Supervised Learning

Recall: Supervised Learning

- We have a training set and a test set, each consisting of a set of examples. For each example, a number of input attributes and a target attribute are specified.
- The aim is to predict the target attribute, based on the input attributes.
- Various learning paradigms are available:
  - Decision Trees
  - Neural Networks
  - SVM
  - ... others ...

Learning of Actions

Supervised Learning can also be used to learn Actions, if we construct a training set of situation-action pairs (called Behavioral Cloning).

However, there are many applications for which it is difficult, inappropriate, or even impossible to provide a “training set”

- optimal control
  - mobile robots, pole balancing, flying a helicopter
- resource allocation
  - job shop scheduling, mobile phone channel allocation
- mix of allocation and control
  - elevator control, backgammon
Reinforcement Learning Framework

- An agent interacts with its environment.
- There is a set $S$ of states and a set $A$ of actions.
- At each time step $t$, the agent is in some state $s_t$.
  It must choose an action $a_t$, whereupon it goes into state $s_{t+1} = \delta(s_t, a_t)$ and receives reward $r_t = R(s_t, a_t)$
- Agent has a policy $\pi : S \rightarrow A$. We aim to find an optimal policy $\pi^*$ which maximizes the cumulative reward.
- In general, $\delta$, $R$, and $\pi$ can be multi-valued, with a random element, in which case we write them as probability distributions $\delta(s_{t+1} = s | s_t, a_t)$, $R(r_t = r | s_t, a_t)$, $\pi(a_t = a | s_t)$

Models of optimality

Is a fast nickel worth a slow dime?

Finite horizon reward $\sum_{i=0}^{h} r_{t+i}$

Infinite discounted reward $\sum_{i=0}^{\infty} \gamma^i r_{t+i}, \quad 0 \leq \gamma < 1$

Average reward $\lim_{h \to \infty} \frac{1}{h} \sum_{i=0}^{h-1} r_{t+i}$

- Finite horizon reward is simple computationally
- Infinite discounted reward is easier for proving theorems
- Average reward is hard to deal with, because can’t sensibly choose between small reward soon and large reward very far in the future.

Probabilistic Policies

There are some environments in which any deterministic agent will perform very poorly, and the optimal (reactive) policy must be stochastic (i.e. randomized).

In 2-player games like Rock-Paper-Scissors, a random strategy is also required in order to make agent choices unpredictable to the opponent.

Comparing Models of Optimality

- Finite horizon, $k = 4$ → $a_1$ is preferred
- Infinite horizon, $\gamma = 0.9$ → $a_2$ is preferred
- Average reward → $a_3$ is preferred
**RL Approaches**

- **Value Function Learning**
  - TD-Learning
  - Q-Learning
- **Policy Learning**
  - Hill Climbing
  - Policy Gradients
  - Evolutionary Strategy
- **Actor-Critic**
  - combination of Value and Policy learning

**Value Function Learning**

Every policy $\pi$ determines a Value Function $V^\pi : S \to \mathbb{R}$ where $V^\pi(s)$ is the average discounted reward received by an agent who begins in state $s$ and chooses its actions according to policy $\pi$.

If $\pi = \pi^*$ is optimal, then $V^*(s) = V^{\pi^*}(s)$ is the maximum discounted reward obtainable from state $s$. Learning this optimal value function can help to determine the optimal strategy.

The agent retains its own estimate $V()$ of the “true” value function $V^*(())$. The aim of Value Function Learning is generally to start with a random $V$ and then iteratively improve it so that it more closely approximates $V^*$. This process is sometimes called “Bootstrapping”.

This is the Value Function $V^\pi$ where $\pi$ is the policy of choosing between available actions uniformly randomly.

**K-Armed Bandit Problem**

The special case of an active, stochastic environment with only one state is called the K-armed Bandit Problem, because it is like being in a room with several (friendly) slot machines, for a limited time, and trying to collect as much money as possible.

Each action (slot machine) provides a different average reward.
**Exploration / Exploitation Tradeoff**

Most of the time we should choose what we think is the best action. However, in order to ensure convergence to the optimal strategy, we must occasionally choose something different from our preferred action, e.g.

- choose a random action 5% of the time, or
- use Softmax (Boltzmann distribution) to choose the next action:

\[
P(a) = \frac{e^{R(a)/T}}{\sum_{b \in A} e^{R(b)/T}}
\]

**Exploration / Exploitation Tradeoff**

I was born to try...

But you’ve got to make choices

Be wrong or right

Sometimes you’ve got to sacrifice the things you like.

- Delta Goodrem

**Delayed Reinforcement**

We may need to take several actions before we can get the good reward.

**Temporal Difference Learning**

Let’s first assume that \( R \) and \( \delta \) are deterministic. Then the (true) value \( V^*(s) \) of the current state \( s \) should be equal to the immediate reward plus the discounted value of the next state

\[
V^*(s) = R(s, a) + \gamma V^*(\delta(s, a))
\]

We can turn this into an update rule for the estimated value, i.e.

\[
V(s_t) \leftarrow r_t + \gamma V(s_{t+1})
\]

If \( R \) and \( \delta \) are stochastic (multi-valued), it is not safe to simply replace \( V(s) \) with the expression on the right hand side. Instead, we move its value fractionally in this direction, proportional to a learning rate \( \eta \)

\[
V(s_t) \leftarrow V(s_t) + \eta \left[ r_t + \gamma V(s_{t+1}) - V(s_t) \right]
\]
Q-Learning

Q-Learning is similar to TD-Learning except that we use a function $Q^\pi : S \times A \rightarrow R$ which depends on a state, action pair instead of just a state.

For any policy $\pi$ the Q-Function $Q^\pi(s,a)$ is the average discounted reward received by an agent who begins in state $s$, first performs action $a$ and then follows policy $\pi$ for all subsequent timesteps.

If $\pi = \pi^*$ is optimal, then $Q^*(s,a) = Q^\pi(s,a)$ is the maximum discounted reward obtainable from $s$, if the agent is forced to take action $a$ in the first timestep but can act optimally thereafter.

The agent retains its own (initially, random) estimate $Q()$ and iteratively improves this estimate to more closely approximate the “true” function $Q^*$.

Theoretical Results

Theorem: Q-learning will eventually converge to the optimal policy, for any deterministic Markov decision process, assuming an appropriately randomized strategy.

(Watkins & Dayan 1992)

Theorem: TD-learning will also converge, with probability 1.

(Sutton 1988, Dayan 1992, Dayan & Sejnowski 1994)
Limitations of Theoretical Results

- Delayed reinforcement
  - reward resulting from an action may not be received until several
time steps later, which also slows down the learning
- Search space must be finite
  - convergence is slow if the search space is large
  - relies on visiting every state infinitely often
- For “real world” problems, we can’t rely on a lookup table
  - need to have some kind of generalisation (e.g. TD-Gammon)

Computer Game Playing

Suppose we want a write a computer program to play a game like
Backgammon, Chess, Checkers or Go. This can be done using a tree
search algorithm (expectimax, MCTS, or minimax with alpha-beta
pruning). But we need:

(a) an appropriate way of encoding any board position as a set of
numbers, and
(b) a way to train a neural network or other learning system to compute a
board evaluation, based on those numbers

Backgammon

Board encoding

Two layer neural network

- 4 units × 2 players × 24 points
- 2 units for the bar
- 2 units for off the board
- 196 input units
- 20 hidden units
- 1 output unit

The input \( s \) is the encoded board position (state),
the output \( V(s) \) is the value of this position (probability of winning).
At each move, roll the dice, find all possible “next board positions”,
convert them to the appropriate input format, feed them to the network,
and choose the one which produces the largest output.
TD-Learning for Episodic Games

Backgammon is an example of an episodic task, in the sense that the agent receives just a single reward at the end of the game, which we can consider as the final value \( V_{m+1} \) (typically, +1 for a win or -1 for a loss). We then have a sequence of game positions, each with its own (estimated) value:

\[
V_t \rightarrow V_{t+1} \rightarrow \ldots \rightarrow V_m \rightarrow V_{m+1} \quad \text{(final result)}
\]

In this context, TD-Learning simplifies and becomes equivalent to using the value of the next state \( V_{t+1} \) as the training value for the current state \( V_t \):

\[
w \leftarrow w + \eta (T - V) \frac{\partial V}{\partial w}
\]

\( w \) = weight
\( \eta \) = learning rate

Q: How do we choose the target value \( T \) ?

In other words, how do we know what the value of the current position “should have been”? or, how do we find a better estimate for the value of the current position?

TD-Gammon

Tesauro trained two networks:

- EP-network was trained on Expert Preferences (Supervised)
- TD-network was trained by self play (TD-Learning)

TD-network outperformed the EP-network.

With modifications such as 3-step lookahead (expectimax) and additional hand-crafted input features, TD-Gammon became the best Backgammon player in the world (Tesauro, 1995).
HC-Gammon was trained by this Hill-Climbing strategy

weights were used to determine value function, but learning optimizes performance of policy directly rather than aiming to make value function more accurate

performance was almost as good as TD-Gammon, but not quite

- gradient information provides more precise updates, particularly for rarely used weights in the network

Policy Learning

There is another class of Reinforcement Learning algorithms which do not optimize a Value function but instead try to optimize the Policy itself, directly.

Normally, we consider a family of policies \( \pi_\theta : S \rightarrow A \) determined by parameters \( \theta \) (for example, the weights of a neural network).

For episodic domains like Backgammon, we do not need a discount factor, and the “fitness” of policy \( \pi_0 \) can be taken as the Value function of the initial state \( s_0 \) under this policy, which is the expected (or average) total reward received in each game by an agent using policy \( \pi_0 \)

\[
\text{fitness}(\pi_0) = V^{\pi_0}(s_0) = \mathbb{E}_{\pi_0}(r_{\text{total}})
\]

Hill Climbing

- Initialize “champ” policy \( \theta_{\text{champ}} = 0 \)
- for each trial, generate “mutant” policy
  \[
  \theta_{\text{mutant}} = \theta_{\text{champ}} + \text{Gaussian noise (fixed } \sigma)\]
- champ and mutant play up to \( n \) games, with same game initial conditions (i.e. same seed for generating dice rolls)
- if mutant does “better” than champ,
  \[
  \theta_{\text{champ}} \leftarrow (1 - \alpha)\theta_{\text{champ}} + \alpha \theta_{\text{mutant}}
  \]
- “better” means the mutant must score higher than the champ in the first game, and at least as high as the champ in each subsequent game.

Policy Gradients

Policy Gradients are an alternative to hillclimbing which use gradient ascent rather than random updates.

Let’s first consider episodic games. The agent takes a sequence of actions

\[
a_1 \ a_2 \ldots a_t \ldots a_m
\]

At the end it receives a reward \( r_{\text{total}} \). We don’t know which actions contributed the most, so we just reward all of them equally. If \( r_{\text{total}} \) is high (low), we change the parameters to make the agent more (less) likely to take the same actions in the same situations. In other words, we want to increase (decrease)

\[
\log \prod_{t=1}^m \pi_0(a_t|s_t) = \sum_{t=1}^m \log \pi_0(a_t|s_t)
\]
Policy Gradients

We wish to extend the framework of Policy Gradients to non-episodic domains, where rewards are received incrementally throughout the game (e.g. PacMan, Space Invaders). Every policy \( \pi_\theta \) determines a distribution \( \rho_{\pi_\theta}(s) \) on \( S \)

\[
\rho_{\pi_\theta}(s) = \sum_{t \geq 0} \gamma^t \text{prob}_{\pi_\theta,t}(s)
\]

where \( \text{prob}_{\pi_\theta,t}(s) \) is the probability that, after starting in state \( s_0 \) and performing \( t \) actions, the agent will be in state \( s \). We can then define the fitness of policy \( \pi \) as

\[
\text{fitness}(\pi_\theta) = \sum_s \rho_{\pi_\theta}(s) \sum_a Q^{\pi_\theta}(s,a) \pi_\theta(a|s)
\]

Note: In the case of episodic games, we can take \( \gamma = 1 \), in which case \( Q^{\pi_\theta}(s,a) \) is simply the expected reward at the end of the game. However, the above equation holds in the non-episodic case as well. The gradient of \( \rho_{\pi_\theta}(s) \) and \( Q^{\pi_\theta}(s,a) \) are extremely hard to determine, so we ignore them and instead compute the gradient only for the last term \( \pi_\theta(a|s) \).

\[
\nabla_\theta \text{fitness}(\pi_\theta) = \sum_s \rho_{\pi_\theta}(s) \sum_a Q^{\pi_\theta}(s,a) \nabla_\theta \pi_\theta(a|s)
\]

REINFORCE Algorithm

We then get the following REINFORCE algorithm:

for each trial

run trial and collect states \( s_t \), actions \( a_t \), and reward \( r_{\text{total}} \)

for \( t = 1 \) to length(trial)

\[
\theta \leftarrow \theta + \eta (r_{\text{total}} - b) \nabla_\theta \log \pi_\theta(a_t|s_t)
\]

end

end

This algorithm has successfully been applied, for example, to learn to play the game of Pong from raw image pixels.
### The Log Trick

\[
\sum_a Q^\pi_0(s,a) \nabla_\theta \pi_0(a|s) = \sum_a Q_{\pi_0}(s,a) \frac{\nabla_\theta \pi_0(a|s)}{\pi_0(a|s)}
\]

\[
= \sum_a Q_{\pi_0}(s,a) \nabla_\theta \log \pi_0(a|s)
\]

So

\[
\nabla_\theta \text{fitness}(\pi_0) = \sum_r \rho_{\pi_0}(s) \sum_a Q_{\pi_0}(s,a) \nabla_\theta \log \pi_0(a|s)
\]

\[
= E_{\pi_0}[Q_{\pi_0}(s,a) \nabla_\theta \log \pi_0(a|s)]
\]

The reason for the last equality is this:

\(\rho_{\pi_0}(s)\) is the number of times (discounted by \(\gamma^t\)) that we expect to visit state \(s\) when using policy \(\pi_0\). Whenever state \(s\) is visited, action \(a\) will be chosen with probability \(\pi_0(a|s)\).

### Actor-Critic

Recall:

\[
\nabla_\theta \text{fitness}(\pi_0) = E_{\pi_0}[Q_{\pi_0}(s,a) \nabla_\theta \log \pi_0(a|s)]
\]

For non-episodic games, we cannot easily find a good estimate for \(Q_{\pi_0}(s,a)\). One approach is to consider a family of Q-Functions \(Q_w\) determined by parameters \(w\) (different from \(\theta\)) and learn \(w\) so that \(Q_w\) approximates \(Q_{\pi_0}\), at the same time that the policy \(\pi_0\) itself is also being learned.

This is known as an Actor-Critic approach because the policy determines the action, while the Q-Function estimates how good the current policy is, and thereby plays the role of a critic.

### Actor Critic Algorithm

for each trial

sample \(a_0\) from \(\pi(a|s_0)\)

for each timestep \(t\) do

sample reward \(r_t\) from \(R(s_t,a_t)\)

sample next state \(s_{t+1}\) from \(\delta(s|s_t,a_t)\)

sample action \(a_{t+1}\) from \(\pi(a|s_{t+1})\)

\[
\frac{dE}{dQ} = -[r_t + \gamma Q_w(s_{t+1},a_{t+1}) - Q_w(s_t,a_t)]
\]

\(\theta \leftarrow \theta + \eta_\theta Q_w(s_t,a_t) \nabla_\theta \log \pi_0(a_t|s_t)\)

\(w \leftarrow w - \eta_w \frac{dE}{dQ} \nabla_w Q_w(s_t,a_t)\)

end

end