UNIVERSITÀ DEGLI STUDI FIRENZE

FLORENCE center for DATA SCIENCE

ABSTRACTS

Seminar D^2 Seminar Series

Florence Center for Data Science 'Double' Seminar Series

Alessio Brini - Duke University Pratt School of Engineering

Title: Reinforcement Learning Policy Recommendation for Interbank Network Stability
(joint work with Gabriele Tedeschi and Daniele Tantari)

Abstract: In this paper, we analyze the effect of a policy recommendation on the performance of an artificial interbank market. Financial institutions stipulate lending agreements following a public recommendation and their individual information. The former is modeled by a reinforcement learning optimal policy that maximizes the system's fitness and gathers information on the economic environment. The policy recommendation directs economic actors to create credit relationships through the optimal choice between a low interest rate or a high liquidity supply. The latter, based on the agents' balance sheet, allows to determine the liquidity supply and interest rate that the banks optimally offer their clients within the market. Thanks to the combination between the public and the private signal, financial institutions create or cut their credit connections over time via a preferential attachment evolving procedure able to generate a dynamic network. Our results show that the emergence of a core-periphery interbank network, combined with a certain level of homogeneity in the size of lenders and borrowers, is essential to ensure the system's resilience. Moreover, the optimal policy recommendation obtained through reinforcement learning is crucial in mitigating systemic risk.

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Title: A Bayesian nonparametric approach to personalized treatment selection

Abstract: Precision medicine is an approach to disease treatment that defines treatment strategies based on the individual characteristics of the patients. Motivated by an open problem in cancer genomics, we develop a novel model that flexibly clusters patients with similar predictive characteristics and similar treatment responses; this approach identifies, via predictive inference, which one among a set of therapeutic strategies is better suited for a new patient. The proposed method is fully model-based, avoiding uncertainty underestimation attained when treatment assignment is performed by adopting heuristic clustering procedures, and belongs to the class of product partition models with covariates, here extended to include the cohesion induced by the normalized generalized gamma process. The method performs particularly well in scenarios characterized by large heterogeneity among the predictive covariates in simulation studies. A cancer genomics case study illustrates the potential benefits in terms of treatment response yielded by the proposed approach. Finally, being model-based, the approach allows estimating clusters' specific random effects and then identifying patients that are more likely to benefit from personalized treatment.