# Tensor Decompositions for Interpretable Machine Learning on Temporal Graphs

PhD position, starting in October 2025

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## Context

Many real-world systems, like the Industrial Internet of Things, e-commerce, and social networks, generate data that can be very well modeled as a temporal graph: a set of triplets $(u, v, t)$ representing an interaction between $u$ and $v$ at time $t$. For example, a triplet may represent that sensor $u$ communicated with sensor $v$ at time $t$, or that client $u$ purchased product $v$ at time $t$. Temporal graphs have gained considerable attention as numerous events of crucial interest —like financial frauds, network attacks, or fake news spread— may be possible to detect by carefully studying temporal graphs [1, 2]. Yet, such studies call for the construction of a large number of machine learning methods for temporal graph analysis —like anomaly detection, link prediction, node classification, temporal community detection, segmentation, or filtering, among others— which remain very hard to define as machine learning methods call for notions of similarity that do not naturally arise in temporal graphs.

Indeed, most machine learning methods rely on the assumption that similar data instances must lead to similar decisions, such as two images of similar features getting classified to similar classes. Yet, in the case of temporal graphs, how to assess if two links are similar? How to assess of two nodes play similar roles? More broadly, how to quantify the similarity of two entire temporal graphs? Unlike Euclidean datasets, temporal graphs lack standard notions of similarity, thus making the construction of machine learning techniques a significant challenge. Current approaches use neural networks to embed temporal graphs into Euclidean spaces where similarity notions can be endowed [3]. However, these neural approaches suffer from two limitations: (i) they focus on embedding atomic structures, such as individual links, nodes, or graph snapshots, rather than entire temporal graphs, limiting their ability to capture dynamic and structural dependencies across the data; and (ii) they are inherently hard to interpret, making it difficult to understand why certain structures are deemed similar or why certain inferences are made.

The goal of this PhD project is to address the aforementioned limitations by developing interpretable methods for measuring the similarity of temporal graphs. To this end, its main goal is to develop new tensor decomposition methods adapted to temporal graphs [4]. Tensor decomposition approaches appear as a natural solution to the problem, as temporal graphs can be naturally represented via three-way tensors, and the decomposition factors open the door to adopt a signal processing vision to the challenge: where the complex temporal graphs are decomposed into their fundamental constituents, or "atoms" [5], based on which meaningful and interpretable similarity metrics can be defined by spotting common atoms across temporal graphs.

## Goals

This PhD work aims to lay the groundwork for interpretable machine learning on temporal graphs by developing interpretable similarity metrics. To achieve this, we pursue three specific objectives:

**Goal 1: A novel tensor decomposition for temporal graphs.** We aim to address the challenge of identifying elementary motifs that are both common and distinct across a set of temporal graphs, which may potentially differ in their sets of nodes and time intervals. Tensor decompositions offer a natural framework for this purpose. However, existing tensor decomposition methods do not fully meet the needs of temporal graph analysis: they fail to jointly account for the binary nature of temporal graphs, their sparsity, their multi-scale patterns, and the differences in temporal and structural resolutions. Furthermore, they are not designed to handle graphs defined on different sets of nodes or time intervals. Our ambition is to build upon recent developments [6, 7, 8] to develop tensor decomposition methods that overcome these limitations.

**Goal 2: Similarity metrics, machine learning tasks, and toolbox.** We plan to exploit our tensor analysis to develop interpretable similarity metrics for temporal graphs. In particular, our decomposition will allow us to express the temporal graph as a combination of elementary motifs weighted by importance coefficients. By comparing the coefficients across instances, we will spot the scales, structures, and dynamics at which they are similar. We will propose therefore a variety of metrics to capture different types of similarities: dynamic, structural, scale-specific, or combinations, and will build on them to derive machine learning algorithms for tasks such as clustering, segmentation, change point detection and link prediction. We plan to integrate all metrics and algorithms into a Python toolbox.

**Goal 3: Application to real-world datasets.** The methodological developments described are general and therefore can be applied in many contexts. We plan to use two to guide and validate our developments:

- **Wikipedia.** Collaborative platforms like Wikipedia and open-source projects such as Linux rely on self-organized groups to achieve large-scale collective actions. However, successful collaborations are more the exception than the rule, despite many studies identifying common patterns among successful projects [9]. Understanding the factors behind their success requires recognizing shared patterns across projects, identifying distinct phases in their development, and understanding the roles of contributors. Temporal graphs provide a natural model for these interactions and we aim to apply our tools to investigate these questions.
- **Industry 4.0.** The Industrial Internet of Things is a rapidly evolving paradigm in which industrial sensors, machines, and other instruments are connected to the internet. In these systems, it is crucial to promptly detect devices with abnormal behavior or sudden abnormal changes in the communication patterns, as they are indicative of faults or attacks [10]. Temporal graphs offer a natural model for these data and we plan to apply our tools to address these challenges.

## Requested profile

We look for highly motivated candidates with relevant experience in computer science, data science, and graph machine learning. Experience in Python programming and signal processing will be a plus.

## Application

Interested candidates are invited to send an e-mail to

- esteban.bautista@univ-littoral.fr
- laurent.brisson@imt-atlantique.fr
- matthieu.puigt@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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