Anomaly Detection with Extreme Value Theory

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May 30, 2017

Contents

Context

General motivations

- Massive usage of the Internet

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    - More and more vulnerabilities

WannaCry ransomware used in widespread attacks all over the world

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$\Rightarrow$ Network security : a major concern

A Solution

- IDS (Intrusion Detection System)
    - Monitor traffic
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- IDS (Intrusion Detection System)
  - Monitor traffic
  - Detect attacks
- 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 (→ attacks)

- Basic scheme

data → ALGORITHM → alerts

Overview

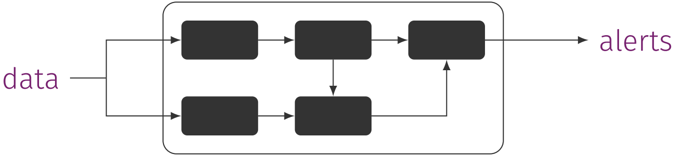
- Basic scheme

$$\text{data} \longrightarrow \boxed{\textsc{Algorithm}} \longrightarrow \text{alerts}$$

- Many ”standard” algorithms have been tested

- Basic scheme

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



Inherent problem

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- The thresholds are often hard-set
  - Expertise
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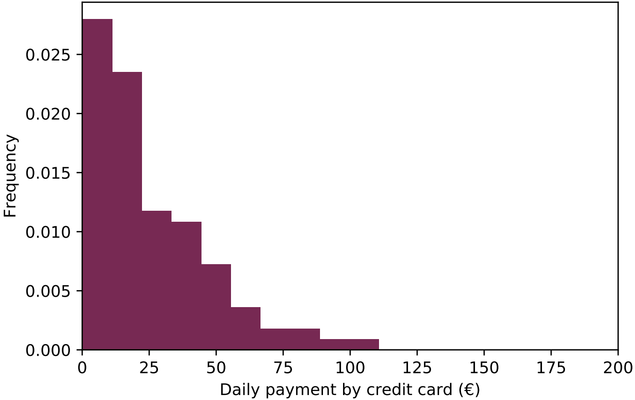
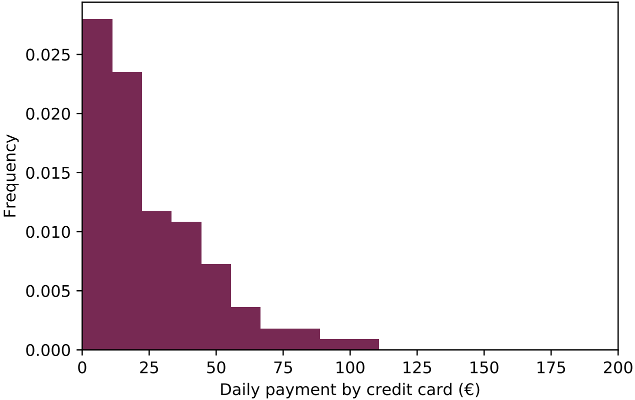
  - Distribution assumption
- **Our idea**: provide dynamic threshold with a probabilistic meaning

Providing better thresholds

My problem

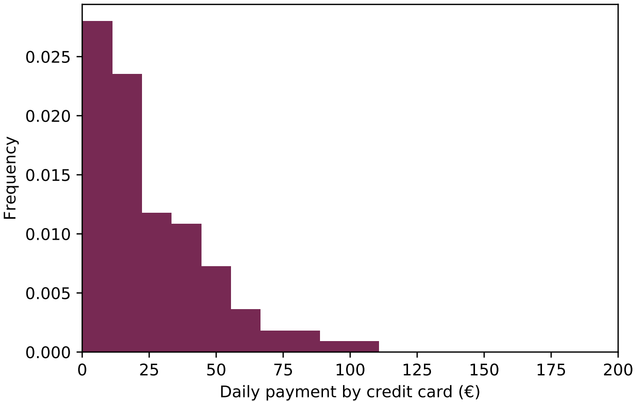


0.025
0.020
0.015
0.010
0.005
0.000
Frequency
0
25
50
75
100
125
150
175
200
Daily payment by credit card (€)



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

Solution 1: empirical approach



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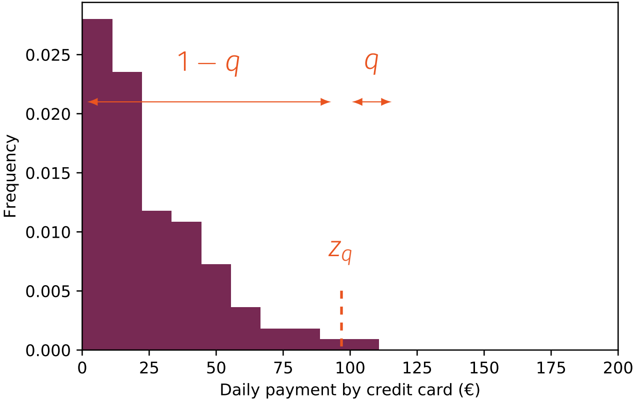

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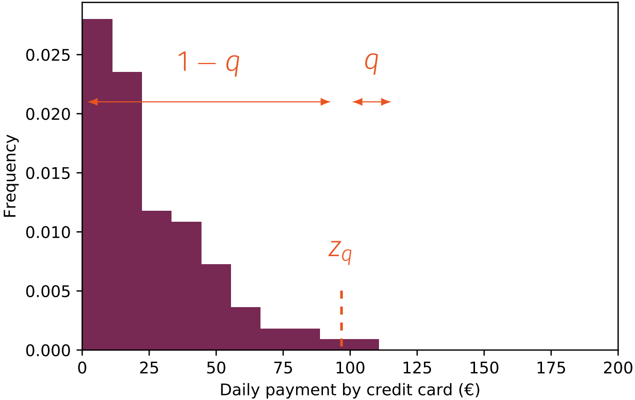
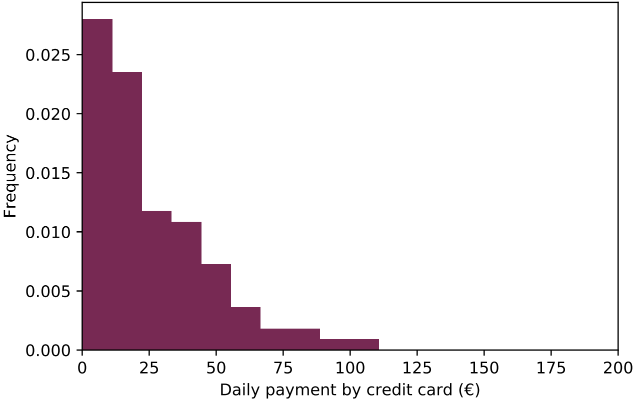


- Drawbacks: stuck in the interval, poor resolution

Solution 2: Standard Model



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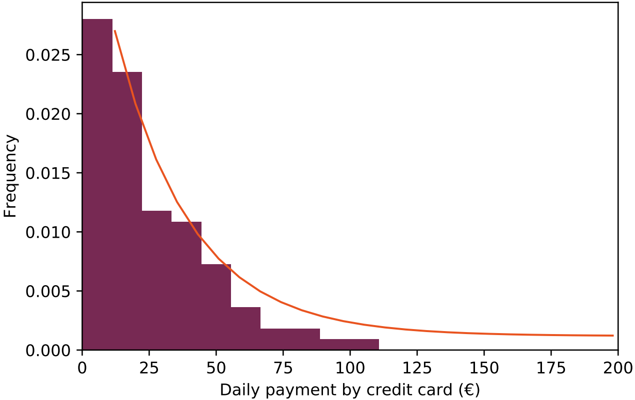

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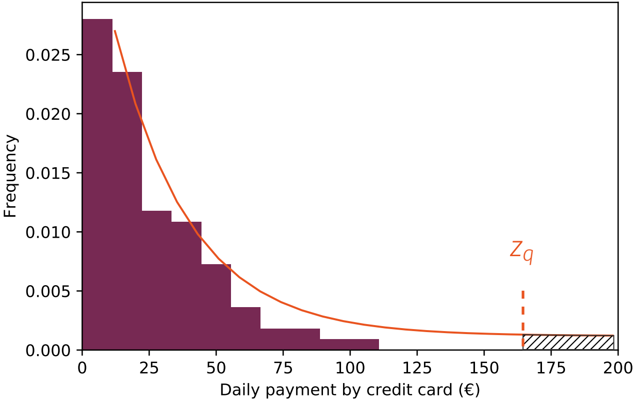

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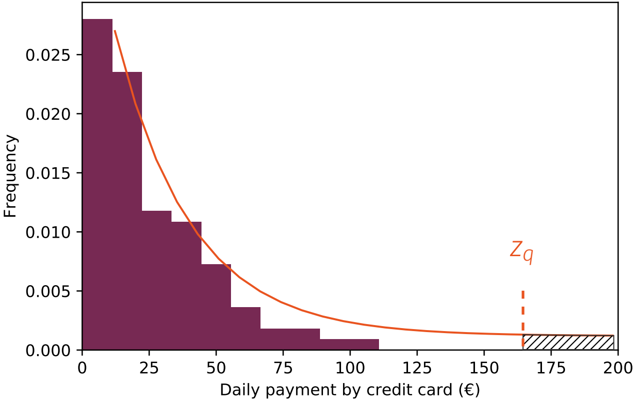
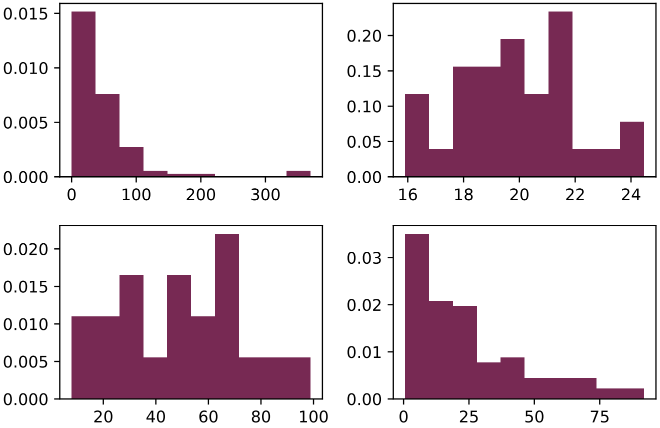


- Drawbacks: manual step, distribution assumption

Realities

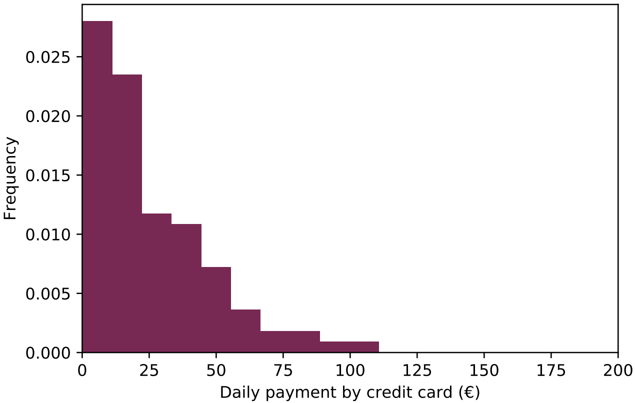


- Different clients and/or temporal drift

Results

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

Inspection of extreme events



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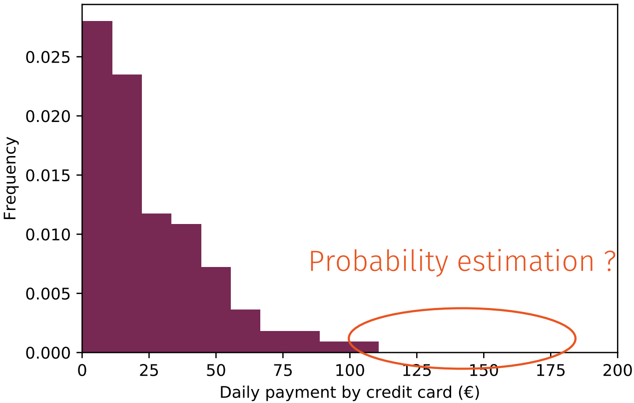

Extreme Value Theory

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

  The extreme values of any distribution have nearly the same distribution (called Extreme Value Distribution)

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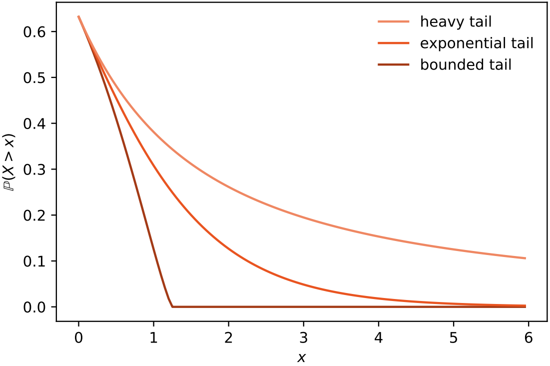

- Let $X_1, X_2, \ldots X_n$ a sequence of i.i.d. random variables with

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- Central Limit Theorem

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An impressive analogy

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- FTG Theorem

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

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

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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

How to use EVT

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

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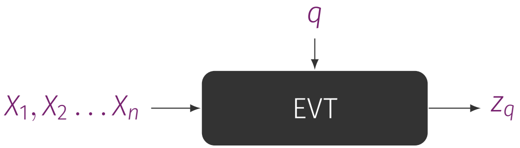

Finding anomalies in streams

Streaming Peaks-Over-Threshold (SPOT) algorithm

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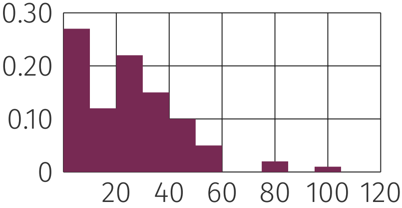
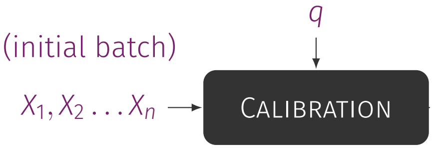
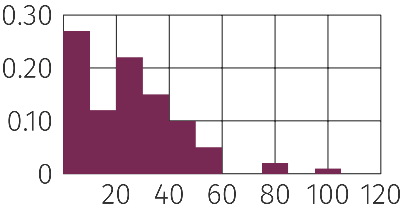
(initial batch)

$X_1, X_2 \dots X_n$




q
(initial batch)
$X_1, X_2 \ldots X_n$
Calibration


0.30
0.20
0.10
0
20
40
60
80
100
120

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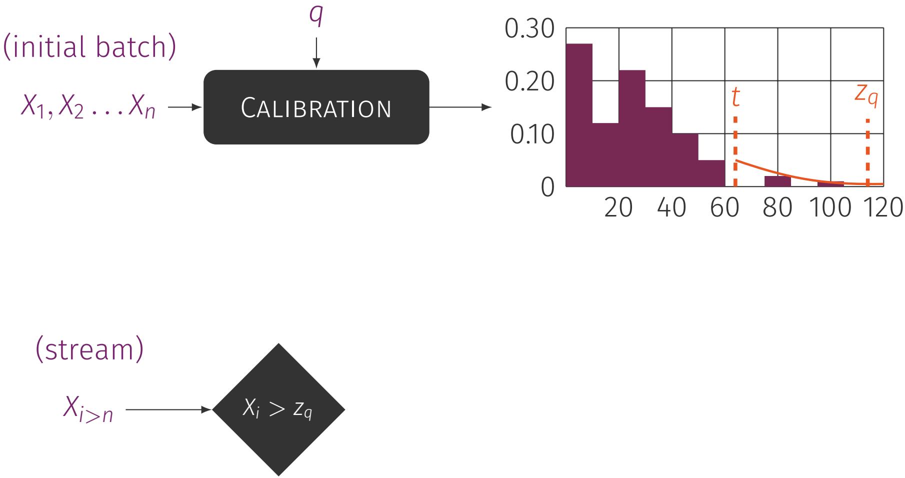
(stream)

$X_{i>n}$

Streaming Peaks-Over-Threshold (SPOT) algorithm



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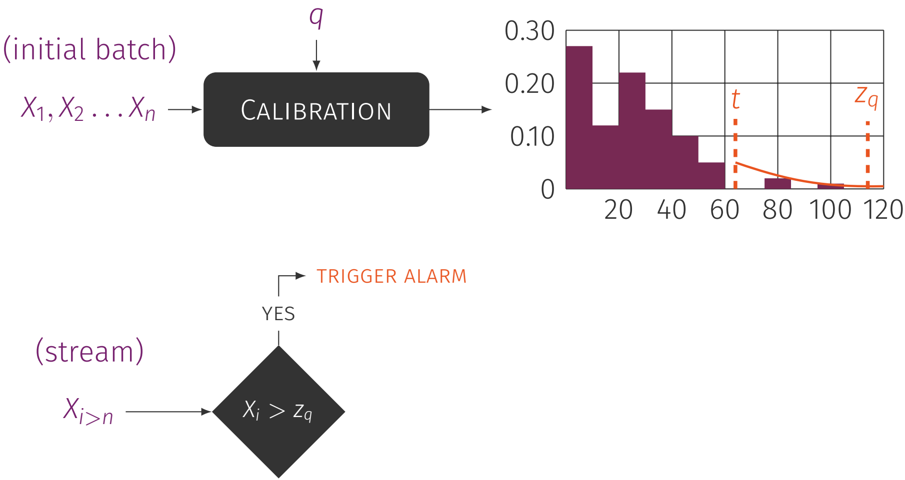

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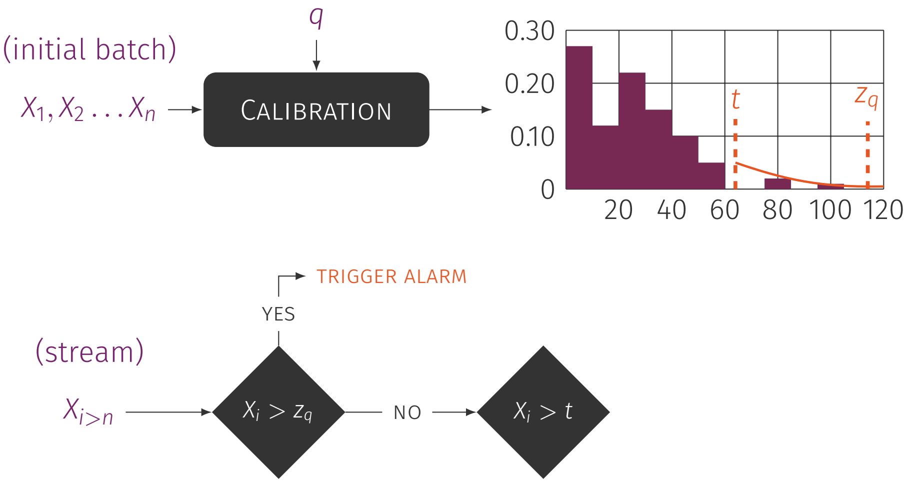

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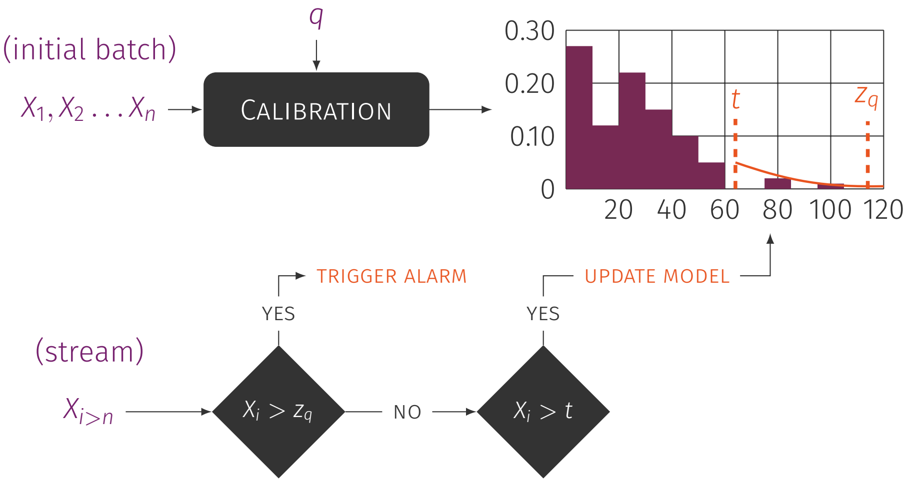

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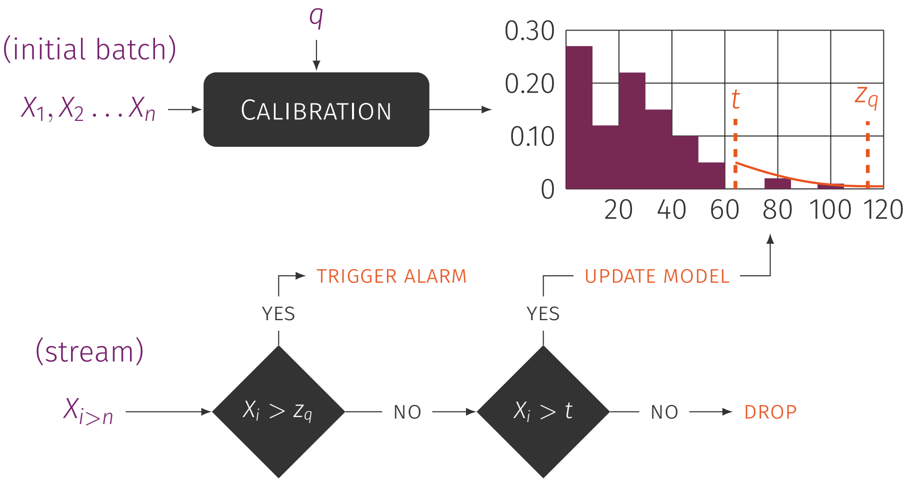

Can we trust that threshold z_q ?

- 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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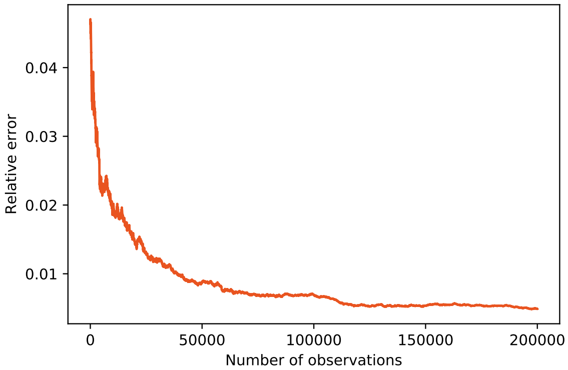
- Averaged relative error



Application to intrusion detection

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- Preprocessing step : raw .pcap $\rightarrow$ NetFlow format (only metadata)

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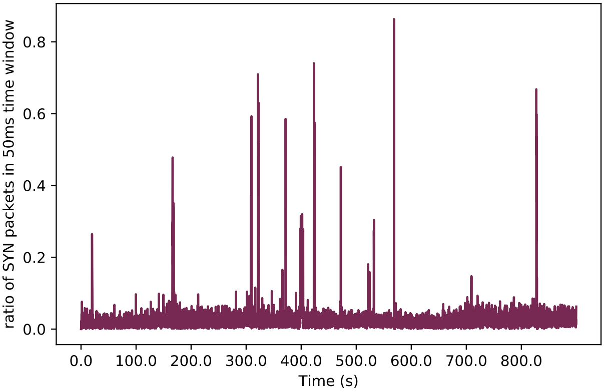

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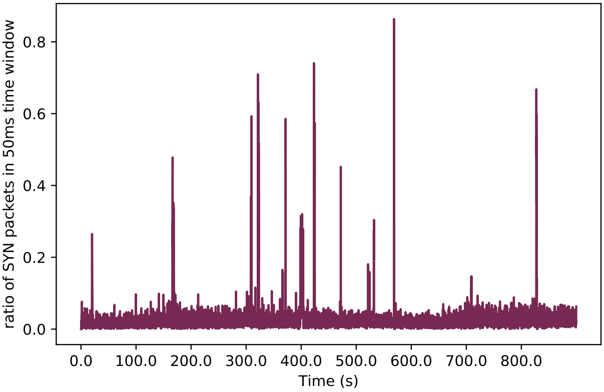

- Goal: find peaks

SPOT RESULTS

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

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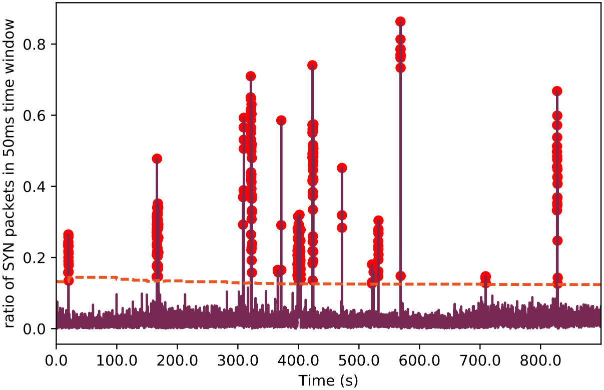

Do we really flag scan attacks ?

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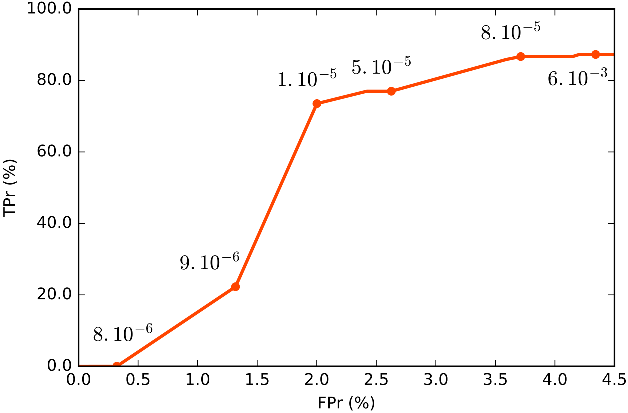

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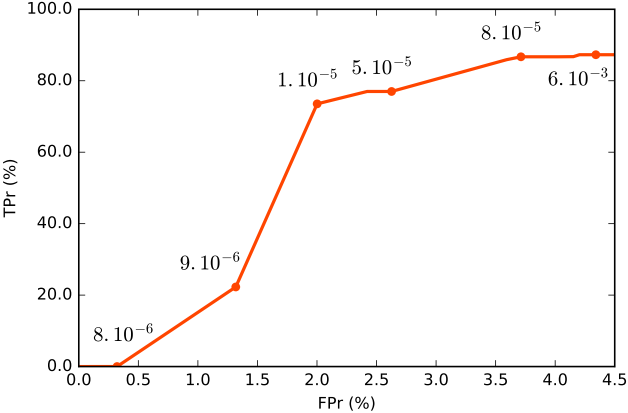

- 86% of scan flows detected with less than 4% of FP

A more general framework

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

SPOT Specifications

- 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)

Other things ?

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  - other fields
  - drifting contexts (with an additional parameter) $\rightarrow$ DSPOT

A recent example

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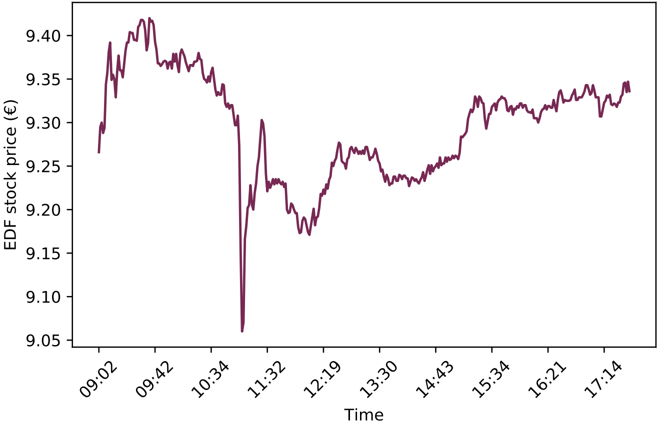
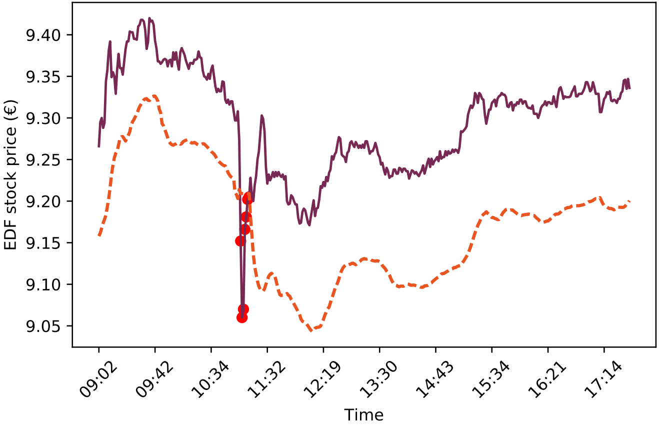
- What about the EDF stock prices ?


9.40
9.35
9.30
9.25
9.20
9.15
9.10
9.05
EDF stock price (€)
09:02
09:42
10:34
11:32
12:19
13:30
14:43
15:34
16:21
17:14
Time

EDF stock prices



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  - But a general tool to monitor online time series in a blind way
- Future: Adapt the method to higher dimensions