Chair Data Science and Artificial Intelligence for Digitalized Industry and Services

Internship project

Subject

Learning Time-Varying Causal Graphs from Time Series

Possibility to continue as a PhD candidate

YES (Funding to be confirmed)

About the chair

The Chair Data Science and Artificial Intelligence for Digitalized Industry and Services (DSAIDIS), lead by Florence d'Alché-Buc, a Professor in the department Image, Data, Signal of Telecom Paris, unites five industrial partners: Airbus Defence & Space, Engie, Idemia, Safran and Valeo. It's general objective is to develop, in collaboration with the partners, teaching and research of the international level.

Its four principal research directions are:

1. Building predictive analytics on time series and data streams.
2. Exploiting large scale, heterogeneous, partially labeled data.
3. Machine Learning for trusted and robust decision.
4. Learning through interactions with environment.

Description of the internship

Supervision

Jhony H. GIRALDO, Maître de Conférences (https://sites.google.com/view/jhonygiraldo),

Aref EINIZADE, Postdoc (https://scholar.google.com/citations?user=ZEQyAaAAAAAJ&hl=en&oi=ao)

Location and dates of the internship

Address : Télécom Paris, 19 Place Marguerite Perey, 91120 Palaiseau

Date of the beginning of the internship : beginning 2024

Team where the thesis will be written

Department IDS, Team Multi-Media (MM)

Keywords

Graph Signal Processing, Causal Graph Process, Time-Varying Graph Learning, Graph Neural Network.

Detailed subject

Graphs are mathematical tools for modeling relationships between pairs of data components and have been widely used for modeling unstructured data. In this context, graph nodes can have values associated with them, which have well-known real-world interpretations, e.g., measured temperature at different geographic sites. Using traditional tools in Signal Processing (SP) and Machine Learning (ML) for dealing with these signals supported on graphs (i.e., graph signals) can lead to information loss, because of not exploiting component interactions embedded in the underlying graph. Recently, the emerging field of Graph Signal Processing (GSP) [2,3] has been introduced to benefit from graph-related information when processing graph signals. Graph Neural Networks (GNNs) [8] have been also developed to extend the classical deep learning (DL) tools to learning from irregular (i.e., graph-based) data. Since the assumption of knowing the underlying graph is not valid in a wide range of real-world scenarios, i.e., processing brain signals, the concept of Graph Learning (GL) [5,6] with emphasis on the GSP concepts has been turned into a emerging topic of research.

In the case of assigning time-varying measures to the graph nodes, we face processing time-varying graph signals time-series supported on graphs. On the other hand, the assumption of having a static (i.e., fixed) graph in all subsequent time intervals is not practical in many applications, e.g., brain signal processing [7], global weather change studying [8], etc. In these scenarios, the casual (i.e., cause-effect) relationships existing between different graph nodes can significantly improve the performance of processing time-varying graph signals. There have been few proposed methods to address this problem. However, almost all of them assume that the different time steps have relationships with only before/after intervals. Besides, their proposed method is specialized to work with just undirected graphs, which is not necessarily valid with real-world graph-based datasets. These limitations seem a **considerable gap** in these concepts to address. For instance, due to the Climate Change, the first months of the year can reveal meaningful similarities with the middle ones. On the other hand, the direction of wind can have significant effect on the prediction performance [8]. Note that, based on real-world research and observations, the practical assumption relies on smooth differences of the spatial graphs with respect to the neighbor underlying graphs. Filling the mentioned gap can have a vast applicability from biology [7] to economics [12] and even traffic forecasting [13]. For instance, by inference of time-varying graphs from existing EEG/MEG brain signals, some well-known diseases or disorders line epilepsy can be detected [7]. In another point of view, changing the spatial pattern of the temperature measurement sites can be discovered as a sign of climate change to prevent or modify environmental activities [8].

The aforementioned concepts and gaps motivate us to develop a method for learning time-varying causal graphs from time series [1] for the generalization of the temporal interactions, with the assumption of smooth graph variations through time. Therefore, in this approach, some concepts related to GSP [2, 3], GL [5, 6], and GNN are going to be exploited to develop a flexible approach to address time-varying causal GL [6]. In this internship, the objective is to fill the gap between undirected and directed graphs to uncover the causality interactions between different (generalized) components of the given time series. We propose to integrate the concepts of Causal Graph Process (CGP) [8] with undirected (smooth) GL approaches [5] to be able to introduce a new and novel model for generation of causal time-varying graph signals [10, 11]. The next step will be extending the developed framework to GNNs to further improve performance [9].

Candidate profile

Student having master 2 research

- Good familiarity or at least motivation in Graph Signal Processing, Graph Learning, and Graph Neural Network with some bases in optimization
- Good level of programming (Python)
- Good command of English

Application

To send to jhony.giraldo@telecom-paris.fr and aref.einizade@telecom-paris.fr:

- Curriculum Vitae

- Personalized motivation letter that explains interest of the candidate in the subject (can be directly in the body of the email)

- Grade reports for recent years

- Contact of a person willing to give recommendation

Incomplete applications will not be considered.

References

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