Lecture 29: Artificial Intelligence

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08/10/2016

Some slides are adapted from CS 188 (Artificial Intelligence)

Announcements

Roadmap

Introduction

Functions

Data

Mutability

Objects

Interpretation

Paradigms

Applications

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- This week (Applications), the goals are:
  - To go beyond CS 61A and see examples of what comes next
  - To wrap up CS 61A!

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  - *Act rationally*
    - A better name for artificial intelligence would be *computational rationality*

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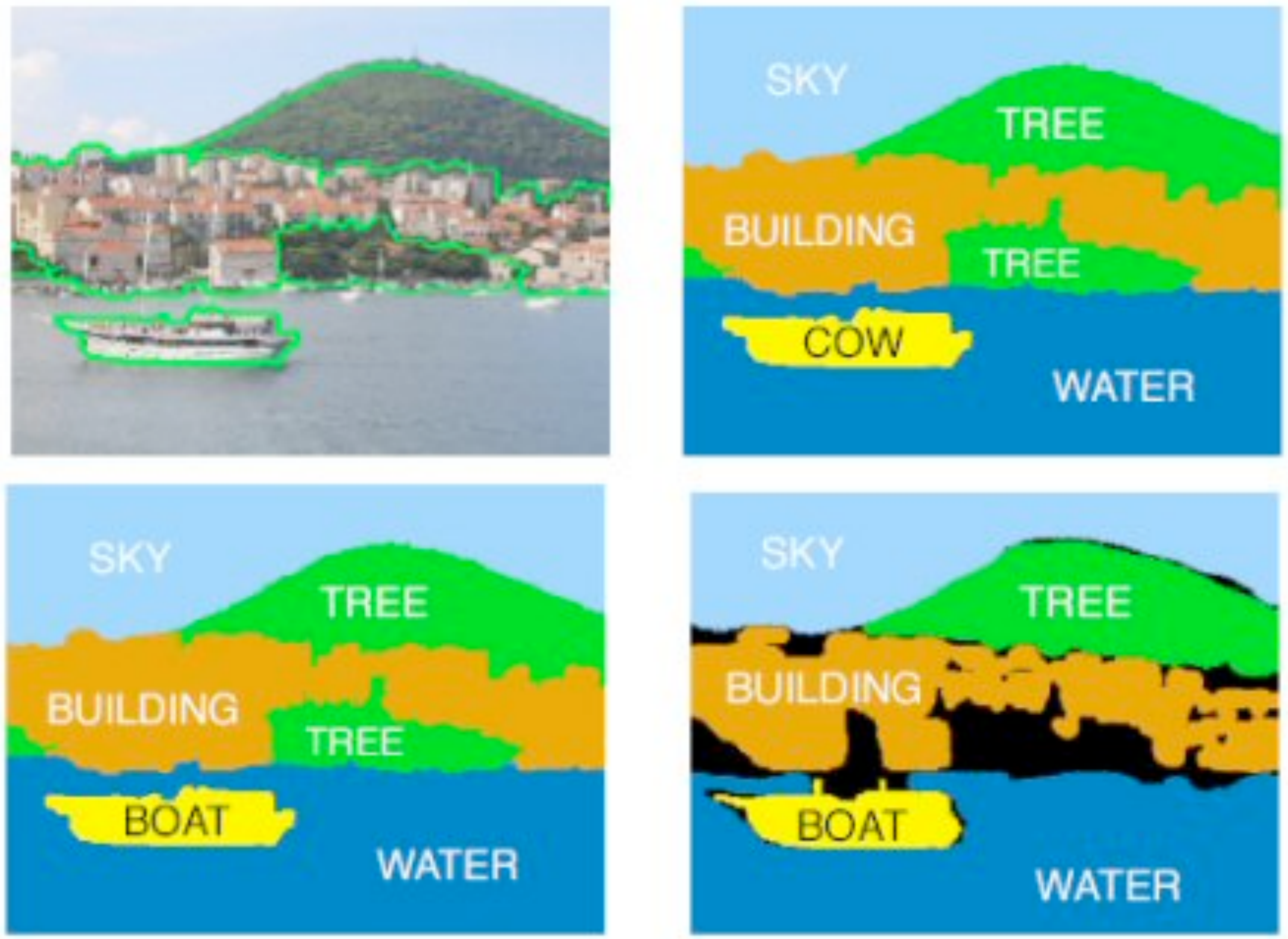

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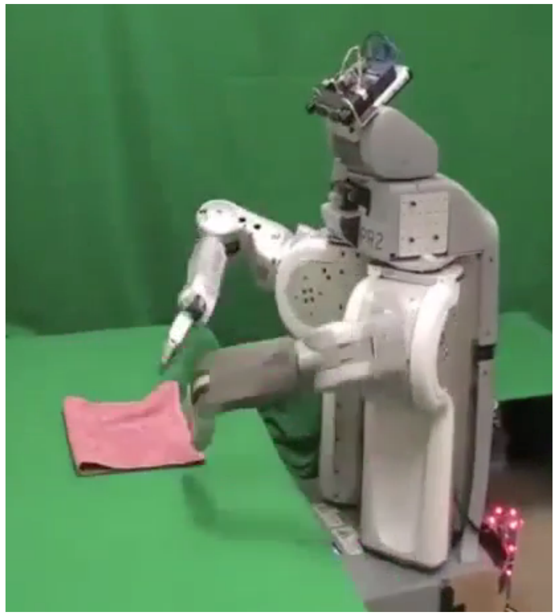

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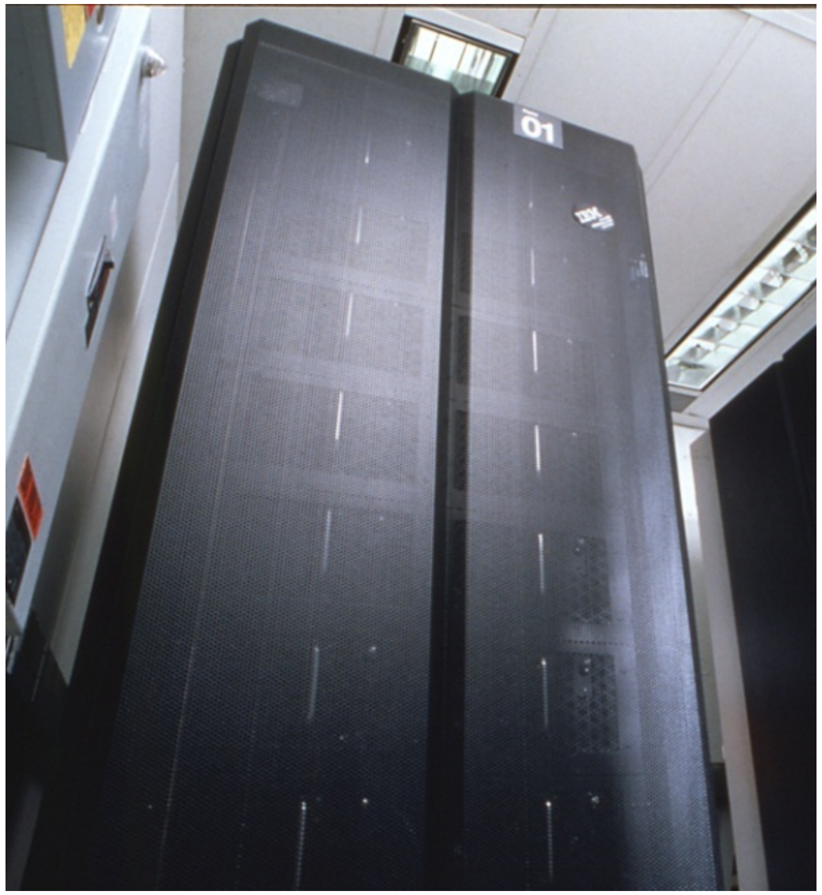

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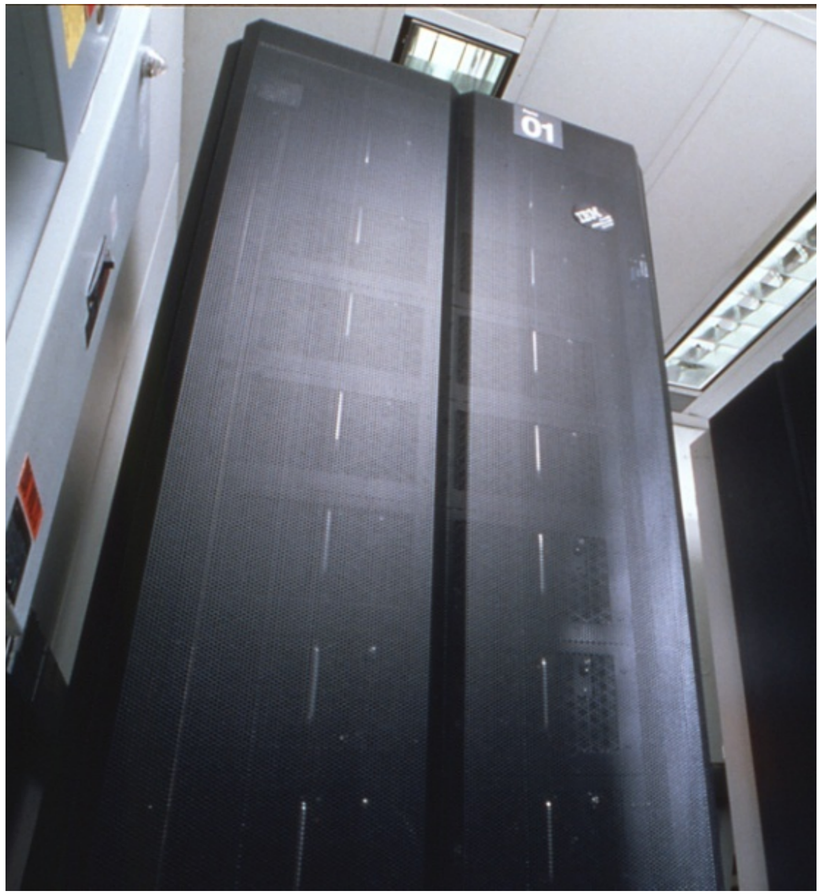


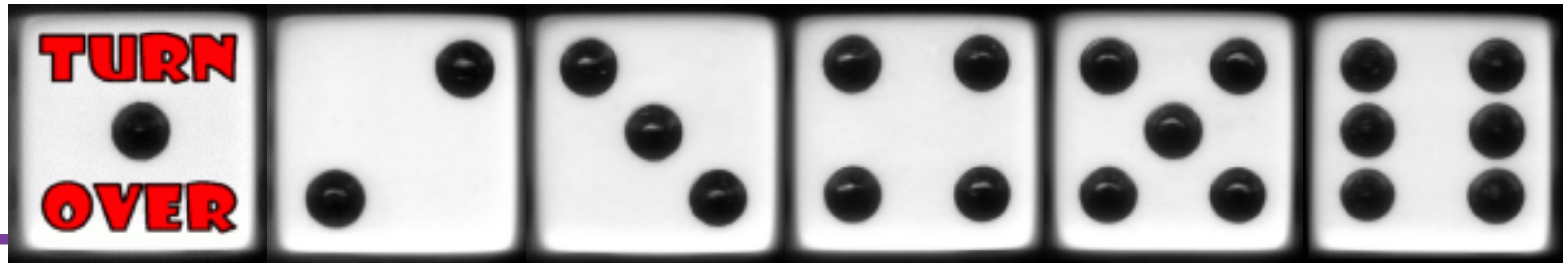
Game Playing

- Games have historically been a popular area of study in artificial intelligence, in part because they drive the study and implementation of efficient AI algorithms
  - If you're interested, two recent-ish results include playing Atari games at human expert levels and playing Go beyond top human levels
- Many breakthroughs in AI research have come from building systems that play games, including advances in:
  - Reinforcement learning (Checkers, Atari)
  - Rational meta-reasoning (Reversi/Othello)
  - Game tree search algorithms (Go)
- We will build AI systems today that play Hog and Ants!

Playing Hog

Using Markov Decision Processes

Hog



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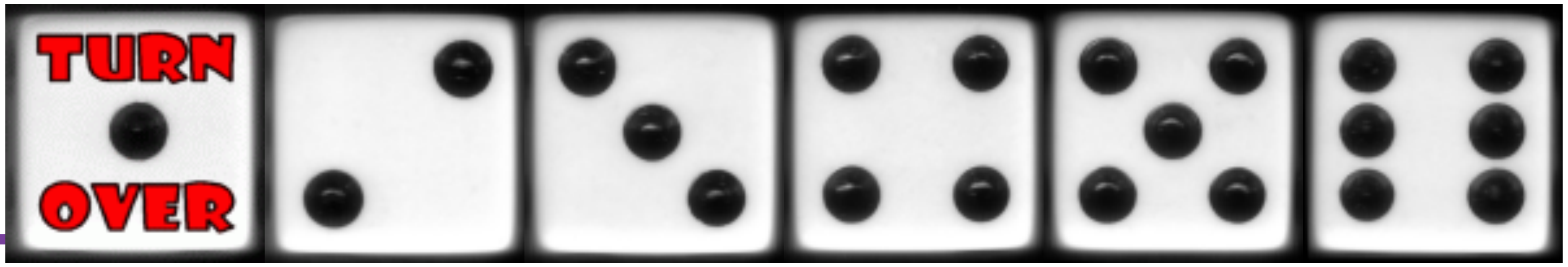

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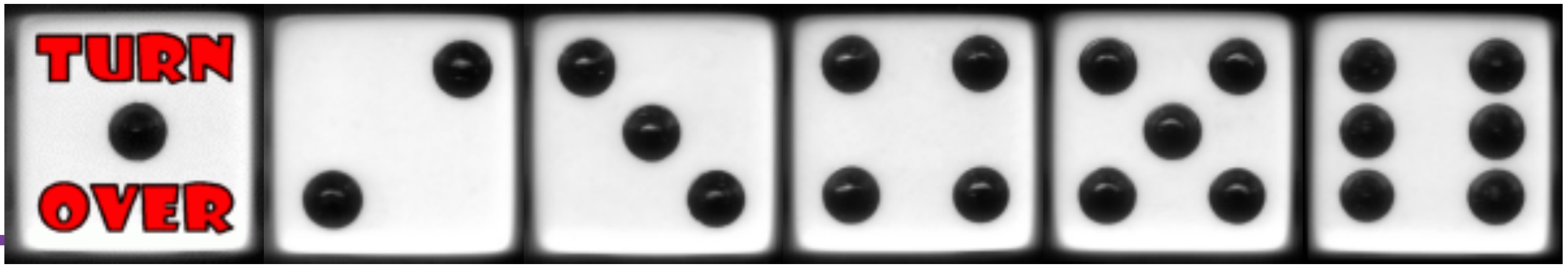

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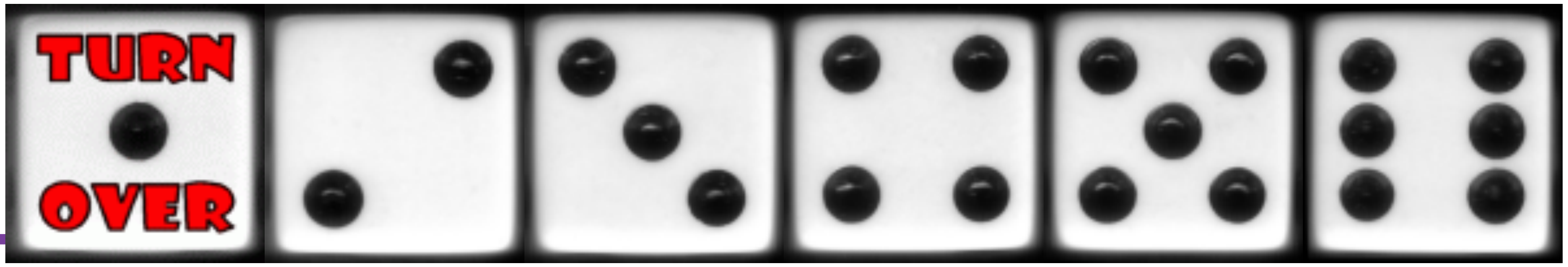

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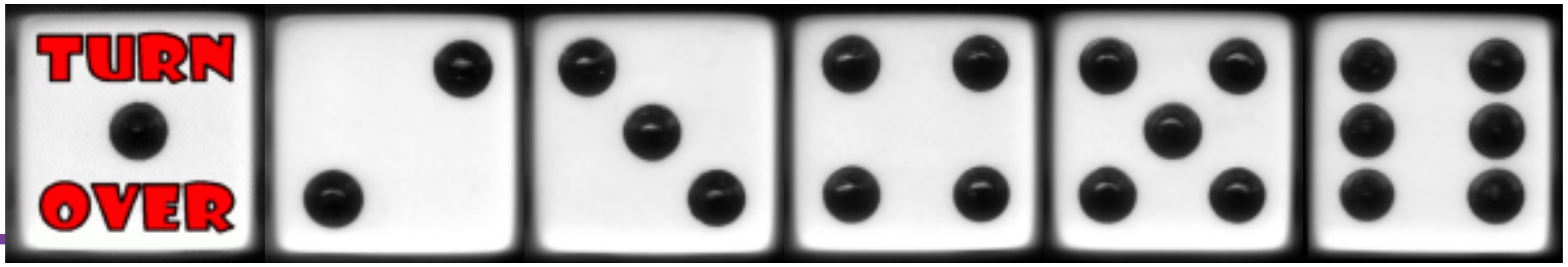

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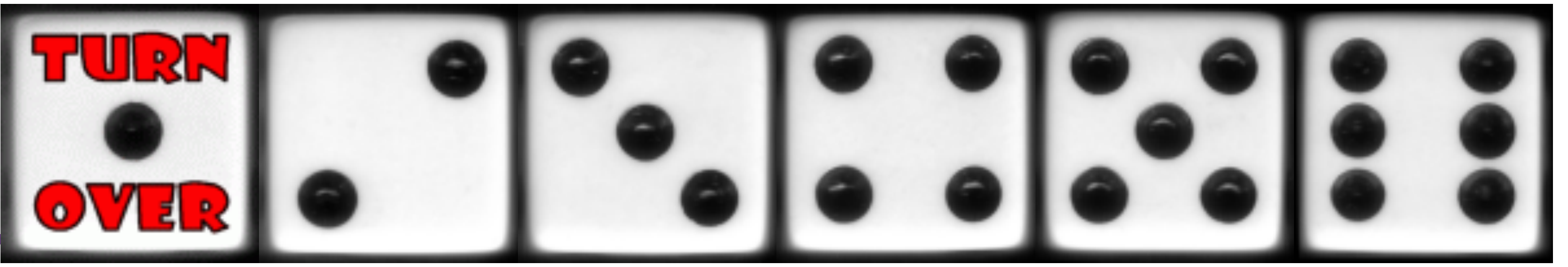

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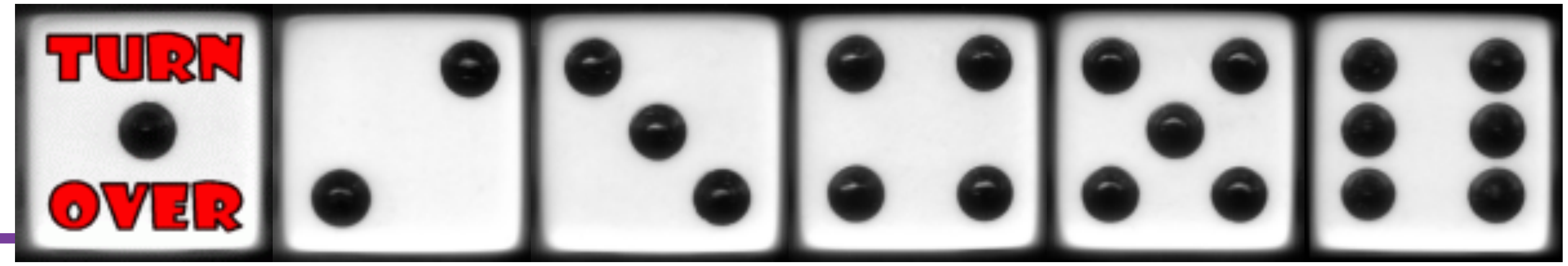

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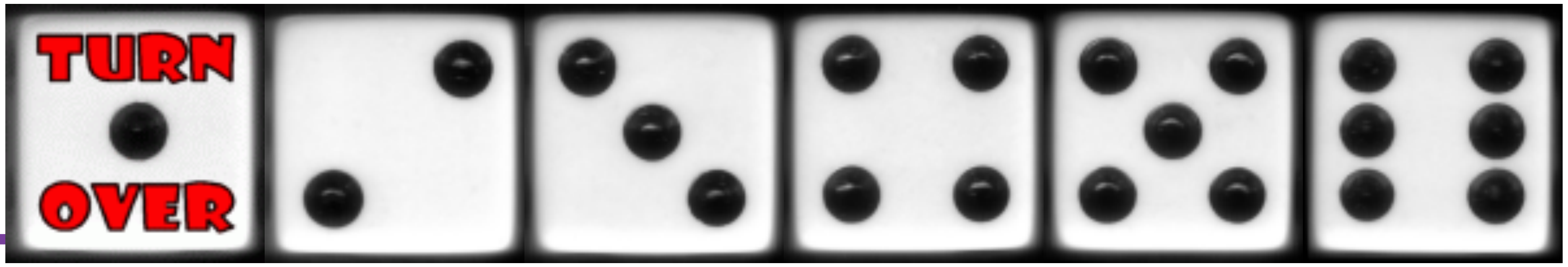

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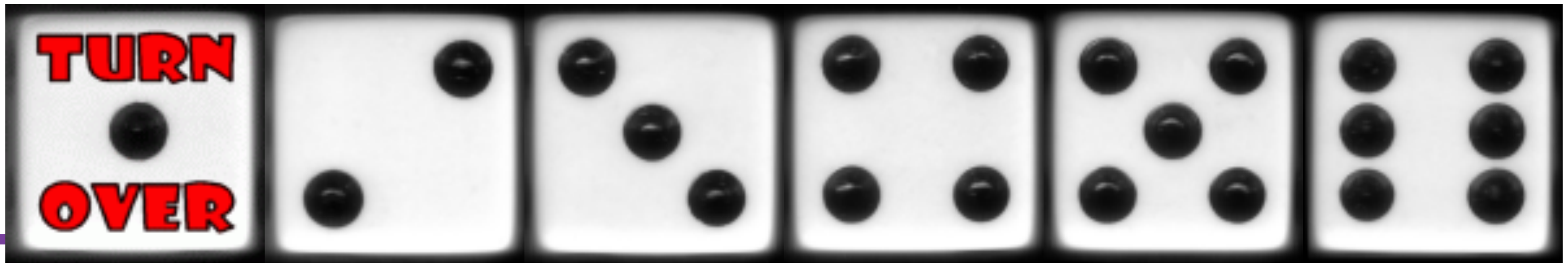

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  - We can get up to ~85% win rate against `always_roll(6)`! I'll show you how, using AI techniques and algorithms

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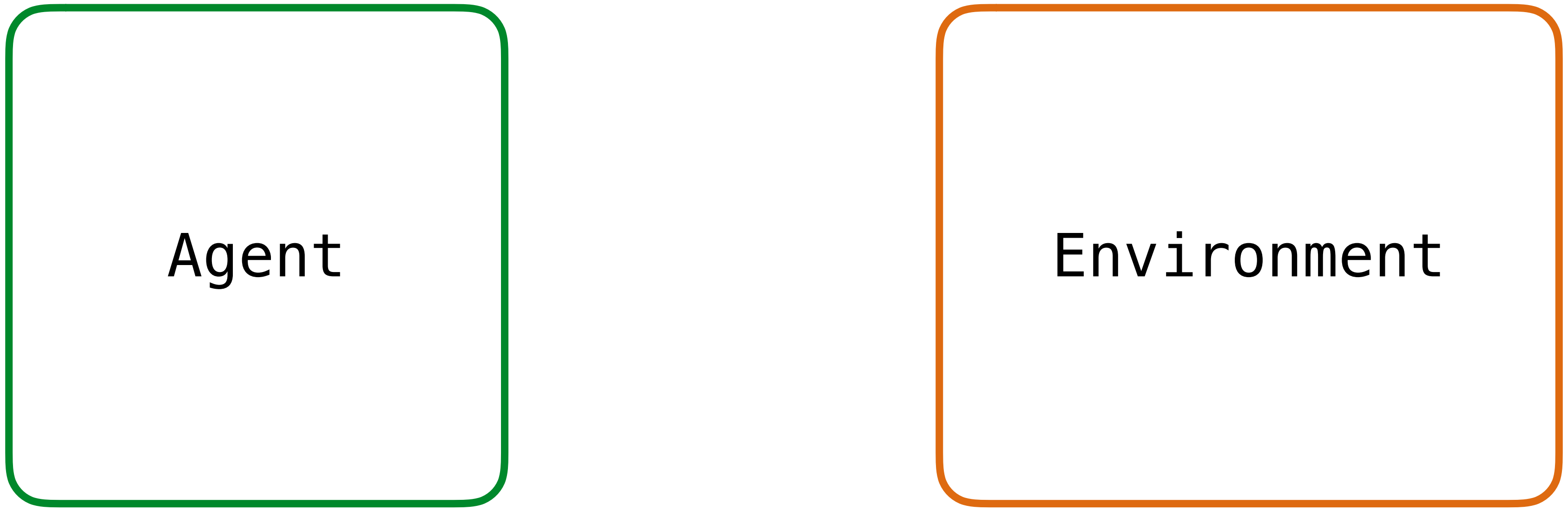

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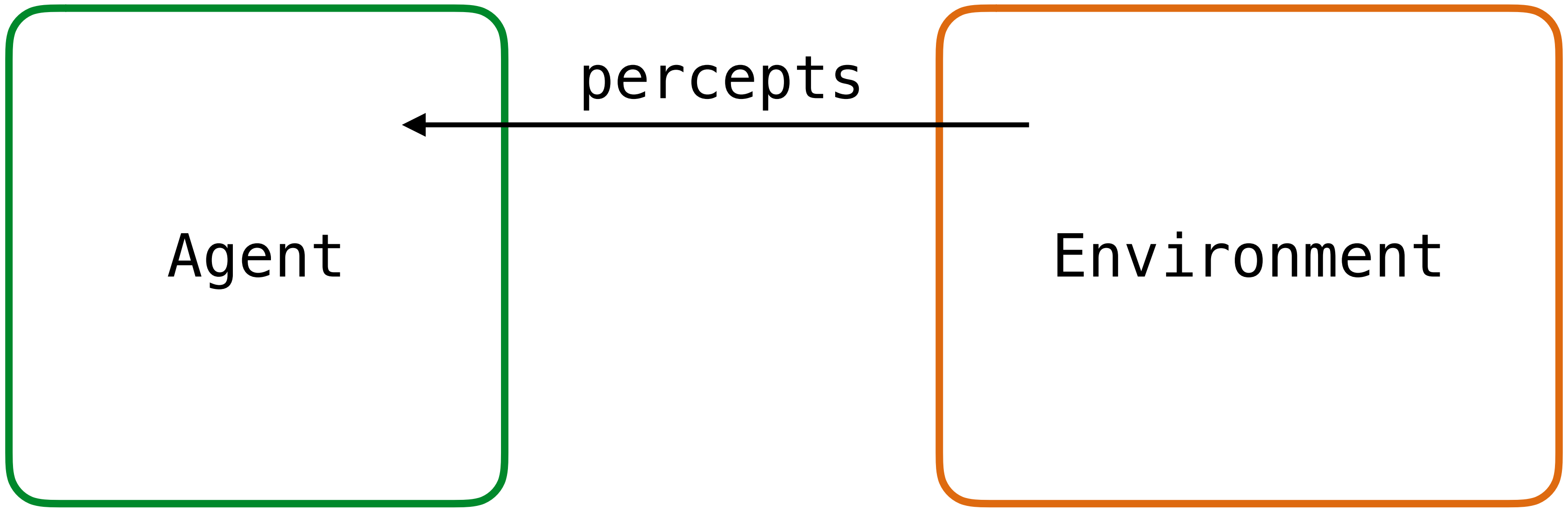

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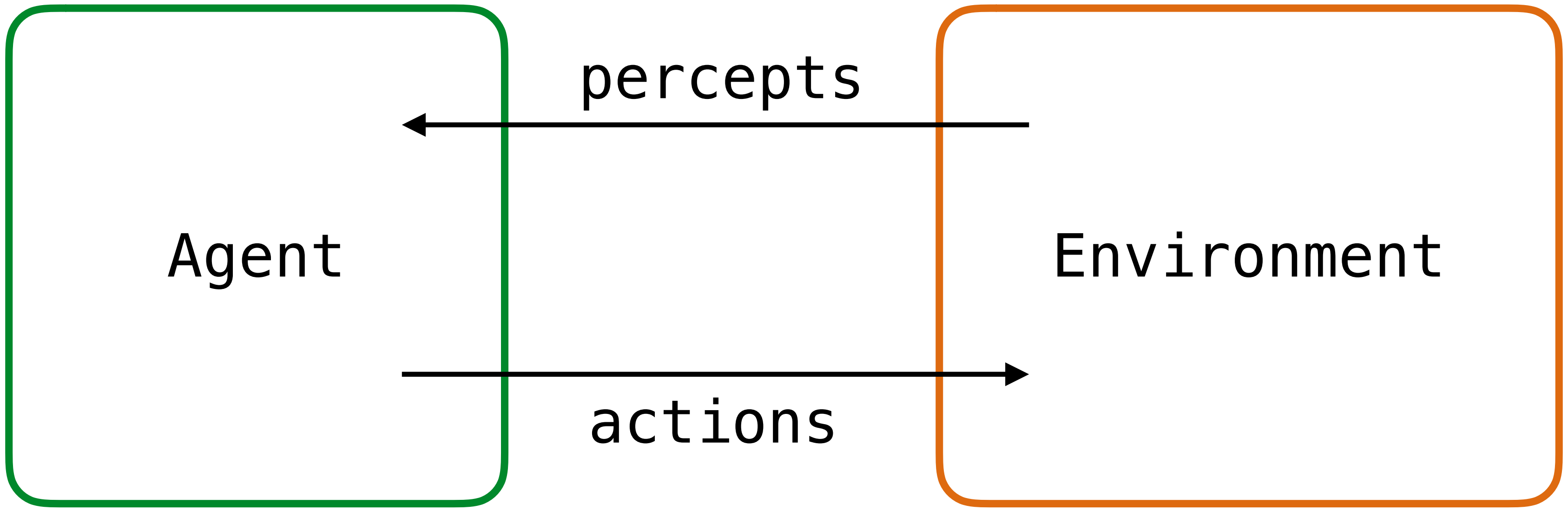

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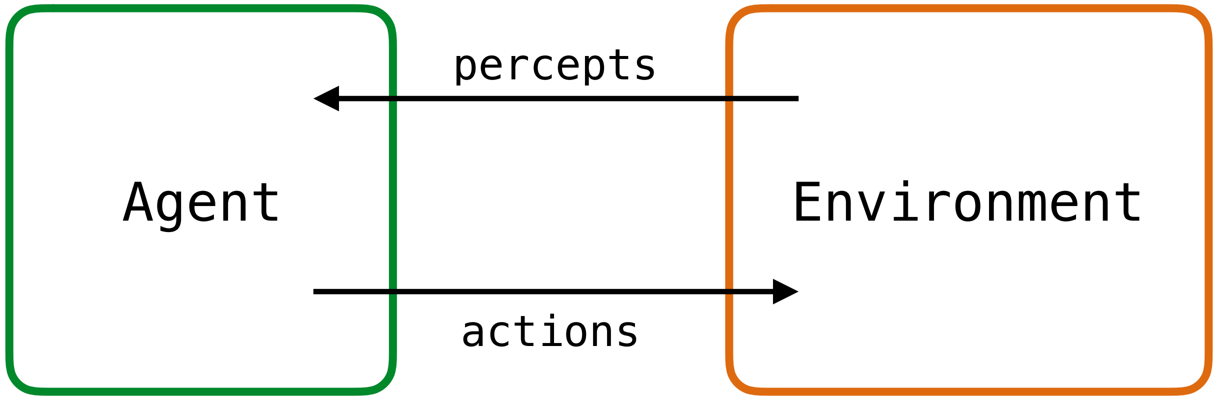

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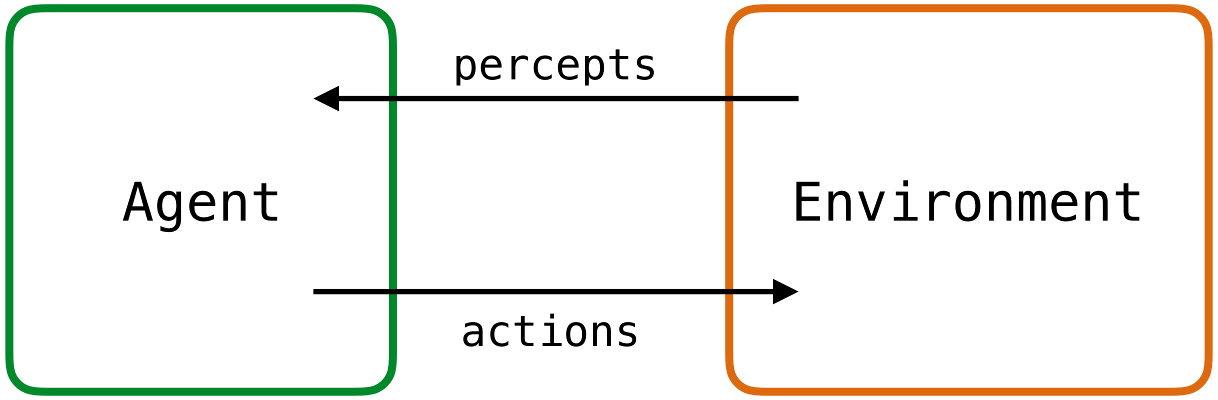

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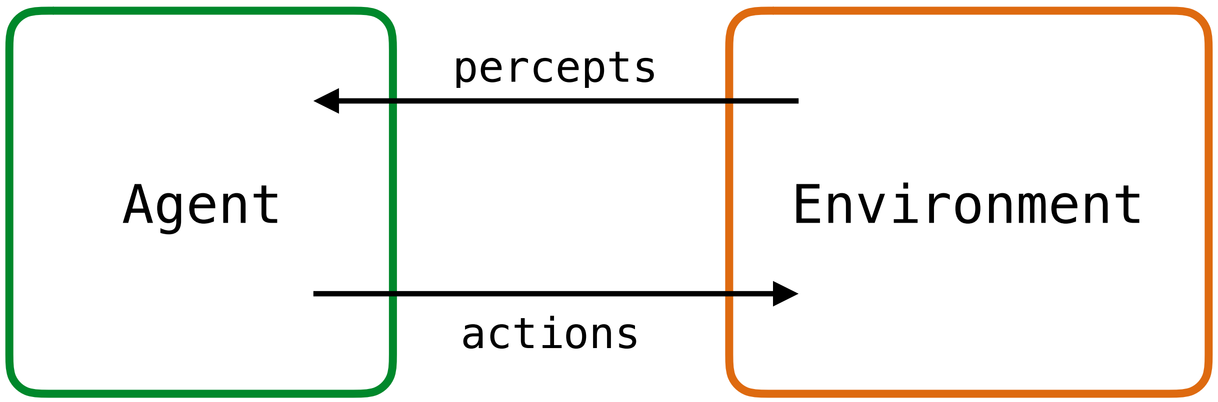

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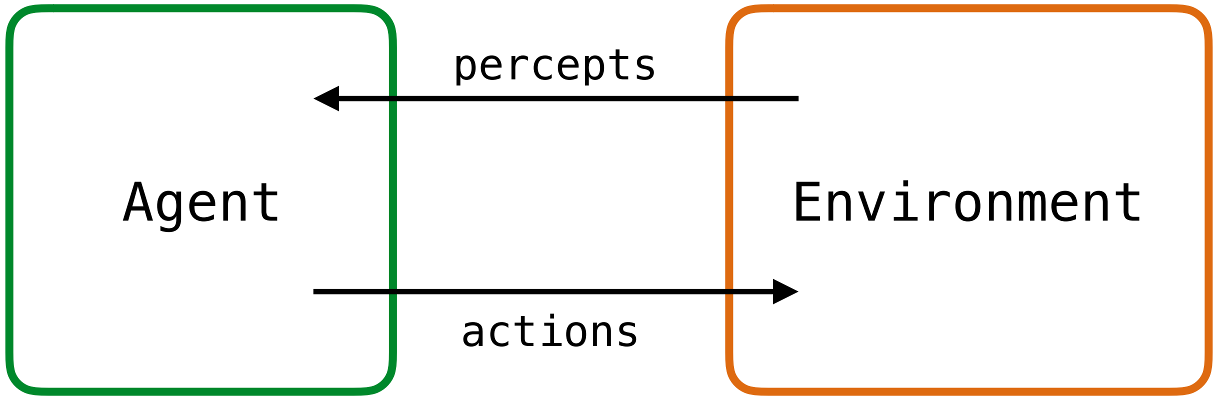

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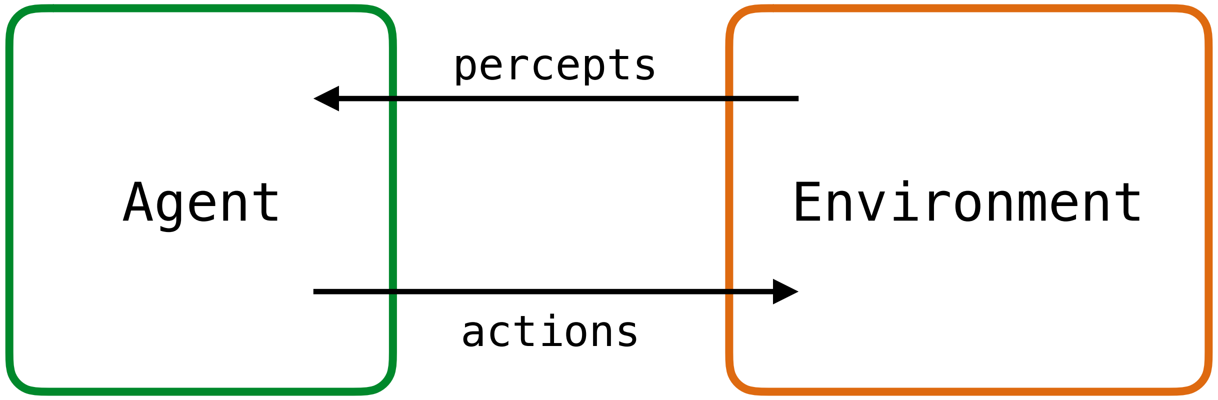

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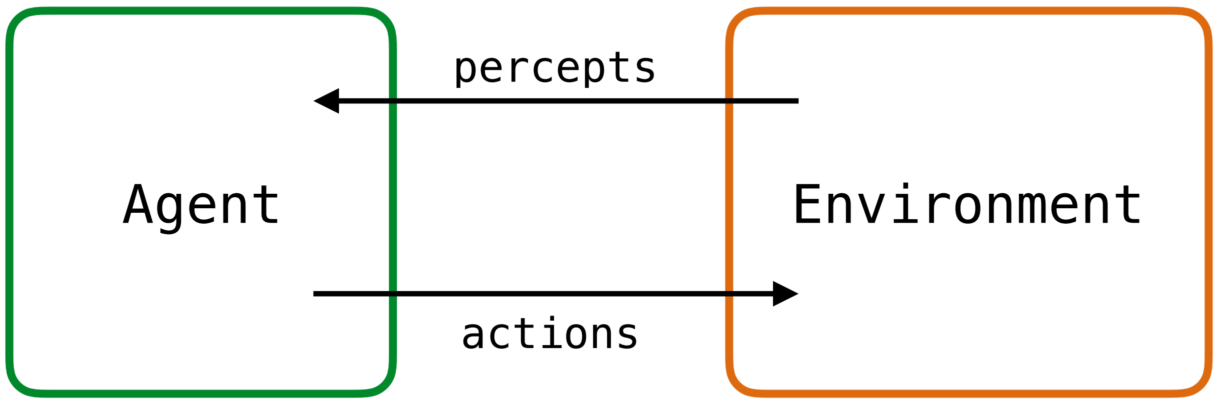

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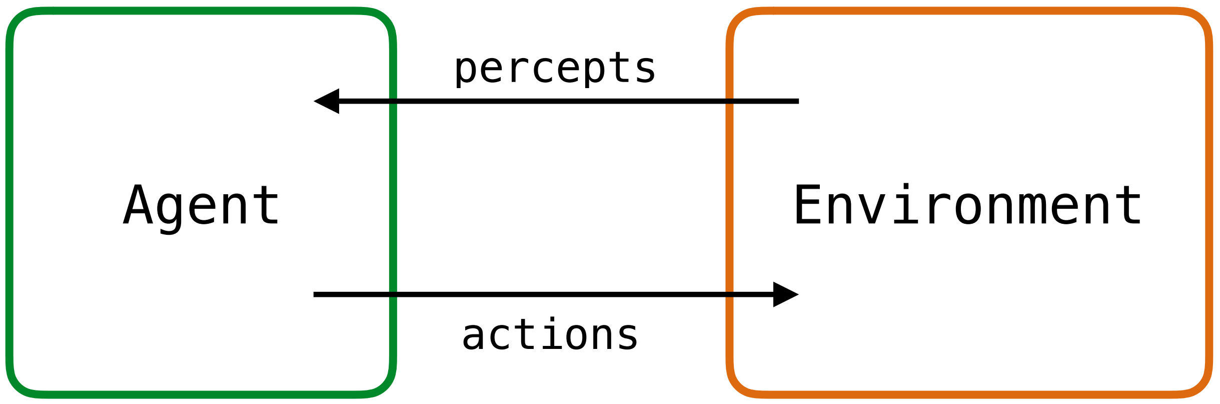

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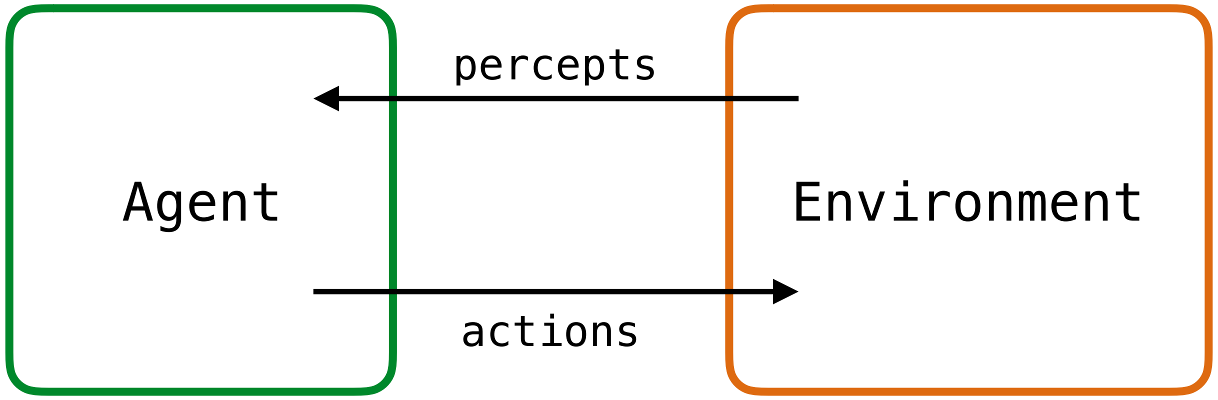

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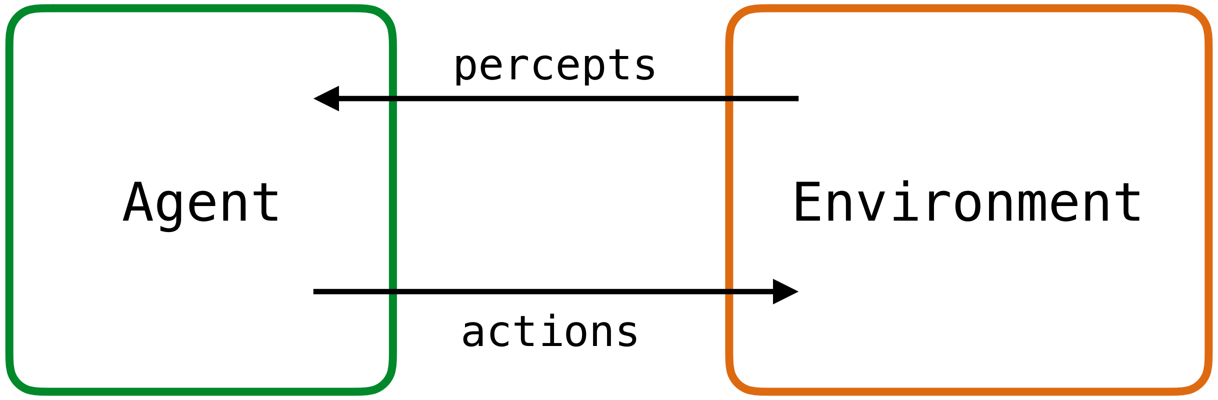

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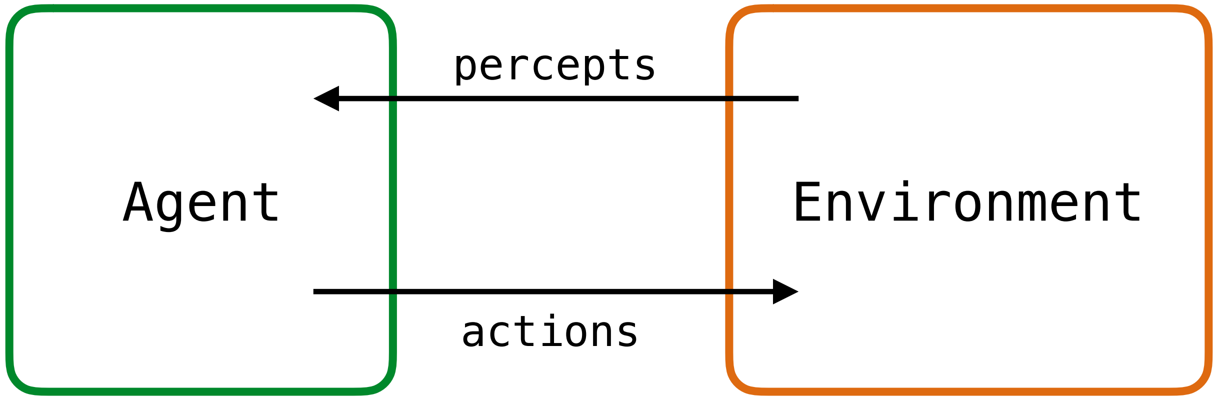
- In AI, the problem we care about is figuring out how the agent should choose its actions, given what it perceives, so as to positively shape its environment



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    - We get this from dice probabilities and rules of the game

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  - We need something that will tell us about which states are more or less likely to win from

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$$V(s) = R(s) + \max_a \sum_{s'} T(s, a, s') V(s')$$

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- We can show that this policy is optimal, under the correct assumptions! But let's not do the math

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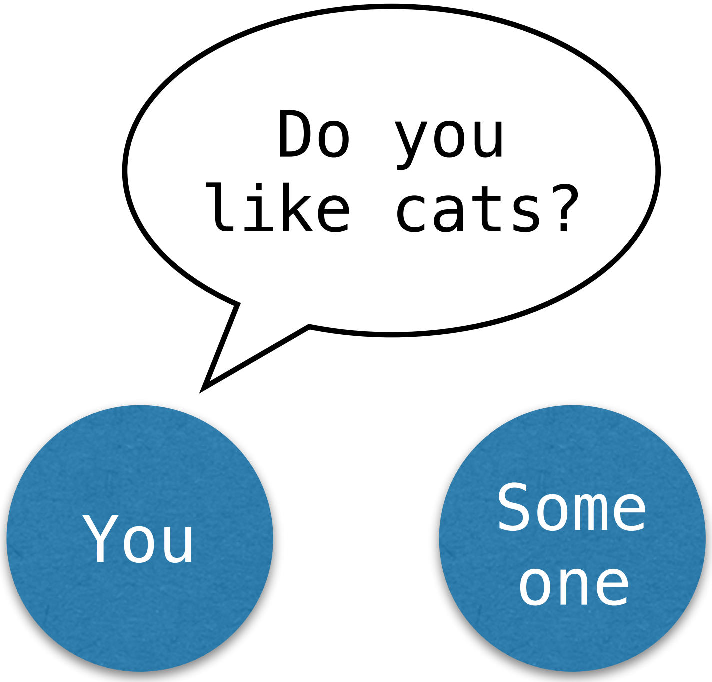

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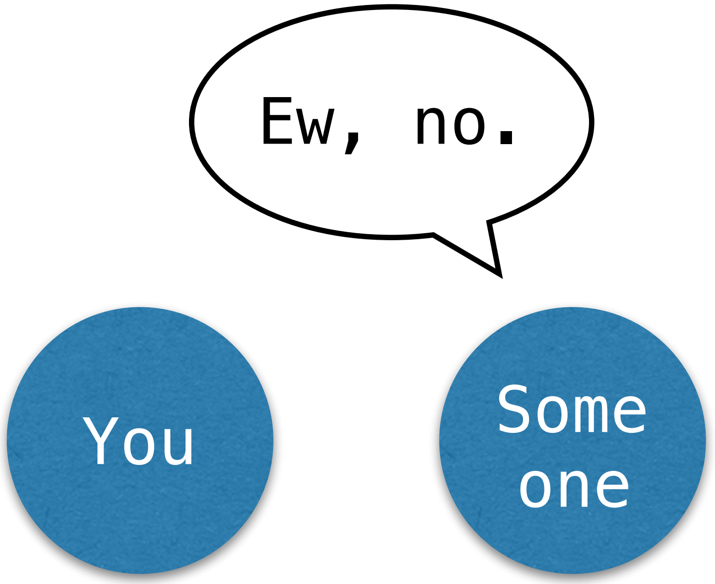

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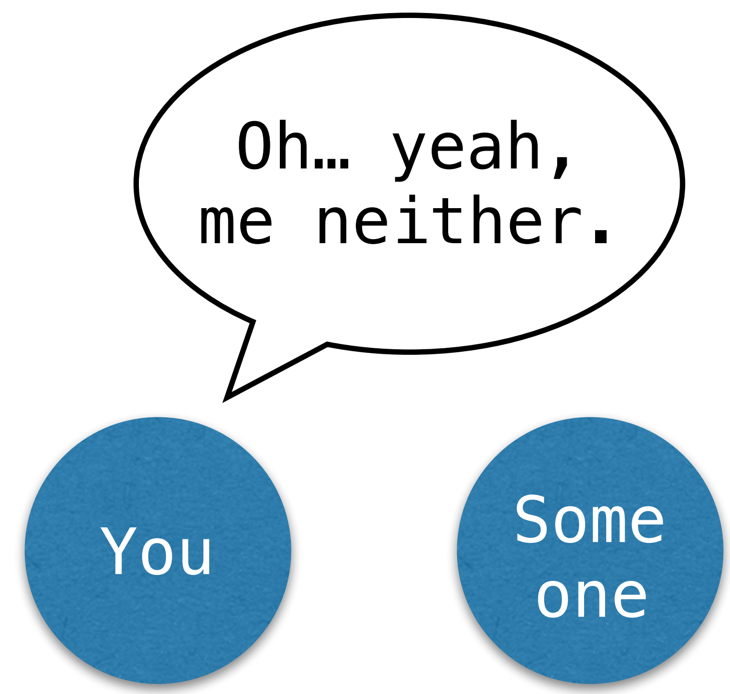

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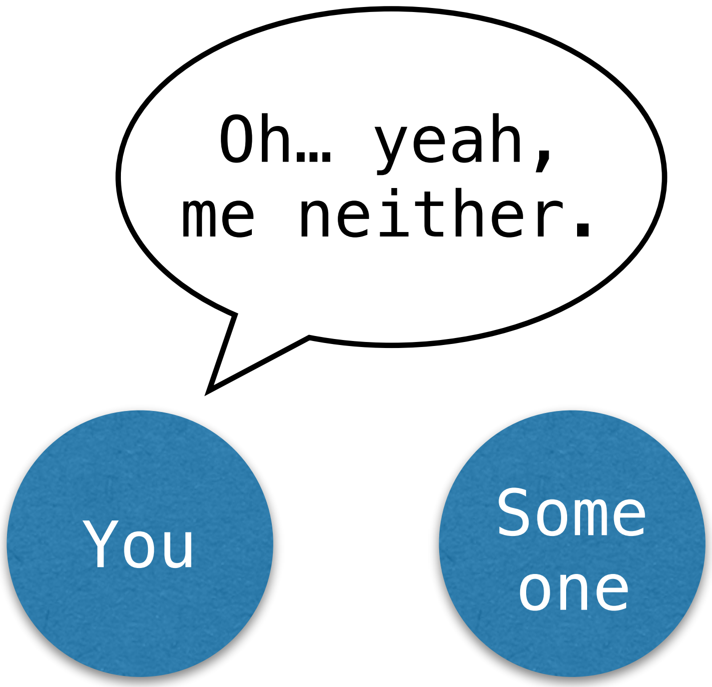

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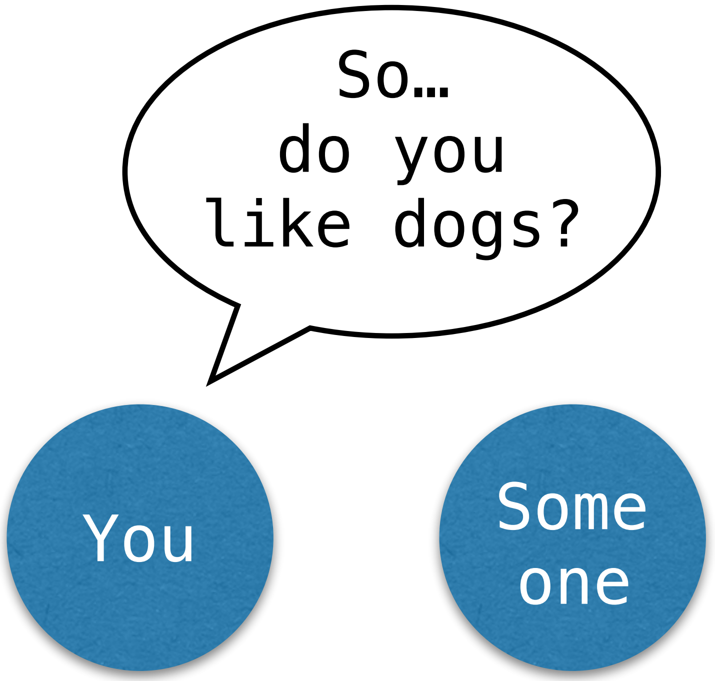

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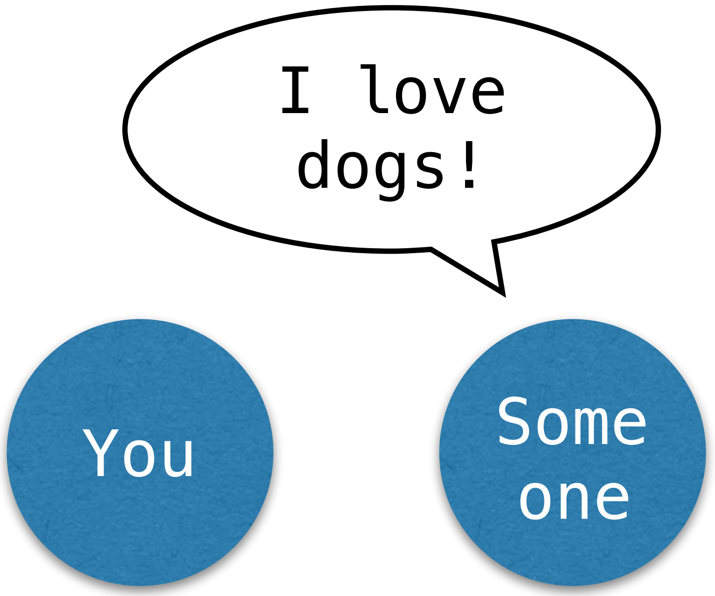

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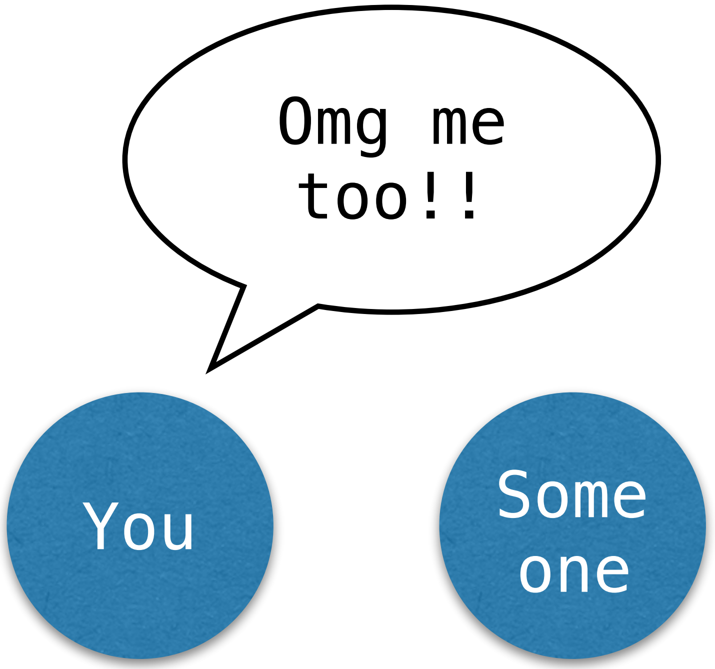

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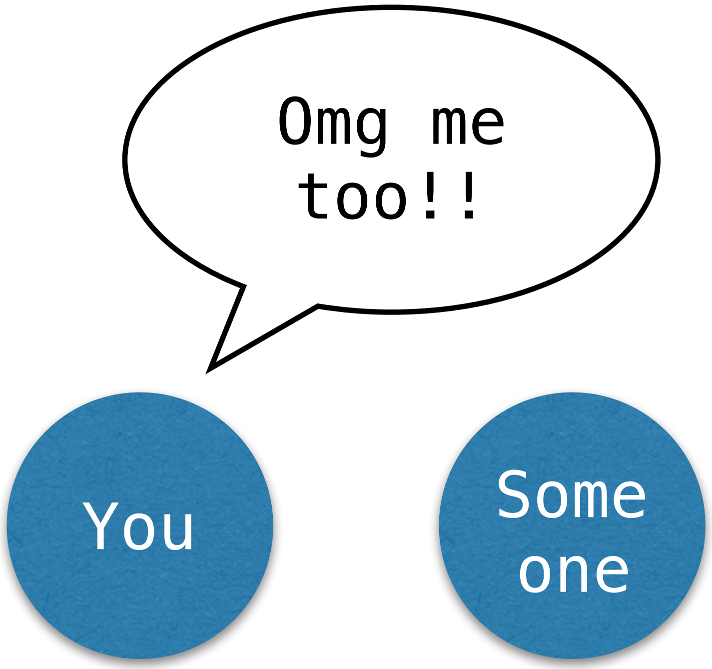

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- Balancing exploration and exploitation is a key problem that RL algorithms must address, and there are many different ways to handle this

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- Game playing is an important and natural domain for much of artificial intelligence research and development
  - We built an agent that plays Hog optimally against `always_roll(6)`, using MDPs and value iteration
  - We built an agent that plays Ants pretty well, using reinforcement learning and rollout-based methods
- However, applications of AI go far beyond games and stretch into almost every area of everyday life
- If you're interested, take:
  - CS 188 (Introduction to Artificial Intelligence)
  - CS 189 (Introduction to Machine Learning)

Thank you