**Ph.D. Dissertation Defense**

**Department of Computer Science & Engineering**

**“KNOWLEDGE-EMPOWERED PROBABILISTIC GRAPHICAL MODELS FOR PHYSICAL-CYBER-SOCIAL SYSTEMS”**

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**ABSTRACT:**There is a rapid intertwining of sensors and mobile devices into the fabric of our lives. This has resulted in unprecedented growth in the number of observations from the physical and social worlds reported in the cyber world. Sensing and computational components embedded in the physical world is termed as Cyber-Physical System (CPS). We demonstrate the role of citizen observations in CPS and propose a novel approach to effectively integrate and perform a holistic analysis of machine and citizen sensor observations. Specifically, we demonstrate the complementary, corroborative, and timely aspects of observations from diverse modalities in Physical-Cyber-Social (PCS) Systems.

Physical processes are inherently complex and embody uncertainties manifesting as machine and citizen sensor observations in PCS Systems. We propose a generic framework to move from observations to decision-making and action in PCS systems consisting of: (a) PCS event extraction, (b) PCS event understanding, and (c) PCS action recommendation. We demonstrate the role of Probabilistic Graphical Models (PGMs) as a unified framework to deal with uncertainty, complexity, and dynamism that help to translate observations into actions. Data driven approaches alone are not guaranteed to be able to synthesize PGMs reflecting real-world dependencies accurately. To overcome this limitation, we propose to empower PGMs using the declarative domain knowledge. Specifically, we propose four techniques: (a) automatic creation of massive training data for learning Conditional Random Fields (CRFs) using domain knowledge of entities used in PCS event extraction, (b) Bayesian Network structure refinement using causal knowledge from Concept Net in PCS event understanding, (c) knowledge-driven piecewise linear approximation of nonlinear time series dynamics using Linear Dynamical Systems (LDS) in PCS event understanding, and (d) transforming knowledge of goals and actions into a Markov Decision Process (MDP) model in PCS action recommendation.

We evaluate the benefits of the proposed techniques on real-world applications involving the Internet of Things (IoT).