Title: Statistically Valid Causal Inference for AI-Native Wireless Networks

Topic Description: The advent of artificial intelligence (AI) in wireless networks has revolutionized their design and architecture, with many network functionalities being replaced by, or integrated with, AI-based algorithms that optimize network operation based on correlations extracted from large observational datasets. While this approach has proven successful in compensating for model and algorithmic deficiencies, allowing networks to adapt to site-specific conditions and find data-driven solutions to intractable optimization problems, it lacks support for many primitive functionalities that remain essential for network operators.

In particular, purely statistical approaches are not interpretable: they cannot quantify the effects of interventions, nor do they support counterfactual analysis, i.e., reasoning about "what-if" scenarios. In contrast, causal inference provides a framework to integrate data-driven methods with domain knowledge accumulated through years of network design, enabling the modeling and understanding of cause–effect relationships between network configurations and key performance indicators. By explicitly accounting for these relationships, causal inference methods can equip network operators with algorithms that harness the advantages of data-driven optimization while preserving interpretability and intervention-aware reasoning. For these reasons, causal inference tools are expected to play a central role in the design of future AI-native networks.

Within this context, the goal of this thesis is to advance the field of causal learning for wireless networks, with a particular emphasis on reliability, statistical validity, and simulation-aided inference. More specifically, the candidate is expected to develop new causal inference algorithms to obtain statistically valid and reliable predictions of intervention effects and counterfactual estimates for key network metrics. The work will leverage recent progress in model-free calibration and anytime-valid sequential statistics, and will also explore simulation-aided inference to incorporate high-fidelity simulators as sources of synthetic data. The developed causal inference methods will equip network operators and designers with principled tools to understand network behavior and to evaluate and optimize intervention strategies safely and effectively before deployment.