

NON-LINEAR REGRESSION FOR BIVARIATE SELF-SIMILARITY IDENTIFICATION. APPLICATION TO ANOMALY DETECTION IN INTERNET TRAFFIC BASED ON A JOINT SCALING ANALYSIS OF PACKET AND BYTE COUNTS

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ICASSP, Shanghai, 25th March 2016



Anomaly detection in Internet traffic

HEADER (20 bytes)	PAYLOAD (variable size)
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- **IP packet:**

- source address
- destination address ...

- **Network monitoring** ← statistical modeling of Internet traffic

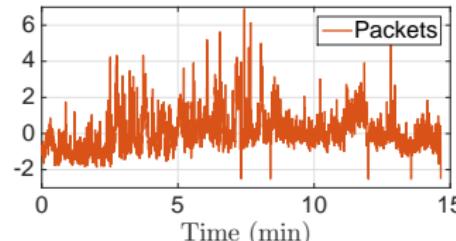
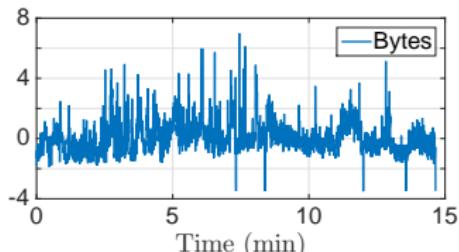
Anomaly detection in Internet traffic

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 - source address
 - destination address ...

- Network monitoring ← statistical modeling of **Internet traffic**

① **Aggregated time serie:** $\begin{cases} \# \text{Packets received / time bins ?} \\ \# \text{Bytes received / time bins ?} \end{cases}$



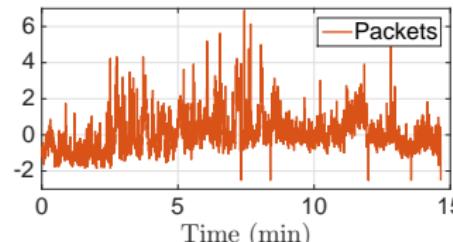
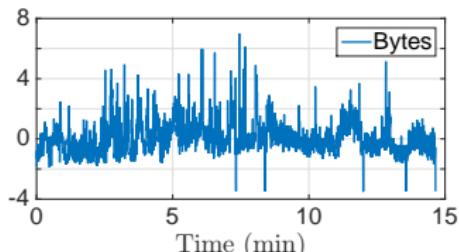
Anomaly detection in Internet traffic

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- **IP packet:**
 - source address
 - destination address ...

- **Network monitoring** ← **statistical modeling** of Internet traffic

- ➊ **Aggregated time serie:** $\begin{cases} \# \text{Packets received / time bins ?} \\ \# \text{Bytes received / time bins ?} \end{cases}$
- ➋ **Statistical modeling:** self-similar process



Statistical modeling of Internet traffic

- **Self-similarity:** time scales from *ms* (ethernet dynamic) to hours (human dynamic) [Abry et al, 2002]
- **Univ. fractional Gaussian noise** → $\underbrace{\text{Hurst parameter } H \in [0, 1]}_{\text{quantify relation accross scales}}$

Past work [Borgnat et al, 2009]

2 univariate analyses

$$\underbrace{\begin{pmatrix} Y^{\text{Byt}} \\ Y^{\text{Pkt}} \end{pmatrix} \leftarrow H^{\text{Byt}}}_{\text{2 independent fGn}} \quad \underbrace{\begin{pmatrix} Y^{\text{Byt}} \\ Y^{\text{Pkt}} \end{pmatrix} \leftarrow H^{\text{Pkt}}}_{\text{2 independent fGn}}$$

Anomaly if $|H^{\text{Byt}} - H^{\text{Pkt}}| \gg 0$

Contribution

1 bivariate analysis

$$\underbrace{\begin{pmatrix} Y^{\text{Byt}} \\ Y^{\text{Pkt}} \end{pmatrix} = W \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \leftarrow H_1}_{\text{mixture of 2 correlated fGn}} \quad \underbrace{\begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \leftarrow H_2}_{\text{mixture of 2 correlated fGn}}$$

Anomaly if $|H_1 - H_2| \gg 0$

Operator Fractional Gaussian Noise

- 2 correlated fGn $(X_1, X_2)^\top$:

$$\Sigma_{X_p, X_{p'}}(s) = \frac{\sigma_{x_p} \sigma_{x_{p'}} \rho_{x_p, x_{p'}}}{2} (|s-1|^{H_p + H_{p'}} - 2|s|^{H_p + H_{p'}} + |s+1|^{H_p + H_{p'}})$$

$$\Sigma_X(0) = \begin{pmatrix} \sigma_{x_1}^2 & \sigma_{x_1} \sigma_{x_2} \rho_x \\ \sigma_{x_1} \sigma_{x_2} \rho_x & \sigma_{x_2}^2 \end{pmatrix}$$

- Condition of existence:

$$g(H_1, H_2, \rho_x) \equiv \Gamma(2H_1 + 1)\Gamma(2H_2 + 1) \sin(\pi H_1) \sin(\pi H_2) - \rho_x^2 \Gamma(H_1 + H_2 + 1)^2 \sin^2(\pi(H_1 + H_2)/2) > 0.$$

- Mixing: $\begin{pmatrix} Y_{\text{Byt}} \\ Y_{\text{Pkt}} \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{1+\gamma^2}} & \frac{\beta}{\sqrt{1+\beta^2}} \\ \frac{-\gamma}{\sqrt{1+\gamma^2}} & \frac{1}{\sqrt{1+\beta^2}} \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \end{pmatrix}$

Objective: estimate $\Theta = (H_1, H_2, \rho_x, \sigma_{x_1}, \sigma_{x_2}, \beta, \gamma)$

Wavelet spectrum

- **Wavelet coefficients:** $D_{y_p}(j, k) = \int_{\mathbb{R}} \psi_{j,k}(t) Y_p(t) dt$

where $\psi_{j,k}(t) = 2^{-j(1/2-\mu)} \underbrace{\psi_0(2^{-j/2}t - k)}_{\text{dilation and translation of } \psi_0}$

and **Fractional integration parameter μ** (default: $\mu = 0$)

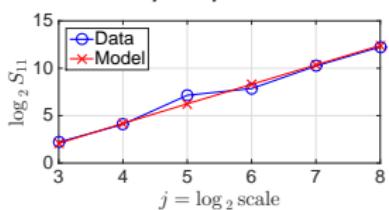
- **Wavelet spectrum:** $(E_{p,p'}(\Theta))_j = \mathbb{E} D_{y_p}(j, k) D_{y_{p'}}(j, k)^*$
 $= + \alpha_{p,p'}^{(1,1)}(\beta, \gamma) \sigma_{x_1}^2 \eta_{j,H_1} 2^{j(2H_1+1+2\mu)}$
 $+ \alpha_{p,p'}^{(1,2)}(\beta, \gamma) \rho_x \sigma_{x_1} \sigma_{x_2} \eta_{j, \frac{H_1+H_2}{2}} 2^{j(H_1+H_2+1+2\mu)}$
 $+ \alpha_{p,p'}^{(2,2)}(\beta, \gamma) \sigma_{x_2}^2 \eta_{j,H_2} 2^{j(2H_2+1+2\mu)}$

→ Empirical estimate: $(S_{p,p'})_j = \frac{2^j}{N} \sum_{k=1}^{N/2^j} D_{y_p}(j, k) D_{y_{p'}}(j, k)^*$

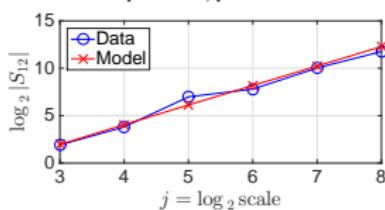
Estimate Θ such as $(E_{p,p'}(\Theta))_j$ fits $(S_{p,p'})_j$ jointly for all j

Non-linear Wavelet Regression Problem

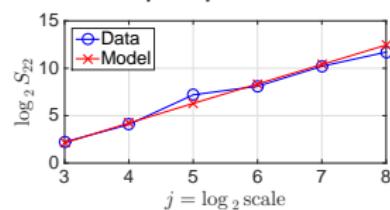
$$p = p' = 1$$



$$p = 1, p' = 2$$



$$p = p' = 2$$



$$\hat{\Theta} = \arg \min_{\Theta \in Q_0} \underbrace{\sum_{p,p'=1}^2 \sum_{j=j_1}^{j_2} \left(\underbrace{\log_2 |(S_{p,p'})_j|}_{\text{Data}} - \underbrace{\log_2 |(E_{p,p'}(\Theta))_j|}_{\text{Model}} \right)^2}_{C(\theta)}$$

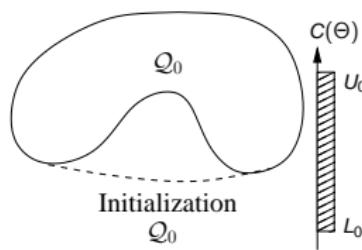
Non-convex optimization problem \longrightarrow Branch & Bound algorithm

[Hansen, 1980]

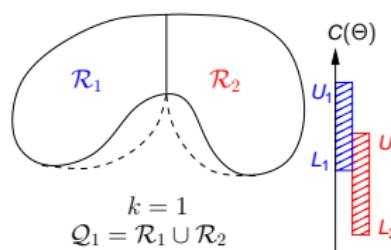
Branch & Bound Algorithm

$$\hat{\Theta} = \arg \min_{\Theta \in \mathcal{Q}_0} C(\Theta) \quad , \text{ non-convex criterion } C \text{ and search space } \mathcal{Q}_0$$

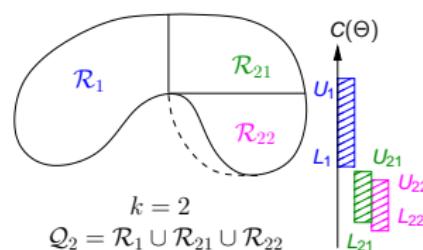
Step 0



Step 1



Step 2 ...



- Bounding over the convex relaxation of \mathcal{Q}_0

- Split \mathcal{Q}_0 into \mathcal{R}_1 & \mathcal{R}_2
- Bounding over the convex relaxation of \mathcal{R}_1 & \mathcal{R}_2

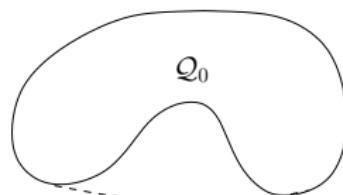
- Split \mathcal{R}_2 into \mathcal{R}_{21} & \mathcal{R}_{22}
- Bounding over the convex relaxation of \mathcal{R}_{21} & \mathcal{R}_{22}
- Discard \mathcal{R}_1

Branch & Bound Algorithm - Initialization

$$\mathcal{Q}_0 = \left\{ \Theta = (H_1, H_2, \rho_x, \sigma_{x_1}, \sigma_{x_2}, \beta, \gamma) \in \mathbb{R}^7 \mid \Theta \in [0, 1]^3 \times [0, \sigma_{\max}]^2 \times [-1, 1]^2, \underbrace{g(H_1, H_2, \rho_x) > 0}_{\text{non convex}}, H_1 \leq H_2 \right\}.$$

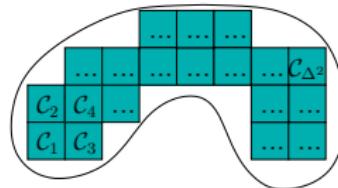
$g(h_1, h_2, \rho_x) > 0 \iff (X_1, X_2)$ correctly defined
 $g(h_1, h_2, \rho_x) > 0$ must not be relaxed !

Proposed solution:



Initialization
 \mathcal{Q}_0

Inner convex relaxation
 \implies



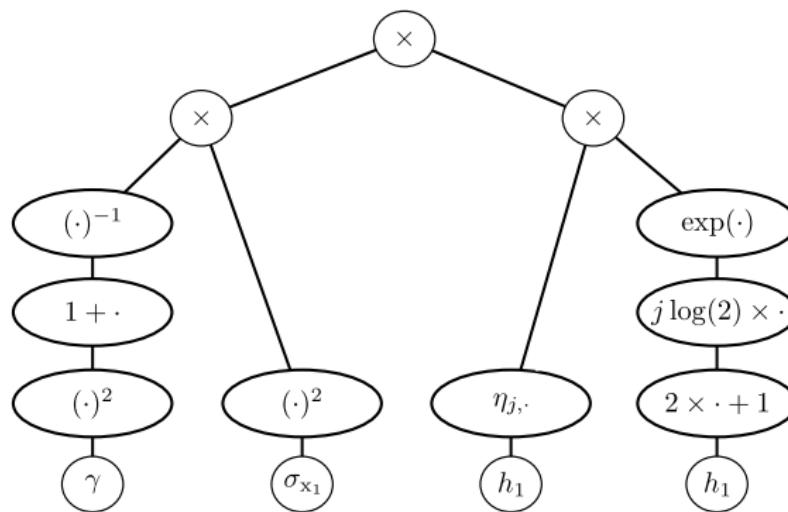
Initialization
 $\mathcal{S}_0 = \cup_{i=1}^{\Delta^2} \mathcal{C}_i$

Branch & Bound Algorithm - Bounding

- **Bounding:** Interval arithmetic [Moore, 1966]

For example, for $j = 2$:

$$(1 + \gamma^2)^{-1} \sigma_{x_1}^2 \eta_{j,h_1} 2^{j(2h_1+1)}$$

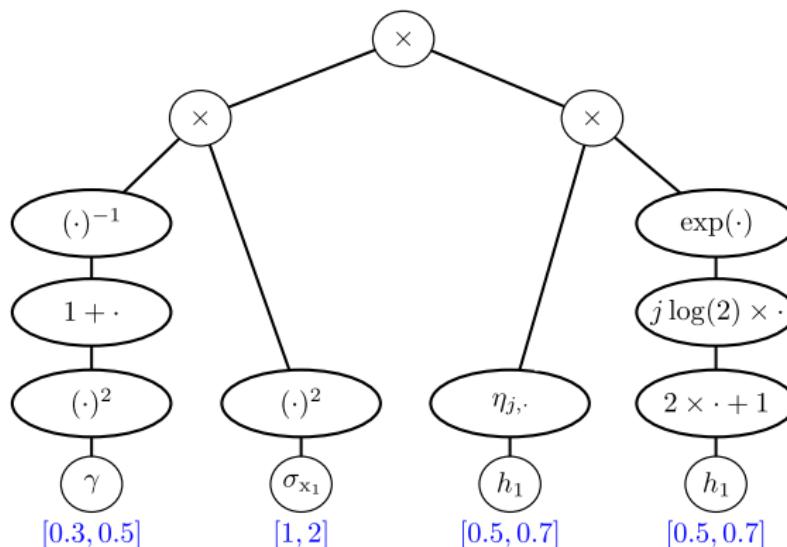


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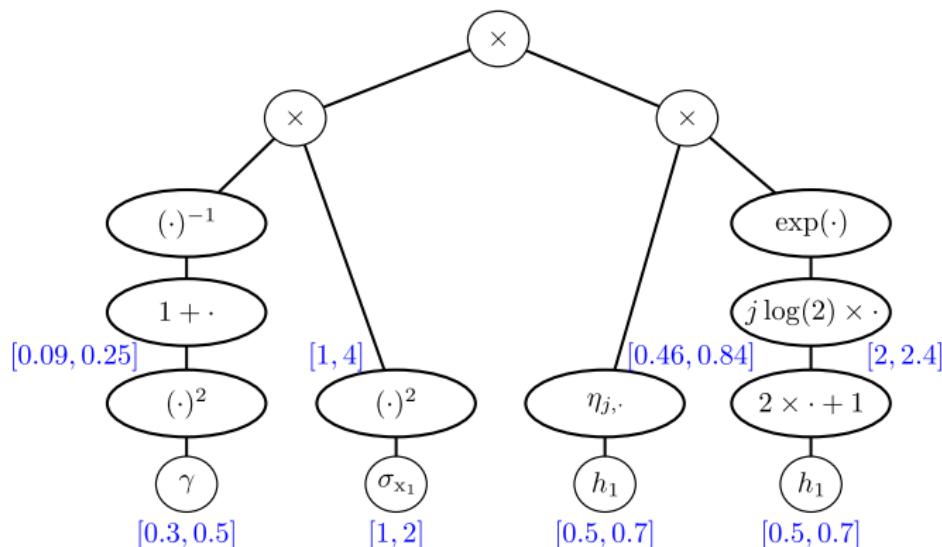


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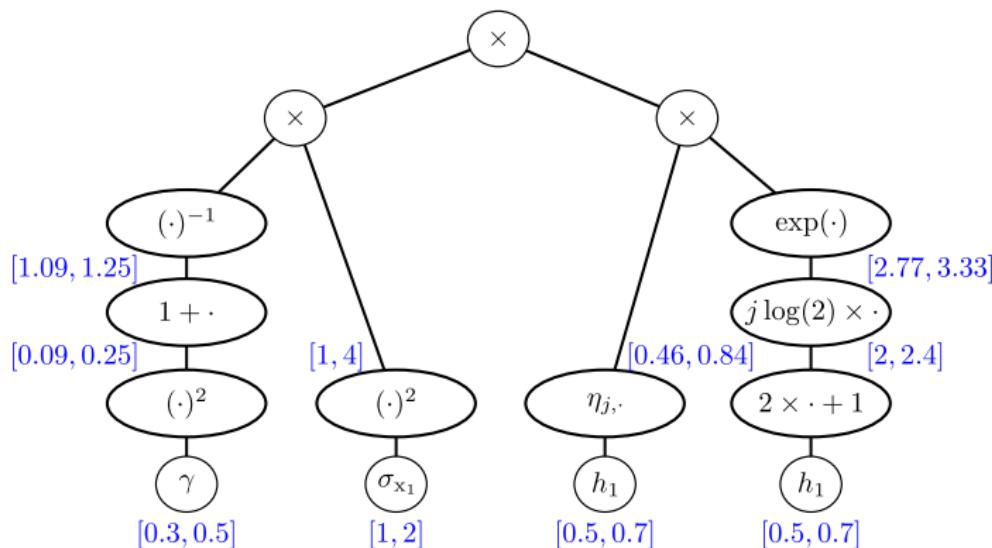


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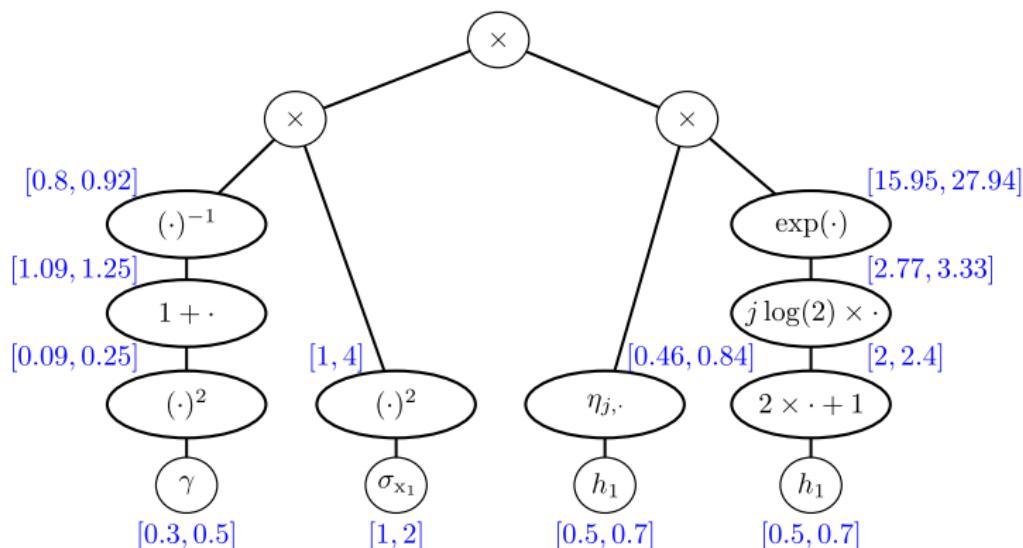


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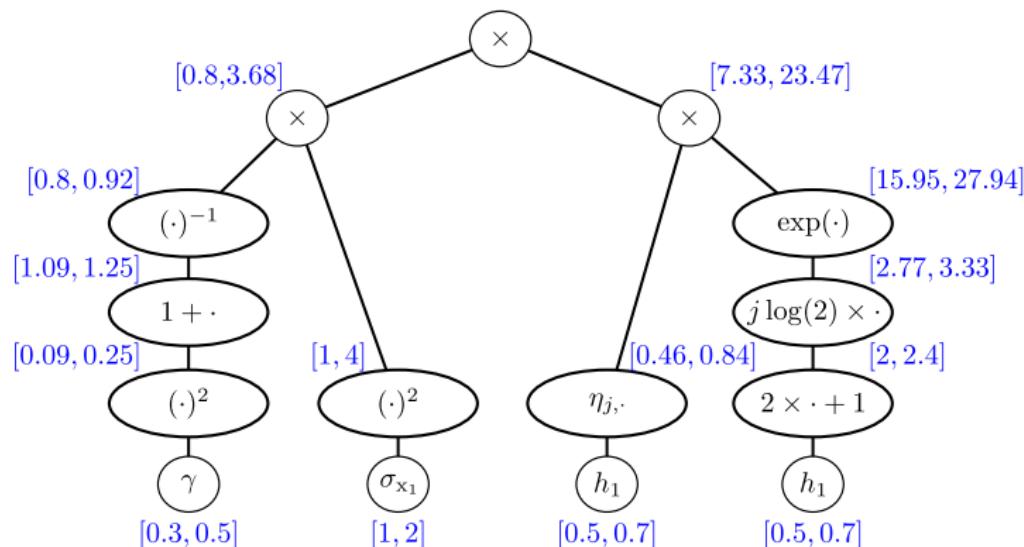


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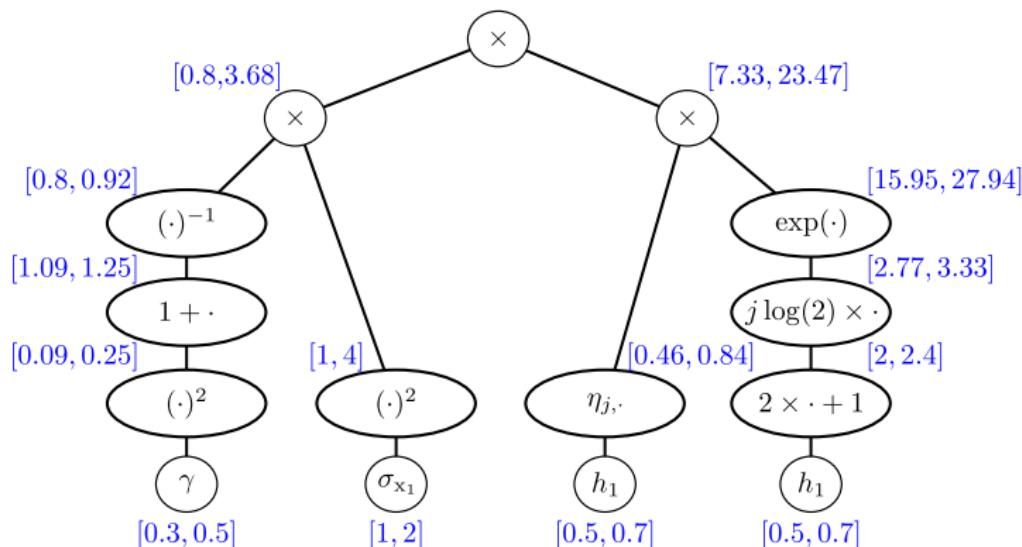


Branch & Bound Algorithm - Bounding

- **Bounding:** Interval arithmetic [Moore, 1966]

For example, for $j = 2$:

$$5.86 \leq (1 + \gamma^2)^{-1} \sigma_{x_1}^2 \eta_{j,h_1} 2^{j(2h_1+1)} \leq 86.37$$

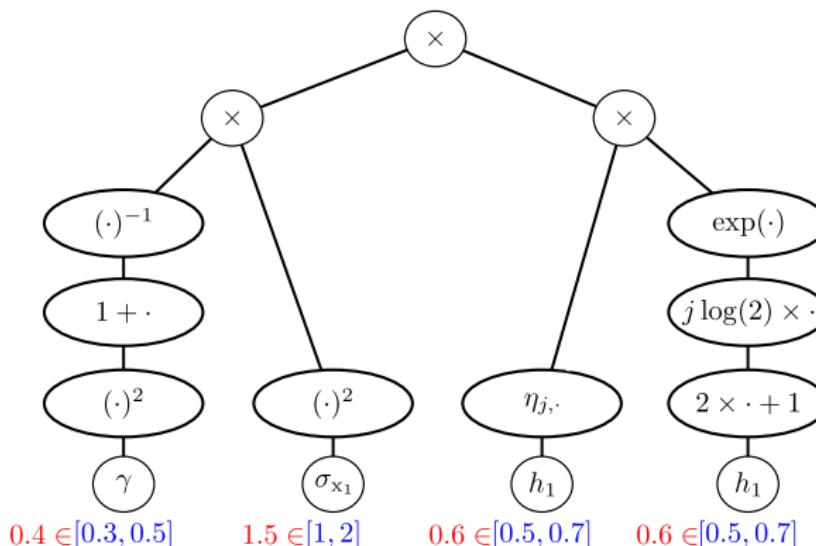


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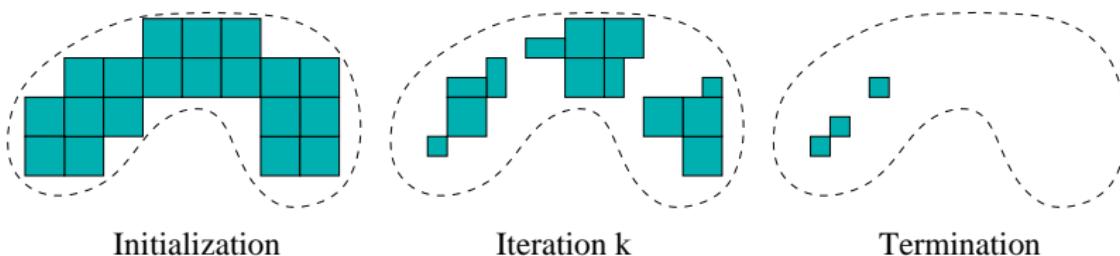
For example, for $j = 2$:

$$5.86 \leq (1 + \gamma^2)^{-1} \sigma_{x_1}^2 \eta_{j,h_1} 2^{j(2h_1+1)} \leq 86.37 \leq 26.50$$



Branch & Bound Algorithm - Termination

- Evolution of the search space:



- **Termination:** size of all regions $<$ size limit

- **Solution:** $\hat{\Theta} = \text{mid}$ (region with lowest upper bound)

Estimation Performance on Synthetic Data

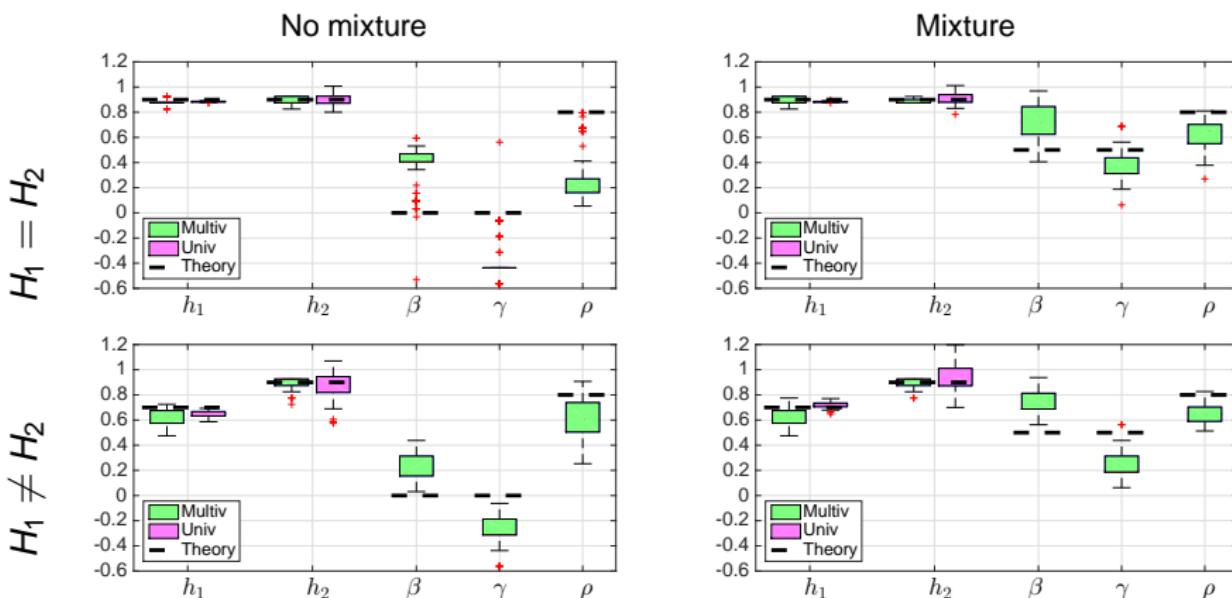


Figure: Four configurations potentially matching Internet Traffic data (only $N = 3600$ samples long).

MAWI Database

- **MAWI repository:**

- WIDE backbone network
(Japan ↔ USA)
- Daily collection of internet traces from 14:00 to 14:15 (JST)
- Each trace ~ 100 to 150 million IP packets
- Packet 5-tuple and timestamps anonymized and publicly available

- **Anomaly detection:** aggregated **Pkt** and **Byt** counts

- ① How to construct a self-reference for normal traffic ?
- ② How to adjust to specificities of real-world data ?

Reference for normal traffic

- **Random projections:** same source address → same sketch

Packets

Source address #1

Source address #2

Source address #3

Source address #3

Source address #1

Source address #4

Source address #n

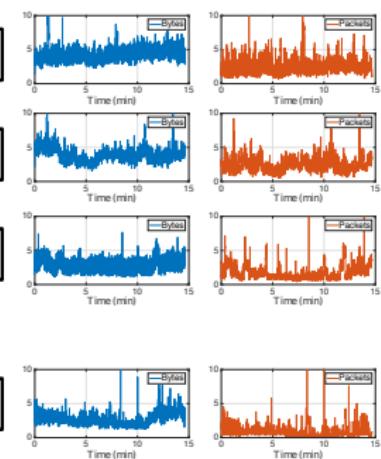
Sketches

Sketch #1

Sketch #2

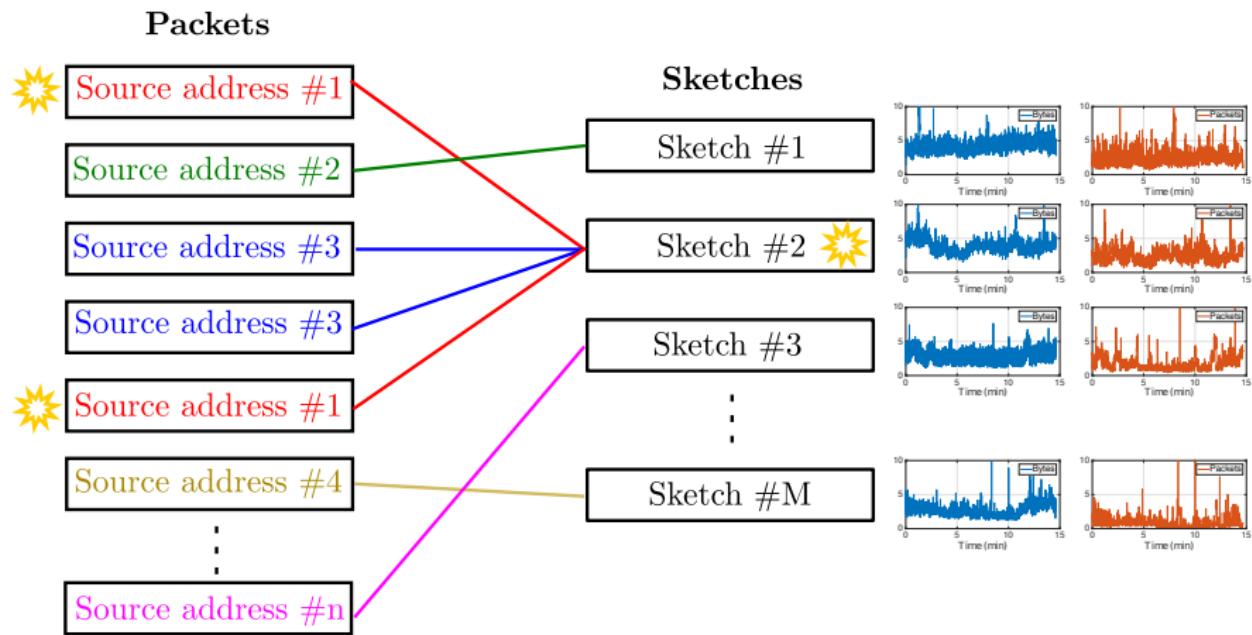
Sketch #3

Sketch #M



Reference for normal traffic

- **Random projections:** same source address → same sketch



Role of fractional integration parameter μ

Biv.fGn requires $H_1, H_2 \in [0, 1]$

- **Wavelet coefficients:** $D_{y_p}(j, k) = \int_{\mathbb{R}} \psi_{j,k}(t) Y_p(t) dt$

where $\psi_{j,k}(t) = 2^{-j(1/2 - \mu_w)} \underbrace{\psi_0(2^{-j/2}t - k)}_{\text{dilation and translation of } \psi_0}$

- **Wavelet spectrum:** $\mathbb{E} D_{y_p}(j, k) D_{y_{p'}}(j, k)^*$

$$\begin{aligned} (E_{p,p'}(\Theta))_j = & + \alpha_{p,p'}^{(1,1)}(\beta, \gamma) \sigma_{x_1}^2 \eta_{j,H_1} 2^{j(2H_1+1+2\mu_B)} \\ & + \alpha_{p,p'}^{(1,2)}(\beta, \gamma) \rho_x \sigma_{x_1} \sigma_{x_2} \eta_{j,\frac{H_1+H_2}{2}} 2^{j(H_1+H_2+1+2\mu_B)} \\ & + \alpha_{p,p'}^{(2,2)}(\beta, \gamma) \sigma_{x_2}^2 \eta_{j,H_2} 2^{j(2H_2+1+2\mu_B)} \end{aligned}$$

H_1 and H_2 shifted by $\mu_B - \mu_w$ into $[0, 1]$

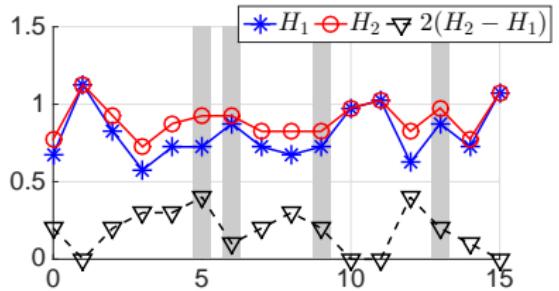
Application to MAWI database

2008 data

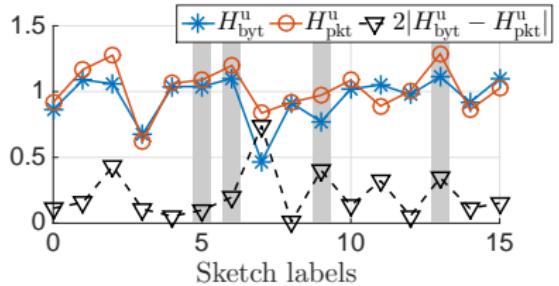
(100% Trinocular anomalies detected)

(96% of Deny-of-Service attacks detected)

Bivariate

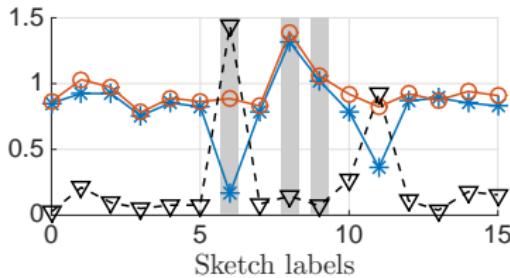
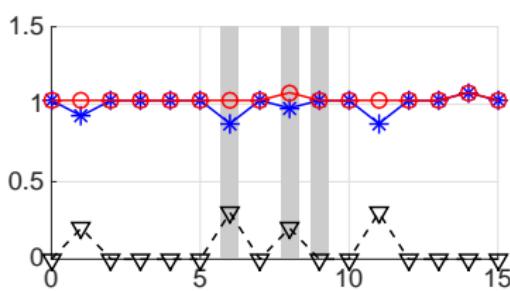


Univariate



2009 data

(100% Trinocular anomalies detected)

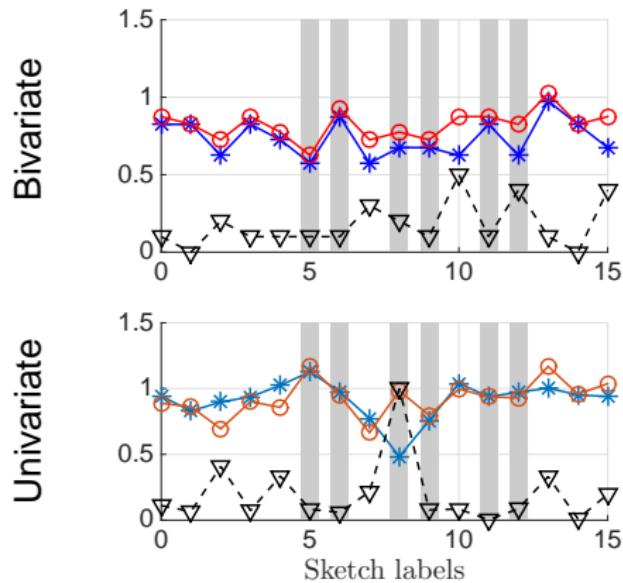


Application to MAWI database

2014 data

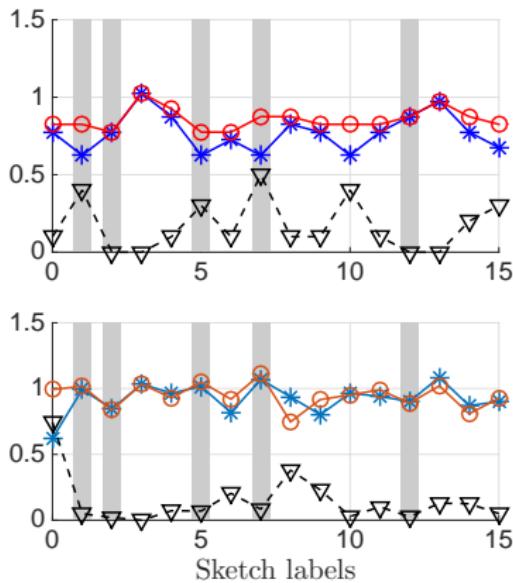
(100% Trinocular anomalies detected)

(100% of Heavy Hitter anomalies detected)



2015 data

(100% Trinocular anomalies detected)



Conclusion

① Joint scaling analysis of Packets and Bytes counts

- Biv.OfGn
- Non-linear wavelet regression problem

② Branch & Bound algorithm

- Toolbox available soon (<http://perso.ens-lyon.fr/jordan.frecon/>)

③ Fractional integration parameter

- permits to adjust to real world data

④ Application to MAWI database

- systematic detection of some anomalies