

Modelling internet round-trip time data

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Outline

- motivation ■
- data ■
- theory ■
- model fitting

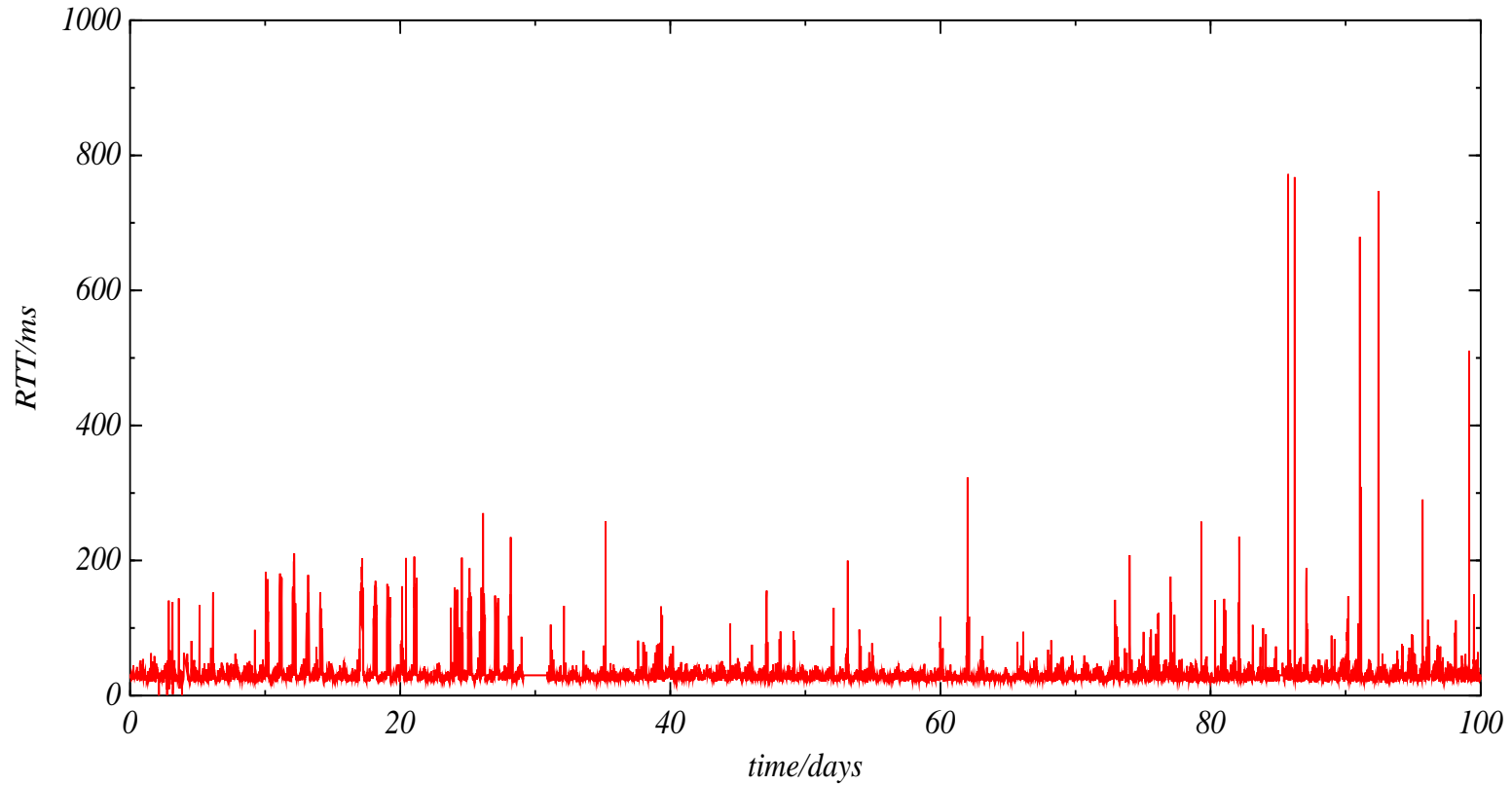
Motivation

- internet as a complex system
- round-trip time (RTT) data forms an intriguing time series
- successful models would allow:
 - ▷ *forecasting*
 - ▷ *simulation*
 - ▷ *understanding*



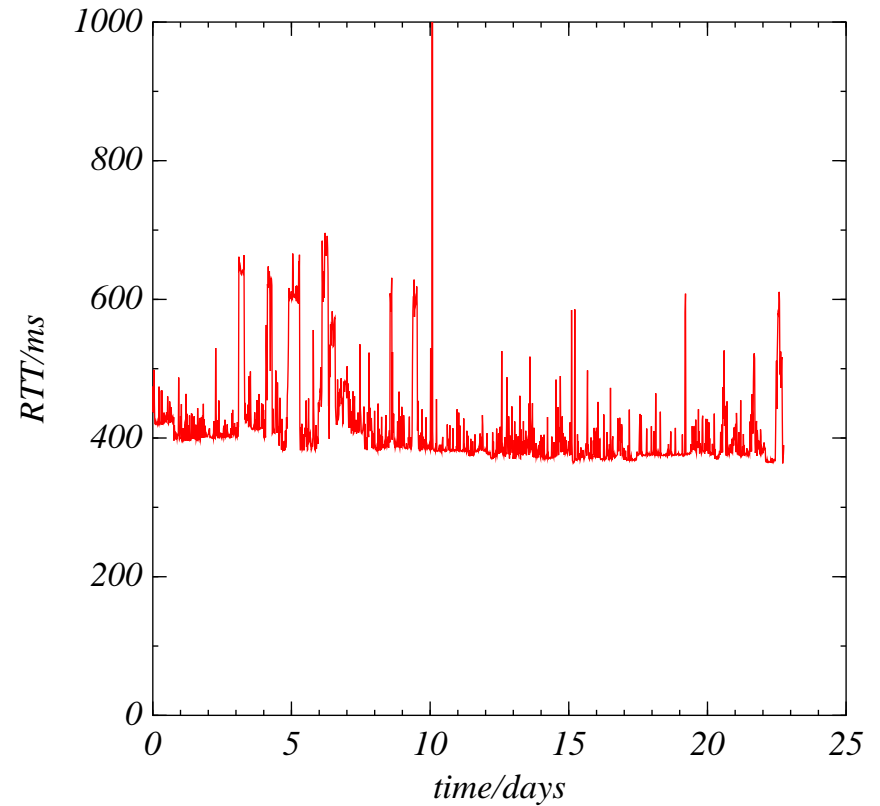
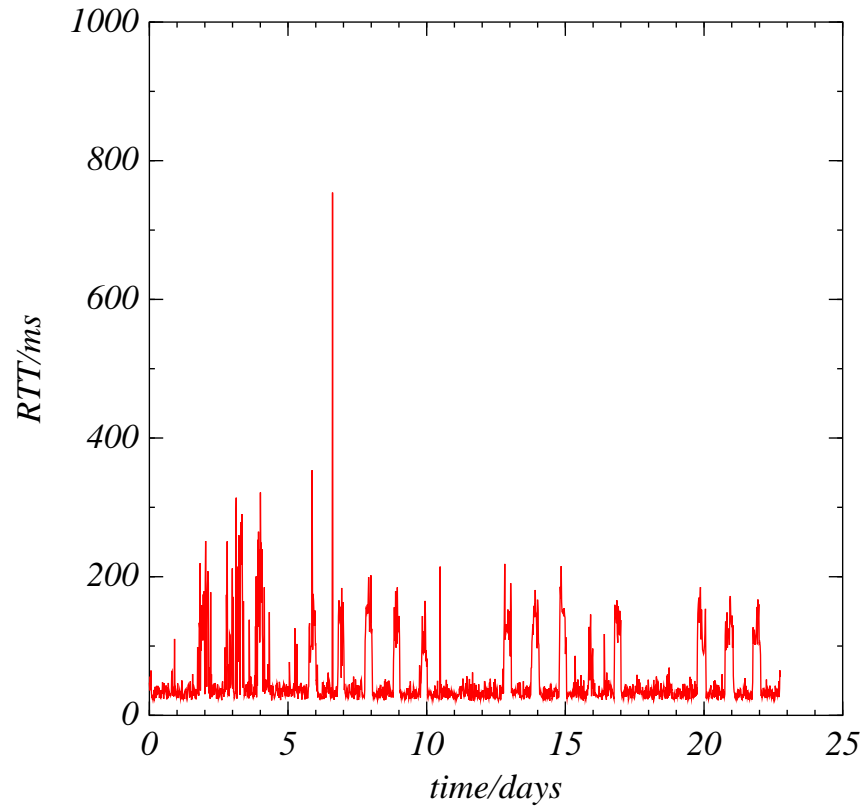
- any model used should incorporate features believed to exist in the data in a *natural* way

Raw data 1



100 days of typical raw data, from `www.edinburgh.ac.uk`

Raw data 2



`www.edinburgh.ac.uk` and `www.chem.uwa.edu.au`

Long-range dependence?

- definition:

$$\lim_{k \rightarrow \infty} \rho(k) k^{2(1-H)} = \text{constant}$$

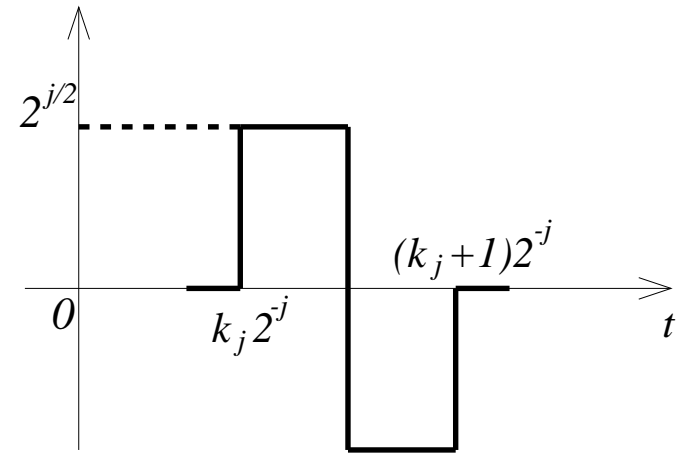
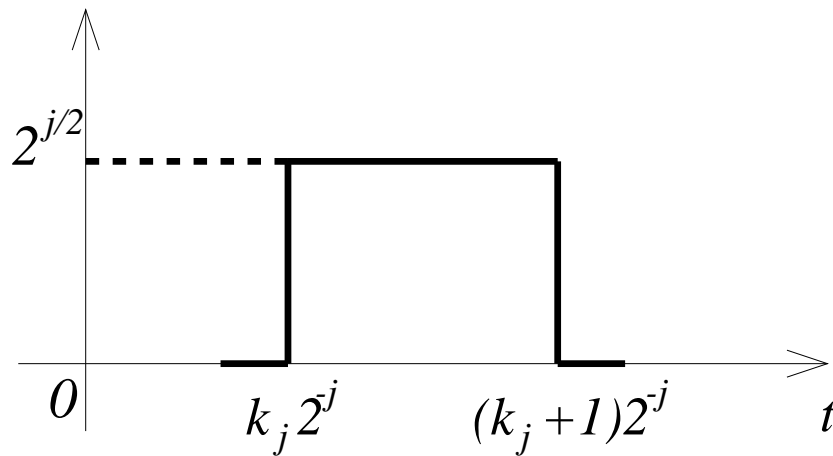
- $0 < \alpha = 2(1-H) < 1$ ■

- useless!

- ▷ *for stationary process only*
- ▷ *large- k limit*
- ▷ *H cannot be estimated in practice even when it exists and is known* ■
- ▷ *tries to reduce complex phenomena to a single number*

Wavelet transform 1

- I use the Haar basis - left: scaling function ϕ ; right: wavelet function ψ



$$\psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k)$$

$$\phi_{j,k}(t) = 2^{j/2} \phi(2^j t - k)$$

Wavelet transform 2

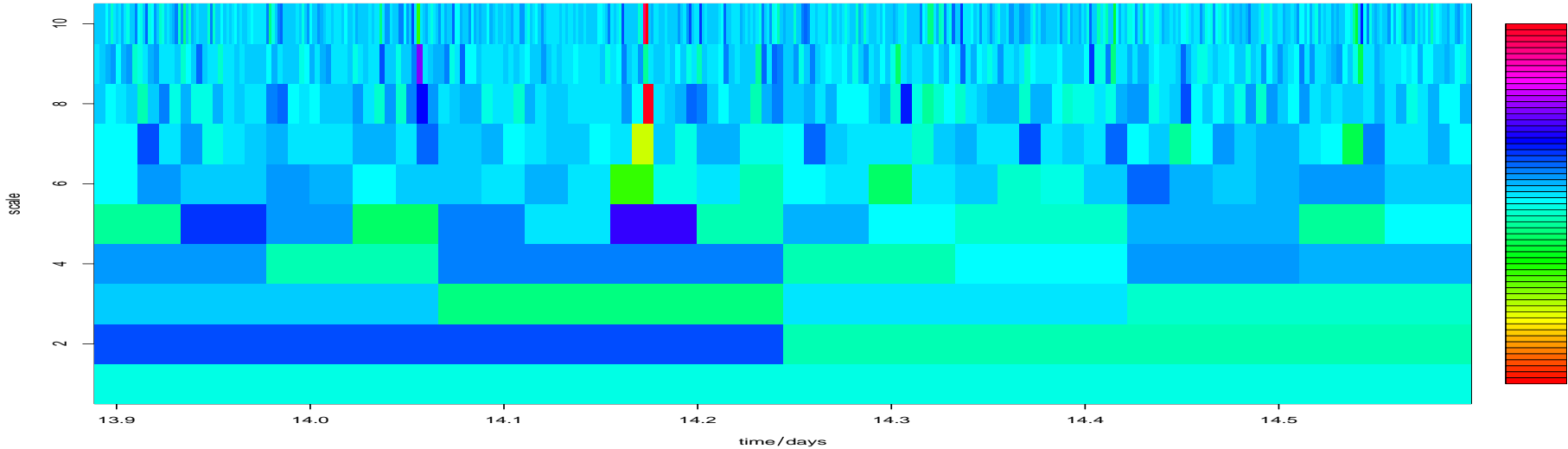
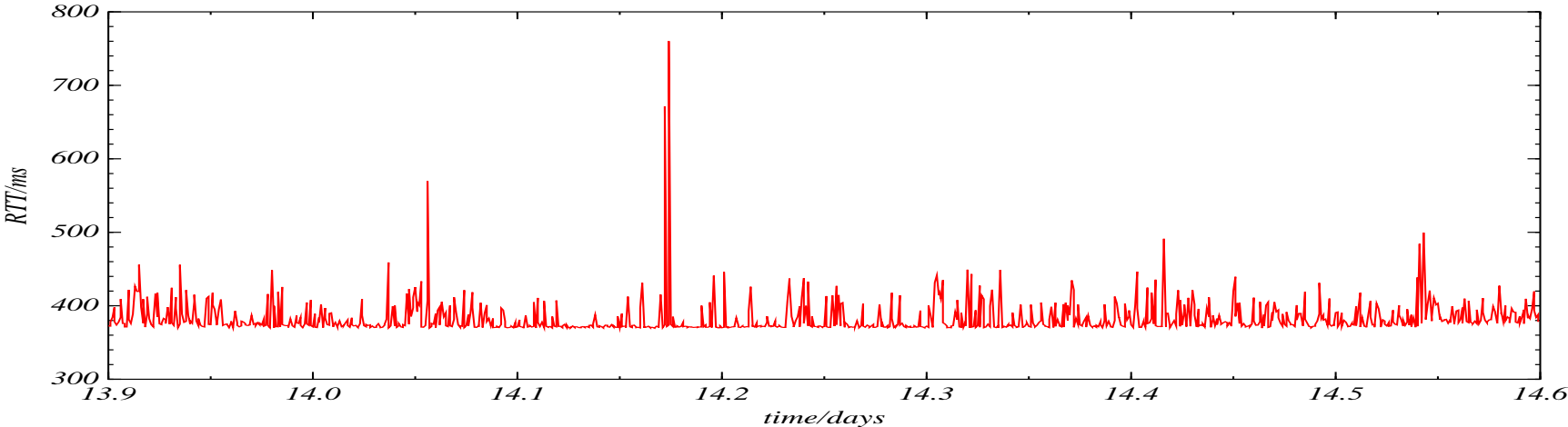
$$f_t = \sum_k U_{0,k} \phi_{0,k}(t) + \sum_{j=0}^J \sum_k W_{j,k} \psi_{j,k}(t)$$

wavelet coefficients, $W_{j,k}$, and *scaling coefficients*, $U_{j,k}$, are defined by

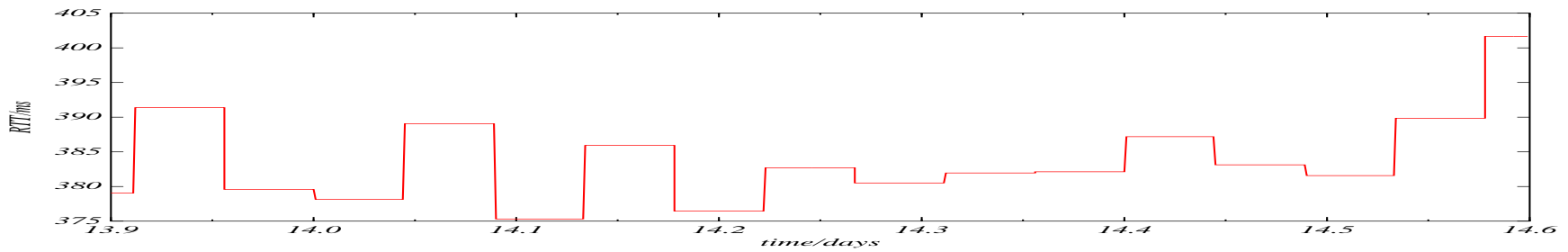
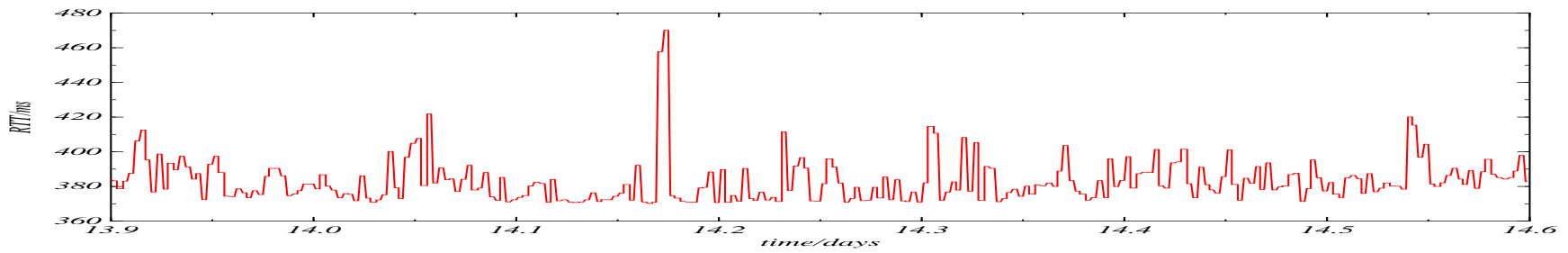
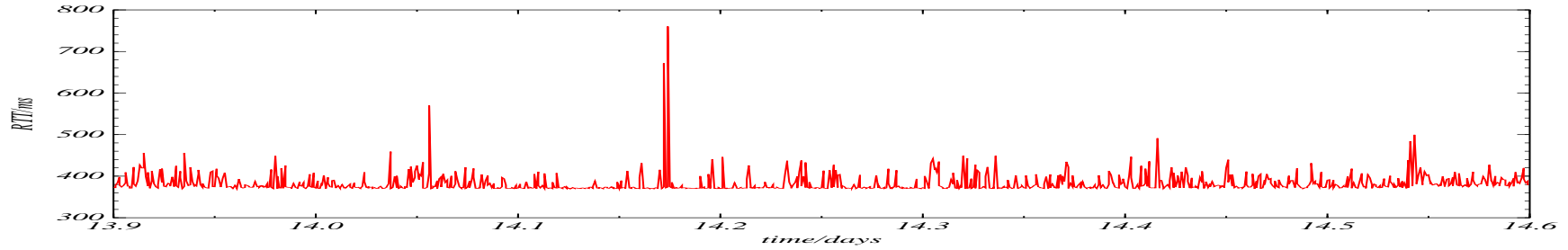
$$W_{j,k} = \sum_{t=1}^T f_t \psi_{j,k}(t)$$

$$U_{j,k} = \sum_{t=1}^T f_t \phi_{j,k}(t)$$

Example wavelet transform 1



Example wavelet transform 2



Information at scales J , $J-1$ and $J-4$

Multifractal spectrum

- g is Lipschitz α at x_0 if α is the supremum of those a such that in a neighbourhood of x_0

$$|g(x) - p_{\lfloor \alpha \rfloor}(x)| = \mathcal{O}(|x - x_0|^a)$$

where $p_{\lfloor \alpha \rfloor}$ is a polynomial of degree $\lfloor \alpha \rfloor$ ■

- Let $f(\alpha)$ be the Hausdorff dimension of the set of points where the Lipschitz exponent is α . This is the *multifractal spectrum* of g ■
- example:
 - ▷ fractal Brownian motion has zero mean and Gaussian increments s. t. the mean square increment at lag Δ is proportional to $|\Delta|^{2H}$
 - ▷ this is a monofractal - $f(\alpha) = \delta(H)$
 - ▷ however, estimates of f from a finite sample will **not** show this delta function behaviour

The multifractal formalism 1

- to estimate $f(\alpha)$ from discrete data, use partition function $\tau(q)$ ■
- For a process $X(t)$, define the *structure function*, $S_j(q)$, by

$$S_j(q) = \sum_{k_j} (2^{-j/2} U_{j,k_j})^q$$

where U_{j,k_j} are Haar scaling coefficients for $X(t)$ ■

- The partition function is then defined as

$$\tau(q) = - \lim_{j \rightarrow \infty} \frac{1}{j} \log S_j(q)$$

■

- Next define

$$f_L(\alpha) = \inf_{q \in \mathbb{R}} (q\alpha - \tau(q))$$

The multifractal formalism 2

- The multifractal formalism shows that

$$f(\alpha) \leq f_L(\alpha)$$

The Legendre transform of the partition function is the concave hull of $f(\alpha)$. $f_L(\alpha)$ is known as the *Legendre spectrum*

- Let us assume that our RTT data is a sample of an underlying continuous process. Assume further that the observable scaling behaviour of $S_j(q)$ is continued beyond the finest measured scale to the limit $j \rightarrow \infty$. That is,

$$S_j(q) \approx 2^{-j\tau(q)}$$

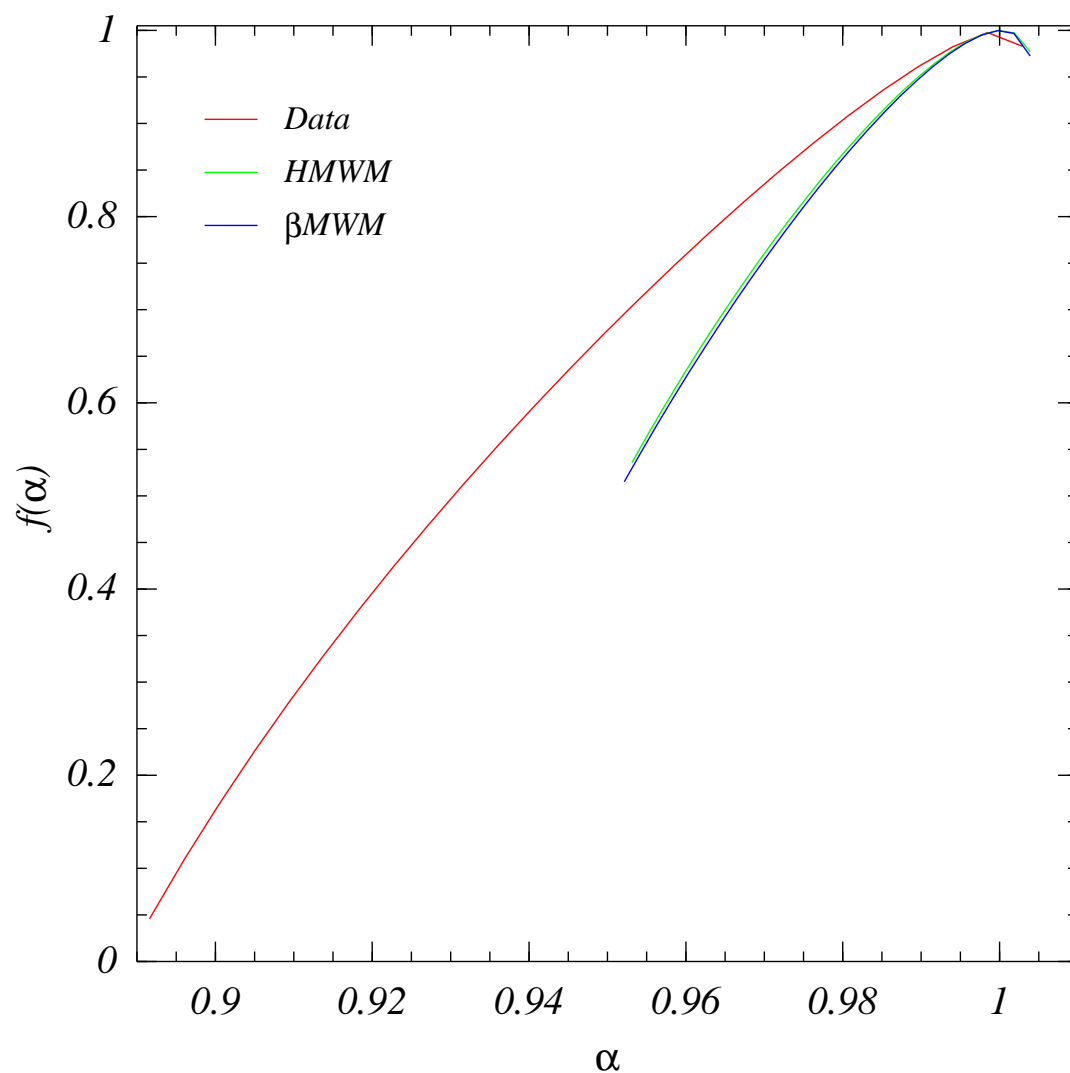
over $j = j_1, \dots, j_2$, where $j_1, j_2 \in [0, J]$

- $\tau(q)$ can be estimated from the gradient of a plot of $\log_2 S_j(q)$ against j over a finite range of scales

Riedi's multifractal wavelet model

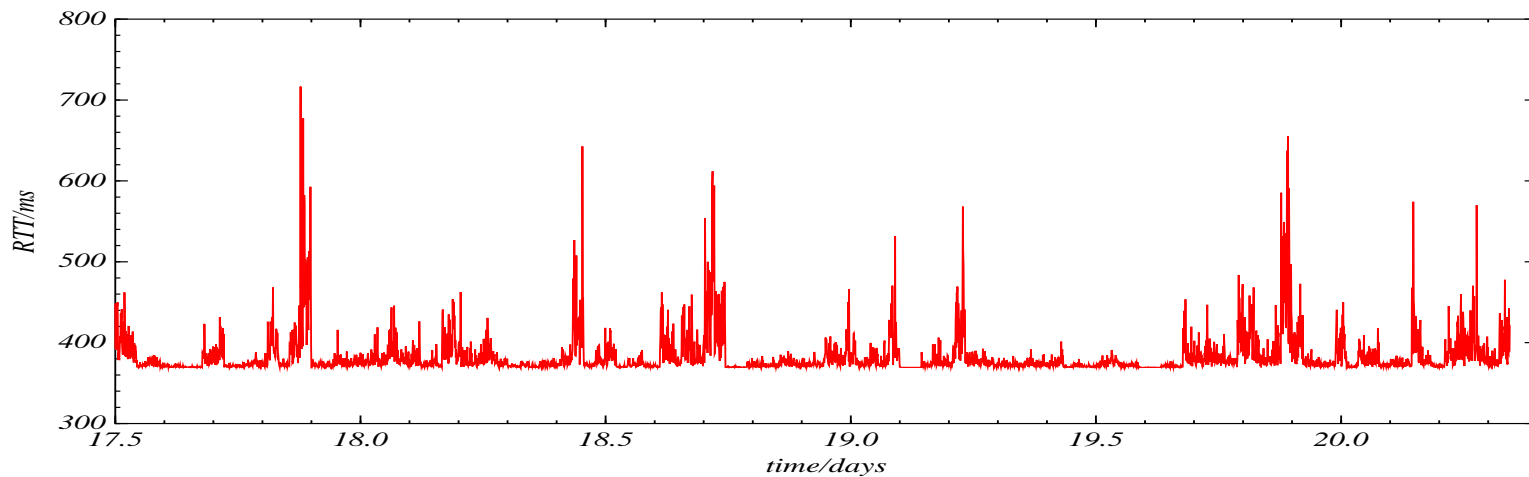
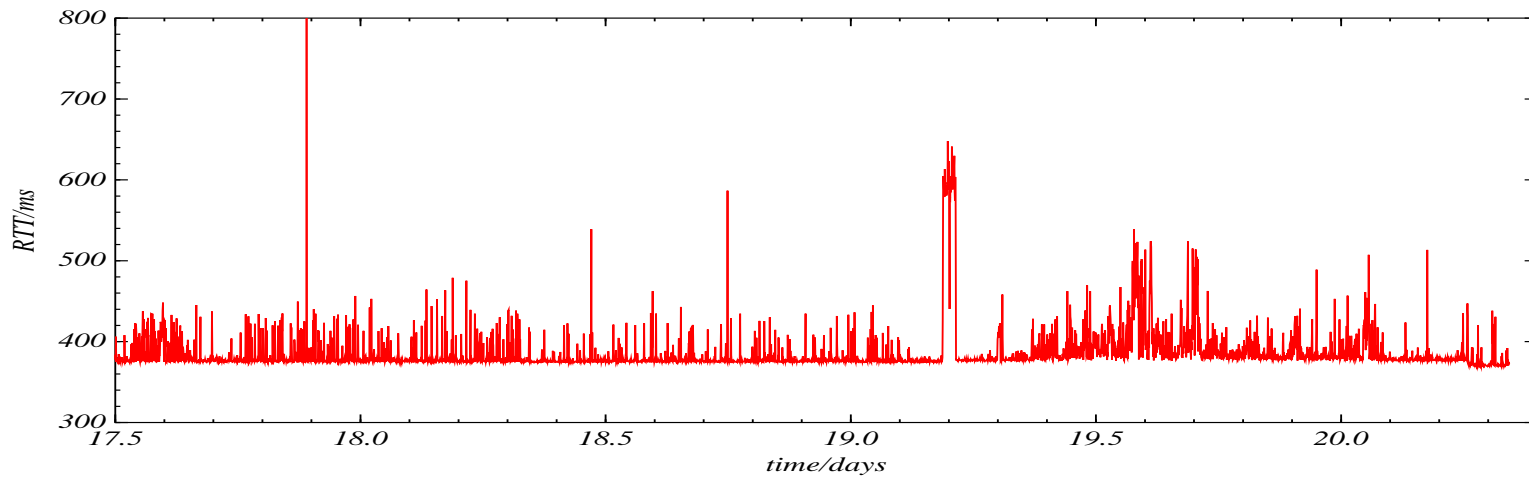
- Riedi and others have proposed a stochastic variant of this type of multifractal model ■
- We let the wavelet coefficients from one scale to the next be iid random variables
 - ▷ *for example, from the Beta distribution* ■
- Fitting to data then involves estimating the parameters in the distribution ■
- simulating involves drawing random variates from the fitted distribution ■
- determinism and preprocessing
 - Always remove any clear deterministic features from the data first:
 - ▷ *trends*
 - ▷ *periodic components*
 - ▷ *baseline shifts*

Example data analysis



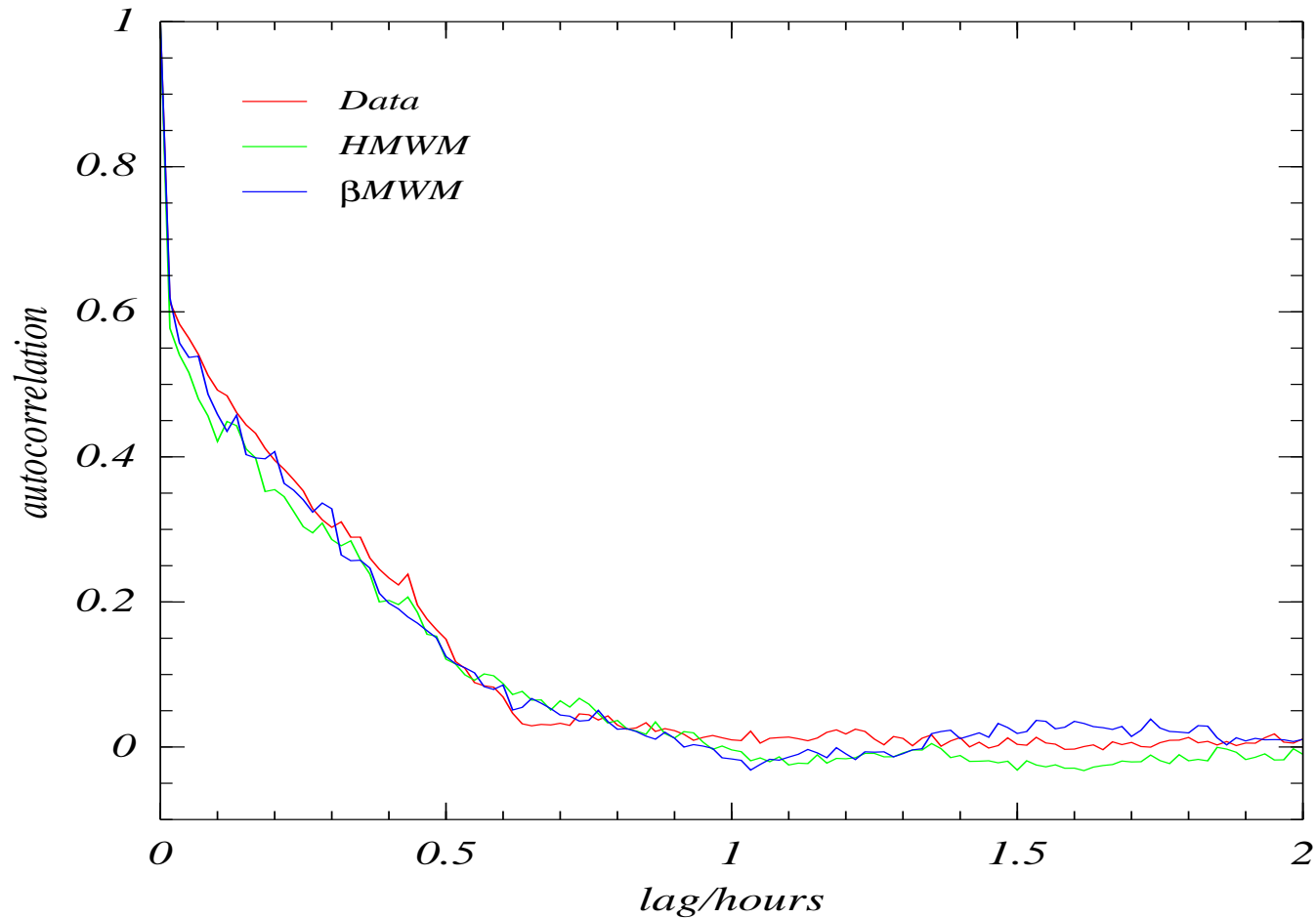
HMWM, β MWM and www.chem.uwa.edu.au multifractal spectra

Realizations



2^{12} points from `www.chem.uwa.edu.au` (top) compared with a β MWM realisation (bottom)

Autocorrelation



www.chem.uwa.edu.au, HMWM, and β MWM autocorrelation

Conclusion and references

- There are many open questions in this type of work and few concrete models ■
- Fitting and parameter estimation is a major problem ■
- Full report and bibliography:
 - ▷ *Analysis and simulation of internet round-trip times*