REPRESENTATION LEARNING FOR ANALYSIS OF COMPLEX COMPETITIVE DECISIONS

ABSTRACT:

Many phenomena studied in marketing and economics are analyzed through the lens of non-cooperative games. Researchers often study empirical behavior of agents in simple games conducted in the lab, but research on complex real-world competitive settings with extensive action spaces and intricate payoff structures is rare due to methodological challenges and data limitations. To bridge this gap, I develop a novel neural network architecture that enables behavioral analysis of complex games by estimating a game's payoff structure (e.g., win probabilities between pairs of actions) while simultaneously mapping agent actions to a lower-dimensional latent space. I structure the neural network to enforce that the latent space encodes strategic similarities between actions in a smooth, linear manner. I apply my method to analyze a unique dataset of over 11 million matches played in a competitive video game with a large array of actions and complex strategic interactions. I find that players select actions that counterfactually would have performed better against recent opponents, demonstrating model-based reasoning. Still, players overly on simple heuristics relative to model-based reasoning to an extent that is similar to findings reported in lab settings. I find that noisy and biased decision-making leads to frequent selection of suboptimal actions, which corresponds to lower player engagement. This demonstrates the limits of player sophistication when making complex competitive decisions and suggests that platforms hosting competitions may benefit from interventions that enable players to improve their decision-making.