Abstract
We present a framework for representing scenarios with complex object interactions, in which a robot cannot directly interact with the object it wishes to control, but must instead do so via intermediate objects. For example, a robot learning to drive a car can only indirectly change its pose, by rotating the steering wheel. We formalize such complex interactions as chains of Markov decision processes and show how they can be learned and used for control. We describe two systems in which a robot uses learning from demonstration to achieve indirect control: playing a computer game, and using a hot water dispenser to heat a cup of water.

Direct Manipulation

Indirect Interaction

Interaction Chain

In the interaction chain, each object is modeled by a Markov Decision Process (MDP). The state of the predecessor object is the action of the successor object.

S_{pred} ≡ A_{succ}

Inverse Transition Function

Experiment

(De)Activation Classifiers

Experiment

Figure 1: Direct Manipulation of Objects

Figure 2: Indirect Interaction with Objects

Figure 3: Interaction Chain for a Car Driving Task

Figure 4: Inverse Transition Function

Figure 5: The robot need to control a car to follow paths with a joystick, using learned interactions.

Interaction Graph

Figure 6: Interaction Graph for a Water Heating Task

Figure 7: Active interactions for (a) moving cup, (b) pouring water, (c) heating water, and (d) dispensing water.

Figure 8: Demonstrated Individual Skills

Figure 9: The robot autonomously sequences learned skills to heat a cup of water: (a) pick up the cup; (b) pour cold water to the machine; (c) place the cup under the machine; (d) press the power button to boil water; (e) press the dispense button to dispense water; (f) move the cup to original position.