Relational Inference On Graphs Using Nonlinear Opinion Dynamics

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From pedestrians to Kuramoto oscillators, interactions between agents govern how a multitude of dynamical systems evolve in space and time. Discovering how these agents relate to each other can improve our understanding of the often complex dynamics that underlie these systems. Recent works learn to categorize relationships between agents based on observations of their physical behavior. These approaches are limited in that the relationship categories are modeled as independent and mutually exclusive, when in real world systems categories are often interacting. In this work, we introduce a level of abstraction between the physical behavior of agents and the categories that define their behavior. To do this, we learn a mapping from the agents' states to their affinities for each category in a graph neural network. We integrate the physical proximity of agents and their affinities in a nonlinear opinion dynamics model which provides a mechanism to identify mutually exclusive categories, predict an agent's evolution in time, and control an agent's behavior. We demonstrate the utility of our model for learning interpretable categories for mechanical systems, and demonstrate its efficacy on several long-horizon trajectory prediction benchmarks where we consistently out perform existing methods.

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