From Poisson Processes to Self-Similarity: a Survey of Network Traffic Models

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Abstract
The paper provides a survey of network traffic models. It starts from the description of the Poisson model, born in the context of telephony, and highlights the main reasons for its inadequacy to describe data traffic in LANs and WANs. It then details two models which have been conceived to overcome the Poisson model's limitations. In particular, the discussion focuses on the packet train model, validated in a Token Ring LAN, and on the self-similar model, used to capture traffic burstiness at several times scales in both Ethernet LANs and WANs. The discussion closes with some examples of usage of those models in LAN and WAN environments.

Keywords: Traffic models, Poisson processes, stochastic processes, compound processes, renewal processes, packet trains, self-similarity, fractals.

Table of Contents

1. Introduction

One important research area in the context of networking focuses on developing traffic models which can be applied to the Internet and, more generally, to any communication network. The interest towards such models is two-fold. First, traffic models are needed as input in network simulations. In turn, these simulations must be performed in order to study and validate algorithms and protocols to be applied to real traffic, and to analyze how traffic reacts to particular network conditions (e.g.: congestion, etc.). Thus, it is essential that the assumed models reflect as much as possible the relevant characteristics of the traffic it is supposed to represent. Second, a good traffic model may lead to a better understanding of the characteristics of the network traffic itself. This, in turn, can help designing routers and devices which handle network traffic. If, for instance, a model which has been well validated shows some correlation between traffic arrivals, this information can be used in order to conceive ad hoc packet handling strategies.

The first traffic model, based on Poisson processes, was born in the context of telephony, where call arrivals could be considered independent and identically distributed and "holding times" followed an exponential distribution. Although initially successful and analytically simple, the Poisson model has proven not suitable to describe data traffic in modern LANs and WANs, where batch arrivals, event correlations and traffic burstiness are important factors. The use of heavy tailed distributions and of self-similarity has become more and more predominant.

The goal of this paper is to point out the most important concepts at the core of the basic traffic models in use, and to show how these models are applied to LANs and WANs.

The remainder of the paper is organized as follows. Section 2 introduces basic concepts about traffic modeling. Section 3 describes the Poisson model and its limitations. Section 4 presents the Packet trains model, intended to overcome some of the Poisson model's limitations and to capture correlation and locality among packet arrivals. Section 5 introduces a mathematical description of self-similarity and explains how the self-similar model differs from traditional ones and allows capturing traffic burstiness at different time scales. Section 6 lists other traffic models in used. Sections 7 show how the models presented in the paper have been applied to traffic in LANs and WANs. Finally, section 8 closes the discussion with concluding remarks.

Back to Table of Contents

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2. Traffic modeling: basic concepts

Internet traffic can be modeled as a sequence of arrivals of discrete entities, such as packets, cells, etc. Mathematically, this leads to the usage of two equivalent representations: *counting processes* and *interarrival time processes*. A counting process $\{N(t)\}_{t=0..\infty}$ is a continuous-time, integer-valued stochastic process, where N(t) expresses the number of arrivals in the time interval *(0,t]*. An interarrival time process is a non-negative random sequence $\{A_n\}$, where $A_n=T_n-T_{n-1}$ indicates the length of the interval separating arrivals *n-1* and *n*. The two kind of processes are related through the following equation:

$$\{N(t) = n\} = \{T_n \le t < T_{n+1}\} = \left\{\sum_{k=1}^{n} A_k \le t < \sum_{k=1}^{n+1} A_k \right\} \quad (1)$$

In case of ***compound*** traffic, arrivals may happen in *batches*, that is, several arrivals can happen at the same instant T_n. This fact can be modeled by using an additional non-negative random sequence $\{B_n\}_{n=1..\infty}$, where B_n is the cardinality of the *n-th* batch. The traffic model is largely defined by the nature of the stochastic processes $\{N(t)\}$ and $\{A_n\}$ chosen, which will be analyzed in the remainder of this paper.

One important issue in the selection of the stochastic process is its ability to describe traffic ***burstiness***. In particular, a sequence of arrival times will be bursty if the T_n tend to form clusters, that is, if the corresponding $\{A_n\}$ sees a mix of relatively long and short interarrival times. Mathematically speaking, traffic burstiness is related to short-terms autocorrelations between the interarrival times. However, there is not a single widely accepted notion of burstiness [frost94traffic]; instead, several different measures are used, some of which ignore the effect of second order properties of the traffic. A first measure is the ratio of peak rate to mean rate, and has the drawback of being dependent upon the interval used to measure the rate. A second measure is the coefficient of variation $c_A=\sigma[A_n]/E[A_n]$ of the interarrival times. A metric considering second order properties of the traffic is the index of dispersion for counts (IDC). In particular, given an interval of time τ, $IDC(\tau)=Var[N(\tau)]/E[N(\tau)]$. Because of the relationship in Eq. (1), IDC includes in the numerator the effects of the autocorrelation between the A_n. Finally, as will be better detailed later, the Hurst parameter can be used as a measure of burstiness in case of self similar traffic.

Back to Table of Contents

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3. The Poisson Model

The Poisson model is the oldest traffic model in use. Introduced in the context of telephony by A. K. Erlang, it shows some limitations when applied to Internet data traffic. In this section we first characterize the model and then point out the issues which make suitable the use of different frameworks.

3.1 Description of the model

Traffic is characterized by assuming that the packet arrivals A_n have the following characteristics:

1. they are *independent*.
2. they are *exponentially distributed* with rate parameter λ: $P\{A_n \leq t\} = 1-e^{-\lambda t}$.

Alternatively, this implies describing the traffic through a counting process satisfying the equation $P\{N(t)=n\} = e^{-\lambda t}(\lambda t)^n/n!$, where $N(t)$ is the number of arrivals at time t.
Poisson processes exhibit the following important analytical properties:

1. The superposition of independent Poisson processes with rates $\lambda_1, \lambda_2, ... \lambda_n$ results in a new Poisson process with rate $\lambda_1+\lambda_2+...\lambda_n$.
2. The number of arrivals in disjoint intervals is statistically independent. This property is also referred to as *independent increments* property, and makes Poisson a *memoryless* process.
3. For an exponential distribution with parameter λ, not only the mean, but also the variance is equal to λ. This leads to a unitary coefficient of variation.
4. According to the Palm-Khintchine theorem, the multiplexing of independent traffic streams approximates a Poisson process if: (i) the traffic streams can be modeled as renewal processes (that is, interarrival times are independent and identically distributed), (ii) as the number of streams increases the individual rates decrease so as to keep the aggregate rate constant.

There are several ways to verify whether a particular arrival process is Poisson [jain86train]. An easy visual way consists in plotting the histogram of the interarrival times and verifying whether it is an exponentially decreasing function.
Alternatively, observing that if $p(t) = \lambda e^{-\lambda t}$ then $log(p(t)) = log(\lambda) - \lambda t$, one can plot the log histogram and check whether it is a linear function. In this case, the rate λ of the process can be easily extrapolated from the intersection with the y-axis (or from the slope of the line).

One special case of the Poisson model is represented by *time-dependent* Poisson processes. This representation is suitable for situations where the mean rate is not constant: in such cases, the rate parameter λ is expressed as a function of the time $\lambda(t)$.

3.2 Traffic burstiness: the limitations of the Poisson model

One basic limitation of the Poisson model is its inability to capture traffic burstiness which characterizes data traffic (as opposed to voice traffic in old telephone systems). Analytically, this can be explained as follows. In any renewal traffic process the autocorrelation function of the $\{A_n\}$ vanishes identically. But, as mentioned above, positive autocorrelation between the $\{A_n\}$ can explain, to a large extent, traffic burstiness. Thus, Poisson is not the appropriate model in case of bursty traffic, especially when traffic burstiness happens on multiple time scales.

Let us illustrate and analyze this concept more in depth. A way to have an intuition about traffic burstiness is to define it in terms of a *time scale* over which bursts occur. If, for instance, we consider a Poisson process with rate λ (e.g.: 100/sec), then the time scale for burstiness is 1/λ (e.g.: 10 msec), and periods of over- or lower-than average activity over much smaller or much larger time scales occur with rapidly decreasing probability. This is in general true in the case of telephone traffic, which is well modeled through Poisson processes. However, as will be detailed later, traffic bursts in data networks tend to happen on many different time scales [paxson95wide], [leland91high], [willinger98selfsimilarity], [leland93selfsimilar], [riedi00toward], which does not fit the Poisson model.

Figure 1, taken from [willinger98where], illustrates the failure of the Poisson model in capturing internet traffic burstiness. The plots on the right hand side represent the trace of traffic arrivals registered in 1995 on a network link connecting a large corporation to the Internet. The plots on the left hand side are obtained by fitting a simple Poisson-based model to the mean and variance of the measured samples. The different rows show distinct time scales: moving from one row to the subsequent the time scale is increased by a factor of 10. The black regions illustrate the area expanded in the previous row. Each point in the first row represents the number of packets during a 100 msec interval, in the second row the number of packets in a 1 sec interval, and so on. Notice that the scale on the y-axis is also varied. As can be observed, the Poisson traffic tends to become smoother as the time scale increases, whereas the original traffic is characterized by a bursty behavior on all the time scales.

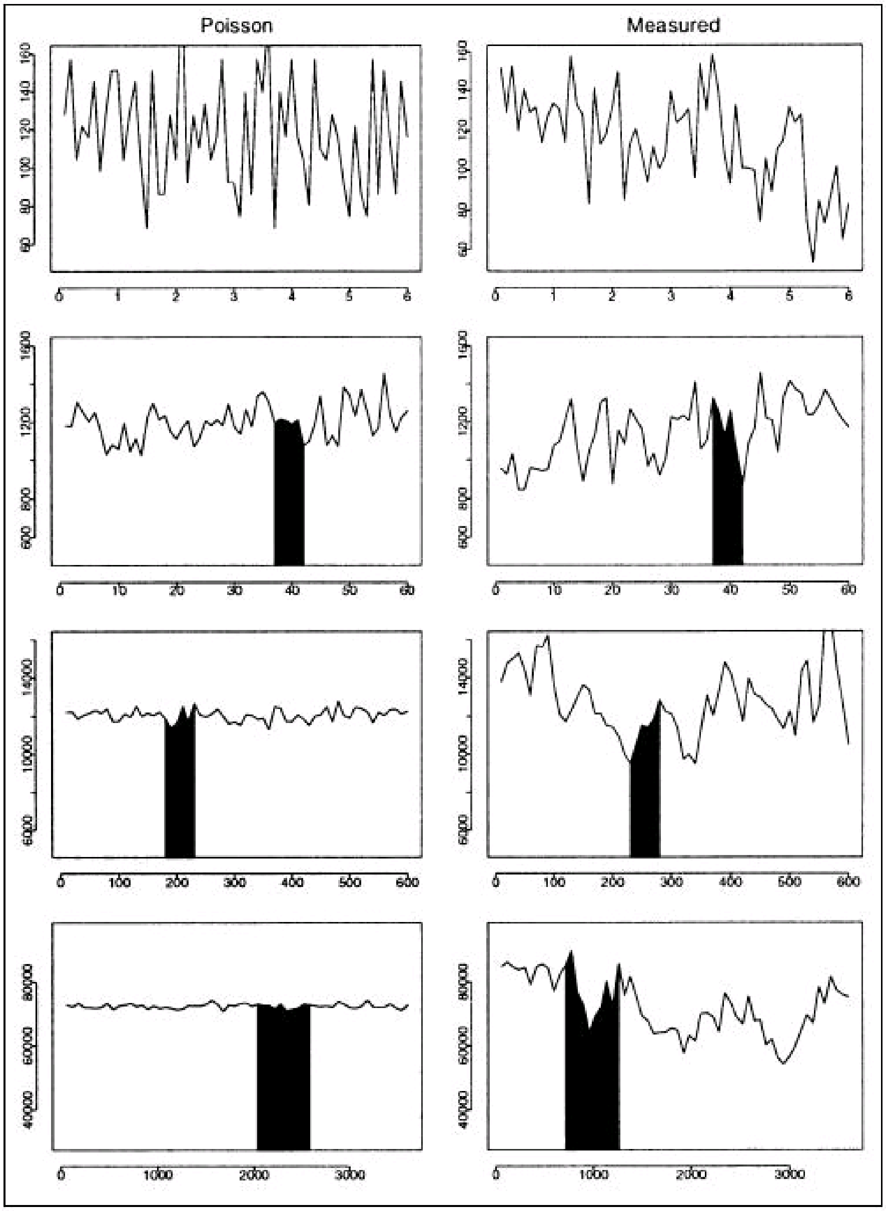

Figure 1: Synthetized traffic from a Poisson model vs. Internet traffic to which its mean and variance were fit, viewed over three orders of magnitude.
(from [willinger98where])

This observation has important practical implications. Poisson-like traffic would be easier to control: above a certain time scale, knowing the long-term arrival rate is enough to characterize the traffic. There would be no need for big buffers in routers or for complicated mechanisms to guarantee quality of service. On the contrary, the kind of burstiness present in the traffic represented on the right hand side does not suggest any conservative operating point. Therefore, sophisticated mechanisms for traffic engineering are required.

One way to represent burstiness through a Poisson model is to use the so called *compound* Poisson process, where packet arrivals happen in bursts (or batches), the interbatch times are independent and exponentially distributed (that is, they represent a Poisson process), and the batch sizes are random. This scenario can be modeled using two processes $\{A_n\}$ and $\{B_n\}$, the first one representing the batch interarrival times and the second the batch sizes. However, as will be detailed in the following sections, different traffic models are preferable to compound Poisson traffic models in that they tackle the problem of burstiness in a more radical way. In particular, multi-scale burstiness is captured by self-similar traffic models. But, before considering self-similarity, let us introduce a simpler traffic model which overcomes other limitations of Poisson.

Back to Table of Contents

4. The Packet Train Model

The Poisson model is based on the assumption that packet arrivals are independent and unpredictable (independent increment property). However, detecting some predictability from the study of arrival patterns would allow designing better packet handling strategies. One could think about predictability as correlation among subsequent packet arrivals. This problem is studied in [jain86train], which proposes an arrival model introducing dependence between packets traveling between the same end-nodes.

In particular, in [jain86train] two distinct models of packet arrival patterns are identified: the *car model* and the *train model*. The former assumes single independent packet arrivals (as in the Poisson model). The latter assumes that groups of packets travel together. The intuition which supports the train model is the following. If packet arrivals are completely independent, then routing decision for packets traveling between the same endpoints are performed independently on routers. This may lead to processing overhead. However, if a train model is assumed, the routing decisions can be taken only when the head of a new packet train is detected and no overhead would incur on subsequent packets belonging to the same train. In addition, a technical consideration further motivates the packet train assumption. Packets sizes in network are limited by buffer sizes and backwards compatibility requirements. On the other hand, file sizes and, in general, sizes of information transmitted over the network tend to increase. This leads to the need to fragment the data into multiple small packets, which will travel between the same endpoints, and, therefore, logically belong to the same packet train.

The model groups into a packet train all the packets flowing between two endpoints A and B and having an inter-car time smaller than a specified number, called *maximum allowed inter-car gap* (MAIG). The inter-car time must be significantly smaller than the inter-train time, that is, the time separating two distinct packet trains. Notice that the direction of the packets (whether from A to B, or from B to A) is not relevant (even if *source trains* and *destination trains* have been also taken into consideration). The intuition behind that is that in some widely used communication protocols (as the request-response one) packets traveling in opposite direction between the same endpoints are correlated. A schematic representation of the packet train model is given in Figure 2.

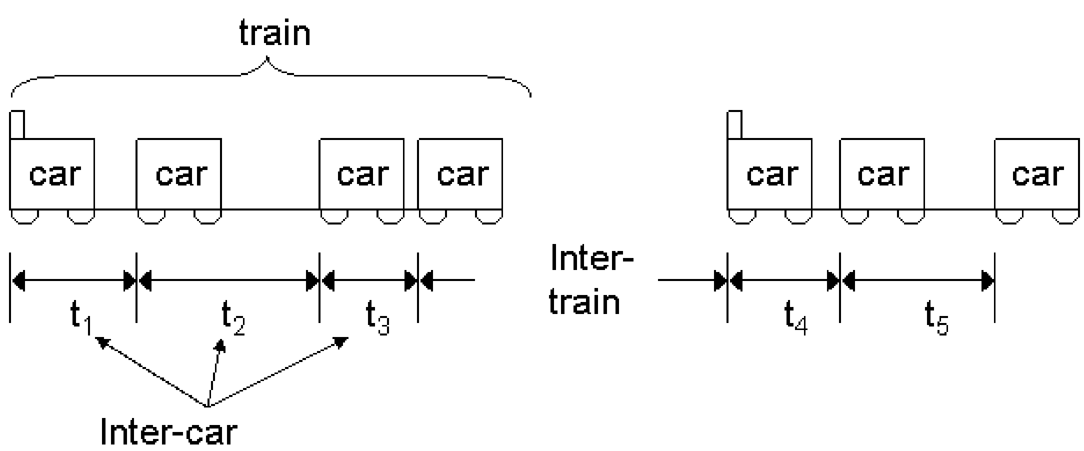

Figure 2: The packet train model: inter-car times must be smaller than inter-train times.
(adapted from [jain86train])

The packet train model has been validated and compared to the Poisson and compound Poisson models on a star-shaped 10 Mbits/s token ring network connecting 33 computers and 5 getaways at the Massachusetts Institute of Technology. In particular, it has been pointed out how, in that simulation environment, the packet arrival times were not exponentially distributed (and therefore the Poisson model could not be applied). The train model has proven be more appropriate. The analysis shows interpacket times within a train exponentially distributed with a not null, and sometimes negative, autocorrelation. This last fact expresses dependence between subsequent packets in the same train, and negative autocorrelation has been explained with the use of the request-response protocol, where requests and acknowledgements are generated quickly whereas responses need more time to be generated.

Despite its merit of addressing limitations of the Poisson model, the packet train model has not been widely applied on other data traffic (e.g.: Ethernet and WAN traffic). Moreover, it does not directly address the issue of multiple time scale burstiness of the Internet data traffic. To this end, we present the self-similar model in the next section.

[Back to Table of Contents](#)

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5. The Self-Similar Model

In this section we first motivate the self-similar model and give a qualitative description of its significance in Internet traffic modeling, and then we present a more rigurous and analytical description of the model itself.

5.1 Spatial and time variability: from Poisson to Fractals

The basic characteristic of the old telephone traffic which made the Poisson model suitable for it is its *limited variability* in both time and space [willinger98where]. In fact, telephone traffic processes are either independent or have temporal correlations that decay exponentially fast; moreover, the distributions of traffic related quantities have exponentially decaying tails. Low variability also implies no or limited burstiness.

However, data networks are characterized by *high or extreme variability* [paxson95wide], [leland91high], [willinger98selfsimilarity], [leland93selfsimilar], [riedi00toward]. Statistically, temporal high variability can be captured by *long-range dependences* [Wiki-Long-range-dep], that is, autocorrelation exhibiting power-law decay. On the other hand, extreme spatial variability can be described through *heavy-tailed distributions with infinite variance* [Wiki-Long-tail-traffic], [willinger98selfsimilarity], the *Pareto distributions* [Wiki-pareto] being an example. Large variability in space and time generally causes the corresponding traffic to manifest *fractal* behavior [Wiki-Self-similarity], that is, to show some statistical properties which repeat themselves at many time scales. As we have anticipated in Section 3.2, the statistical property of interest is, in this context, traffic burstiness.

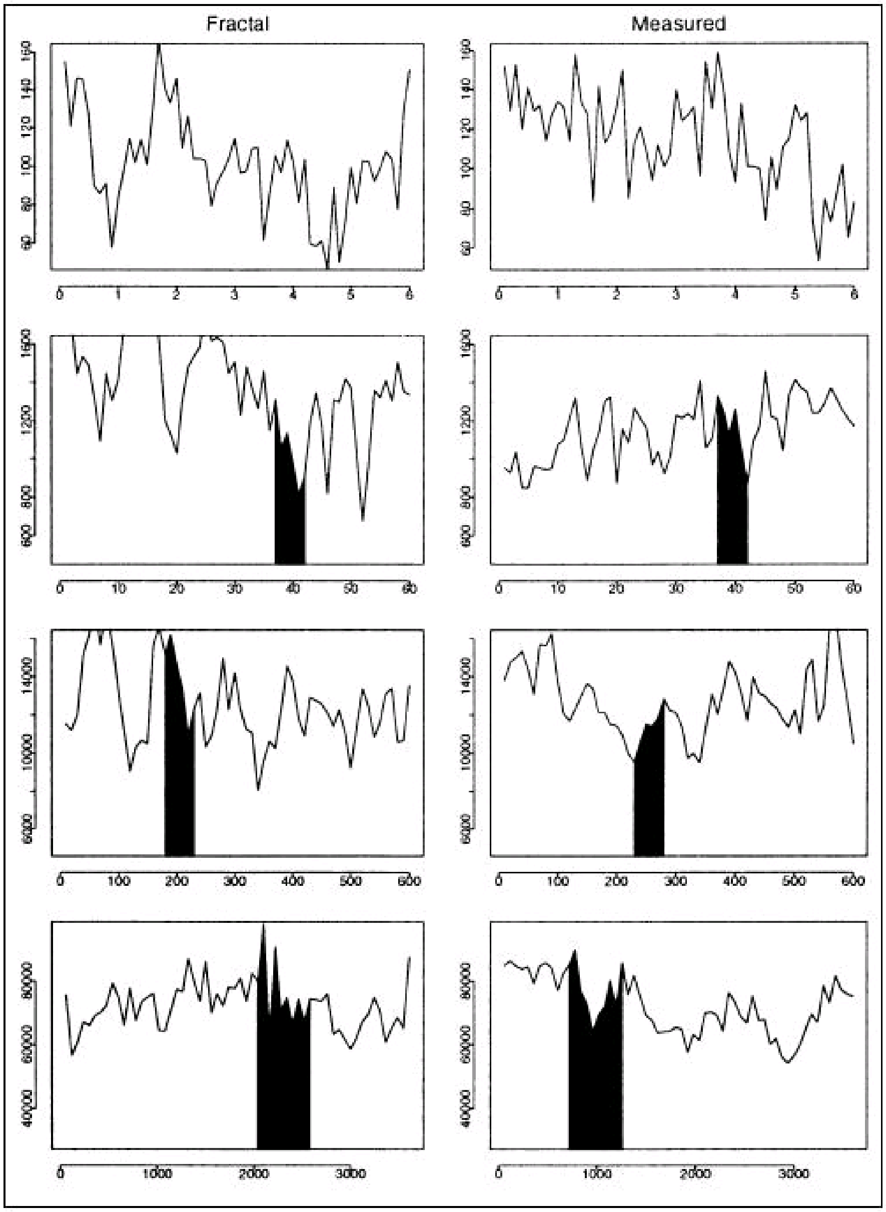

Figure 3: Synthesized traffic from a simple fractal model vs. Internet traffic to which its mean, variance, and Hurst parameter (H) were fitted, viewed over three orders of magnitude.
(from [willinger98where])

In Figure 3 the traces of Figure 1 are represented again but, on the left hand side, the fractal (or self-similar) model obtained by fitting the traffic mean, variance and Hurst parameter is displayed. As can be seen, this model exhibits burstiness at all time scales as the original traffic.

5.2 An analytical view of self similarity

The concept of self-similarity in the communication area was first introduced by Mandelbrot [mandelbrot65]. However, it's not until the Eighties that it was applied in the context of modeling traffic burstiness. Let us now analyze the mathematical foundations at the basis of self-similarity [leland93selfsimilar], [leland93selfsimilar].

Let $X = (X_t$: t = 0, 1, ...) be a covariance stationary stochastic process; that is, a process with constant mean μ, constant variance σ, and autocorrelation function $r(k)=E[(X_t-\mu)(X_{t+k}-\mu)]/E[(X_t-\mu)^2]$ that depends only on k. In particular, let's assume that $r(k) \sim k^{-\beta} L_1(k)$, with $0 < \beta < 1$ and L_1 slowly varying at infinity. Let $X^{(m)} = (X^{(m)}(k)$: t = 1, 2, ...) a new *aggregate* time series obtained by averaging the original time series X over non overlapping blocks of size m. The aggregate $X^{(m)}$ defines also a covariance stationary process with autocorrelation function $r^{(m)}$.

The process X is called *(exactly second-order) self-similar* with self-similarity (or *Hurst*) parameter $H=1-\beta/2$ if all the aggregate processes $X^{(m)}$ have the same autocorrelation function as X. In other words, X is exactly self similar if it is indistinguishable from its aggregate processes at least with respect to their second order properties.
The process X is called *(asymptotically second-order) self-similar* if, for large m, the corresponding aggregated time series have fixed correlation structure (determined by β).

To make the discussion more concrete and give an intuition about the meaning of this mathematical formulation, let us consider the example in Figs. 1 and 3. The time series in the first row represents the X process. The second row reports the aggregate process $X^{(10)}$, the third row shows $X^{(100)}$, and the last one reports $X^{(500)}$.

Notice that traditional stochastic processes have the property that, as m increases, the correlation function of the aggregated processes tends to 0. In other words, as m increases, the aggregated processes $X^{(m)}$ tend to a sequence of independent, identically distributed random variables (that is, covariance stationary white noise). On the contrary, the correlation function of (exactly or asymptotically) self-similar processes is nondegenerate. Also, remember that the concept of burstiness is in general bound to a non zero correlation between packet interarrival times.

In conclusion, two are the basic characteristics which distinguish self-similar processes from conventional stochastic processes:

1. Aggregation brings to time series which are visually indistinguishable from one another (that is, self-similar), but clearly different from pure noise. On the contrary, traditionally traffic models tend to converge to pure noise after increasing the time scale of 2 or 3 orders of magnitude (as exemplified in Figs. 1 and 3, where one order or magnitude was enough in the case of Poisson model to obtain white noise).
2. When trying to fit traditional traffic models to self-similar traffic data, the number of parameters needed typically increases with the sample size. On the contrary, self-similar traffic models can capture the behavior of self-similar traffic data with a minimum number of parameters. *Minimality* is an essential property of any good model.

Having discusses the basic concepts, we show in the next sections how LAN and WAN traffic has been characterized according to the presented models.

Back to Table of Contents

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6. Other Traffic Models

For completeness, we list here other traffic models. For a more exhaustive description, the reader can refer to [frost94traffic].

6.1 Renewal Traffic Models

As mentioned above, in renewal traffic models packet interarrival times are represented as independent identically distributed events. Since they lack of intercorrelation between the events, these models are in general inadequate to capture traffic burstiness.

Several renewal traffic models have been proposed beside the Poisson one. ***Bernoulli processes*** can be seen as the discrete-time equivalent of Poisson models. If the interarrival times in a renewal process are of the so-called "phase type", we refer to ***phase-type renewal processes***. Those processes can be modeled as the time to absorption in a continuous-time Markov chain [Wiki-Markov].

6.2 Markov Traffic Models

Important classes of models are the Markov, Markov renewal and Markov Modulated traffic models. In particular, they have the merit of introducing some non zero autocorrelation in the $\{A_n\}$. Thus, they can capture some traffic burstiness.

In a simple ***Markov*** traffic model, the interarrival times are exponentially distributed with different λ_i. A probability matrix is used in order to determine the rate parameter λ_i which should be used according to the system state i. In turn, the progress of the system state can be modeled through a Markov chain [Wiki-Markov]. The basic implication of this fact is the following: the conditional probability distribution of the system state in the future depends only on its current state (and not on its state in the past).

Markov-renewal models are more general: they allow the interarrival times to be arbitrarily distributed, and constrain the distribution to depend upon both the current state of the system and the interarrival interval. The state of the system is again modeled through a Markov chain.

Markov-modulated traffic models are characterized by an auxiliary Markov process which evolves in time and its current state controls the probability function of the underlying traffic mechanism. A particular subclass is the one of *Markov-modulated Poisson processes*, where the underlying model is Poisson.

In [lombardo98accurate] a Markov-based model for MPEG traffic is proposed. The authors show how the model captures both inter-group of frames and intra-group of frames correlation. Finally, they use the model to estimate the loss probability in an ATM multiplexer loaded by a MPEG video source and an aggragate of external traffic. [elsayed00superposition] introduces a methodology to approximately characterize the superposition process of $N \geq 2$ arbitrary Markov renewal processes. In particular, the resulting process is modeled by a Markov renewal process with a state space growing with N. [robert95markov] introduces and validates a modulated Markov process which produces self-similarity on a finite time scale.

6.3 Autoregressive Traffic Models

Autoregressive traffic models define the next random variable in the sequence as a function of the previous ones, according to a given window. A particular class uses a linear function.

Autoregressive traffic models have been used in the modeling of video streaming traffic, were temporal locality between frames can be expressed by modeling a frame as a function of the previous ones. The reader is addressed to [alheraish] for a survey on autoregressive models in the context of videoconferencing systems.

6.4 Transform-Expand-Sample

Another model used in the context of video streaming is the *transform-expand-sample* (TES). Specifically, TES has been used for VBR video streams, and takes advantage of the fact that consequent frames change very little and that only scene changes and other forms of discontinuity in the video stream can cause a change in the rate of the video.

The interested reader can find an analytical description of TES and some possible extensions to the basic model in [reichl97].

Back to Table of Contents

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7. Application of the Models

In this section, we show how the above models have been applied to LAN and WAN traffic.

7.1. Modeling LAN traffic

Several papers [leland91high], [leland93selfsimilar], [riedi00toward] focused on the self-similar nature of Ethernet traffic. Figure 4 provides an intuition of this fact, in that it represents an Ethernet trace exhibiting a bursty behavior, and which looks similar to itself on different time scales (from a time unit of 0.1 sec to 100 sec). Further analysis of the Ethernet traces was performed over a 27-hour and a 4-year period. In both cases, the self-similar behavior of the traffic was confirmed.

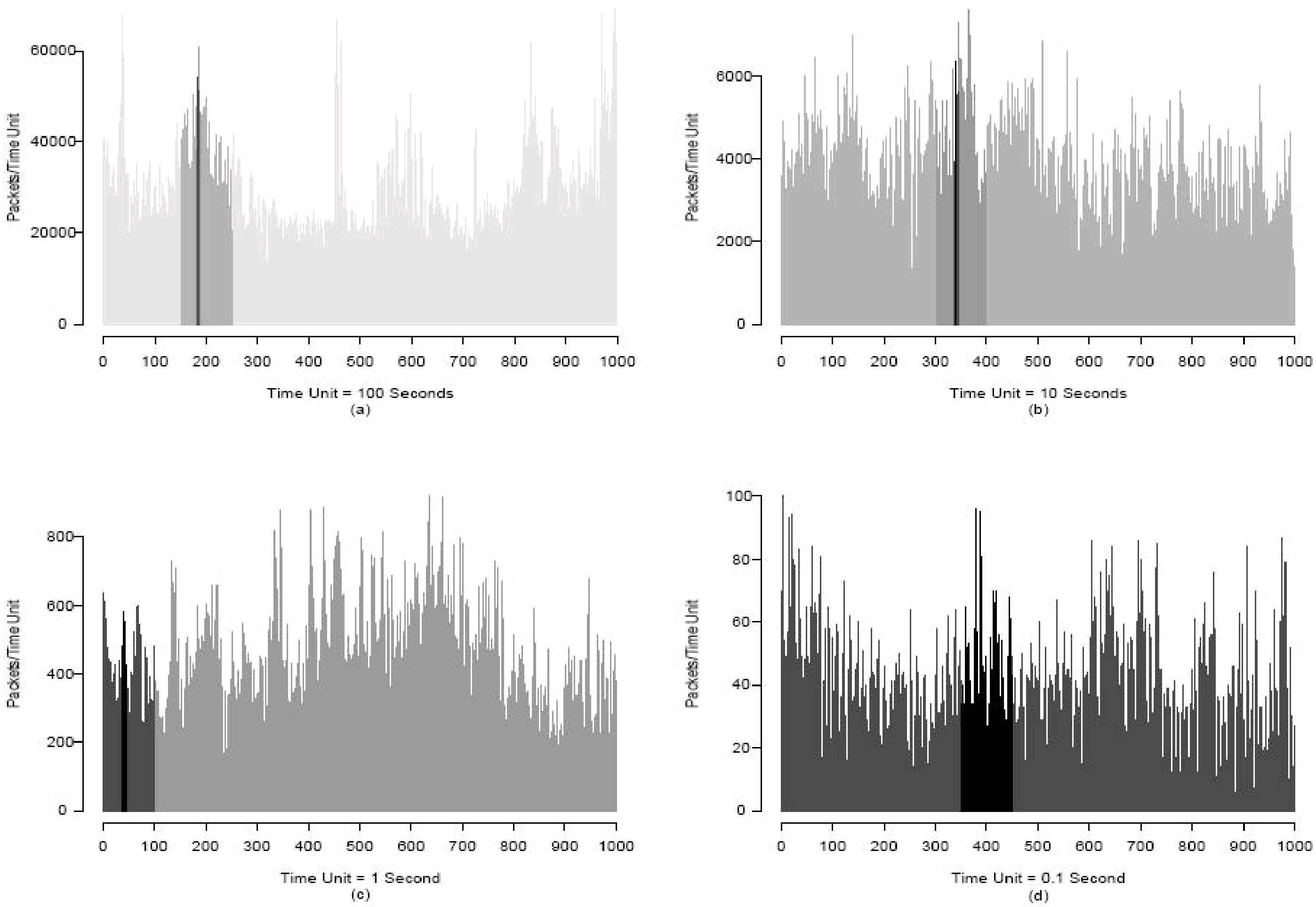

Figure 4: A pictorial representation giving an intuition of the self-similar behavior of Ethernet traffic: burstiness at different time scales is evident.
(from [#leland93selfsimilar])

A second step is a classification of the traffic in *internal* and *remote or external*. The former consists of all packets internal to the LAN, and the latter of all the packets which originate in one LAN but are routed into another LAN. The study shows that, in term of the self-similar traffic, external traffic does not differ from the internal one (which is represented in Fig. 4).

7.2. Modeling WAN traffic

The application of self-similarity and heavy tailed distributions to WAN Internet traffic has been the subject of a fair amount of literature. Some interesting results are reported in [paxson95wide] and [willinger98selfsimilarity], where traffic is analyzed on an application specific basis. In particular, the authors distinguish *control traffic*, representing the *arrivals of user sessions* (e.g.: TELNET connections, etc.) from real *data traffic*. Moreover, they classify both kind of traffic depending on the application protocol (TELNET, FTP, SMTP, NNTP) which originates it. An analysis on different time scales is performed on several traces from wide-area network traffic. It is shown how different traffic models apply depending on the context.

The results can be summarized as follows:

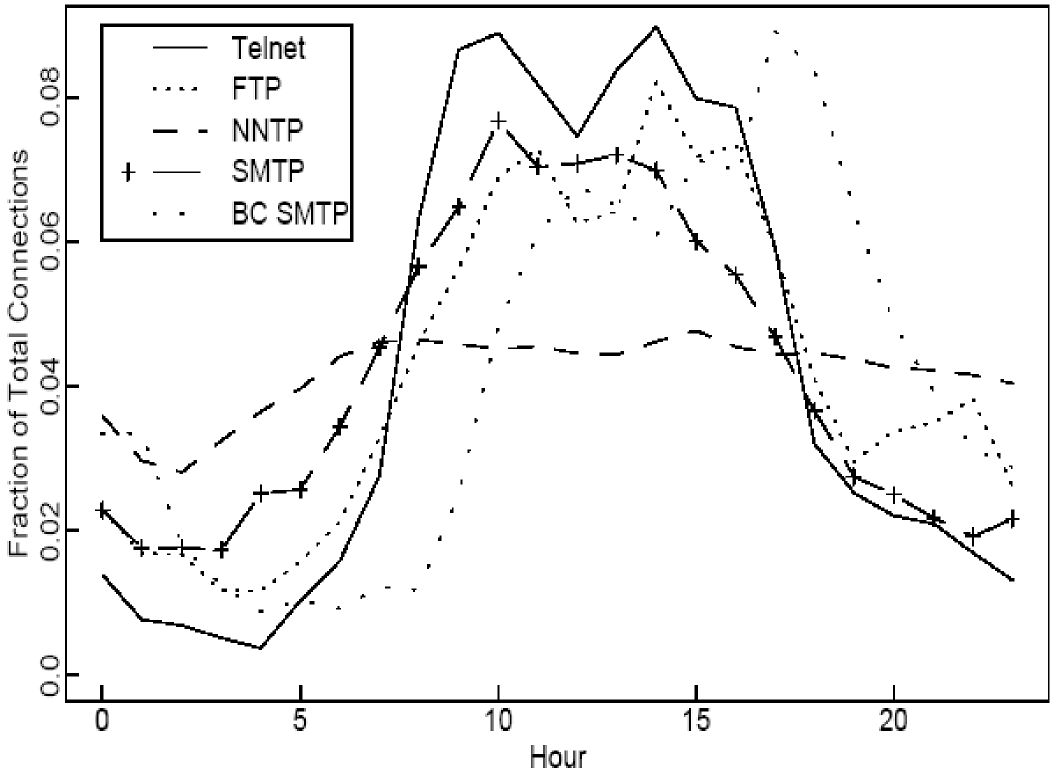

Figure 5: Mean hourly connection arrival rates of several TCP sessions on a WAN scenario.
(from [#paxson95wide])

Connection control traffic: As can be seen in Fig. 5, the daily variation of the connection rate does not allow the use of an homogeneous Poisson process over a whole day for any of the considered protocols. Therefore, smaller time intervals (e.g.: one hour long) will be considered.

- TELNET connections and FTP sessions arrivals: They can be modeled through a homogeneous Poisson process, both for a one hour and a 10 minute interval.
- SMTP connection arrivals: If 10 minute time intervals are used, they can be modeled as compound Poisson processes. However, consequent SMTP interarrival times show consistent positive auto-correlation, which would make a self-similar model more suitable. The positive autocorrelation can be explained by mailing list explosions which make one connection trigger another one.
- NNTP and WWW connection arrivals: They cannot be clearly represented through a Poisson model even over a 10 minute time intervals. In case of NNTP, this can be due to the fact that, within network news propagation, a NNTP connection can spawn a secondary connection, as network news is received from one peer and propagated to the other. In case of WWW, new connections get continuously generated during browsing in a kind of chain process.

Data traffic: No traffic data can be modeled through a Poisson process, independent of the application originating it. In fact, Poisson model would underestimate the traffic burstiness. Therefore, a self-similar model is assumed. Moreover, in the case of TELNET packet interarrivals and FTPDATA bursts, the Pareto distribution is adopted because of the heavy tailed nature of the traffic.
Back to Table of Contents

8. Conclusions

In this paper, we surveyed different traffic models, focusing on the Poisson and Self-similar models. The two differ substantially in that the former assumes independence between the interarrival times and is unable to capture traffic burstiness, whereas the latter can directly represent the fact that Internet traffic exhibits bursty behavior on different time scales. We looked at the usage of these models in the context of Ethernet LANs and WANs. The analysis shows that self-similar models is in general suitable for represent data traffic. In the case of WAN, Poisson processes can still be used (on a one hour time and smaller time scales) in order to model arrivals of TELNET connections and FTP sessions.
Back to Table of Contents

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Back to Table of Contents

List of Acronyms

- **LAN** Local Area Network
- **WAN** Wide Area Network
- **TCP** Transmission Control Protocol
- **TELNET** Teletype Network
- **FTP** File Transfer Protocol
- **SMTP** Simple Mail Transfer Protocol
- **NNTP** Network News Transfer Protocol
- **WWW** World Wide Web
- **TES** Transform Expand Sample

Back to Table of Contents

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Back to Raj Jain's home page