# Anomaly Detection in Link Streams

Internship Research


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| **Keywords** | Anomaly Detection, Random Sampling, Link Streams, AutoML |


## Context

Anomaly detection of link streams refers to identifying unusual patterns, structures, or suspicious behaviors, in a sequence of edges that arrive continuously over time, see Figure 1 for an example. This research area is crucial in cybersecurity, system failures, social network analysis, or network attacks. Detecting anomalies in link streams presents several challenges, *inter alia*, (i) *dynamic nature*: since the graph evolves over time, algorithms need to operate in an online and real-time manner to process the continuous flow of new edges and nodes, (ii) *scalability*: link streams can be large-scale with billions of edges requiring highly scalable algorithms with low computational and memory overhead, (iii) *lack of labeled data*: in many real-world settings, it is hard to obtain labeled data (ground truth), as result, researchers concentrate on identifying randomly injected links considered as anomalies.

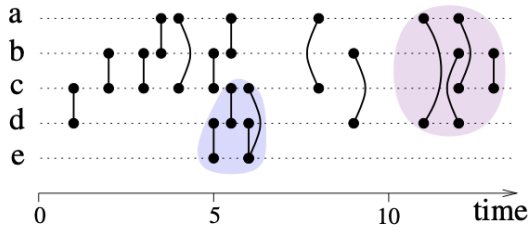


Figure 1: From [1]. A l ink stream: temporal interactions between *a, b, c, d e* over time range $[0, 15]$. Interactions in shaded areas may be traces of frauds or attacks.

Multiple solutions have been proposed in the literature to detect anomalies [2, 3] in streaming graphs, including traditional graph-theoretic techniques and modern machine learning-based approaches. However, these methods often face limitations in effectively addressing the diverse challenges inherent in link streams, which prevents their ability to accurately detect anomalous node behaviors.

## Objectives

In this project, we propose a novel algorithm to detect both real and artificially generated anomalies in link streams, addressing current limitations and challenges in this domain. An envisaged solution consists of two key components that work in tandem to enhance detection accuracy and manage computational demands:

First, the aim is to use a reservoir sampling technique [4] alongside a sliding window mechanism. The reservoir maintains a fixed-size collection of historical links, preserving a representative subset of the graph's evolution over time. Meanwhile, the sliding window continuously tracks the most recent links in the evolving graph, ensuring that short-term dynamics are captured effectively. This dual approach is inspired by techniques such as the one presented in [5] and enables our model to handle the streaming nature of link data with minimal memory overhead. By combining long-term and short-term views of the graph, the proposed approach preserves essential structural patterns without the need to store the entire graph history, thus ensuring scalability and adaptability in the face of large, evolving link streams (addressing thus the challenges (i) and (ii) previously mentioned).

Second, to tackle the challenge of the scarcity of ground truth data, we would develop an automated framework that leverages multiple state-of-the-art methods for anomaly injection and detection methods, as summarized in [2, 3]. This component of the framework generates both synthetic and real-world-like anomalies, simulating realistic suspicious behaviors to evaluate detection robustness (to address the challenge (iii). For final anomaly

scoring of nodes, we propose two aggregation strategies to enhance the accuracy and reliability of detection: (i) a mean-based approach, where scores from various detection methods are averaged to provide a balanced view, capturing general patterns of abnormality, or (ii) a weighted scoring system that dynamically adjusts each method's contribution based on its historical performance, inspired by approaches such as in [6].

**Expected outcomes and contributions:**

- The proposed solution will be rigorously documented, including theoretical analysis, algorithmic details, and an extensive experimental study to validate the proposed solution. The work will also feature a comparative evaluation against current state-of-the-art methods, showcasing the performance gains achieved in terms of detection accuracy, scalability, and robustness to different types of anomalies.
- To support transparency and further research, a fully documented open-source implementation will be provided. This will include all source code, datasets, and experimental configurations used, allowing researchers and practitioners to reproduce and build upon our work easily.

## Internship

The project is dedicated to a Master's thesis (or equivalent) student dedicated to the objectives of the project. The student will do his/her master's thesis in either of the teams concerned with the project namely ComplexNetworks and RO.

## Skills

- Master level research internship M2 to equivalent (stage de fin d'études ingénieur).
- Expertise in Python programming.
- Sound knowledge in graphs and machine learning.

## Gratification

According to current regulations.

## Contact to apply

Send the following documents (exclusively in PDF format) to maroua.bahri@lip6.fr and mehdi.naima@lip6.fr:

- A cover letter explaining your qualifications, experiences, and motivation for this topic.
- Curriculum vitae.
- Transcripts of grades from the third year of your bachelor's degree, the first year of your master's degree, and any available grades from the second year of your master's degree (or equivalent for engineering schools).
- If possible, recommendation letters.
- If possible, a link to repositories of personal projects (e.g., GitHub).

## References


[1] "Labcom fit." `https://www-complexnetworks.lip6.fr/~latapy/fit/`. Accessed: 2024-10-30.

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