Learning to localize anomalies and optimize itineraries through a general AI framework for combinatorial optimization in temporal graphs

PhD position, starting in October 2025

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Context

Numerous application domains like the Internet, transportation systems, or financial systems, generate data that can be very well modeled as a temporal graph: a set of time-stamped links (u, v, t) representing an interaction between nodes u and v at time t. For instance, in the Internet, nodes can represent computers and links can represent the packets between them. In transportation networks, nodes can represent bus or train stations and links can represent their scheduled travels. In a financial network, it may also be that nodes represent bank accounts and links represent their transactions. Figure 1 gives an illustration of temporal graphs.

When coping with a temporal graph, a fundamental problem that frequently arises is the one of identifying a subset of interactions that best optimizes a given property, like density, cut size, durations, distances, etc. Namely, in anomaly detection, the task consists in spotting the subgraph whose features maximally deviate from a normality reference. In cybersecurity, the identification of DDoS attackers essentially amounts to identifying the group of nodes densest traffic activity. In a transportation network, finding optimal routes calls to spot the time-respecting walk minimizing cost, length, minimum duration. Yet, the majority of these subset search problems are NP-hard combinatorial optimization problems: meaning that one must explore an exponentially large number of candidate solutions in order to find the optimal one.

To tackle combinatorial problems, two possibilities arise: (i) heuristic and approximation algorithms; and (ii) artificial intelligence models that learn to map problem instances to their solutions. The former is a traditional and well understood approach but that lacks flexibility and, in the temporal graph case, still offers poor tradeoffs between computation time and solution quality. The latter is an emergent perspective that has already been successfully employed to learn combinatorial problems on static graphs [1]. Yet, its potential remain to be explored in the context of temporal graphs. The main goal of this PhD project is to address this open question.

Goals

This PhD project aims to explore the potential of machine learning models to quickly produce high quality solutions to combinatorial optimization problems in temporal graphs. We target three sub-goals.

Goal 1: end-to-end learning framework. We aim to develop an end-to-end learning framework for general combinatorial optimization in temporal graphs. In particular, we aim to identify how to construct a loss that can be used to train a neural model so that it learns to map instances of a given problem to their solutions. Similar

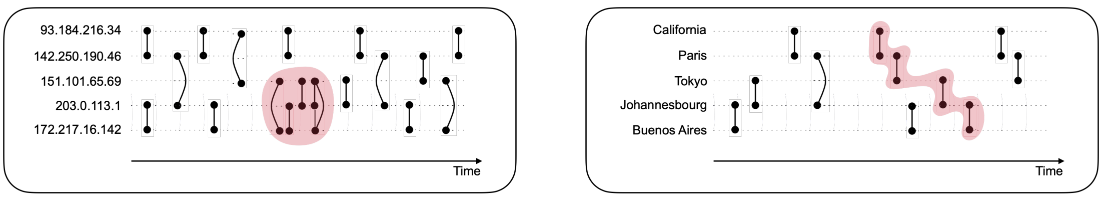

Figure 1: Communications between computers (left) and flights between airports (right) can be modeled as temporal graphs. Shaded areas highlight subsets with maximal density (left) or quickest exploration time (right), which are crucial to spot cyber-attacks or optimal delivery strategies, yet they involve solving combinatorial optimization problems.

frameworks have already been proposed for static graphs [2, 3], thus our specific goal is to extend such results to temporal graphs.

Goal 2: a novel filter-based architecture. We aim to develop a new neural architecture, pluggable into our framework, that leverages a signal processing vision. More precisely, we plan to tackle the combinatorial optimization challenge as a filtering one: where links are individually processed and filtered-out if they do not belong to the solution set. This perspective is already used by spectral algorithms in static graphs [4]. Thus, we hypothesize that they can be extended to the temporal case. In particular, we aim to build upon a recent framework [5] allowing to study temporal graphs in a spectral domain where filters can be defined.

Goal 3: high-impact applications. Two applications will guide and validate our developments.

- **Anomaly localization.** Sensor failures, computer attacks, traffic accidents, or other important issues can be detected by searching for subsets of the temporal graph that behave abnormally. Yet, while anomaly detectors allow to identify the existence of abnormal events, they do not allow to identify the subset of entities causing the events [6]. To localize them, the detector must be run with every possible subset as input until the one that produces the maximum anomaly score is identified, thus being a combinatorial optimization problem. Current solvers rely on assumptions about the topology of the anoamlies [7], but they are not satisfactory as anomalies are by definition hard to characterize and to predict. Thus, we aim to use our architecture to produce solutions without making such strong assumptions.
- **Temporal graph exploration.** In transportation systems with scheduled travels, such as trains between cities (e.g. Paris $\rightarrow$ Brest at 6 AM), or buses in a city (e.g. stop A $\rightarrow$ stop B at 3 PM), several fundamental questions arise, such as whether there is an itinerary allowing to visit every destination, or which exploration schedule allows to visit the most stops in a given time interval. Interestingly, these questions are instances of the temporal graph exploration problem: the problem of finding a time-respecting walk that visits all vertices as fast as possible. However, this problem has been shown to be NP-hard, thus consisting of a combinatorial optimization problem. Several approximation algorithms have been proposed but they have not achieved approximation ratios of practical utility [8]. Our aim is to produce practical algorithms that can scale well.

Requested profile

We look for highly motivated candidates with relevant experience in computer science, graph algorithms, and/or deep learning. Experience in Python programming and operations research will be a plus.

Application

Interested candidates are invited to send an e-mail to

- esteban.bautista@univ-littoral.fr
- rym.guibadj@univ-littoral.fr
- gilles.roussel@univ-littoral.fr

while attaching the documents that can support their application:

- your resume;
- a cover letter;
- your transcripts from the last year of B.Sc to the last year of M.Sc. (if the latter is already available);
- two reference letters or the names and means of contact of two academic advisers.

Applications will be reviewed on a rolling basis until the position is filled.

References

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