Computing Science (CMPUT) 455

Search, Knowledge, and Simulations

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Part V

RL, AlphaGo and Beyond

455 Today - Lecture 21

- Introduction to Reinforcement Learning (RL)
- TD-Gammon, an early example of reinforcement learning with neural nets

Coursework

- Assignment 4 (due **Tue, Dec 14**)
- Reading and activities: Sutton RL tutorial + slides
- Quiz 11: Neural Networks and Deep Learning (double length)

Reinforcement Learning

- Reinforcement Learning (RL) introduction
- Credit assignment problem
- Learning from rewards and temporal differences
- TD-gammon as early example
- Training by RL
- Deep RL

Reinforcement Learning (RL)

- Activity - watch the tutorial and slides by Rich Sutton
- Brief review in class only
- Focus on what we need for AlphaGo
- Discuss Gerry Tesauro's TD-Gammon program
  - Early big success story for RL in heuristic search
  - Early example of neural nets in games

Basic Concepts of RL

- Observe input S_t (state of game at time t)
- Produce move, action A_t
- Observe reward (quality of action) R_{t+1}
  - Note that reward occurs at *next* timestep
  - Often, the reward is *delayed*
  - Games: reward only at end of game

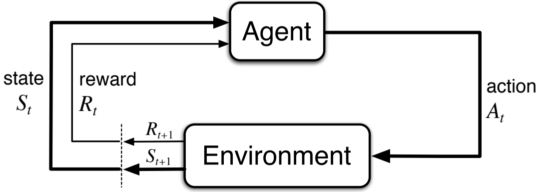

Figure 3.1: The agent–environment interaction in a Markov decision process.

Image source: [Sutton & Barto 2020]

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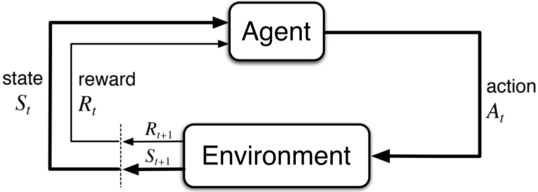
- Interaction produces a trajectory: $S_0, A_0, R_1, S_1, A_1, \ldots$



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RL vs Supervised Learning in Games

Supervised Learning

- Label for each move
    - Good/bad, expert move/not expert move
- Learn - minimize prediction error on given data set
- Can use mathematical optimization techniques, e.g. gradient descent

Reinforcement Learning

- Reward for whole game sequence only
- Learn - try to improve gameplay by trial and error
- Need to solve the credit assignment problem

Credit Assignment Problem

- Reward for (possibly long) sequence of decisions
- No direct reward for each single move decision
- How can we tell which moves are good or bad?
- Distribute reward from end of game over all actions
- Difficult problem
- RL provides the most popular answers
- Main idea: if same action happens in many different sequences, we can learn if it leads to more wins or losses

Value Functions

- Extremely widespread approach to solving the credit assignment problem: value-based reinforcement learning
- Estimate one or both of:
  - State-value function:

$$v_\pi(s) = \mathbb{E}\left[\sum_{t=0}^{T} R_t \,\middle|\, S_0 = s, A_t \sim \pi(S_t)\right]$$

  - Action-value function:

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- Play out a bunch of games using policy π
- Find the average total return from every trajectory that starts from s, a
- In fact, we can do better!
- Find average total return from every **sub-trajectory** that starts from s, a

Policy Improvement Theorem

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- If we already knew the optimal π we would be done!
- It turns out that greedily optimizing with respect to any policy π will produce a new policy that is guaranteed to be *weakly better at every state*.

Policy Improvement Theorem

Let π and π' be any pair of (deterministic**) policies.
If $q_\pi(s, \pi'(s)) \geq v_\pi(s) \quad \forall s \in \mathcal{S}$, then $v_\pi(s) \geq v_{\pi'}(s) \quad \forall s \in \mathcal{S}$.

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Question: What complication am I glossing over here?

Self-Play

- Standard reinforcement learning is a single-agent problem
- "Expected reward from following a policy" is ill-defined, because it depends on the other player's policy
- Solution: self-play
- Each policy is part of "the environment" for the other
- Train policies simultaneously

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- Conceptually straightforward
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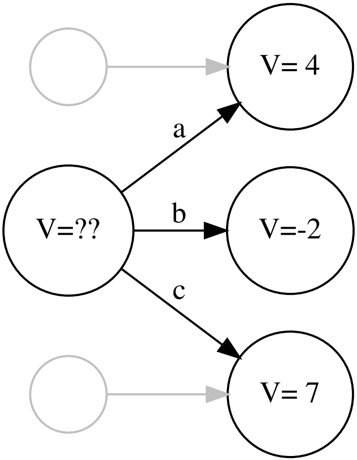
Disadvantages:

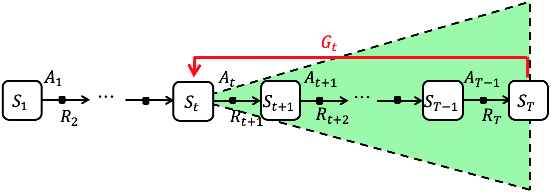
- Estimates of one state's value are not used to improve estimates of another
- Can only estimate the value of states and actions that are visited sufficiently often in some trajectory
- $\Longrightarrow$ Slow, data-inefficient



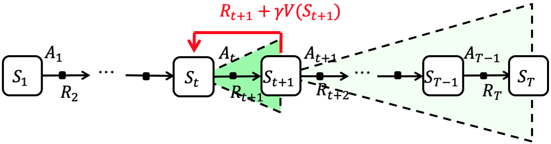
Temporal Difference (TD) Learning and $TD(\lambda)$

- Sutton (1988)
- Learn a model - a function from inputs to outputs
- Given only action sequences and rewards
- Learns a prediction (what is the best move?)
- Samples the environment (plays games)
- Compares learned estimate in each state with reward
- Learns from the difference
- Discount factor λ for future rewards
- The sooner after the current state the reward happens, the higher the effect

MC vs. TD



MC learning



TD learning

TD High-level Ideas

- Usually, predictions from states closer to the end are more reliable
- We can adjust earlier predictions, “trickle down”
- Bootstrapping - learn predictions from other predictions
- Whole process is grounded in the true final rewards
- This is one successful approach to solving the credit assignment problem in practice

Function Approximation

- Tabular learning: Value of each state / state-action is tracked separately
- Function approximation: Learn a model of values instead
  - Based on features of the state / state-action
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- Disadvantage: Over-generalization. Different states can be conflated if the features are insufficiently detailed.

Review - Backgammon

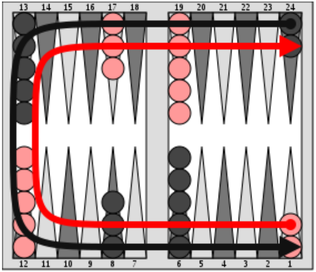

Image source: `https://en.wikipedia.org/wiki/Backgammon`

- Racing game played with dice
- Players race in opposite directions on the 24 *points*
- Single pieces can be captured and have to start from the beginning
- Doubling cube - play for double stakes, or resign
- Gammon and backgammon - win counts more if opponent is far behind

Tesauro's Neurogammon and TD-Gammon

- Neurogammon (Tesauro 1989)
- Plays backgammon using neural networks
- First program to reach "strong intermediate" human level, close to expert
- Beat all (non-learning) opponents at 1989 Computer Olympiad
- Beat many intermediate level humans,
  lost to an expert player

Neurogammon Architecture

- Six separate networks, for different phases of the game
- Fully connected feed-forward nets
- One hidden layer
- Trained with backprop
  - Supervised learning from 400 expert games
- One more network to make doubling cube decisions
  - Trained on 3000 positions, hand-labeled

Limitations of Neurogammon

- Hand-engineered features are difficult to create
- Human experts cannot explain much of what they are doing in a form that can be programmed
- Human expert games are difficult to collect, and are not perfect

TD-Gammon

- TD-Gammon (Tesauro 1992, 1994, 1995)
- Training by self-play
- Learns from the outcome of games
- Uses Temporal Difference (TD) Learning

TD-Gammon Architecture

- 198 inputs - 8 per point, 6 extra information (pieces off the board, toPlay)
- Single hidden layer, tried 10..80 hidden units
- Sigmoid activation function
- Output: one number, winning probability of input position
- Trained by $TD(\lambda)$ with $\lambda = 0.7$, learning rate $\alpha = 0.1$
- 200,000 training games, 2 weeks on high-end workstation
- Small (1-3-ply) Alphabeta search

TD-Gammon - Examples of Weights Learned

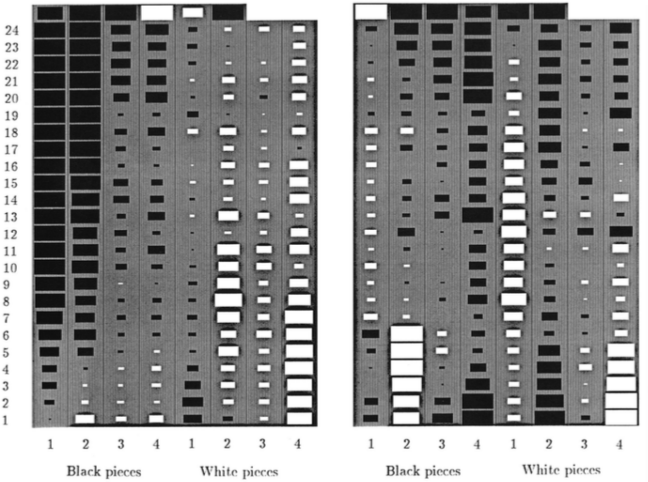

Image source: Tesauro, Practical Issues in Temporal Difference Learning, Machine Learning, 1992

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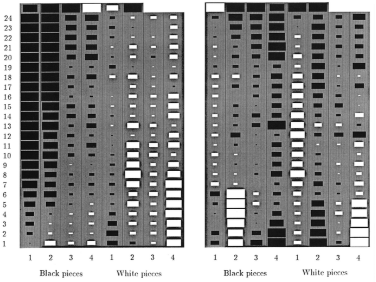

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- Weights from input to two of the 40 hidden units
- Both make sense to human expert players
- Left: corresponds to who is ahead in the race
- Right: probability that attack will be successful

TD-Gammon Impact

- Much stronger than Neurogammon
- Close to top human players
- Changed opening theory
- Changed the way the game is played by human experts
- For many years, the most impressive application of RL

Computer Backgammon Now

- Programs generally follow the TD-Gammon architecture
- Bigger, faster, longer training
- Endgame databases with exact winning probabilities
- Considered almost perfect
- Much stronger than humans

Summary of RL Introduction

- Reinforcement learning for learning from self-play
- TD-Gammon as early success story
- Very small (for todays standard) net with 1 hidden layer
- World class performance
- Trained by RL, more specifically the $TD(\lambda)$ algorithm