A Chain of Problems in Teletraffic

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Collaborators:  Patrice Abry, András Gefferth, Nicolas Nohn,
Traffic Modelling in 1988

Papers between 1966 and 1987 (P. F. Pawlita, ITC-12, Italy)

- Queueing theory: several thousand
- Traffic measurement: around 50.
Tele–Traffic in 2001

Measurement Practice

- Recognition of measurement, not just routine quantification, but discovery.
- Widespread monitoring of LAN’s, ISP networks, national infrastructures.....
- Large scale programs for Internet, from routine monitoring to ultra high resolution.
- Emergence of numerous small & large scale active probing efforts.
- Huge advances in measurement accuracy.

Renaissance in Modelling

- Return of science 101: Observation and inspiration before model.
- Return of verification: Evaluating usefulness against real data.
- New model paradigm as standard: Characteristic scale $\rightarrow$ scale invariance.
- New model classes: Source, link, network, and closed loop.
- New problems: Active, multi-route, and high resolution measurements.

Stimulus to Theory

- Statistical estimation: For time series with infinite moments and/or scaling.
- Queueing Theory: Dealing with sub-exponential (eg LRD) input processes.
- Analysis: Network feedback, and properties of new models.
The Scientific Method Meets Tele-Traffic – A Set of Interconnected Problem Domains

1: Traffic Data Collection
2: Traffic Data Analysis
3: Statistical Tools
4: Traffic Discoveries
5: Traffic Modelling
6: Offshoots
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:
  - **TCP**: HTTP, FTP, SNMP, ... (for reliable data)
  - **UDP**: VoIP, DNS, NTP,... (for real time)
- Passive measurement: watch complex mix pass by a fixed point.
- For each packet:
  - Could capture all or part (eg just the header).
  - Must timestamp.
- Key concept, a flow (collection) of packets.
Traffic Data Collection: Flows

**IP flow**: set of packets with the same 5-tuple

<table>
<thead>
<tr>
<th>IP protocol</th>
<th>Sources Address</th>
<th>Destination Address</th>
<th>Source Port</th>
<th>Destination Port</th>
</tr>
</thead>
</table>

Diagram showing time series data.
Traffic Data Collection: Active Areas

- Hardware for high speed packet capture ( > 10 Gpbs ).
- Algorithms for on-line calculation and storage of
  - Packet level statistics.
  - Flow tracking and flow statistics.
- Schemes for traffic sampling.
A Link in the Chain: Packet Thinning

The Problem:

- Begin with thinned packet data: retention probability $q$.
- Aim: to recover density $\{p_k\}$ of $P$, number of packets in a flow.

From $P$ to $P(q)$:

$$
p_k^{(q)} = \sum_{j=k}^{\infty} \Pr\{k \text{ packets after thinning} \mid j \text{ packets before thinning}\} p_j
= \sum_{j=k}^{\infty} \binom{j}{k} q^k (1 - q)^{j-k} p_j.
$$

Simple formula for flow size after thinning:
Inverting:

\[ p_j = \sum_{n=j}^{\infty} \binom{n}{j} \frac{(-1)^{n-j}}{q^n} (1 - q)^{n-j} p_n(q), \]

only converges for \( q \in [0.5, 1] \).

For serious thinning, need something else:

\[ G_p(z) = G_p(q) \left( \frac{z - (1 - q)}{q} \right) \quad \text{for} \quad z \in \bar{D}(1 - q, q). \]
Theoretical inversion is easy, but practically ill-posed. Solution is flow thinning:

Similar conclusions hold for spectrum of packet arrival process.
Traffic Data Analysis

A Diverse Set of Practices:

- Data initially filtered according to:
  - Packet versus Bytes.
  - Protocol, and/or application type.
  - Source and/or Destinations, or sets thereof.
  - Degree of burstiness.
  - Packet rate and/or round-trip time.
  - Resolution level (router summary stats → dedicated trace runs).
  - Time series of interest (counts per bin, inter-arrival times).

- Semi-experiments.

- Statistical ideas applied:
  - Estimation of second-order: covariance, spectrum, variance-time, wavelet energy.
  - Heavy tail estimation.
  - Marginal distributions.
  - Wavelet based estimation for scaling processes.
  - Principal Component Analysis.

- Metrics of Interest:
  - Packet Loss, delay, delay variation, round-trip time.
  - Routing stability.
  - Time-scale dependent burstiness, second-order or multifractal.
Traffic Data Analysis: Active Areas

- Router protocol performance and stability.
- Origins of scaling behaviour.
- Rate variability in flows.
- End-to-end delay and loss performance.
- Round-trip time characterisation.
- Localisation of bottlenecks.
- Traffic modelling (both open and closed loop).
- Traffic matrix calculation.
A Link in the Chain: Semi-Experiments
Original TCP Data
Permutation of Flows [A-Perm]
Original Order Poisson Arrivals [A-Pord]

(a smooth form of *internal shuffling*)

EXPERIMENT

DATA

Time
Original Order Poisson Arrivals [A-Pord]
Permuted Poisson Arrivals [A-Pois]
Permutted Poisson Arrivals [A-Pois]

![Graph showing data points and curves for different distributions: Data, [A-Perm], [A-Pord], and [A-Pois]. The graph plots log2 Variance(j) against scale j, with scales ranging from 0.016 to 1024].

- Data
- [A-Perm]
- [A-Pord]
- [A-Pois]
What have we learned so far?

Flow Arrival Manipulation

- Correlations between flows can be neglected
  - No need for session level hierarchical models
  - TCP dynamics between flows can be neglected
- For IP modelling, flow arrivals can be modelled as Poisson
  - Justifies an assumption commonly used in traffic modelling.

**Note:** true flow arrival process is LRD.
The Semi-Experimental Method

Replacing selected aspects of data with model substitutes

Benefits

- Understand the impact of a particular feature on overall statistics
- Enables ‘convenient’, highly flexible virtual experimentation
- Avoids need to model all aspects simultaneously
- Enables physically meaningful parameters to be directly targeted

Classes of manipulations performed:

[A] on Flow Arrival process
[P] on Packet arrival process within a flow
[S] Selection of flows according to number of packets, duration, rate, address, burstiness ....
[T] Truncation of flows according to number of packets, duration, silence duration ....

A Modelling Continuum:

primitive SE → compound SE → class search SE → semi-model → physical model
(neutral model) (multi-aspect) (model choosing) (1 data aspect) (no data)
Statistical Tools

One Uses What One Has, What is Needed?

- Improved estimators for heavy tails.
- Increased robustness to non-stationarities (which don’t matter).
- Improved hypothesis tests for non-stationarities (which do).
- Reliable confidence intervals for mean estimates for LRD processes.
- Confidence intervals for variance, covariance.... for LRD processes.
- Formal test for multi versus mono-fractality.
- Low complexity algorithms for all of the above.

Some of these are active areas in the statistics literature - but more is needed.
A Link in the Chain: Constancy of Scaling Exponents

The Problem: How to determine if a scaling exponent $\alpha$ is constant in time?

Properties of a Wavelet Estimator $\hat{\alpha}$

- **Procedure**: estimation independent of details of scaling.
- **Bias**: the estimator is approximately unbiased.
- **Variance**: variances close to Cramer-Raò lower-bound and known.
- **Robustness**: semi-parametric, insensitive to deterministic trends and slow variation in variance
- **Computational load**: complexity of order $O(n)$, on-line algorithm.
- **Gaussiannity**: Estimates approximately Gaussian.
- **Uncorrelated**: $m$ adjacent blocks: estimates approximately decorrelated.

The $\{\hat{\alpha}_1, \ldots, \hat{\alpha}_m\}$ approximately obey $\hat{\alpha}_i \sim N(\alpha_i, \sigma_i^2)$ where the $\sigma_i^2$ are known, but the $\alpha_i$ unknown.
Null hypothesis $H_0$: the exponents are identical, $H_1$: they differ.

Can map problem to an UMPI test (here $\sigma_i = \sigma$):

$$H_0: \theta = \sum (\alpha_i - \bar{\alpha})^2 / \sigma^2 = 0$$
$$H_1: \theta > 0$$

Critical Region: $V = \sum (\hat{\alpha}_i - \bar{\alpha})^2 / \sigma^2 > C$ (one-sided).

$H_0$ is rejected if $V > C$.

$V$ distributed as *non-central* Chi-squared variable with $m - 1$ degrees of freedom and non-centrality parameter $\theta$.

$m$ dimensional problem has been reduced to 1-D by symmetry.
Application to Ethernet Traffic
Traffic Discoveries

- Self-Similarity of Ethernet Traffic
- Heavy tailed flow sizes.
- Ubiquity of Long Range Dependence (LRD)
  - In packet and byte arrival processes.
  - In different networks.
  - Different time series.
  - Over time.
- Heterogeneity in Traffic.
- Routing instability.
- Mice and Elephants phenomenon.
The reference Bellcore trace, ‘pAug’, is close to *Fractional Gaussian Noise*. 
Traffic Discoveries

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For active areas, see traffic analysis!
The Idea: That ‘20%’ of packets account for ‘80%’ of impact.

- Most often applied to flow volume: distribution of $P$ is heavy tailed.
- But, can also be applied to traffic rate.
- Is really time-scale dependent.
Aims of Modelling

- To support tele-traffic engineering:
  - Network dimensioning/design.
  - Capacity planning.
  - Quality of service provision.
  - Admission control.
  - Congestion control.

- Understanding of traffic:
  - Statistically.
  - In terms of network ‘physics’ - meaningful models.
  - Separating the generic from the fortuitous.

- Artificial traffic generation.
- Statistical traffic prediction.
- To capture the essentials parsimoniously....
- To inspire theory!
Traffic Modelling: Examples

- Self-Similar Model: Fractional Brownian Motion.
- LRD ‘models’.
- On/Off Model.
- Multifractal models.
- Markovian Models.
- Closed loop models of TCP.
- Cluster Models.
The Self-Similar Traffic Model

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

The unique Gaussian processes which are stationary and have stationary increments are described by:

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

Corresponding traffic models:

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

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

where
\[ Z_H(t) = \sum_{i=1}^{t} X_H(i), \quad W(t) = \sum_{i=1}^{t} R(i). \]
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 \( H \).
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 $\Pr(B > x) \sim cx^{-\alpha}$, $\beta_{\text{LRD}} = 3 - \alpha$, $c_r = \frac{c(1-\lambda)^3}{(\alpha-1)\mathbb{E}[A]}$.
  - Efficient generation ($O(1)$ computation and state)

**Corresponding traffic rate models:**

- as active/silence sources.
- as building blocks for a compound source, eg.
  - $N \uparrow$, $p = \Pr(\text{On}) \to 0$, $\lambda = \text{const}$, $h = \text{const}$: $\to M/G/\infty$
  - $N \uparrow$, $p = \text{const}$, $\lambda = \text{const}$, $h \to 0$: $\to fGn$
Seek statistically and physically meaningful stationary point process models.
Semi-Experiment Outcomes

Flow Arrival Manipulation
- Correlation between flows can be neglected,
- For IP modelling, flow arrivals can be modelled as Poisson,
- [A-Clus]: knee of $Y$ affects knee of $X$!

Packets within Flow Manipulation
- LRD not caused by arrival process of packets within flows,
- Small scale behaviour governed by structure within flows,
- Finite Poisson process a reasonable 0-th order model,
- [P-Pois]: indistinguishable from [P-Uni],
- [P-ConstR]; [P-ScaledR]: rate acts like a scale parameter,

Flow Selection
- Observed LRD caused by heavy-tailed flow volumes,
- [S-Thin]: random thinning consistent with independent flows,
- [S-Dur]: also kills LRD (flow duration slaved to volume),
- [S-Pkt]: LRD still present even without heavy tail!

Flow Truncation Manipulation
- [T-Pkt]: also kills LRD, makes $X$ tend to $Y$,
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 \( A \):
  \[ G_i(t) = \sum_{j=1}^{P(i)} \delta( t - \sum_{l=1}^{j-1} A_i(l) ) \]

Parameters

- Flow arrivals: constant intensity \( \lambda_F \)
- Flow structure:
  - Packet arrivals: \( A, \ \frac{1}{E_A} = \lambda_A < \infty, \) \( \text{cf: } \Phi_A(\omega), \omega > 0 \)
  - Flow volume: \( P, \ \mathbb{E}P = \mu_P < \infty, \) \( \text{pgf: } G_P(z) = \sum_{j=0}^{\infty} p_j z^j, |z| \leq 1. \)
Properties of $X(t)$, and Model Features

- $\lambda_X = \mu_P \lambda_F$ (does not involve $\lambda_A$)
- Point process, hence inherently ‘positive’
- Physically meaningful structure and parameters
- Fourier spectrum $\Gamma_X(\nu)$ known
- Inter-arrival distribution known (in principle)
- Simple direct simulation (except transient)
- Potentially tractable queueing theory
Fourier Spectrum

\[ \Gamma_X(\nu) = \lambda_F \left( \frac{\mu_p}{\lambda_A} \Gamma_c(\nu) + (S_\nu(\omega) + S_\nu(-\omega)) \right), \]

\( \Gamma_c(\nu) \): spectrum of stationary renewal process with inter-arrivals \( A \), and

\[ \mathcal{R}(S_\nu(\omega)) = \frac{\Phi_\lambda(\omega)}{(1 - \Phi_\lambda(\omega))^2}(G_P(\Phi_\lambda(\omega)) - 1). \]

Verify LRD:

\[ \mathcal{R}(S_\nu(\omega)) \xrightarrow{\omega \to 0} LB(\beta)(2\pi \lambda_A)^{2-\beta} \omega^{-(2-\beta)} \to \infty \]
\[ \mathcal{R}(S_\nu(\omega)) \xrightarrow{\omega \to \infty} -\frac{\cos(c\pi/2)}{(b\omega)^c} \to 0 \]

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

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

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

\[ j^{**}_{PGR} = - \log_2 \lambda_A + \frac{1}{2 - \beta} \left( \log_2 \mu_P - \log_2 (2LB(\beta)) - \log_2 c \right) \]
Data and Model hard to distinguish at all aggregation levels
Offshoots

Data and It’s Analysis Generates New Questions!

- **Use of Wavelets**
  - A way to use DWT to study spectra of discrete time series.
  - Joint estimation of scaling exponent and prefactor.

- **Nature of Discrete Self-Similarity**
  - showing that fGn not the only type of 2nd order SS.
Stationary second-order discrete time series $X(t)$
Correlation function $\rho(k)$ and correlation-time function $\phi(n) = \sum_{k=0}^{n-1} \sum_{i=-k}^{k} \rho(i)$.
Second-order self-similarity is equivalent to: $\phi(nm) = \phi(n)\phi(m)$.
fGn is a solution with $\phi^*(n) = n^{2H}$, $H \in [0, 1]$ others?  Yes! the ‘Almost Periodic’ family.
Conclusion: Begin Again for Active Traffic Data!

1: Traffic Data Collection.

2: Traffic Data Analysis.

3: Statistical Tools.

4: Traffic Discoveries.

5: Traffic Modelling.

6: Offshoots...........................