1. Lecture: Large Dimensional Network Models in Finance

Over the last years, network analysis has become an active topic of research, with numerous applications in macroeconomics and finance. In a nutshell, network analysis is concerned with representing the interconnections of a large panel as a graph: the vertices of the graph represent the variables in the panel, and the presence of an edge between two vertices denotes the presence of some appropriate measure of dependence between the two variables. This course is focused on the theory and practice network analysis techniques for applications in finance and economics.

Outline:

- Introduction to graphs: Random Graphs, Erdos-Renyi Graphs, Power-law Graph, Stochastic Block models
- Empirical Application 1: simulating and plotting random graphs (in python)
- Modeling contemporaneous dependence. Partial Correlations Network.
- LASSO estimation of large dimensional (network) models
- Empirical Application 2: Modeling the contemporaneous dependence of the constituents of the S&P 100
- Modeling temporal dependence. Granger Networks, Connectedness Table
- Empirical Application 3: TBA

After having completed this course, you will be able to:

• Understand the basic concepts of network theory, including: vertices, edges, network properties, random graphs, etc.
• Model contemporaneous and dynamic dependence in large panels of time series
• Estimate large dimensional network models (using LASSO estimation)
• Identify network structures such hubs and communities

2. Lecture: Probabilistic Programming for Bayesian inference.

The use of Artificial Intelligence (AI) based on Machine Learning (ML) is becoming pervasive in decision making in a variety of settings. In this context, quantification and communication of well-calibrated uncertainty is crucial, as it helps stakeholders understand when and to what extent they should trust the model's predictions and recommendations.

In this course, we provide an overview of different approaches to uncertainty quantification. We first look at Bayesian Inference, which yields model parameters that are not mere point estimates but whole distributions and effectively provides a measure of uncertainty of the model's predictions on a new data point in the form of posterior probability distributions. We then introduce an approach called Conformal Prediction, that allows ML practitioners to compute a measure of uncertainty for every sample prediction in a model-agnostic and distribution-free fashion. The course combines theoretical and practical content by using examples and exercises written in Python using probabilistic programming and ML libraries.

3. Lecture: Natural Language Processing

This course will introduce some basic concepts of NLP (Natural Language Processing), starting with simple text pre-processing techniques such as tokenization and part-of-speech tagging, and moving on to more complex tasks such as term and entity recognition, social media processing, and sentiment and hate speech detection, as well as adaptation to different languages. The techniques will be demonstrated using GATE, one of the most widely used toolkits for NLP, which is freely available and open source. Practical exercises and relevant materials will be provided for participants to try out the applications, and to experiment with building their own simple tools.

Lecture pre-requisites:

No experience with NLP, GATE, or programming is required. Participants will be asked to download and install the GATE toolkit in advance on their laptops. The course is suitable for researchers from all disciplines.