and found that running multiple predictors (mean, median, and AR models) simultaneously and forecasting with the one currently exhibiting the smallest prediction error produced the best results on his measurements [35].

Closest to the work described in this paper is that of Sang and Li [31], who analyzed the prospects for multi-step prediction of network traffic using ARMA and MMPP models. Their analysis is based on continuous time ARMA and MMPP models driven by Gaussian noise sources. Making the assumption that such models are appropriate, they then developed analytic expressions for how far into the future prediction was possible before errors would exceed a bound, and for how this limit was affected by traffic aggregation and smoothing of measurements. They found that both aggregation and smoothing monotonically increased predictability. They then fit such models to several traces and evaluated the resulting models' parameters and noise variances to determine the maximum prediction interval for the traces. Only their WAN traces could be predicted significantly into the future and then only after considerable smoothing.

We have reached the following conclusions from our study.

- Generalizations about the predictability of network traffic are very difficult to make. Network behavior can change considerably over time and space. Prediction should ideally be adaptive and it must present confidence information to the user.
- Aggregation appears to improve predictability. WAN traffic is generally more predictable than LAN traffic. In this we agree with the work of Sang and Li and with the results of the earlier studies.
- Smoothing often does not monotonically increase predictability. About 50% of the long traces in our study exhibit a "sweet spot," a degree of smoothing at which predictability is maximized, contradicting the work of Sang and Li. However, most of the remainder of the long traces show the monotonic increase with smoothing that Sang and Li claim.

[1] http://www.cs.northwestern.edu/∼RPS

• There are some differences in the predictability of wavelet-approximated and binning-approximated traces, although they are not large. Both approximation approaches are effective.

• There are clearly differences in the performance of different predictive models. An autoregressive component is clearly indicated, although it often is helpful to also have a moving average component and an integration. Fractional ARIMA models are effective, but do not warrant their high cost for prediction.

In the following, we first describe the traces on which our study is based. Next, we describe our results for predicting binning approximation signals. This is followed by a parallel presentation of our results for predicting wavelet approximation signals. Finally, we describe the structure of a multi-resolution prediction system and conclude.

II. Traces

Our study is based on the three sets of traces shown in Figure 1. The NLANR set consists of short period packet header traces chosen at random from among those collected by the Passive Measurement and Analysis (PMA) project at the National Laboratory for Applied Network Research (NLANR) [27]. The PMA project consists of a growing number of monitors located at aggregation points within high performance networks such as vBNS and Abilene. Each of the traces is approximately 90 seconds long and consists of WAN traffic packet headers from a particular interface at a particular PMA site. We randomly chose 180 NLANR traces provided by 13 different PMA sites. The traces were collected in the period April 02, 2002 to April 08, 2002. We have developed a hierarchical classification scheme for the traces based on their first and second order statistics. [2] In summary, we identified 12 classes. For the present study, we worked with 39 of the traces, covering each of the classes we identified.

The AUCKLAND set, which we focus on in detail in this paper, also comes from NLANR's PMA project. These traces are GPS-synchronized IP packet header traces captured with a DAG3 system at the University of Auckland's Internet uplink by the WAND research group between February and April 2001. These also represent aggregated WAN traffic, but here the durations for most of the traces are on the order of a whole day (86400 seconds). Our classification approach netted 8 classes here. For the present study, we chose 34 traces, collected from February 20, 2001 to March 10, 2001, which cover the different classes.

[2] A technical report on our classification scheme and classifications for all of the traces of Figure 1 will be forthcoming.

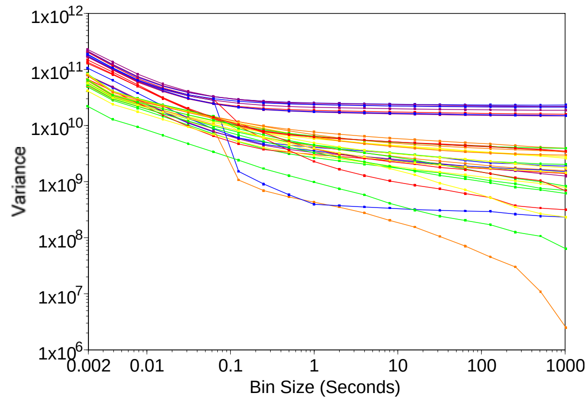

Fig. 2. Signal variance as a function of bin size for the AUCKLAND traces.

The BC set consists of the well known Bellcore packet traces [25] which are available from the Internet Traffic Archive [3]. There are four traces. Two of them are hour-long captures of packets on a LAN on August 29, 1989 and October 5, 1989, while the other two are day-long captures of WAN traffic to/from Bellcore on October 3, 1989 and October 10, 1989.

While the packet traces represent "ground truth" for prediction, the predictors that we study require discrete-time signals. To produce such a signal, we bin the packets into non-overlapping bins of a small size and average the sizes of the packets in a particular bin by the bin size. This result is an estimate of the instantaneous bandwidth usage that becomes more accurate as the bin size declines. It is important to note that as the bin size decreases the variance of the resulting signal increases. It is this variance that we are trying to model with a predictor. Figure 2 shows this effect for the 34 AUCKLAND traces. Notice that the graph is in on a log-log scale. The linear relationship and gradual slope we can see on the xgraph for bin sizes greater than 125 ms indicate that the traces are likely long-range dependent with a Hurst parameter near one [3] The more abrupt slope for smaller binsizes indicates that H declines in that region.

The linear time series models that we evaluate attempt to model the autocorrelation function (ACF) of a discrete-time signal in a small number of parameters. If there is no autocorrelation function, there is nothing to model and a linear approach is bound to fail. For this reason, we studied the autocorrelation functions of our traces in considerable detail at different bin sizes. For space reasons, we can not go into detail about this study here. Instead, we shall show representative ACFs from our three different trace sets to explain our choice of presenting detailed results for the AUCKLAND set. We show ACFs at a bin size of 125

[3] We will report in more detail in the future.

Name	Number of Raw Traces	Classes	Studied	Duration	Range of Resolutions
NLANR	180	12	39	90 s	1,2,4,...,1024 ms
AUCKLAND	34	8	34	1 d	0.125, 0.25, 0.5,..., 1024 s
BC	4	n/a	4	1 h, 1 d	7.8125 ms to 16 s

Fig. 1. Summary of the trace sets used in the study.

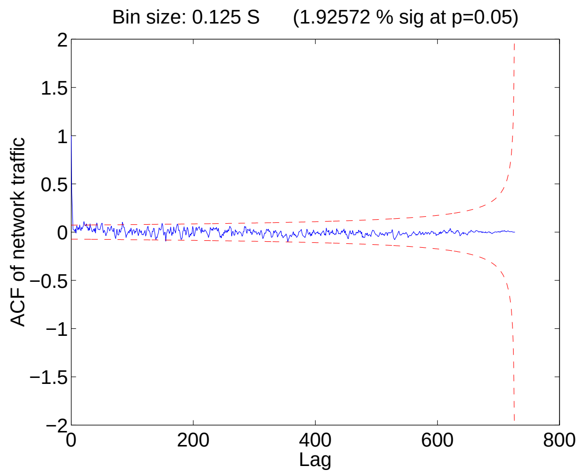

Fig. 3. Autocorrelation structure of an NLANR trace that is not predictable using linear models.

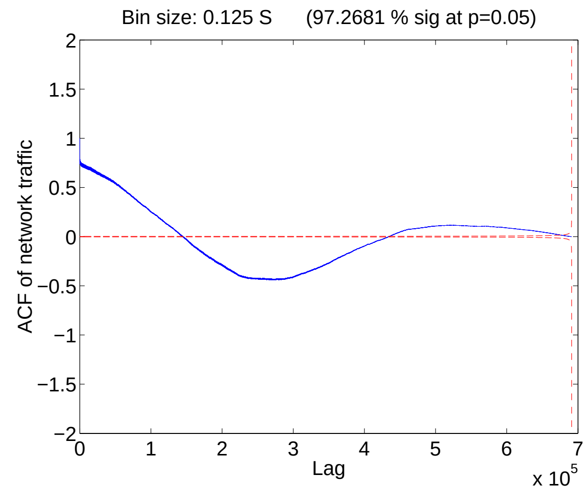

Fig. 4. Autocorrelation structure of an AUCKLAND trace that is likely to be very predictable using linear models.

ms for each trace.

Figure 3 shows the ACF of a representative NLANR trace. For any lag greater than zero, the ACF effectively disappears. This signal is clearly white noise and the prospects for predicting it using linear models are very dim. Only 2% of the autocorrelation coefficients rise to significance at a significance level (p-value) of 0.05. 80% of our NLANR traces exhibit this sort of behavior. For the other 20%, more than 5% of the autocorrelation coefficients are significant, but none are very strong. In these cases we can not claim that the signals are white noise, but it is likely that linear models will not do very well.

Figure 4 shows the ACF of a typical AUCKLAND trace. Obviously, the plot is quite different from what we have seen in the previous figure. Over 97% of the autocorrelation coefficients are not only significant, but quite strong. We can also see a low frequency oscillation, which is likely the diurnal pattern. We expect that such a trace will be quite predictable using linear models. 80% of the AUCKLAND traces have similar strong ACFs.

Figure 5 shows the ACF of a BC LAN trace. It is clearly not white noise, and yet it does not have the strong behavior of the AUCKLAND traces. We would expect that such a trace is predictable using linear models to some extent. All of the BC traces have similar ACFs that are suggestive of predictability.

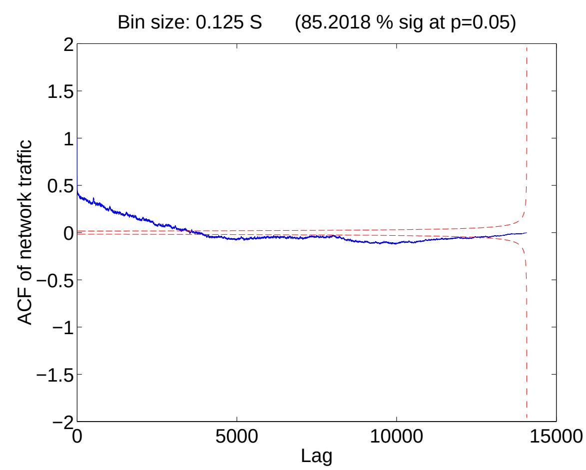

Fig. 5. Autocorrelation structure of a BC LAN trace.

Subsequent sections of the paper will mainly discuss the prediction of the AUCKLAND traces using linear time series models. We focus on these traces for three reasons. First, there is little hope for predicting the vast majority of the NLANR traces because of their disappearing ACFs. Second, the strength of the ACFs in the AUCKLAND traces allow us to focus on how predictability is affected by the resolution of the signal. Third, unlike the BC traces, the AUCKLAND traces are very long and we have many of them. This lets us consider a wide range of resolutions. We will, however, provide examples of the predictability of the NLANR and AUCKLAND traces for comparison.

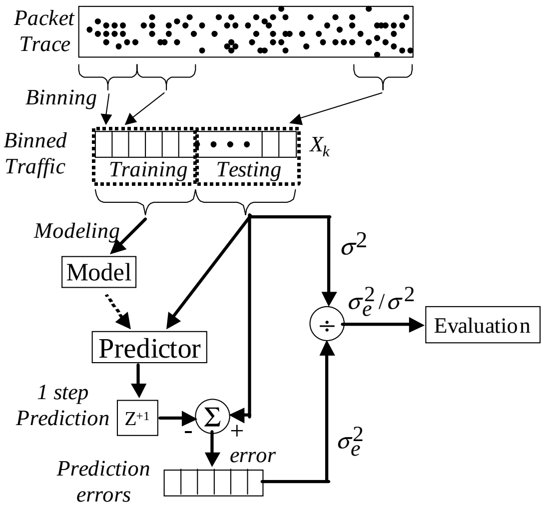

Fig. 6. Methodology of binning prediction.

III. Predictability of binning approximations

To create binning approximation signals in general, we simply bin the packet traces according to the chosen bin size. If we want to support a variety of bin sizes that are integer multiples, we can simply start with the smallest bin size and produce coarser approximations recursively.

Figure 6 illustrates our methodology for evaluating the predictability of a given packet trace at a given bin size. We slice the discrete-time signal produced from binning (X_k) in half. We fit a predictive model to the first half and create a prediction filter from it. We stream the data from the second half of the trace through the prediction filter to generate one-step-ahead predictions. We difference these predictions and the values they predict to produce an error signal. We then compute the ratio of the variance of this error signal (the MSE, σ_e^2) to the variance of the second half of the binning approximation signal (σ^2). The smaller this ratio, the better the predictability.

We evaluated the performance of the following models: MEAN, LAST, BM(32), MA(8), AR(8), AR(32), ARMA(4,4), ARIMA(4,1,4), ARIMA(4,2,4), and ARFIMA(4,-1,4). MEAN uses the long-term mean of the signal as a prediction. Its predictability ratio is typically 1.0 for obvious reasons. LAST simply uses the last observed value as the prediction for the next value. BM(32) predicts that the next value will be the average of some window of up to the 32 previous values. The size of the window is chosen to provide the best fit to the first half of the signal. MA(8) is a moving average model of order 8. AR(8) and AR(32) are autoregressive models of order 8 and 32, respectively. ARMA(4,4) is a model with 4 autoregressive parameters and 4 moving average parameters. ARIMA(4,1,4) and ARIMA(4,2,4) are once and twice integrated ARMA(4,4) models. Unlike the other models, they can capture a simple form of non-stationarity. The ARFIMA(4,-1,4) model is a "fractionally integrated" ARMA model that can capture the long-range dependence of self-similar signals. AR, MA, ARMA, and ARIMA models are classical time series models well covered by Box, et al [7]. ARFIMA models are well covered in more recent literature [20], [18], [5]. The RPS technical report [15] also provides an explanation of these models as well as a detailed description of the implementations we use here. The same implementations are used for offline and online analysis in RPS.

A. AUCKLAND traces

For each of the 34 AUCKLAND traces, we performed the analysis described above with each of the different predictors. We studied 14 different bin sizes: 0.125 s, 0.25 s, 0.5 s, 1 s, 2 s, 4 s, 8 s, 16 s, 32 s, 64 s, 128 s, 256 s, 512 s, and 1024 seconds. In the discussion that follows, we plot the predictability ratio versus bin size for all the predictors except MEAN. We have elided MEAN since the other predictors typically do much better and including MEAN makes it difficult to see how the other predictors stack up.

It is also important to note that some data points in the graphs are missing. Given enough data it is always possible to fit a model to a trace and glean an estimate of its predictive power from the quality of the fit. However, producing a predictor from the model and sending new data through it as we do often reveals that the model is not as good as the fit might imply. We have elided points in two cases. The first case is when the predictor became unstable as evidenced by a gigantic prediction error. This is sometimes the case with the ARIMA models, which are inherently unstable because they include integration. The second case is when there are insufficient points available to fit the model. This happens at large bin sizes for large models like the AR(32) and the ARFIMA(4,-1,4). Fewer than 5% of points have been elided and we have tried to make it obvious where this happens.

The characteristics of prediction on the AUCKLAND traces falls into three classes, representatives of which are shown in Figures 7 through 9.

The behavior of Figure 7 occurs in 15 of the 34 traces. The most interesting feature here is that the graph shows concavity for all predictors: we can clearly see a "sweet spot" for the traffic prediction. In other words, there is an optimal bin size around 32 seconds at which the trace is most predictable. As we noted in the introduction, this contradicts the conclusions of earlier papers. Because it occurs in half of the AUCKLAND traces, we do not believe that it is a coincidence. The location of the sweet

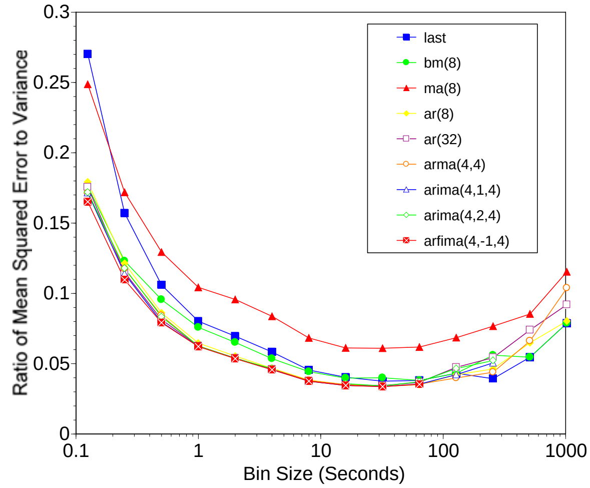

Fig. 7. Predictability ratio versus bin size of AUCKLAND trace 31 (20010309-020000-0).

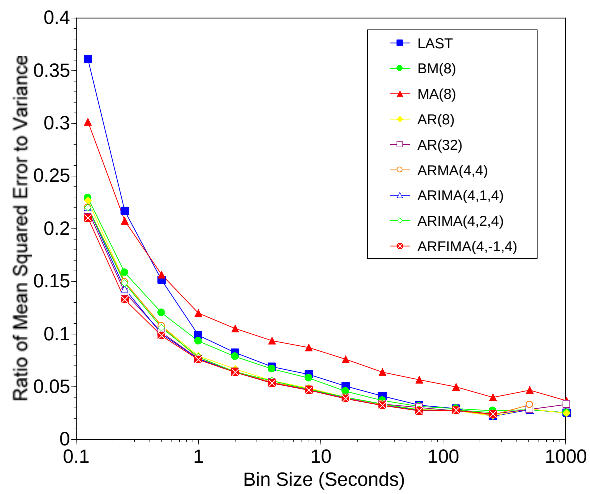

Fig. 8. Predictability ratio versus bin size of AUCKLAND trace 23 (20010305-020000-0).

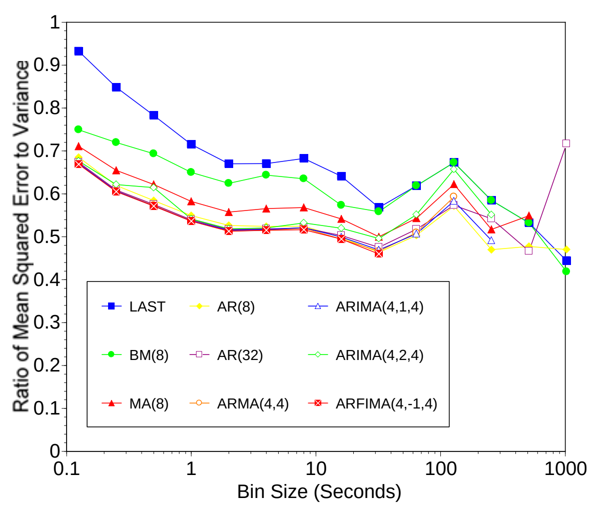

Fig. 9. Predictability ratio versus bin size of AUCKLAND trace 20 (20010303-020000-1).

spot varies from trace to trace. In some traces it occurs at quite small bin sizes, which suggests that it is not an artifact of the fact that we are fitting and predicting on smaller amounts of data as we increase bin size. It is clearly an artifact of the data itself.

The behavior of Figure 8 occurs in 14 of the 34 AUCKLAND traces and is commensurate with conclusions from earlier papers. There is no "sweet spot" here and it is clear that predictability converges to a high level with increasing bin size.

Both of these figures also show significant differences between the performance of the predictors. In general, it is important to have an autoregressive component to the prediction. Fractional models do quite well, but the performance of classical models such as large ARs is close enough to suggest that the extra costs of the fractional models are probably not warranted.

Figure 9 shows an uncommon behavior, seen on 5 of the 34 AUCKLAND traces. Unlike the two previous kinds of traces, here we have a strong impression of disorder: there are multiple peaks and valleys at different bin sizes. The relative performance of the different predictive models remains much the same, however.

Our general conclusions about the 34 AUCKLAND traces are the following:

- All of the traces are predictable in the sense that their predictability ratio is less than one. Furthermore, 80% of the traces show strong divergences from one, indicating high predictability. Figures 8 and 9 are examples of traces that are highly predictable. In each of these examples, the predictability ratios are less than 0.4 for all of the predictors at all of the bin sizes. In many cases the ratios are less than 0.1, meaning that the predictor explains 90% of the variation of the signal. This confirms our initial judgment of the predictability of the AUCKLAND traces based on the ACFs from Section II.
- There is considerable variation among the predictors. In almost in all cases, LAST, BM, and MA predictors will perform considerably worse. The other six predictors have similar performance except with very large bin sizes where LAST or MA often gives the best results. This is probably due to the fact that there are insufficient data points to produce good fits for some of the predictors at such bin sizes.
- The predictability of a trace varies considerably with bin size. There is often a "sweet spot" at which predictability is maximized. The location of the "sweet spot" varies from trace to trace and so is most likely a property of the data. We are trying to understand the origins of this phenomenon. Equally often, predictability increases with bin size, approaching a limit.

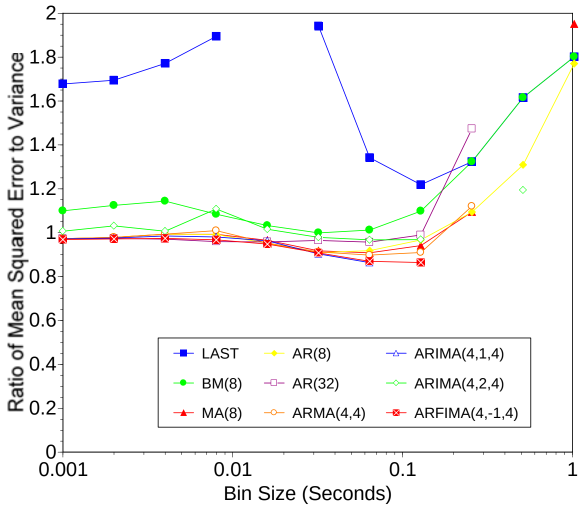

Fig. 10. Predictability ratio versus bin size of a representative NLANR trace (ANL-1018064471-1-1).

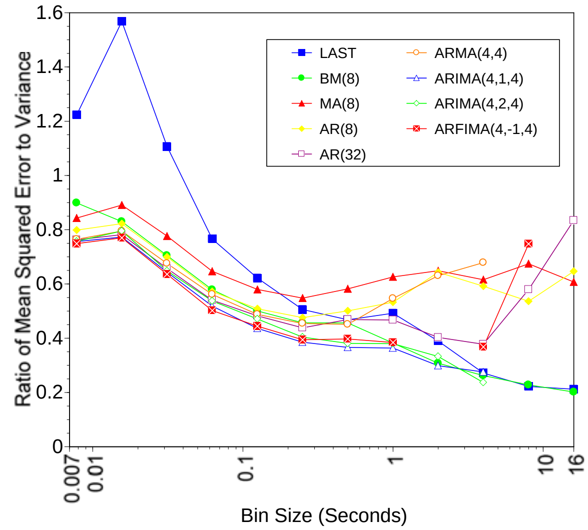

Fig. 11. Predictability ratio versus bin size of a representative BC trace (BC-pOct89).

B. NLANR traces

Because the NLANR traces are only 90 seconds long, we can not use the same range of bin sizes as we did for the AUCKLAND traces. Instead, we chose the following bin sizes: 1, 2, 4, 8, 16, 32, 64, 128, 256, 512, and 1024 ms. Figure 10 shows the predictability ratio for a representative NLANR trace. As we might expect given the ACF behavior described in Section II, this trace is basically unpredictable, turning in predictability ratios around 1.0 or worse for most of the predictors at all the different bin sizes. About 80% of the NLANR traces display similar unpredictability. For the 20% of the traces with non-vanishing ACFs, we see some modicum of predictability, but it is very weak.

C. BC traces

In Figure 11 we show the performance of the predictors on a BC LAN trace. As the trace is only 1700 seconds long, we have chosen 12 different bin sizes, ranging from 0.0078125 second to 16 seconds, doubling at each step. The predictability here is not as good as for the AUCKLAND traces, although it is much better than for the NLANR traces. All of the BC traces behave similarly. ARIMA models are the clear winner for these traces.

IV. Predictability of Wavelet Approximations

Binning is an intuitive mechanism for producing multi-resolution views of network behavior. Wavelet-based mechanisms provide a more powerful approach to providing such views because they are parameterized by a wavelet basis function which can be chosen appropriately to optimize for different properties. In fact, the wavelet approach we describe here, when parameterized with the simplest wavelet basis function, the Haar wavelet, is equivalent to the binning approach of the last section. Abry, et al provide a very nice discussion of this equivalence [2]. In the following, we use a D8 wavelet [12], which provides a much smoother multi-resolution analysis than binning/Haar.

Researchers have applied wavelet-based techniques to understand network traffic and packet traces for some time. As we noted earlier, the self-similar nature of network traffic was an important discovery in the early 90s. Abry, et al, have developed wavelet-based techniques to estimate the Hurst parameter, the degree of self-similarity [1]. Feldmann, et al have extensively used wavelets to characterize network traffic as multi-fractal [16] and to study the impact of this property on control mechanisms such as TCP congestion control [17]. Riedi, et al have shown how to use wavelets to synthesize network traffic [29], computing results in an efficient manner that appear to match real Ethernet traces visually and statistically. Our work is the first of which we are aware that empirically studies the *predictability* of wavelet approximations of real network traffic.

Before discussing our predictability results, it is important to describe to the reader what is meant by a wavelet-based multi-resolution analysis. Figure 12 shows this qualitatively. The figure shows an input signal X_k, representing an appropriately sampled, fine-grain binning of a network bandwidth trace. The input signal is being decomposed into three resolutions composed of *approximations* and *details*. By traversing the approximation tree ($approx_j$, j increasing), we observe that each of the plots not only have fewer points, but describe a coarser ap-

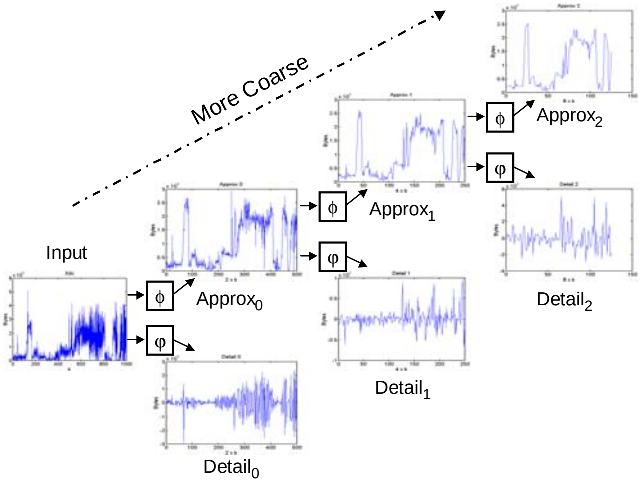

Fig. 12. Multi-resolution analysis of three scales.

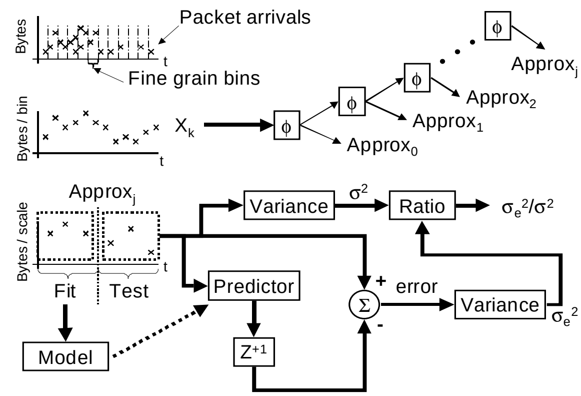

Fig. 13. The test methodology.

proximation of the underlying input signal. Each successive approximation contains half the number of points and captures half of the frequency content of the previous approximation. Even though as j increases each approximation has fewer points, each graph is still covering the same period of time. The $approx_j$ are the wavelet approximation signals described in the introduction. By observing the details, we can qualitatively see that the amount of information taken away from each approximation at subsequent levels is the detail. That is, $approx_j = approx_{j-1} - detail_j$. The filters ψ and ϕ are derived from the wavelet basis function, in this case the D8 wavelet.

The following discussion is informed by the work of Mallat [26], Daubechies [12], and Abry, et al [2]. The structure shown in the figure is the discrete wavelet transform (DWT), a mathematical transformation for representing a 1-dimensional discrete time signal X_k. Intuitively, the DWT splits a 1-dimensional signal into a 2-dimensional signal representing time and scale (like frequency) information. The input signal is represented in terms of shifted and dilated versions of a prototype band-pass wavelet function $\psi_{j,k}$ and shifted versions of a low pass scaling function $\phi_{j,k}$, based on the scaling function, ϕ_0 and the mother wavelet basis function, ψ_0. The relationship between these functions are

$$\{\phi_{j,k}(t) = 2^{-j/2}\phi_0(2^{-j}t - k), k \in \mathcal{Z}\}$$

and

$$\{\psi_{j,k}(t) = 2^{-j/2}\psi_0(2^{-j}t - k), k \in \mathcal{Z}\}.$$

To generate an accurate multi-resolution view of the input signal, the functions ψ_0 and ϕ_0 are chosen so that they are of sufficiently high order (typically determined empirically) and constitute an unconditional Riesz basis. More details on the properties of the wavelet and scaling functions can be found in Daubechies [12] and Newland [28, Chapter 17]. Multi-resolution analysis (MRA) first coined by Mallat [26], consists of a collection of nested subspaces $\{V_j\}_{j \in Z}$ such that:

$$V_j \subset V_{j-1}.$$

Multi-Resolution analysis projects the signal X_k into each of the approximation subspaces V_j. The approximation signal is then given by the following relationship:

$$approx_j(t) = (Proj_{V_j} X_k)(t) = \sum_k a_x(j,k)\phi_{j,k}(t).$$

The coefficients $a_x(j,k)$ are defined through the inner product of the input signal X_k with $\phi_{j,k}$,

$$a_x(j,k) = \langle X_k, \phi_{j,k} \rangle.$$

Similarly, the detail signal is given by the following relationship:

$$detail_j(t) = (Proj_{W_j} X_k)(t) = \sum_k d_x(j,k)\psi_{j,k}(t),$$

where the coefficients $d_x(j,k)$ are defined through the inner product of the input signal with $\psi_{j,k}$,

$$d_x(j,k) = \langle X_k, \psi_{j,k} \rangle.$$

Based on the above, a resource signal can be represented without loss of information using the coarsest grain approximation signal and the underlying details. This is shown in the following relationship:

$$ResourceSignal, X_k = approx_J(t) + \sum_{j=0}^{J} detail_j(t)$$

To evaluate the predictability of wavelet approximation signals, we use the methodology shown in Figure 13. As

Binsize in seconds	Approximation scale	Number of points	Bandlimit frequency
0.125	Input = 0.125 binsize	n	$f_s/2$
0.25	0	$n/2$	$f_s/4$
0.5	1	$n/4$	$f_s/8$
1	2	$n/8$	$f_s/16$
2	3	$n/16$	$f_s/32$
4	4	$n/32$	$f_s/64$
8	5	$n/64$	$f_s/128$
16	6	$n/128$	$f_s/256$
32	7	$n/256$	$f_s/512$
64	8	$n/512$	$f_s/1024$
128	9	$n/1024$	$f_s/2048$
256	10	$n/2048$	$f_s/4096$
512	11	$n/4096$	$f_s/8192$
1024	12	$n/8192$	$f_s/16384$

Fig. 14. Scale comparison between binning and multi-resolution analysis based on the number of bins and scales used in the AUCKLAND study (n = number of points at 0.125 second binning).

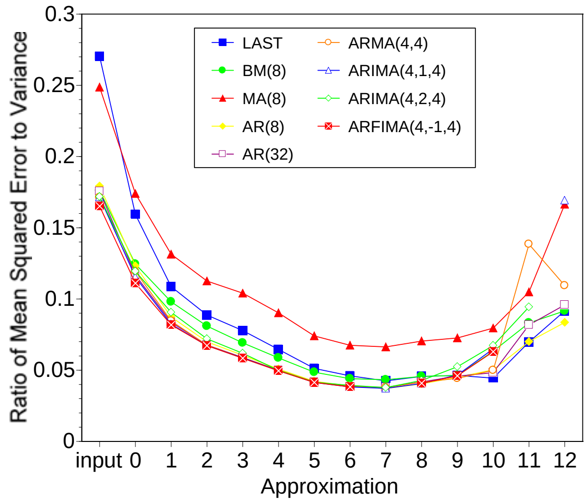

Fig. 15. Predictability ratio versus approximation scale AUCKLAND trace 31 (20010309-020000-0).

with the binning study, we begin with the packet header trace. We perform a fine-grain binning that produces a highly dynamic discrete time signal, which we denote X_k. We can think of this signal as sampled at a rate f_s and bandlimited to a frequency of $f_s/2$. This signal is sent through a multi-resolution analysis using D8 wavelets, only using the approximations ($approx_j$) for analysis. The analysis is implemented using our Tsunami Wavelet Toolbox, discussed further in the next section. For each approximation, $j \in J$, we run a prediction test that is comparable to that for binning. We fit a predictive model to the first half of the approximation signal, and then perform one-step-ahead predictions on the second half. The prediction models are the same as those used in Section III. The one-step-ahead predictions are differenced from the corresponding test interval, and an error signal is generated. We then measure predictability as the ratio of the variance of the error signal (the MSE, σ_e^2), to the variance of the test interval (σ^2). As before, the smaller this ratio is, the more predictable the trace is.

As we noted earlier, a D8-based analysis produces different, smoother approximations than the binning approach. For this reason, we reasonably expect (and see) different predictability from the traces. In most cases the behavior is similar, but there are some clear distinctions that we will call out. In our analysis, we have matched the time scale of binsize to that of the approximation subspace. In other words, there are the same number of points in a wavelet approximation signal as in its corresponding binning approximation signal. This is shown in Figure 14. The figure also indicates the bandlimited frequency at each scale. In addition, we plot the predictability of the input signal to match with the binning study. Our input signal is equivalent to the smallest binsize from the binning study.

A. *AUCKLAND traces*

For each of the 34 AUCKLAND traces, we studied the predictability of 13 scales of wavelet approximations. As with the binning study we have elided the MEAN predictor and data points that resulted from unstable predictors or having insufficient data to fit a model. There are two principle differences between the wavelet and binning results. The first is that we found four classes of behavior instead of three. The second is that monotonically increasing predictability with increasing approximation is much less common with the wavelet-based approach. We are exploring reasons for this difference.

The behavior of Figure 15 occurs in 13 of the 34 AUCKLAND traces. The figure uses the same trace as Figure 7 from the binning study. As before, we can clearly see that there is a "sweet spot", the approximation scale at which predictability is maximized—there is concavity in the figure for all predictors. As before, this behavior does not appear to be a coincidence since it shows up in a number of traces at different levels of approximation. As with binning, this behavior contradicts the earlier results of Sang and Li.

Figure 16 shows behavior that occurs in 11 of the 34 AUCKLAND traces. It is similar to the behavior we saw in five traces in the binning study and represented in Figure 9. However, here it is far more common. Again, there is a non-monotonic relationship between the approximation scale and the predictability.

Figure 17 shows behavior that occurs in 7 of the 34

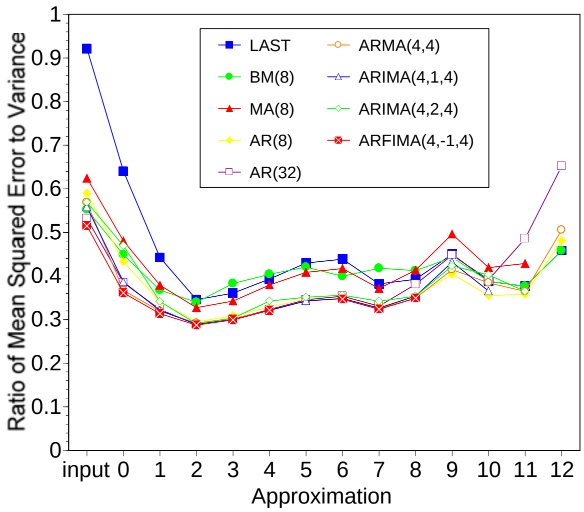

Fig. 16. Predictability ratio versus approximation scale for AUCKLAND trace 11 (20010225-020000-0).

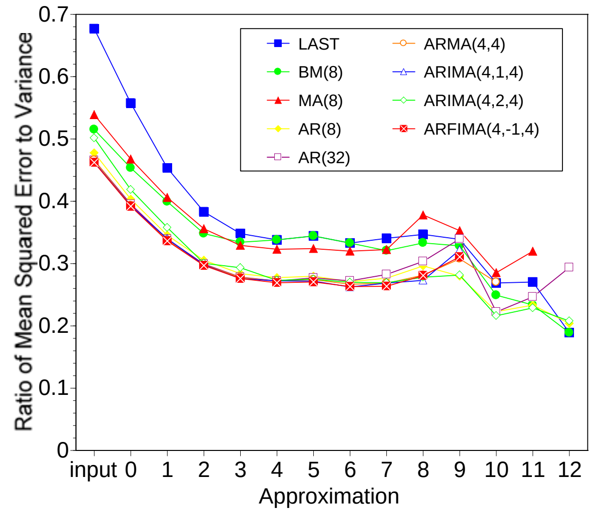

Fig. 18. Predictability ratio versus approximation scale for AUCKLAND trace 4 (20010221-020000-1).

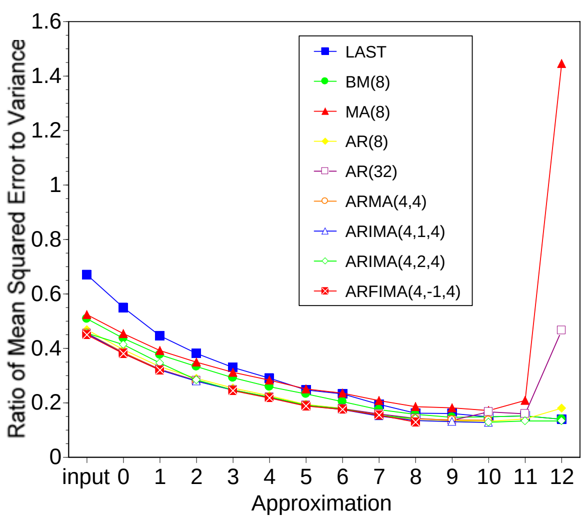

Fig. 17. Predictability ratio versus approximation scale for AUCKLAND trace 32 (20010309-020000-1).

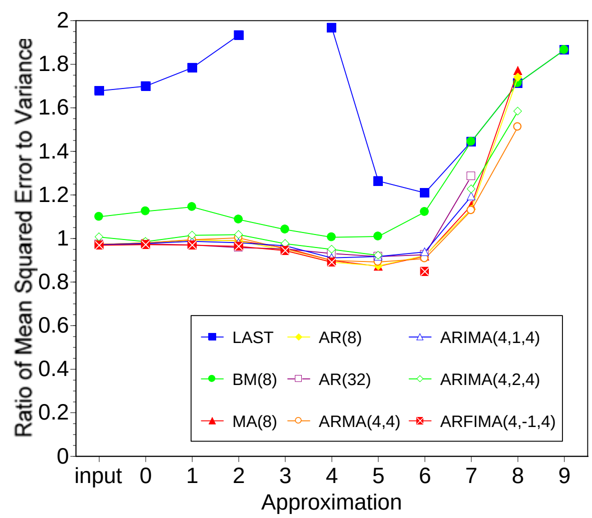

Fig. 19. Predictability ratio versus approximation scale of a representative NLANR trace (ANL-1018064471-1-1).

AUCKLAND traces. Except for the outliers, this shows the monotonic relationship that was conjectured in earlier work. Note that it is an uncommon behavior in our study.

Figure 18 shows the final class of behavior in the AUCKLAND traces, which occurs in 3 of the 34. Here the predictability ratio reaches a plateau and then becomes even more predictable at the coarsest resolutions. Interestingly, this is a kind of behavior that we did not see in the binning study.

The generalizations we draw are much the same as for the binning study:

- Most of the traces show a high degree of predictability, which confirms what we concluded from the ACFs of Section II. On a trace-by-trace basis, the predictability ratio of the binning study is similar to that of the wavelet study when we have similar classes of behavior.
- While there is considerable variation in the performance of the predictors, it is clearly a good idea to have an autoregressive component to the prediction filter. An integrative component is also useful.
- There is often a “sweet spot”, the approximation scale at which predictability is maximized.
- There is an additional class of behavior with wavelets compared to binning.

B. NLANR traces

As we noted earlier, most of the the NLANR traces typically have an empty autocorrelation structure, which suggest that there is little predictability. As we might expect, wavelet approximations do not change this. Figure 19 shows typical results using the same trace as Figure 10. As before, the prediction error variance is essentially the

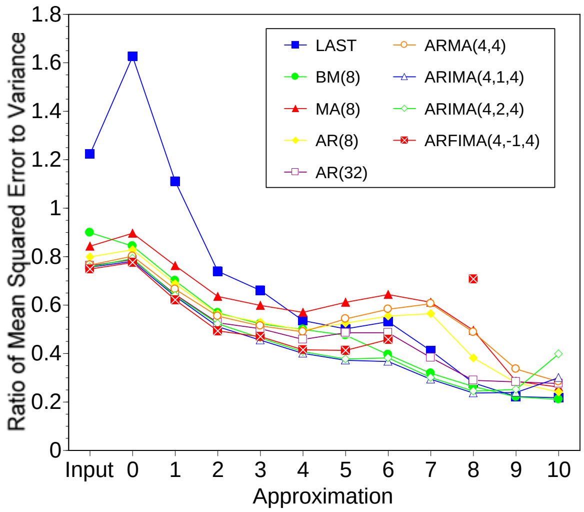

Fig. 20. Predictability ratio versus approximation scale of a representative BC trace (BC-pOct89).

same as the signal variance.

C. BC traces

Figure 20 shows prediction results for wavelet approximations of the same BC LAN trace studied using binning in Figure 11. We see very similar performance using wavelet approximation signals and binning approximation signals.

V. System

Several groups have developed online wavelet systems for purposes other than resource signal dissemination and prediction. One such system, WIND, uses wavelet-based scaling analysis to detect network performance problems [21]. Another online system performs online estimates of the Hurst parameter (a measure of self-similarity) at the router in order to make adaptive changes in congestion control, or to provide up to date information about traffic dynamics without storing all of the data for offline analysis [30].

We are incorporating multi-resolution analysis using wavelets (and binning, using Haar wavelets) into our toolbox for building resource measurement and prediction systems, RPS. Initially, we see it serving two purposes. The first is to decouple sensors of resource signals (such as host load, network bandwidth, and disk bandwidth), and the applications and tools that are interested in their outputs. We would run the sensor at a natural and appropriate rate, do an online multi-resolution decomposition, and stream the approximations and details into separate multicast channels. An application would subscribe to only the approximations and details necessary to reconstruct the sensor's output to the resolution it requires, using just the bandwidth necessary for that resolution. Other applications could subscribe to other subsets of the approximations and details. An initial study on the prospects for this are given in an earlier paper [32]. Other techniques, such as wavelet denoising, for further compression of the signal could be applied before it is sent over the network. Our second purpose is to support predictions of sensor output at many different timescales, such as was described in the introduction's discussion of the Message Transfer Time Advisor.

The basis of these efforts is our Tsunami toolbox, which we have used in the wavelet study of Section IV. Tsunami is a C++ implementation of forward and reverse wavelet transforms, delay blocks, and other relevant DSP blocks that are parameterizable by underlying datatypes and wavelet basis functions. In addition, it can support arbitrary decompositions of the frequency spectrum (i.e., wavelet packets) beyond "traditional" octave decompositions. Furthermore, Tsunami is designed to be incorporated into distributed monitoring systems and thus supports both offline and online operation. In particular, it supports block, streaming, and dynamic transforms. Dynamic transforms can increase the number of approximation scales in the decomposition, adaptively, according to the amount of data acquired, or under application control. We are currently integrating Tsunami into RPS and building online and offline wavelet-based resource signal dissemination and prediction tools as described above. Tsunami will be publicly released with the next version of RPS. We are also in the process of writing a technical report on Tsunami.

VI. Conclusions

We have presented an empirical study of the predictability of network traffic at different resolutions using linear models. Our results are similar for two methods of producing different resolutions: binning and wavelet approximations. We found that making generalizations about predictability is very difficult in practice because networks tend to vary in behavior considerably over time and space. The behavior at many aggregation points appears to have little predictability using linear models. On the other hand, in situations where predictability exists, it is the case that increased traffic aggregation is correlated with enhanced predictability. This agrees with earlier results. Our study contradicts earlier work in that we find that predictability does not necessarily monotonically increase with smoothing. About half of the predictable traces we studied have degrees of smoothing at which predictability is maximized. We found that having an autoregressive component to the predictive models is important.

We are currently working on building online resource signal dissemination and prediction systems based on the Tsunami wavelet toolbox and the RPS system. Tsunami will be incorporated into the next public release of RPS. Once we have a functioning online prediction system, we expect to study the effects of using adaptive prediction filters, such as Kalman filters, in multi-resolution prediction. This work will be the next step toward the Message Transfer Time Advisor.

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