



Graphs in OT Testing Graph Abnormality Application to a Real OT Data Set Ongoing & Future Works References

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Testing Abnormality of a Sequence of Graphs: Application to Cybersecurity

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SECKIOT

Outline

- 1 Graphs in OT
- 2 Testing Graph Abnormality
- 3 Application to a Real OT Data Set
- 4 Ongoing & Future Works

Standard approaches to detect an attack

- Solutions in IT (Information Technology) not sufficient to stop OT attacks (Raman, Ahmed et Mathur 2021)
- Firms use attacks history signature-based methods (Umer et al. 2022), but
 - what happens with a novel type of attack?
 - What happens if the signature is not well-chosen?
- Anomaly detection is the most efficient to stop a new attack since it can detect deviation of the normal behaviour (Raman, Ahmed et Mathur 2021)

Thus we focus on signature-free anomaly detection...

Graph anomaly detection

Graphs as natural structures to detect attack Neil et al. 2013

"Attacks do not happen in isolation on a single endpoint. Instead, they are exhibited across multiple endpoints, and in the communications between these endpoints."

- OT: up to our knowledge, no graph anomaly detection
- IT: graphs have been already used, for instance:
 - Calls of binary functions (Cohen, Yger et Rossi Nov 2021)
 - Stream of messages sent between IP addresses (in classification see Xiao et al. 2020; Abou Rida, Parrend et Amhaz 2021, in unsupervised learning with community detection, auto-encoder and scan statistics see Ding et al. 2012; Neil et al. 2013; Leichtnam et al. 2020)
- But only one statistical work to test if there is an anomaly (Neil et al. 2013), otherwise **poor statistical framework**...

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Our solution for testing abnormality of a graph

- 1 Learn a normal behaviour (distribution $\mathbb{P}_0$) over a sequence of graphs $\mathcal{G} = (\mathcal{G}_i)_{1 \leq i \leq n}$ with a flexible family $\mathcal{F}$ of probability distributions such that $\mathbb{P}_0 \in \mathcal{F}$
- 2 Test if a new graph $\mathcal{G}_i$ has the normal behaviour ($i \geq n + 1$)

$$\begin{cases} H_0 : \mathcal{G}_i \sim \mathbb{P}_0 \\ H_1 : \mathcal{G}_i \not\sim \mathbb{P}_0 \end{cases}$$

Use the general bootstrap principle

Compute the distribution of the log-likelihood L_0 of the distribution $\mathbb{P}_0$ with a bootstrap to get a quantile $q_{0.05}$: for $i \geq n + 1$, H_0 is said to hold if $L_0(\mathcal{G}_i) \geq q_{0.05}$

Choosing between different competitors

Retain the distribution family $\mathcal{F}$ which products **the greater power** for a given alternative distribution $\mathbb{P}_1$ ($i > n$)

$$H_1 : \mathcal{G}_i \sim \mathbb{P}_1$$

The distribution $\mathbb{P}_1$ represents a kind of attack, thus different scenarios to be tested...

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Tuning the hyperparameters for a targeted level

- We use the dataset of [a firm in OT](#) (confidential)
- It is split into 3 datasets: a learning dataset to learn $\mathbb{P}_0$, a validation dataset to [tune the hyperparameter for a targeted level](#), a test dataset to estimate the (unbiased) level

Model	Hyperparameter	Empirical level	Time of learning
SBM	$K = 30$	4%	46 hours
Gaussian kernel	$h = 90$	5%	1/2 hours
Poisson kernel	$h = 150$	10% ¹	1/2 hours

1. This model was not flexible enough to reach the targeted level of 5% ▶

Two realistic hypotheses H_1 : "star" and "path"

According to Neil et al. 2013, **star and directed path** in graphs are typical of cyber attacks.

Star construction

Star of size $\theta_s \in \llbracket 1, N - 1 \rrbracket$ with β edges on each couple of nodes

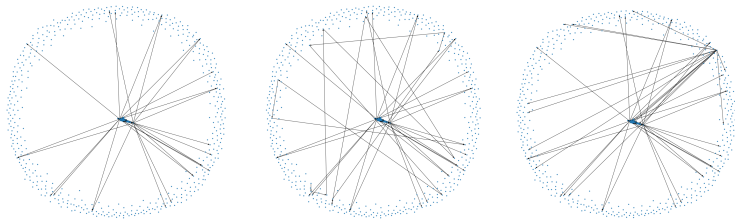
- Take a normal graph from the test set
- Choose uniformly a node k which will be the center of the star
- Choose uniformly θ_s nodes in $\{1, \dots, N\}_{\{k\}}$
- Add a value β on the edges of the star

Path construction

Directed path of length $\theta_p \in \llbracket 1, N \rrbracket$ with β edges on each couple of nodes

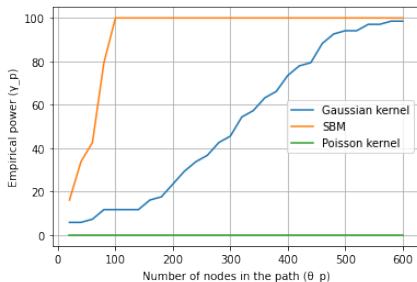
- Take a normal graph from the test dataset
- Choose uniformly θ_p nodes
- Add a value β on the edges of the path

Illustrating star and path

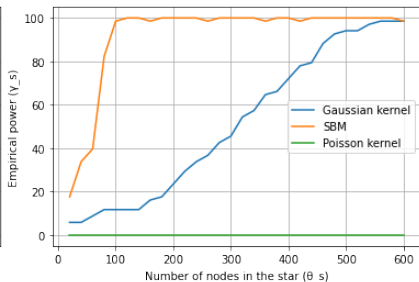


Normal graph (left), graph with a path (middle), graph with a star (right)

Empirical power



Empirical power for the path



Empirical power for the star

The SBM greatly outperforms Gaussian and Poisson kernels

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Ongoing work: a sparse SBM as a new competitor (1/3)

- The SBM showed promising results
- However, 99% of the data in the adjacency matrices equal 0
- SBM doesn't take into account this great sparsity

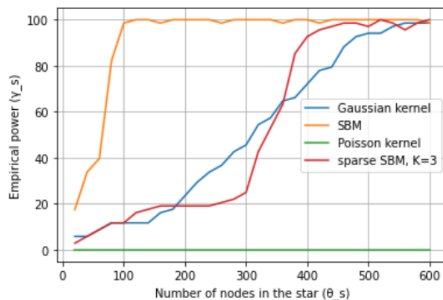
Definition of the sparse SBM

We take into account sparsity by changing the Poisson distribution with a mixture of a Dirac in 0 and a Poisson truncated in 0 ($\beta \in [0, 1]$, $\lambda \in \mathbb{R}_+$):

$$F(x; \beta, \lambda) = \mathbb{1}_{x=0}\beta + \mathbb{1}_{x \neq 0}(1 - \beta) \frac{\lambda^x}{(e^\lambda - 1)x!}$$

Ongoing work: a sparse SBM as a new competitor (3/3)

Empirical power of the star with the sparse SBM ($K = 3$)



The sparse SBM gives poor result in comparison with the SBM, thus this exploring work should be still continued...

Future works

- Pursue competitor proposals for $\mathbb{P}_0$
- Use scan statistics for relaxing iid assumption?
- Accelerate/avoid SMB-like estimation (hierarchical SBM?)
- Adapt the test to multiple testing (Benferroni correction)
- Investigate other real OT data sets
- Try different values of split Δ_t

Thank you for your attention



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