Past Present and Future of Scaling Behaviour in Telecommunications Networks

Darryl Veitch

http://www.cubinlab.ee.mu.oz/~darryl

Department of Electrical & Electronic Engineering
The University of Melbourne
Papers between 1966 and 1987 (P. F. Pawlita, ITC-12, Italy)

- Queueing theory: several thousand
- Traffic measurement: around 50.
• Passive and Active Measurement Workshop (PAM): 2000 → ...
  ≈ 30 papers, 110 attendees.

• Internet Measurement Conference (IMC): 2001 → ...
  ≈ 80 papers, 200 attendees.
What are we Measuring?

- **Internet Protocol** (IP) packets, the unit of transport across networks.
- Data split into packets, with: **header, payload**.
- Payload carries higher layer protocols: **TCP, UDP, ICMP**.
- Protocols support services & applications, more protocols:
  - **TCP**: HTTP, FTP, SNMP, ... (for reliable data)
  - **UDP**: VoIP, DNS, NTP,... (for real time)
- For each packet:
  - Could filter based on criteria (address, type, size, ...)
  - Could capture all or part (e.g. just the header).
  - Must **timestamp**.
- Key concept, a **flow** (collection) of packets.
Two Point Processes from Traffic

Flow arrivals: \( Y(t) \)

Packet arrivals: \( X(t) \)

Most common time series extracted are packets or bytes per bin
Prelude to a Paradigm

Seeing Packet Traffic

• 1991: ISDN (Hellstern, Wirth, Yan, Hoeflin) – infinite moments.
• 1991: Ethernet (Leyland, Wilson) – bursts at all time scales.
• 1993: Ethernet (Erramilli, Willinger) – fractal properties.

Packet traffic does not look Poisson (or simple Markovian models)
The Self-Similarity of Ethernet Traffic

The reference Bellcore trace, ‘pAug’, is close to Fractional Gaussian Noise.
The Arrival of Fractal Traffic

Believing Packet Traffic

• 1993: Ethernet (Leyland, Taqqu, Willinger, Wilson) – Self-Similar Traffic.
• 1994: CCSN/SS7 (Duffy, McIntosh, Rosenstein, Willinger) – Self-Similar.
• 1994: Internet (Paxson, Floyd) – Failure of Poisson modelling.
• 1994 → · · · LAN’s across the world see – Self-Similarity.
• 1994: Web docs (Cunha, Bestavros, Crovella) – Heavy tailed file sizes.
Analysis of Trace ‘pAug’

ETHERNET: bytes per 12ms bin.

Logscale Diagram, $N=2$ [ $(j_1, j_2) = (3, 15)$, $\alpha_{\text{est}} = 0.59$, $Q = 0.011384$ ], $D_{\text{init}}$
What does it mean?

- No characteristic time-scale controlling the dynamics / statistics.
- Statistically, All scales (in a range) are equivalent, under a renormalisation.
- Radical temporal burstiness: no natural burst scale.
- Key parameters no longer special scales, but relations across scales.
- Absolute quantities → scale dependent quantities.
- Affects system description, behaviour, measurement ....

Exact statistical self-similarity ($H$-SS):

$$\{X(t), t \in \mathcal{R}\} \overset{d}{=} \{c^H X(t/c), t \in \mathcal{R}\}, \forall c > 0,$$
The First Self-Similar Traffic Model

Fractional Gaussian Noise (fGn) and Fractional Brownian Motion (fBm)

The unique Gaussian processes which are

\[ \text{Stationary; } \operatorname{Cov} \left[ X_H(k) \right] = \frac{1}{2} \left[ (k - 1)^{2H} + 2k^{2H} + (k + 1)^{2H} \right] \]

\[ \text{Stationary Increments; } \operatorname{Var} \left[ Z_H(k) \right] = k^{2H} \]

Corresponding traffic models:

Rate: \( R(t) = \mu + \sigma X_H(t) \)

Total Traffic: \( W(t) = \mu t + \sigma Z_H(t) \)

where \( Z_H(t) = \sum_{i=1}^{t} X_H(i) \), \( W(t) = \sum_{i=1}^{t} R(i) \).
The Long–Range Dependent (LRD) Traffic Models

LRD definition: a slowly decaying covariance
\[ \Gamma_X(k) \sim c_r k^{-\beta}, \quad 0 < \beta < 1, \]
where \( \beta = 2 - 2H \).

Corresponding traffic rate model:
\[ R(t) = \mu + \sigma X_{\beta, c_r, k^*}(t). \]

LRD more general than H-SS:
- Second order description only, not necessarily Gaussian!
- Has been called second order asymptotically self-similar (but careful!)
- Heavy tail ‘begins’ only after some cutoff scale \( k^* \).
- Tail may be ‘thin’, low mass (small \( c_r \)), independent of variance!
- Small scale structure unspecified.
- At a minimum, three correlation parameters, not just \( H \).
The accepted physical *origin* of (asymptotic) self-similarity in packet and byte counts is heavy tailed distribution of file sizes.
The Arrival of Fractal Traffic

Believing Packet Traffic

• 1994: CCSN/SS7 (Duffy, McIntosh, Rosenstein, Willinger) — Self-Similar.
• 1994: Internet (Paxson, Floyd) — Failure of Poisson modelling.
• 1994 → · · · LAN’s across the world see — Self-Similarity.
• 1994: Web docs (Cunha, Bestavros, Crovella) — Heavy tailed file sizes.
• 1995: Video (Beran, Sherman, Taqqu, Willinger) — roughly Self-Similar.
Non-Gaussian LRD – the On/Off Source

- Alternating renewal process: \( \{A_i\} \) i.i.d. \( \{B_i\} \) i.i.d.
- LRD if \( A \) or \( B \) heavy tailed:
  - If \( \Pr(B > x) \sim cx^{-\alpha} \), \( \beta_{\text{LRD}} = 3 - \alpha \), \( c_r = \frac{c(1-\lambda)^3}{(\alpha-1)E[A]} \).
  - Efficient generation (\( O(1) \) computation and state)

Corresponding traffic rate models:
- as active/silence sources.
- as building blocks for a compound source, eg.
  - \( N \uparrow, p = \Pr(\text{On}) \to 0, \lambda = \text{const}, h = \text{const}: \to M/G/\infty \)
  - \( N \uparrow, p = \text{const}, \lambda = \text{const}, h \to 0: \to fGn \)
Wavelets are ideal for scaling processes, as they are localised time-scale tools.

- From the mother wavelet, $\psi_0(u)$, satisfying $\int \psi_0(u) du = 0$ one defines the
- Wavelet ‘bases’ $\psi_{a,t} = \frac{1}{|a|} \psi_0 \left( \frac{u-t}{a} \right)$ note dilation with scale!
- Continuous Wavelet Transform of $X(t)$ is coefficients: $T_X(a, t) = <X, \psi_{a,t}>, a \geq 0$.
- Discrete Wavelet Transform are the same coefficients, but only those on the dyadic grid: $d_X(j, k) = T_X(a = 2^j, k2^j)$. These can be calculated in an $O(n)$ algorithm.
- The number of vanishing moments, i.e., the largest $N \geq 1$ such that $\int t^k \psi(t) dt \equiv 0$ for $k = 0, 1, \ldots N - 1$, controls the ability to ‘cancel’ LRD and even non-stationarity.
Measuring the Scaling Exponent using Wavelets

Use the Discrete Wavelet Transform (DWT), to transform to a time-scale domain. At each scale $j$ have a detail process:

$$\left\{ d(j, k), \ k = 1, 2, \ldots n_j \right\}$$

Statistical benefits:
- Detail processes quasi-decorrelated
- No LRD in the wavelet domain!
- So classical statistics, $1/n$ convergence.

Spectral definition of LRD is $\Gamma_X(\nu) \sim c_f |\nu|^{-\alpha}$, $|\nu| \to 0$, with $\alpha \in (0, 1)$.

For (stationary) LRD expect energy at octave $j$ of:

$$E[d(j, \cdot)^2] = 2^{j\alpha} c_f C,$$

Unbiased estimate is

$$\mu_j = \frac{1}{n_j} \sum_{k=1}^{n_j} |d_X(j, k)|^2$$

Identify scaling as straight lines, with slope $= \alpha$ in log-log plot:

$$LD : \log_2 \mu_j \text{ vs. } j$$
Analysis of Trace ‘pAug’

ETHERNET: bytes per 12ms bin.

Logscale Diagram, $N=2$  $[(j_1,j_2) = (3,15), \alpha_{est} = 0.59, \quad Q = 0.011384 ]$, $D_{init}$
Robustness to Linear Trends

- $\circ$ : D–Whittle (fGn)
- $*$ : Wavelet (D2)

Estimated $H$

Amplitude of the linear trend

- 0.75
- 0.8
- 0.85
- 0.9
- 0.95

Amplitude of the linear trend

Estimated $H$
Robustness to Level Shift

Part I: $H = 0.81$

Part II: $H = 0.79$

Full trace: $H = 0.80$
Beyond ‘Simple Scaling’, New Challenges in WAN Traffic

The ‘Self-Similarity’ model has limits

- Only really asymptotic: true for ‘large scales’, \( \approx 1 \) second \( \rightarrow \) LRD models
- Really requires Gaussianity – often far from the case!
- Range of scales where valid may not be crucial for engineering purposes.
High Amplitude Burstiness at Small Scale

So small scales are much harder ...
Examples of Scaling in Traffic: 2nd Order Wavelet Analysis

ETHERNET: bytes per 12ms bin.

INTERNET: new connections per 10ms bin.

Logscale Diagram, \( N=2 \) \( [ (j_1,j_2) = (3,15), \alpha \text{--est} = 0.59, Q = 0.011384 ], D_{initial} \)

Logscale Diagram, \( N=2 \) \( [ (j_1,j_2) = (8,19), \alpha \text{--est} = 0.59, Q = 0.81665 ] \)
Biscaling in TCP Arrivals

All Connections

TCP

UDP

HTTP

SMTP
Multifractality: sets of given local regularity $h$ are fractal, with dimension $D_H(h)$.

Measurement of Multifractality: (assuming an appropriate 'Multifractal formalism')

Wavelet $q$th order moments: $\mathbb{E}|d_X(j, k)|^q \sim C \cdot 2^{\alpha q j}, \; j \to 0$.

Estimating the LHS from data using

$$S_q(j) = \frac{1}{n_j} \sum_k |d_X(j, k)|^q,$$

and measure the slopes $\hat{\alpha}_q = \zeta(q) + q/2$ in a log-log plot (the ‘MD’).

Instead of testing for linearity of $\zeta(q)$ vs $q$, look for $\zeta(q)/q$ vs $q$ constant.

If $H$-SS: $\zeta(q) = qH$, $\zeta(q)/q = H$. 
An example: TCP Connections per bin

Multiscale analysis, small scales
An example: TCP Connections per bin

$$\zeta_q / q$$ against $$q$$

Conclusion:

- Small scales: **Non-trivial** multiscaling, eg Multifractal.
- Large scales: **Trivial** multiscaling, eg H-ss model.
A Short History of Multifractal Traffic Modelling

- 1997: Ethernet (Taqqu, Teverovsky, Willinger) – not MF
time domain | discrete packet and byte counts | $\delta = 10\text{ms}$.
- 1997: TCP, LAN gateway (Riedi, Véhel) – MF at ‘high freq’
increments | packet sizes, iat’s, packet and byte counts | $\delta = 150\text{ms}$.
- 1998: Ethernet (Abry, Veitch) – not MF
wavelet distributions | continuous time byte counts.
wavelet domain; discrete packet counts | $\delta = 10\text{ms}$ | large & small regimes
- 1998: TCP, WAN (Feldmann, Gilbert, Willinger) – MF at small, Mono large
wavelet domain | discrete packet counts | $\delta = 10\text{ms}$.
- 1999: ISP and simulated (Feldmann, Gilbert, Huang, Willinger) – MF at small, but dirty
wavelet domain | discrete packet counts | $\delta = 10\text{ms}$.
wavelet distributions | TCP connection counts | $\delta = 10\text{ms}$ | CI’s used.
- 2001: TCP, WAN (Roux, Veitch, Abry, Huang, Flandrin, Micheel) – IDC, but $\approx$ mono.
wavelet distributions | TCP connection counts, packet iar’s and counts, byte counts $\delta = 10\text{ms}$ | CI’s used
- 2003: TCP, WAN, high rate (Zhang, Ribeiro, Moon, Diot) – Mono everywhere
wavelet domain | discrete byte counts | $\delta = 10\text{ms}$ | CI’s used
- 2003: TCP, WAN, high rate (Hohn, Veitch, Abry) – Empirical scaling misleading?
wavelet domain | continuous packet counts | $\delta = 5\mu\text{s} \rightarrow 5\text{ms}$ | CI’s used | $q = 2$
- 2004: TCP, WAN, high rate (Hohn, Veitch, Abry) – No clear evidence for scaling!
wavelet domain | continuous packet counts | $\delta = 5\mu\text{s}$ | CI’s used | $q = 0.5 \cdots 6$
Beyond Power-Law Scaling: Infinitely Divisible Cascades

Self-Similarity: \( \mathbb{E}|d(j, k)|^q = C_q (2^j)^{qH} = C_q \exp(qH \ln(a)) \)
- A single scaling parameter \( H \)
- Power-laws

Multi-Scaling: \( \mathbb{E}|d(j, k)|^q = C_q (2^j)^{H(q)} = C_q \exp(H(q) \ln(a)) \)
- A collection of parameters: \( H(q) \)
- Power-laws

Infinitely Divisible Cascade: \( \mathbb{E}|d(j, k)|^q = C_q \exp(H(q)n(a)) \)
- Two collections of parameters: \( H(q), n(a) \)
- No Power-Law!
- but separability of order \( q \) and scale \( a \).

But! relative power-laws remain:
\[
\mathbb{E}|d_X(j, k)|^q = C_{p,q} \left( \mathbb{E}|d(j, k)|^p \right)^{H(q)/H(p)}
\]
- tested by plotting \( \log_2 S_q(j) \) vs \( \log_2 S_p(j) \), if passes,
- \( H(q) \) and \( n(a) \) can be estimated.
Testing for IDC in TCP Connection Arrivals

Estimation of $H_p(q) = H_1(0.5)$, $N = 3$

Estimation of $H_p(q) = H_1(1)$, $N = 3$

Estimation of $H_p(q) = H_1(1.5)$, $N = 3$

Estimation of $H_p(q) = H_1(2)$, $N = 3$

Estimation of $H_p(q) = H_1(2.5)$, $N = 3$

Estimation of $H_p(q) = H_1(3)$, $N = 3$

Estimation of $H_p(q) = H_1(4)$, $N = 3$

Estimation of $H_p(q) = H_1(5)$, $N = 3$

Estimation of $H_p(q) = H_1(6)$, $N = 3$
Unlike MS, IDC hypothesis is valid over both scaling ranges.
A Short History of Multifractal Traffic Modelling

- **1997**: Ethernet (Taqqu, Teverovsky, Willinger) – not MF  
  time domain discrete packet and byte counts \( \delta = 10\text{ms} \).
- **1997**: TCP, LAN gateway (Riedi, Véhel) – MF at ‘high freq’  
  increments packet sizes, iat’s, packet and byte counts \( \delta = 150\text{ms} \).
- **1998**: Ethernet (Abry, Veitch) – not MF  
  wavelet distributions continuous time byte counts.
- **1997-8**: TCP, LAN gateway (Feldmann, Gilbert, Willinger, Kurtz) – MF small, Mono large  
  wavelet domain; discrete packet counts \( \delta = 10\text{ms} \) large & small regimes
- **1998**: TCP, WAN (Feldmann, Gilbert, Willinger) – MF at small, Mono large  
  wavelet domain discrete packet counts \( \delta = 10\text{ms} \).
- **1999**: ISP and simulated (Feldmann, Gilbert, Huang, Willinger) – MF at small, but dirty  
  wavelet domain discrete packet counts \( \delta = 10\text{ms} \).
- **1999-2000**: TCP, WAN (Veitch, Abry, Flandrin, Chainais) – IDC holds over large and small  
  wavelet distributions TCP connection counts \( \delta = 10\text{ms} \) CI’s used.
- **2001**: TCP, WAN (Roux, Veitch, Abry, Huang, Flandrin, Micheel) – IDC, but \( \approx \) mono.  
  wavelet distributions TCP connection counts, packet iat’s and counts, byte counts \( \delta = 10\text{ms} \) CI’s used
- **2003**: TCP, WAN, high rate (Zhang, Ribeiro, Moon, Diot) – Mono everywhere  
  wavelet domain discrete byte counts \( \delta = 10\text{ms} \) CI’s used
- **2003**: TCP, WAN, high rate (Hohn, Veitch, Abry) – Empirical scaling misleading?  
  wavelet domain continuous packet counts \( \delta = 5\mu s \rightarrow 5\text{ms} \) CI’s used \( q = 2 \)
- **2004**: TCP, WAN, high rate (Hohn, Veitch, Abry) – No clear evidence for scaling!  
  wavelet domain continuous packet counts \( \delta = 5\mu s \) CI’s used \( q = 0.5 \cdots 6 \)
Where Did the Evidence Go?

- Use of confidence intervals
- Estimators can be fooled: artifacts / low-power
- Lack of physical basis
Use of Confidence Intervals

- Marginal Evidence $\rightarrow$ need better tools
  - must assess goodness of fit
  - need better estimators: know/reduce bias, reduce variance/know CI
  - more sophisticated quality criterion
  - formal hypothesis test
Estimators can be fooled

Scale invariance of discontinuities, plus noise

Level Transition leads to ‘Pseudo slopes’ (Gamma-Renewal process)

Need tests with high power - but is it enough?
Lack of Physical Basis

- No insight into why should be MF - can’t independently test
- Consistency with ‘network physics’ not built in

But can a physical model account for the scaling at all $q$?
Semi-Experiments on Packet Arrivals
Original TCP Data

DATA

EXPERIMENT

Time
Permutation of Flows [A-Perm]
Poisson (Barlett-Lewis) Cluster Processes

Definition

- A Poisson process of seeds (flows), initiating independent groups of points (packets):

\[ X(t) = \sum_i G_i(t - t_F(i)) \]

- Group: a finite renewal process with \( P \) points and inter-arrival distribution \( A \):

\[ G_i(t) = \sum_{j=1}^{P(i)} \delta \left( t - \sum_{l=1}^{j-1} A_i(l) \right) \]

Parameters

- Flow arrivals: constant intensity \( \lambda_F \)
- Flow structure:
  - Packet arrivals: \( A, \frac{1}{EA} = \lambda_A < \infty \), cf: \( \Phi_A(\omega), \omega > 0 \)
  - Flow volume: \( P, \ E P = \mu_P < \infty \), pgf: \( G_P(z) = \sum_{j=0}^{\infty} p_j z^j, |z| \leq 1 \).
Fourier Spectrum

\[ \Gamma_X(\nu) = \lambda_F \left( \frac{\mu_P}{\lambda_A} \Gamma_g(\nu) + (S_g(\omega) + S_g(-\omega)) \right), \]

\( \Gamma_g(\nu) \): spectrum of \textit{stationary} renewal process with inter-arrivals \( A \), and

\[ \mathcal{R}(S_g(\omega)) = \frac{\Phi_A(\omega)}{(1 - \Phi_A(\omega))^2} \left( G_P(\Phi_A(\omega)) - 1 \right). \]

Verify LRD:

\[ \mathcal{R}(S_g(\omega)) \quad \omega \to 0 \quad \sim LB(\beta)(2\pi\lambda_A)^{2-\beta} \omega^{-(2-\beta)} \to \infty \]

\[ \omega \to \infty \quad \sim -\frac{\cos(c\pi/2)}{(b\omega)^c} \to 0 \]

where \( B(\beta) = \psi(1 - \beta) \cos(\pi\beta/2)/(2\pi)^{(2-\beta)} > 0 \)

\textbf{Properties}

- \( \lambda_F \) just a variance multiplier: ‘more of same’
- has scale parameter \( 1/\lambda_A \) if \( A \) has: \( \Gamma_X(\omega; \lambda_F, \lambda_A, c, F_P) = \Gamma_X(\omega/\lambda_A; \lambda_F, 1, c, F_P) \)
- Two terms dominating small-large scales
  - First term (small scales): scaled renewal process, no detailed \( P \) dependence
  - Second term (large scales): LRD, no \( A \) dependence beyond \( \lambda_A \)
Modelling a Typical Auckland IV Trace

\[ j^*_{GR} = - \log_2 \lambda_A + \log_2 \left( \frac{\pi^2 (c + 1)}{3 \epsilon c^2} \right) \]

\[ j^{**}_{PGR} = - \log_2 \lambda_A + \frac{1}{2 - \beta} \left( \log_2 \mu_p - \log_2 (2LB(\beta)) - \log_2 c \right) \]
Empirical Multiscaling for Cluster Model

$q = 0.5$

$q = 1$

$q = 2$

$q = 3$

$q = 4$

$q = 6$
Empirical Multiscaling for the Data

\[ 2^{-q} \log_2 S_q(j) \]

For different values of \(q\):
- \(q = 0.5\)
- \(q = 1\)
- \(q = 2\)
- \(q = 3\)
- \(q = 4\)
- \(q = 6\)
Conclusion: no reason to conclude for multifractals, empirical evidence is spurious
So is There Scaling Behaviour Beyond LRD?

Multifractal or IDC behaviour may exist for some components of some time series in networks today, or in the future, but to be sure the statistical shortcomings must be addressed!

- Use of confidence intervals
- Estimators can be fooled: artifacts/low-power
- Lack of physical basis
The Packet Arrival Process, Clusters?
Naive Intuition: Clusters are Flows
More Realistically: Flows Interleave
Reality Check: Clusters Lost in Clustered Fog
Unassisted: where are the clusters now?
Need more powerful ways to detect ‘signal in noise’, which test for *structure*.

In terms of model choice, akin to re-emphasizing prediction (and in particular sample path ‘deterministic’ prediction), over ensemble distributional agreement.