Degree-based Outlier Detection within IP Traffic Modelled as a Link Stream

Audrey Wilmet[1], Tiphaine Viard[1],
Matthieu Latapy[1], Robin Lamarche-Perrin[2]

[1]Laboratoire d'informatique de Paris 6 (LIP6) - Complex Networks Team http://www.complexnetworks.fr/
[2]Institut des Systèmes Complexes Paris Île de France (ISC-PIF)

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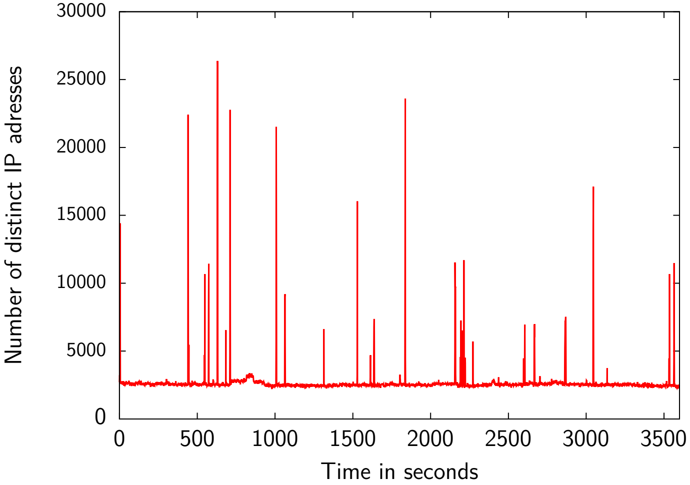
June 26-29, 2018

Context and Goals

Detect outliers, identify their cause, remove them from IP traffic:



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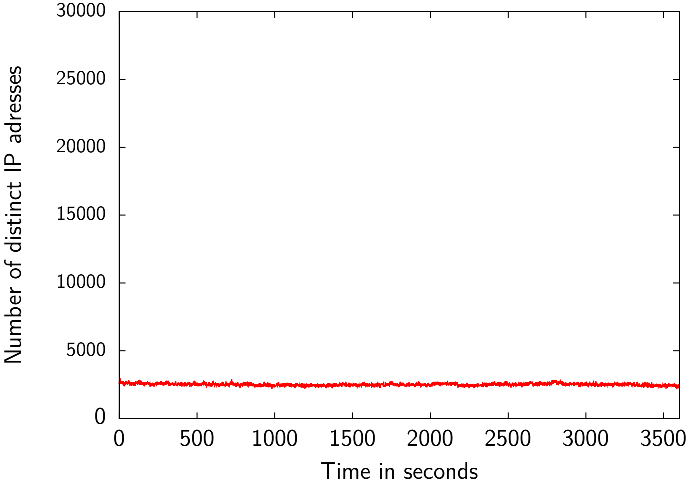


IP Traffic as a Link Stream

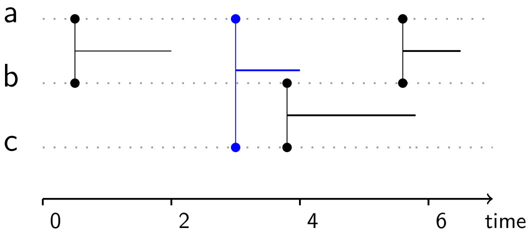
Link stream constructed from 1h of IP Traffic (MAWI):

– Nodes = IP addresses

– Interactions = packet exchanges

– Link stream construction:

Two nodes are linked together from time t_1 to time t_2 if they exchanged at least one packet every second within this time interval.



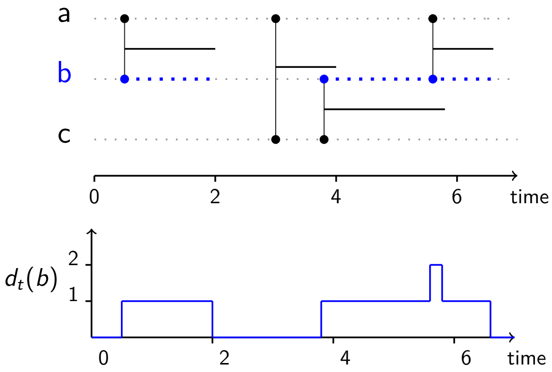
ex: nodes a and c interact from $t_1 = 3$ to $t_2 = 4$

→ M. Latapy *et al.*, 2017 ; T. Viard *et al.*, 2017.

Degree of (v, t)

$d_t(v)$ = Number of neighbours of node v at time t

Example: degree profile of b



Our Approach

Introduction

Our Approach

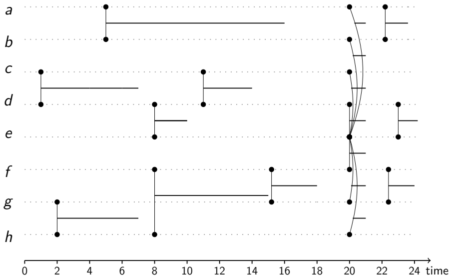
Our Method

Conclusion

① Detection : example

- Detection:

Find observations of the degree which deviate statistically from others.



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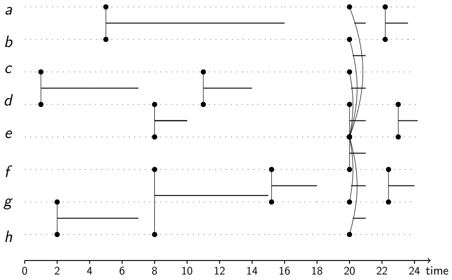
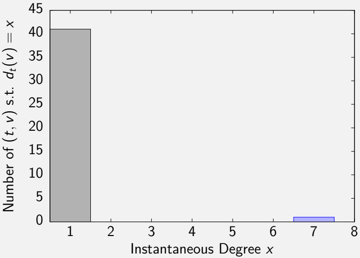


Degree distribution

on all couples (v, t):



① Detection : example

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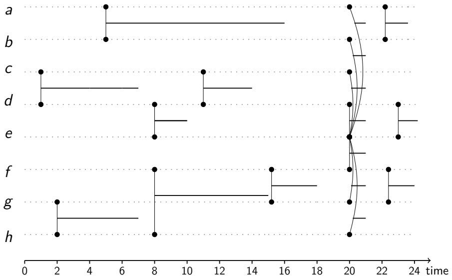
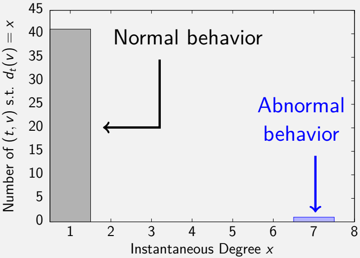


Degree distribution on all couples (v, t):

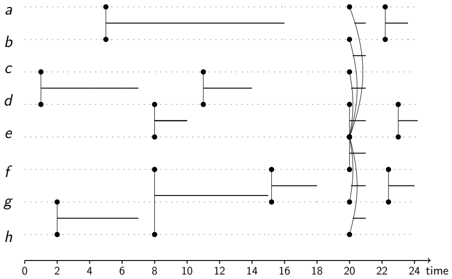
Detected outlier:
$\Rightarrow$ *outlying observation* $d_t(v) = 7$



② Identification : example

- Identification:

Find entities which are responsible for the outlying degree observation.



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Identified outlier:

② Identification : example

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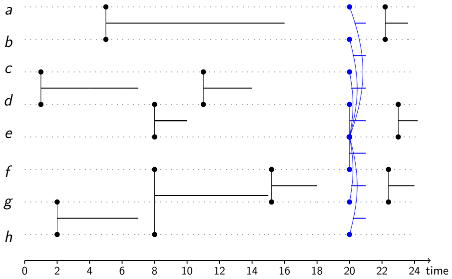


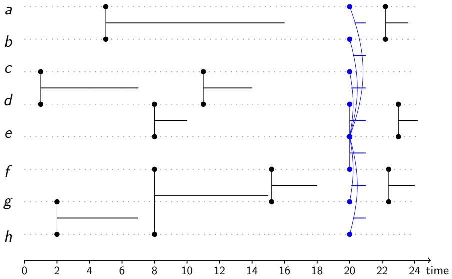
Detected outlier:
$\Rightarrow$ *outlying observation* $d_t(v) = 7$.

Identified outlier:
$\Rightarrow$ *the set :* $\{(e, t) \mid t \in [20, 21[\}$

③ Removal : example

- Removal:

Remove identified entities from the link stream.



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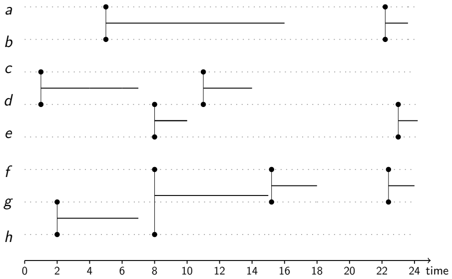

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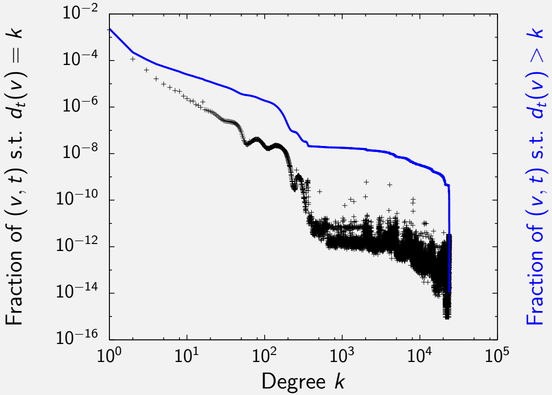
Removed outlier:
$\Rightarrow \cancel{\{(e,t) \mid t \in [20,21[\}}$

① Detection in our data

Link stream constructed from 1h of IP Traffic (MAWI)

↓

Degree distribution on all couples (v, t):

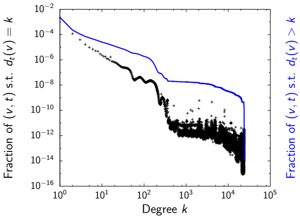


Difficulties

Outlier = Activity that deviates from the usual one

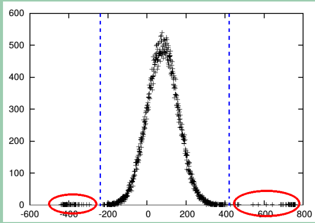
Find an outlier $\Longleftrightarrow$ Find the normality

✗



Heterogeneous

✓

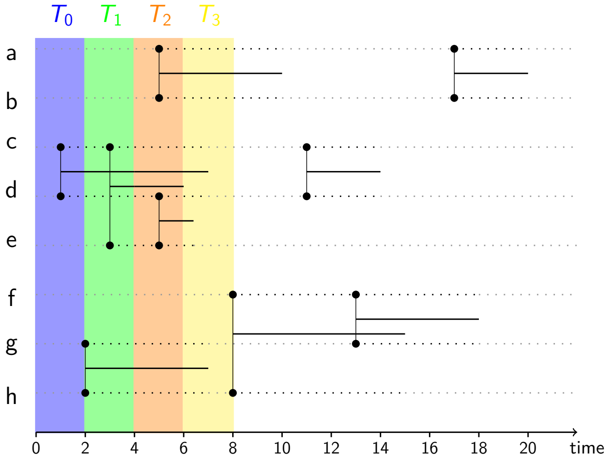


Homogeneous with outliers

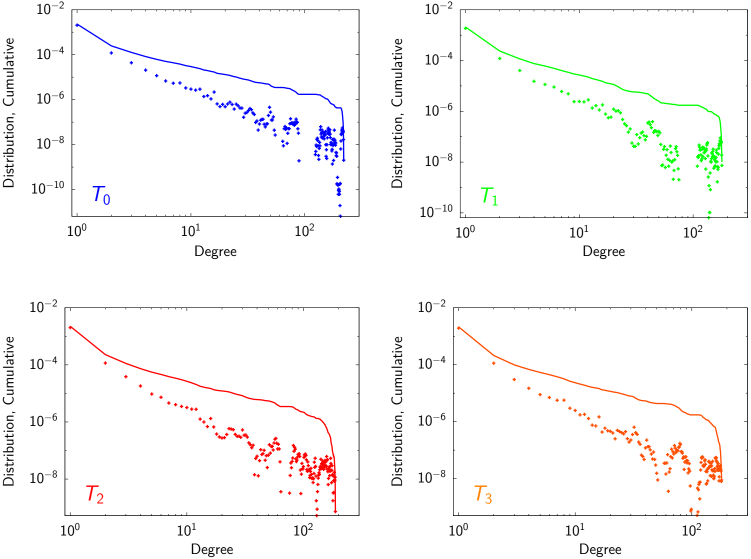
Our Method

Local Degree Distributions

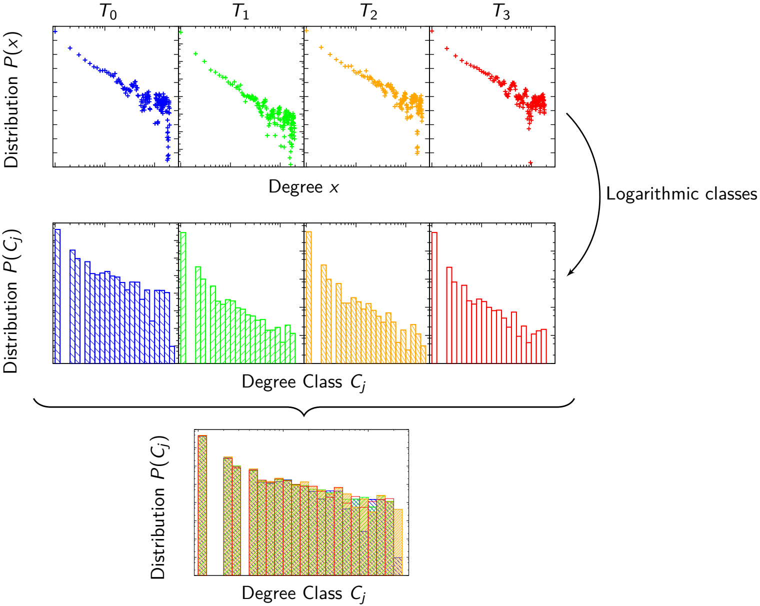
Degree observation on substreams with a duration of 2 seconds.



Local Distributions Similarity



Comparison of Local Distributions



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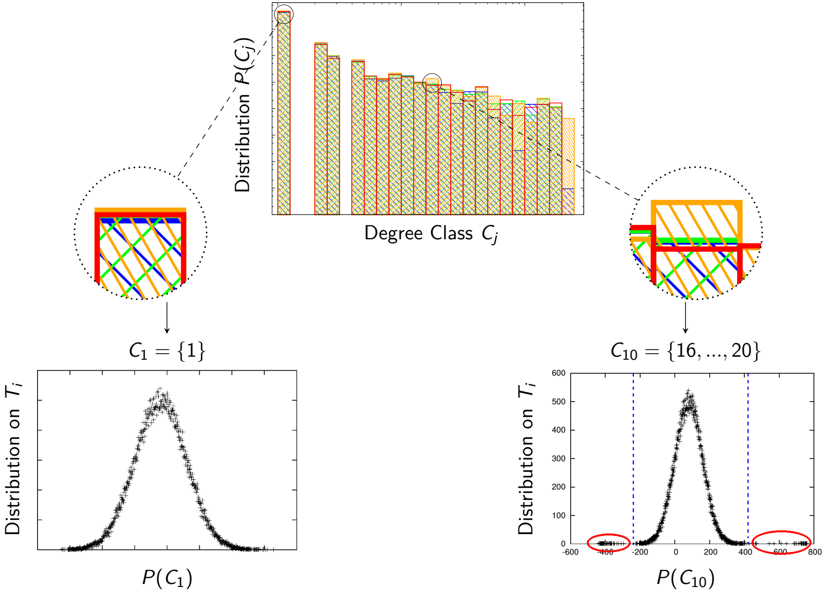
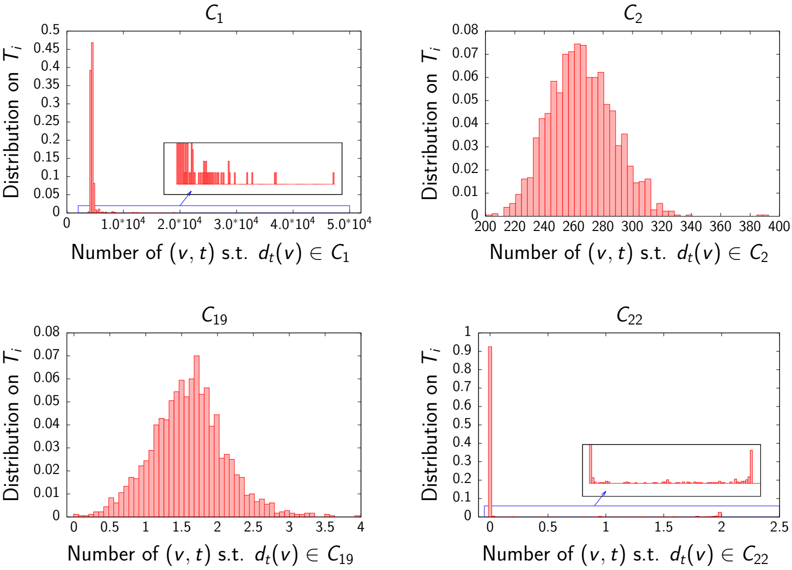


Results: Homogeneous Distributions



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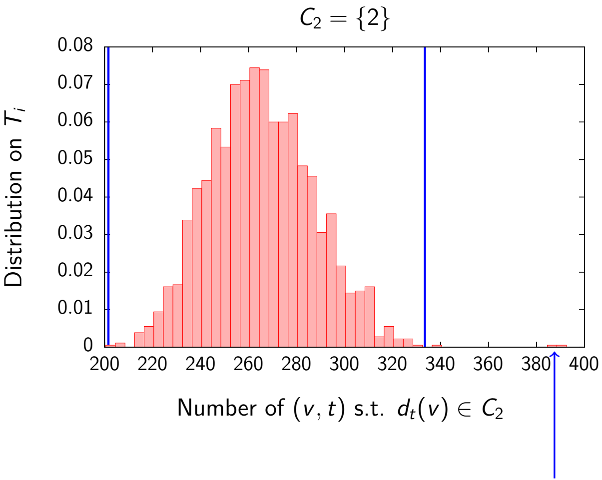


There are a lot more couples (v, t) for which $d_t(v) \in C_2$ during T_9 than during the majority of other time slices.

Overview of our method

Comparison of local distributions

↓

Detection of outliers

Identification: difficulties

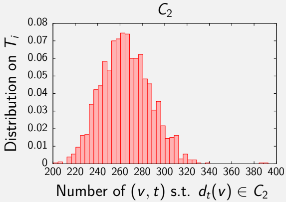
Detected Outlier $= 2$ informations
$\Rightarrow$ time slice T_i + degree class C_j

How to find responsible entities ?

How to identify detected outliers ?

Previous example:

Detected Outlier $\Rightarrow$ T_9 and C_2



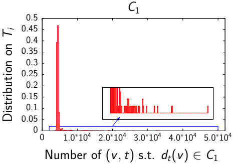
Difficulty: there are numerous (v, t) within C_2 during T_9

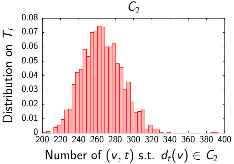
Which of them are abnormal ?

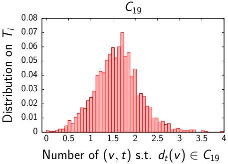
Identification

- Low degree classes:

outlier = normal + abnormal traffic

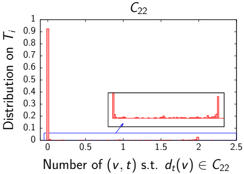


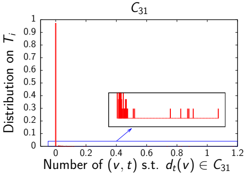


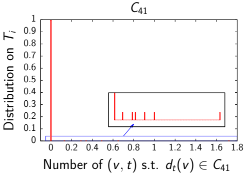


- High degree classes:

outlier = abnormal traffic only







→ Direct identification possible in high degree classes only

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Distributions Similarity
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Validation
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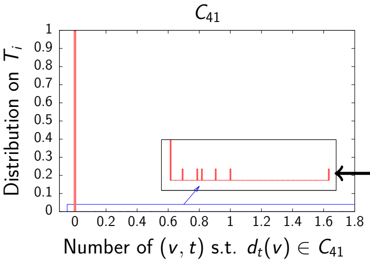
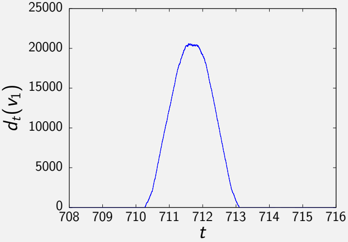
Identification in High Degree Classes



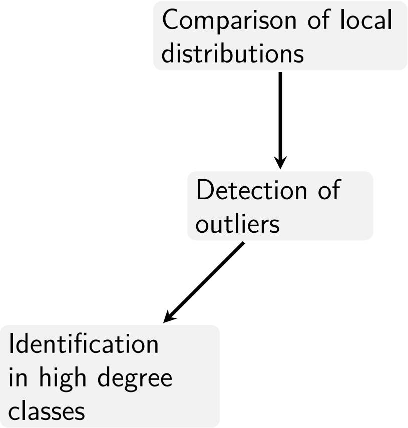
Detected Outlier:
$\Rightarrow \; T_{335} = [710, 712[$ and C_{41}

Identified outlier:
$\{(v_1, t) \mid t \in [710.3, 713.1[\}$

v_1 is the only node having a degree within C_{41} during T_{335}

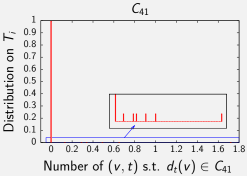


Overview of our method

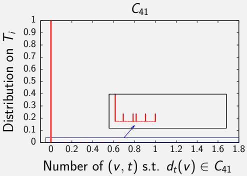


Removals of identified outliers

Disappearance of the detected outlier in the C_{41} distribution:

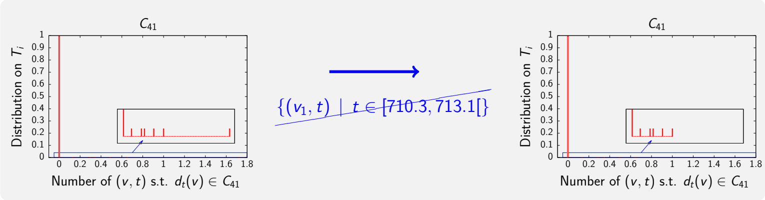


$\cancel{\{(v_1, t) \mid t \in [710.3, 713.1[\}}$

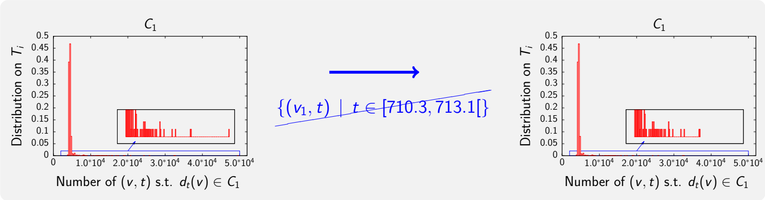


Removals of identified outliers

Disappearance of the detected outlier in the C_{41} distribution:

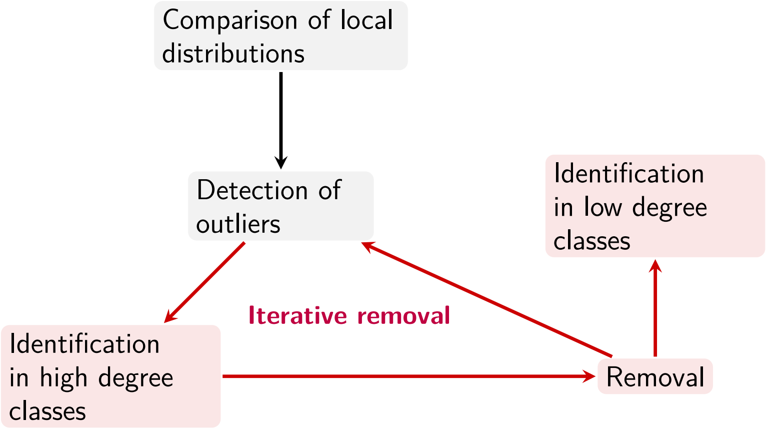


... as well as in a smaller degree class distribution:



$\Rightarrow$ Allows to identify low degree classes outliers among neighbours of the removed node.

Overview of our method



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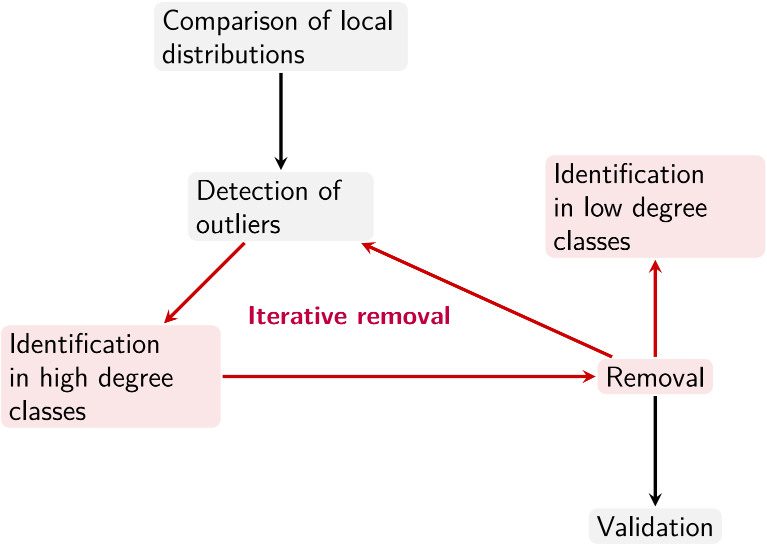
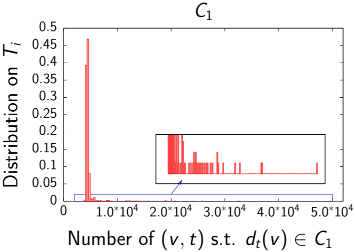
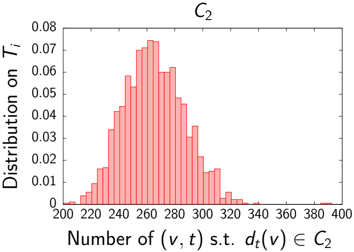
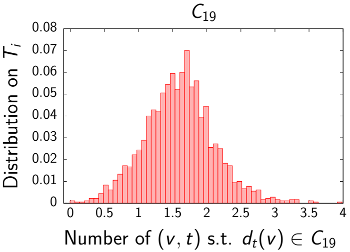


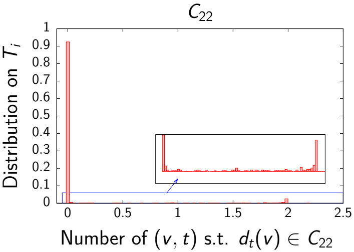
Degree Classes Distributions After Removals

Disappearance of most outliers without creation of negative outliers.









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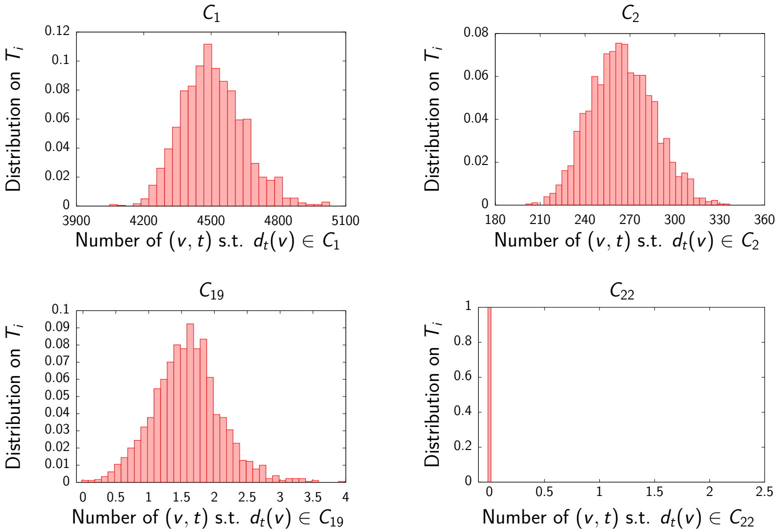
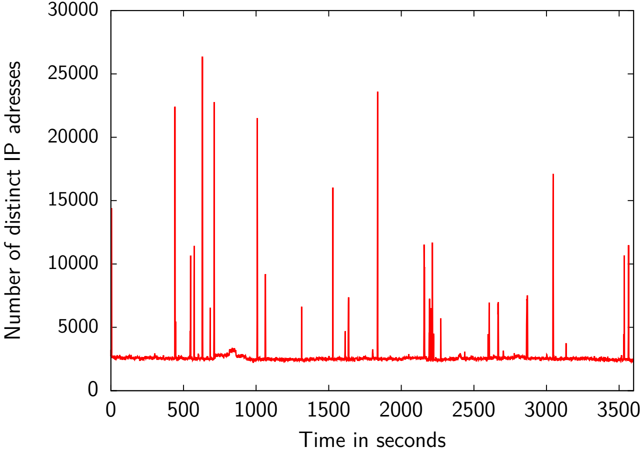


Creation of normal traffic

Number of detected outliers: $1,358$
Number of identified outliers: $1,163 =$ 85% of the detected outliers

$\Rightarrow$ Consequence on the number of distinct IP addresses per second.



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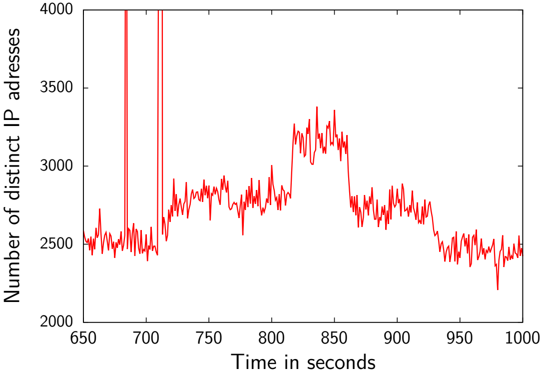

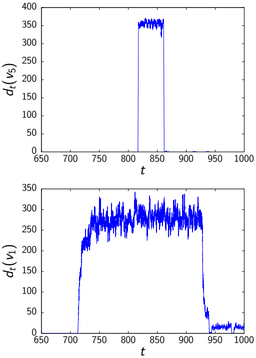

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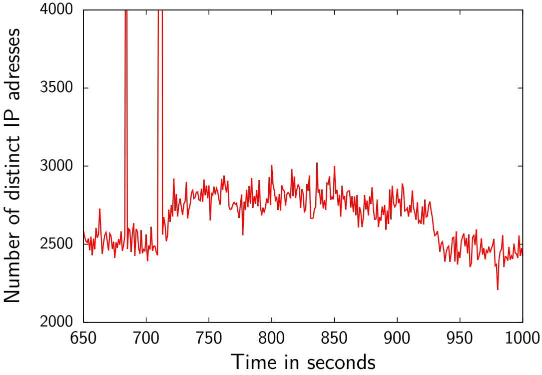

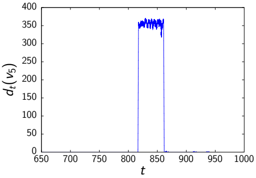

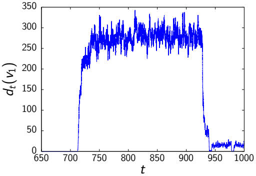

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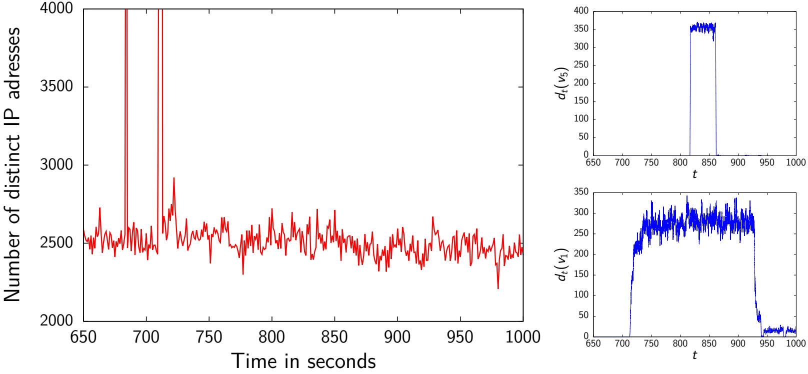

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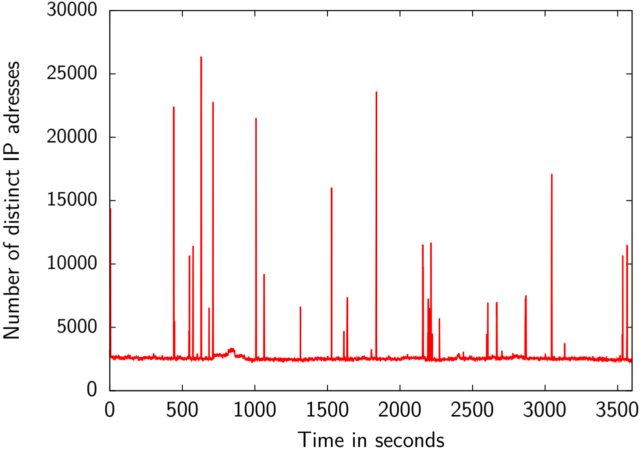

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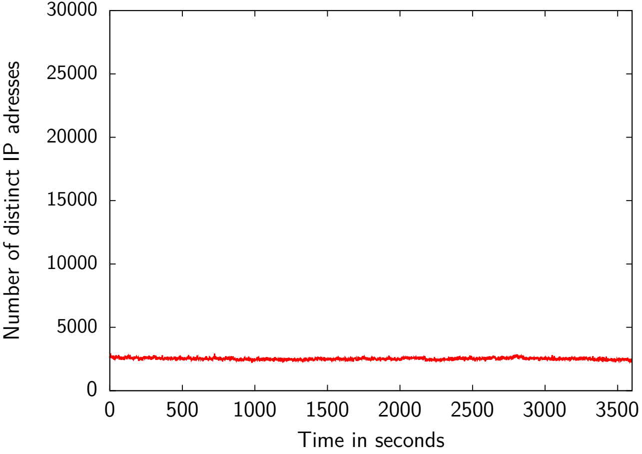

Conclusion

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Design of a method to detect and precisely identify outliers in heterogeneous distributions:

– Structural and temporal similarity evaluation of distributions.

– Modelling of IP traffic as a link stream.

$\rightarrow$ IP with anomalous degree profile, network scans.

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$\rightarrow$ Validation: Creation of normal traffic (w.r.t $d_t(v)$).

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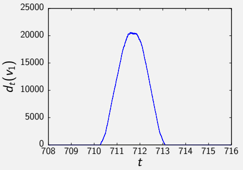
Thank you for your attention !

Identification: details

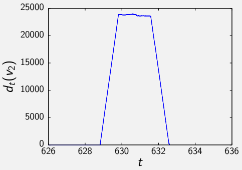
Detected Outlier $=$ time slice T_i $+$ degree class C_j

$$= \quad \{(v,t) : v \in C_{41} \text{ and } t \in T_{504} = [1008, 1010[\}$$

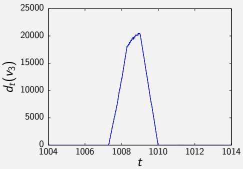
Nodes $\in C_{41}$:



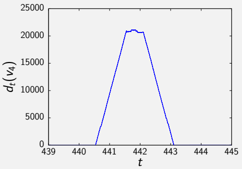
Abnormal on $I_{v_1} = [710.3, 713.1[$



Abnormal on $I_{v_2} = [628.8, 632.6[$



Abnormal on $I_{v_3} = [1007.3, 1010[$



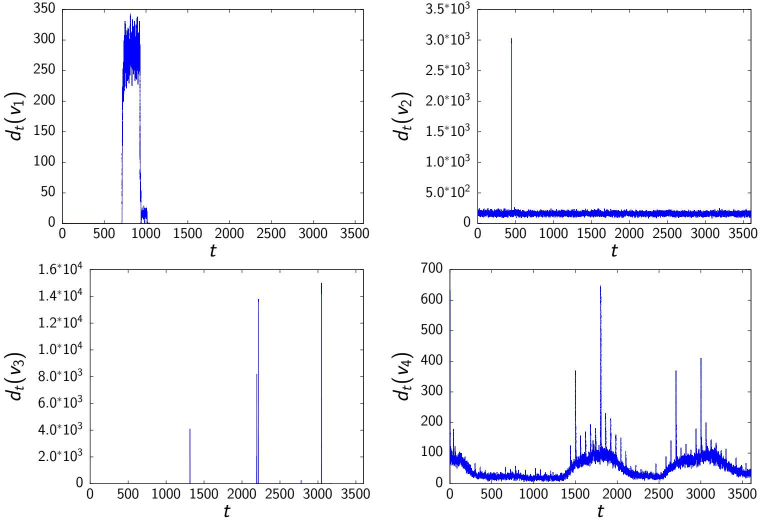
Abnormal on $I_{v_4} = [440.5, 443.2[$

$$I_{v_1} \cap T_{504} = \emptyset$$
$$I_{v_2} \cap T_{504} = \emptyset$$
$$I_{v_3} \cap T_{504} \neq \emptyset$$
$$I_{v_4} \cap T_{504} = \emptyset$$

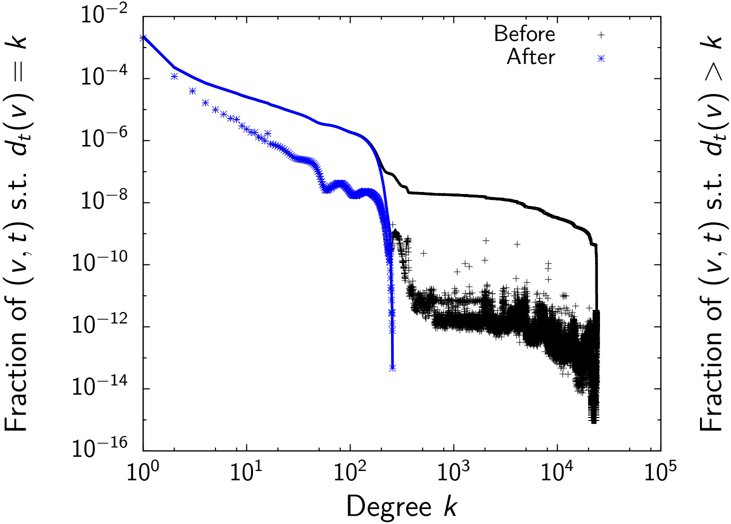
Identified outlier:

$\{(v_3, t) : t \in I_{v_3}\}$

Degree Profiles of 4 identified nodes



Degree Distribution : before and after



Classes construction

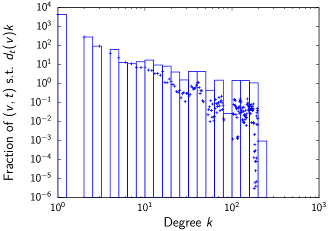
Need to respect the heterogeneous nature of the distribution:
- have low degree couples (v, t) which contains most of the traffic in isolated classes,
- take into account that the degree of nodes along time fluctuates and that generally: the larger the degree the larger the fluctuations.

$\Rightarrow$ logarithmic degree classes

In logarithmic scale: points spaced of the same distance represent values in the same ratio r

lin: $k_j \longrightarrow k_{j+1} = k_j + r$

log: $k_j \longrightarrow k_{j+1} = k_j \times r$ and $log(k_{j+1}) = log(k_j) + log(r)$



In our method:
$log(k_{j+1}) = log(k_j) + 0.1$

Other construction:
$\{1\}, \{2\}, ...\{9\}, \{10, ..., 19\}, \{20, ..., 29\}, ..., \{90, ..., 99\}, \{100, ...199\}$, etc.