Mechanical Engineering Dissertation Defense

Temporal Logic for Causality, Learning, and Control: A Unified Framework for Data-Driven Inference and Decision-Making

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Abstract

This dissertation presents a unified framework for integrating temporal logic, causal reasoning, and data-driven learning and control. Motivated by the growing reliance on intelligent systems operating in dynamic and uncertain environments, the work emphasizes interpretability, fairness, and robustness alongside performance. The presented research spans causal inference, temporal logic inference, neural-symbolic learning, reinforcement learning, and privacy-preserving control, contributing to the theoretical and algorithmic foundations of trustworthy autonomous systems.

The dissertation first introduces Temporal-Logic-Based Causal Fairness Analysis (TL-CFA), a framework that combines causal reasoning and temporal logic to quantify and analyze algorithmic discrimination over time. TL-CFA captures delayed and cumulative unfair effects often missed by static fairness measures and is validated through case studies on health inequity and gender pay gaps.

Next, a logic-based approach to causal discovery using Signal Temporal Logic (STL) is developed. The resulting framework constructs interpretable causal diagrams that capture both structural and temporal persistence of causal influence, merging statistical, logical, and information-theoretic reasoning for time-series data.

Extending causal reasoning to decision-making, Counterfactually-Guided Causal Reinforcement Learning with Reward Machines (CGC-RL) leverages counterfactual sequences from observational data to guide reward shaping, improving policy learning efficiency while preserving policy invariance.

Two complementary frameworks are then proposed for STL inference. The first, Weighted Graph-Based STL Inference Using Neural Networks, learns spatial-temporal properties as weighted graph-based STL formulas that retain interpretability while achieving competitive accuracy. The second, Uncertainty-Aware STL Inference, incorporates interval trajectories and robust semantics to handle uncertainty in real-world data, significantly improving computational efficiency and robustness.

The dissertation further addresses data-driven model discrimination for switched nonlinear systems with unknown dynamics and temporal logic specifications, introducing algorithms that jointly infer system dynamics and specifications for real-time model-task discrimination.

Finally, a Distributed Differentially Private Control Synthesis framework is presented for multi-agent systems with Metric Temporal Logic (MTL) specifications, enabling agents to meet local and global tasks while maintaining differential privacy.

Collectively, these works establish a coherent foundation for interpretable, causal, and temporally grounded learning and control, advancing the integration of logic and causality in modern intelligent systems.

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