In this thesis, we consider the problem of designing algorithms to enable computational systems to reason about the future behavior of intelligent agents given rich observations of their environments, as well as to use this reasoning for control. We primarily employ the frameworks of Imitation Learning and Reinforcement Learning to formulate and situate our work. We contribute forecasting approaches to excel in diverse, realistic, single and multi-agent domains. These include (1) sparse models to generalize from few demonstrations of human daily activity, (2) adaptive models to continuously learn from demonstrations of human driving behavior, and (3) factorized multi-agent models to reason about the future interactions of agents. We also contribute control approaches to excel in diverse domains, including (5) incentivized forecasting, which encourages an artificial agent that only has access to partial observations of state to learn predictive state representations in order to perform a task better, and an approach to (6) leverage a probabilistic forecasting model as the backbone for flexible, controlled behavior.