Master’s Research Internship 2025

Title:	Machine Learning Framework for Temporal Graph Exploration
Supervisors:	Esteban Bautista, Rym Guibadj
Internship duration:	6 months
Place:	LISIC laboratory - Université du Littoral Côte d’Opale (Calais or St-Omer sites)

Context

In transportation systems with scheduled travels — such as trains between cities (e.g. Paris → Brest at 6 AM), flights between airports (e.g. Lyon → Madrid at 2 PM), buses within metropolitan areas (e.g. stop A → stop B at 3 PM), etc. — several fundamental questions arise. Is there an itinerary that allows an agent to visit every city/airport/stop? If multiple such itineraries exist, what is the fastest one? How can we identify the travel schedule that visits the most cities/airports/stops within a pre-defined time window? These questions, central to improving logistics and network planning, can be seen as instances of the temporal graph exploration problem (TEXP) : the problem of finding a time-respecting walk in a temporal graph that visits all vertices as fast as possible. Indeed, solving TEXP has implications beyond transporation systems, as identifying optimal routes is also crucial in cybersecurity and fraud detection systems. However, TEXP has been shown to be NP-hard meaning that computing exact solutions becomes impractical for large temporal graphs [1].

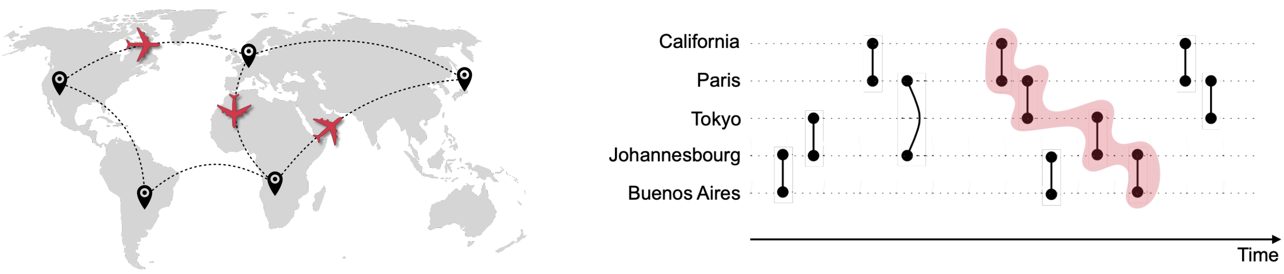

Figure 1: Flights in an airport network (left panel) can be modeled as time-stamped edges in a temporal graph (right panel). Identifying the quickest itinerary that visits all cities is an NP-hard problem, even if travels durations and directions are omitted as done in the figure. Links in the shaded area represent such an itinerary. Note that an agent starting from Tokyo would be unable to visit all cities.

Efficient approximation and heuristic algorithms have been proposed to solve the TEXP as a combinatorial optimization problem (COP). However, these solutions still provide a poor tradeoff between speed and the quality of the retrieved solutions [2, 1]. The Graph Neural Networks (GNNs) have been successfully used as learning frameworks for COPs by learning distributions from which low-cost valid solutions to the problem can be obtained [3]. Even though there is a recent surge of works extending graph neural networks to process temporal graphs, no work has yet tackled the TEXP problem from the machine learning perspective. This internship project aims to address this challenge.

Goal

We aim to tackle the TEXP problem from the machine learning perspective by building on the unsupervised framework for combinatorial optimization proposed in [4]. Specifically, we aim to (1) leverage this framework to derive a custom loss function, based on the Erdős probabilistic method, that optimizes for time-respecting walks; and (2) explore recent architectures that implement temporal walk-based embedding modules [5], that offer a more effective inductive bias for TEXP than traditional GNNs whose aggregation function loses track of the origin of events in multi-hop neighborhoods.

Requested profile

This internship is directed at students with various backgrounds (computer science, data science, operations research, complex systems) but with a strong interest in combinatorial optimization and graph machine learning.

To apply, please send an e-mail to {esteban.bautista, rym.guibadj} [at] univ-littoral.fr while attaching the documents that can support your 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.

Funding

This internship will be funded by the ANR project ANR-23-CPJ1-0048-01.

References

[1] T. Erlebach and J. T. Spooner, "Parameterised temporal exploration problems," *Journal of Computer and System Sciences*, vol. 135, pp. 73–88, 2023.

[2] T. Erlebach, M. Hoffmann, and F. Kammer, "On temporal graph exploration," *Journal of Computer and System Sciences*, vol. 119, pp. 1–18, 2021.

[3] Q. Cappart, D. Chételat, E. B. Khalil, A. Lodi, C. Morris, and P. Veličković, "Combinatorial optimization and reasoning with graph neural networks," *Journal of Machine Learning Research*, vol. 24, no. 130, pp. 1–61, 2023.

[4] N. Karalias and A. Loukas, "Erdos goes neural: an unsupervised learning framework for combinatorial optimization on graphs," *Advances in Neural Information Processing Systems*, vol. 33, pp. 6659–6672, 2020.

[5] M. Jin, Y.-F. Li, and S. Pan, "Neural temporal walks: Motif-aware representation learning on continuous-time dynamic graphs," *Advances in Neural Information Processing Systems*, vol. 35, pp. 19874–19886, 2022.