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School of Arts and Sciences

Department of Statistics

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Designing experiments on social, healthcare, and information networks.

Wednesday, April 17th, 2024
11:50 AM
96 Frelinghuysen Road, CoRE Building, Room 431

Zoom Meeting: Meeting ID: 969 0606 4706
Password: 745339

https://rutgers.zoom.us/j/96906064706?pwd=ZklvbExpRVBJQ3c5dUhhYTFuR2ZrZz09
Light refreshments will be served in Hill 452, 11:15am

Abstract: Designing experiments that can estimate causal effects of an intervention when the units of analysis are connected through a network is the primary interest, and a major challenge, in many modern endeavors at the nexus of science, technology and society. Examples include HIV testing and awareness campaigns on mobile phones, improving healthcare in rural populations using social interventions, promoting standard of care practices among US oncologists on dedicated social media platforms, gaining a mechanistic understanding of cellular and regulation dynamics in the cell, and evaluating the impact of tech innovations that enable multi-sided market platforms. A salient technical feature of all these problems is that the response(s) measured on any one unit likely also depends on the intervention given to other units, a situation referred to as "interference" in the parlance of statistics and machine learning. Importantly, the causal effect of interference itself is often among the inferential targets of interest. On the other hand, classical approaches to causal inference largely rely on the assumption of "lack of interference", and/or on designing experiments that limit the role interference as a nuisance. Classical approaches also rely on additional simplifying assumptions, including the absence of strategic behavior, that are untenable in many modern endeavors. In the technical portion of this talk, we will formalize issues that arise in estimating causal effects when interference can be attributed to a network among the units of analysis, within the potential outcomes framework. We will introduce and discuss several strategies for experimental design in this context centered around a useful role for statistics and machine learning models. In particular, we wish for certain finite-sample properties of the estimator to hold even if the model catastrophically fails, while we would like to gain efficiency if certain aspects of the model are correct. We will then contrast design-based, model-based and model-assisted approaches to experimental design from a decision theoretic perspective.

Bio: Edoardo M. Airoldi is the Millard E. Gladfelter Professor of Statistics and Data Science, and a Professor of Finance (by courtesy), in the Fox School of Business, at Temple University. He also serves as Director of the Fox School's Data Science Center. Previously, Airoldi was at Harvard University, where he founded and directed the Harvard Laboratory for Applied Statistics & Data Science, until 2018. Airoldi earned his PhD in Computer Science from Carnegie Mellon University and has worked in various industry roles before and after his PhD, including at companies like Facebook and Google.

Airoldi is a distinguished researcher with over 150 publications in top in journals across statistics, computer science, and general science, including in the Annals of Statistics, the Journal of the American Statistical Association, the Journal of the Royal Statistical Society (Series B), the Journal of Machine Learning Research, the Proceedings of the National Academy of Sciences, and Nature, and more than 42,000 citations. His current research focuses on statistical methodology and theory for designing and analyzing randomized experiments and observational studies in complex settings, and on modeling and inferential issues that arise in analyses that leverage network data. He has collaborated with tech and finance leaders such as Google, Microsoft, and DE Shaw among many others.

Airoldi has received numerous honors and awards, including the Outstanding Statistical Application Award from the American Statistical Association, a Sloan Fellowship, an NSF CAREER Award, among many others. He has delivered a plenary talk at the National Academy of Sciences Sackler Colloquium on "Causal Inference and Big Data," in 2015, and he has given an IMS Medallion Lecture at the Joint Statistical Meetings, in 2017. Besides, he is an elected Fellow of the Institute for Mathematical Statistics, since 2019, and of the American Statistical Association, since 2020.