Anomaly Detection with Extreme Value Theory

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April 26, 2017

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Context

—o Massive usage of the Internet

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· More and more vulnerabilities

1 Tbps DDoS Attack

Powered By 150,000 Hacked IoT Devices

How the Carbanak cybergang stole $1bn
A targeted attack on a bank

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- ○ Massive usage of the Internet
  - · More and more vulnerabilities
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- ○ Awareness of the sensitive data and infrastructures

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⇒ Network security :
a major concern

—○ IDS (Intrusion Detection System)
- Monitor traffic
- Detect attacks

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  - Monitor traffic
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- Current methods : rule-based
  - Work fine on common and well-known attacks
  - Cannot detect new attacks
- Emerging methods : anomaly-based
  - Use the network data to estimate a normal behavior
  - Apply algorithms to detect abnormal events ($\rightarrow$ attacks)

—o Basic scheme

$$\text{data} \longrightarrow \boxed{\text{ALGORITHM}} \longrightarrow \text{alerts}$$

–o Basic scheme

data $\longrightarrow$ ALGORITHM $\longrightarrow$ alerts

–o Many "standard" algorithms have been tested

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- Many "standard" algorithms have been tested
- Complex pipelines are emerging (ensemble/hybrid techniques)

—◦ Algorithms are not magic
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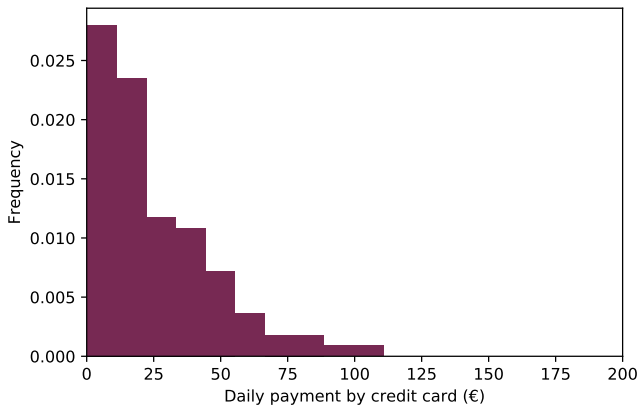 · But the decision often rely on a human choice

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- Expertise
- Fine-tuning
- Distribution assumption

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—○ The thresholds are often hard-set
  · Expertise
  · Fine-tuning
  · Distribution assumption

—○ **Our idea**: provide dynamic threshold with a probabilistic meaning

Providing better thresholds

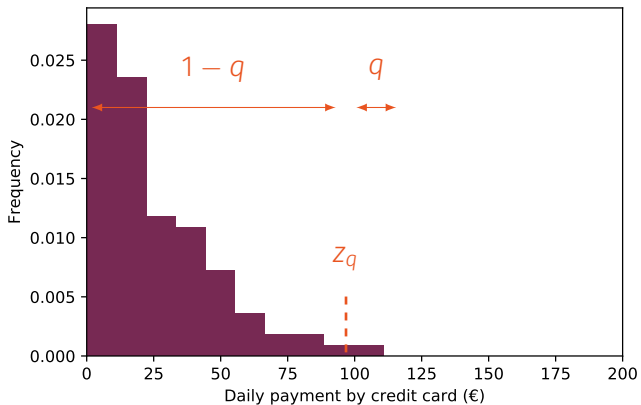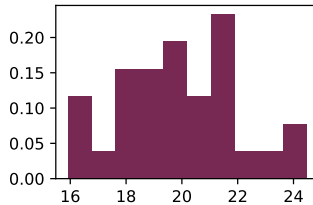—○ How to set z_q such that $\mathbb{P}(X\text{€} > z_q) < q$?

Drawbacks: stuck in the interval, poor resolution

— Drawbacks: manual step, distribution assumption

—◦ Different clients and/or temporal drift

PROPERTIES	Empirical quantile	Standard model
statistical guarantees	Yes	Yes
easy to adapt	Yes	No
high resolution	No	Yes

—○ Main result (Fisher-Tippett-Gnedenko, 1928)

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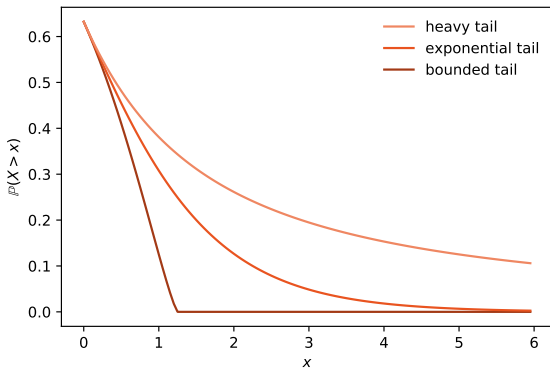
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$$\frac{S_n - n\mu}{\sqrt{n}} \xrightarrow{d} \mathcal{N}(0, \sigma^2)$$

—o FTG Theorem

$$\frac{M_n - a_n}{b_n} \xrightarrow{d} \mathrm{EVD}(\gamma)$$

—○ Second theorem of EVT (Pickands-Balkema-de Haan, 1974)

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The excesses over a high threshold follow a Generalized Pareto Distribution (with parameters γ, σ)

⊸ What does it imply ?
- we have a model for extreme events
- we can compute z_q for q as small as desired

- $\multimap$ Get some data $X_1, X_2 \ldots X_n$
- $\multimap$ Set a high threshold t and retrieve the excesses $Y_j = X_{k_j} - t$ when $X_{k_j} > t$

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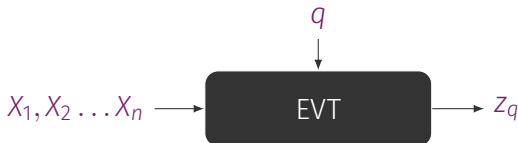
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$$q$$

$$X_1, X_2 \ldots X_n \longrightarrow \boxed{\text{EVT}} \longrightarrow z_q$$

Finding anomalies in streams

(initial batch)

$X_1, X_2 \ldots X_n$

q

(initial batch)

$X_1, X_2 \ldots X_n \longrightarrow$ CALIBRATION

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q

$X_1, X_2 \ldots X_n \longrightarrow$ **Calibration** $\longrightarrow$

t

(initial batch)

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t z_q

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(stream)

$X_{i>n}$

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q

t $\quad z_q$

(stream)

$X_{i>n} \longrightarrow X_i > z_q$

YES $\longrightarrow$ TRIGGER ALARM

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—∘ An example with ground truth : a Gaussian White Noise
- 40 streams with 200 000 iid variables drawn from $\mathcal{N}(0,1)$
- $q = 10^{-3} \Rightarrow$ theoretical threshold $z_{th} \simeq 3.09$

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  · 40 streams with 200 000 iid variables drawn from $\mathcal{N}(0,1)$
  · $q = 10^{-3} \Rightarrow$ theoretical threshold $z_{th} \simeq 3.09$
—◦ Averaged relative error

Application to intrusion detection

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- 15 min a day of real traffic (.pcap file)
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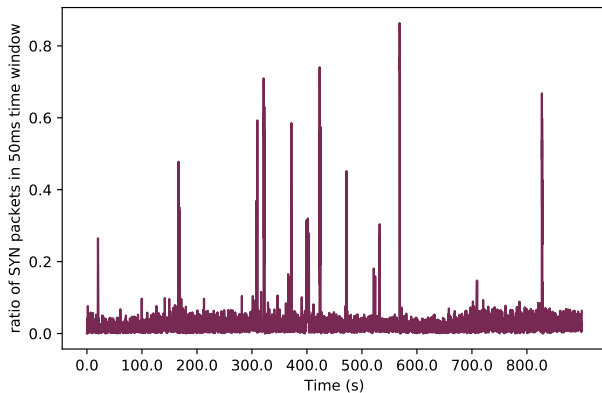—o Preprocessing step : raw .pcap → NetFlow format (only metadata)

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— Goal: find peaks

- Parameters : $q = 10^{-4}, n = 2000$ (from the previous day record)

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—○ 86% of scan flows detected with less than 4% of FP

A more general framework

—o A single main parameter q

- With a probabilistic meaning $\rightarrow \mathbb{P}(X > z_q) < q$
- False Positive regulator

⊸ A single main parameter q
  - With a probabilistic meaning $\rightarrow \mathbb{P}(X > z_q) < q$
  - False Positive regulator

⊸ Stream capable
  - Incremental learning
  - Fast ($\sim$ 1000 values/s)
  - Low memory usage (only the excesses)

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- · compute upper and lower thresholds
- · other fields
- · drifting contexts (with an additional parameter) → DSPOT

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—o What about the EDF stock prices ?

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Conclusion

- Context: A great deal of work has been done to develop anomaly detection algorithms
- Problem: Decision thresholds rely on either distribution assumption or expertise
- Our solution: Building dynamic threshold with a probabilistic meaning
    - Application to detect network anomalies
    - But a general tool to monitor online time series in a blind way
- Future: Adapt the method to higher dimensions