AI Planning for Autonomy

12. n-step reinforcement learning

Learning quicker using look-aheads

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Agenda

Agenda

Reinforcement Learning – Some Weaknesses

In the previous lecture, we looked at two fundamental temporal difference (TD) methods for reinforcement learning: Q-learning and SARSA.

These two methods have some weaknesses in this basic format:

1. Unlike Monte-Carlo methods, which reach a reward and then backpropagate this reward, TD methods use bootstrapping (they estimate the future discounted reward using $Q(s, a)$), which means that for problems with sparse rewards, it can take a long time to for rewards to propagate throughout a Q-function.
2. Both methods estimate a Q-function $Q(s, a)$, and the simplest way to model this is via a Q-table. However, this requires us to maintain a table of size $|A| \times |S|$, which is prohibitively large for any non-trivial problem.
3. Using a Q-table requires that we visit every reachable state many times and apply every action many times to get a good estimate of $Q(s, a)$. Thus, if we never visit a state s, we have no estimate of $Q(s, a)$, even if we have visited states that are very similar to s.
4. Rewards can be sparse, meaning that there are few state/actions that lead to non-zero rewards. This is problematic because initially, reinforcement learning algorithms behave entirely randomly and will struggle to find good rewards. Remember the Freeway demo from the previous lecture?

Reinforcement Learning – Some Improvements

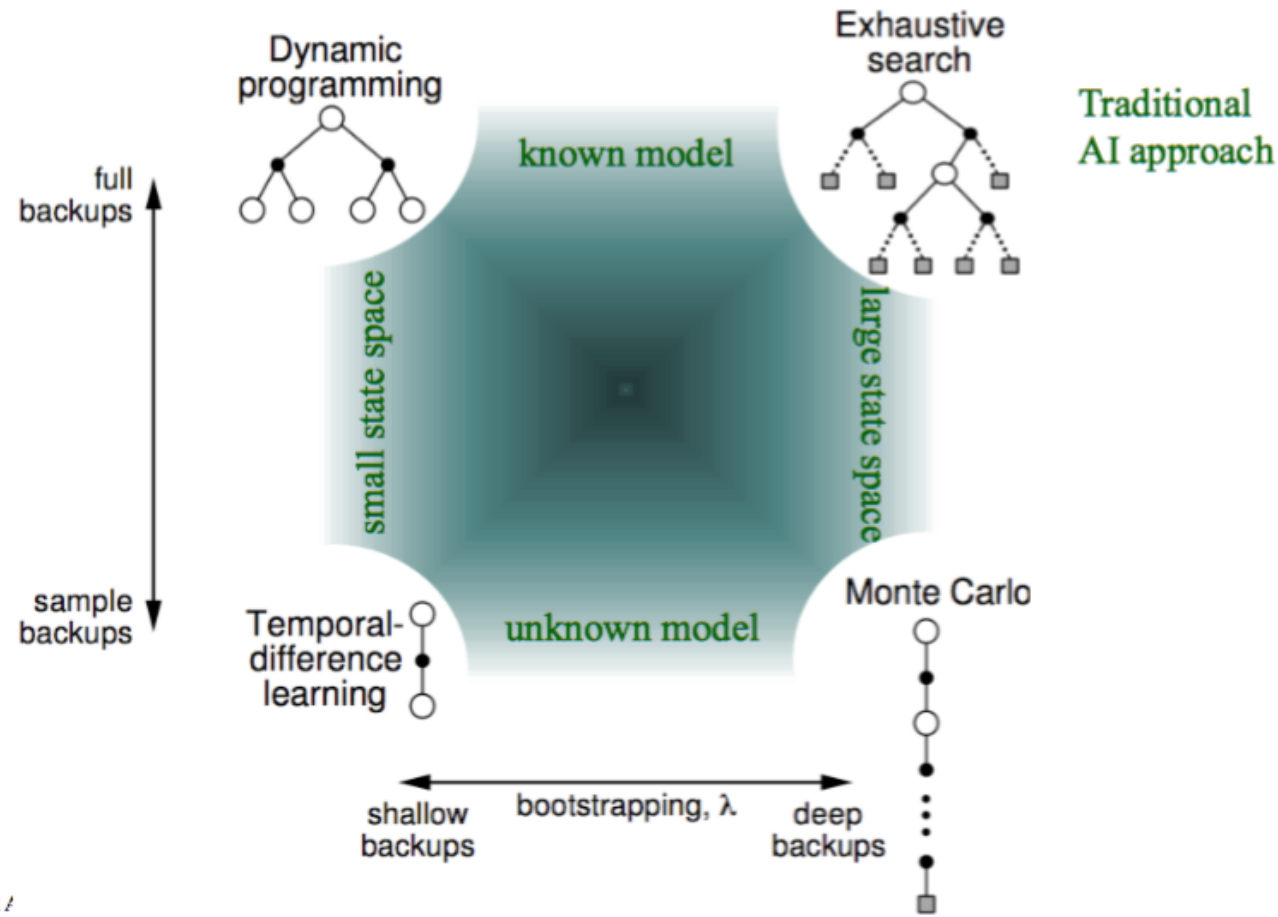
To get around these limitations, we are going to look at three simple approaches that can improve temporal difference methods:

1. *n-step temporal difference learning*: Monte Carlo techniques execute entire traces and then backpropagate the reward, while basic TD methods only look at the reward in the next step, estimating the future wards. n-step methods instead look n steps ahead for the reward before updating the reward, and then estimate the remainder. *This lecture!*
2. *Approximate methods*: Instead of calculating an exact Q-function, we approximate it using simple methods that both eliminate the need for a large Q-table (therefore the methods scale better), and also allowing use to provide reasonable estimates of $Q(s, a)$ *even if we have not applied action a in state s previously*. *Next lecture!*
3. *Reward shaping and Value-Function Initialisation*: If rewards are sparse, we can modify/augment our reward function to reward behaviour that we think moves us closer to the solution, or we can guess the optimal Q-function and initial $Q(s, a)$ to be this. *Next lecture!*

Agenda

Approaches to AI Planning and Learning

n-step TD learning comes from the idea used in the image below. Monte Carlo methods uses 'deep backups', where entire traces are executed and the reward backpropagated. Methods such as Q-learning and SARSA use 'shallow backups', only using the reward from the 1-step ahead. n-step learning finds the middle ground: only update the Q-function after having explored ahead n steps.



R. S. Sutton and A

TD(λ)

We will look at TD(λ), in which λ is the parameter that determines n: the number of steps that we want to look ahead before updating the Q-function. Thus, TD(0) is just 'standard' reinforcement learning, and TD(1) looks one step beyond the immediate reward, TD(2) looks two steps beyond, etc.

Both Q-learning and SARSA have n-step version. We will look at TD(λ) more generally, and then show an algorithm for n-step SARSA. The version for Q-learning is similar.

Discounted Future Rewards (again)

When calculating a discounted reward over a trace, we can re-write as:

$$\begin{aligned} G_t &= r_1 + \gamma r_2 + \gamma^2 r_3 + \gamma^3 r_4 + \dots \\ &= r_1 + \gamma(r_2 + \gamma(r_3 + \gamma(r_4 + \dots))) \end{aligned}$$

If G_t is the value received at time-step t, then $G_t = r_t + \gamma G_{t+1}$

In TD(0) methods such as Q-learning and SARSA, we do not know G_{t+1} when updating $Q(s, a)$, so we estimate using bootstrapping:

$$G_t = r_t + V(s_{t+1})$$

That is, the reward of the entire future from step t is estimated as the reward at t plus the estimated (discounted) future reward from $t + 1$. $V(s_{t+1})$ is estimated using the maximum expected return (Q-learning) or the estimated value of the next action (SARSA).

This is a *one-step return*.

Truncated Discounted Rewards

However, we can estimate a two-step return:

$$G_t^2 = r_t + \gamma r_{t+1} + V(s_{t+2})$$

or three-step return:

$$G_t^3 = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \gamma^3 V(s_{t+2})$$

or n-step returns:

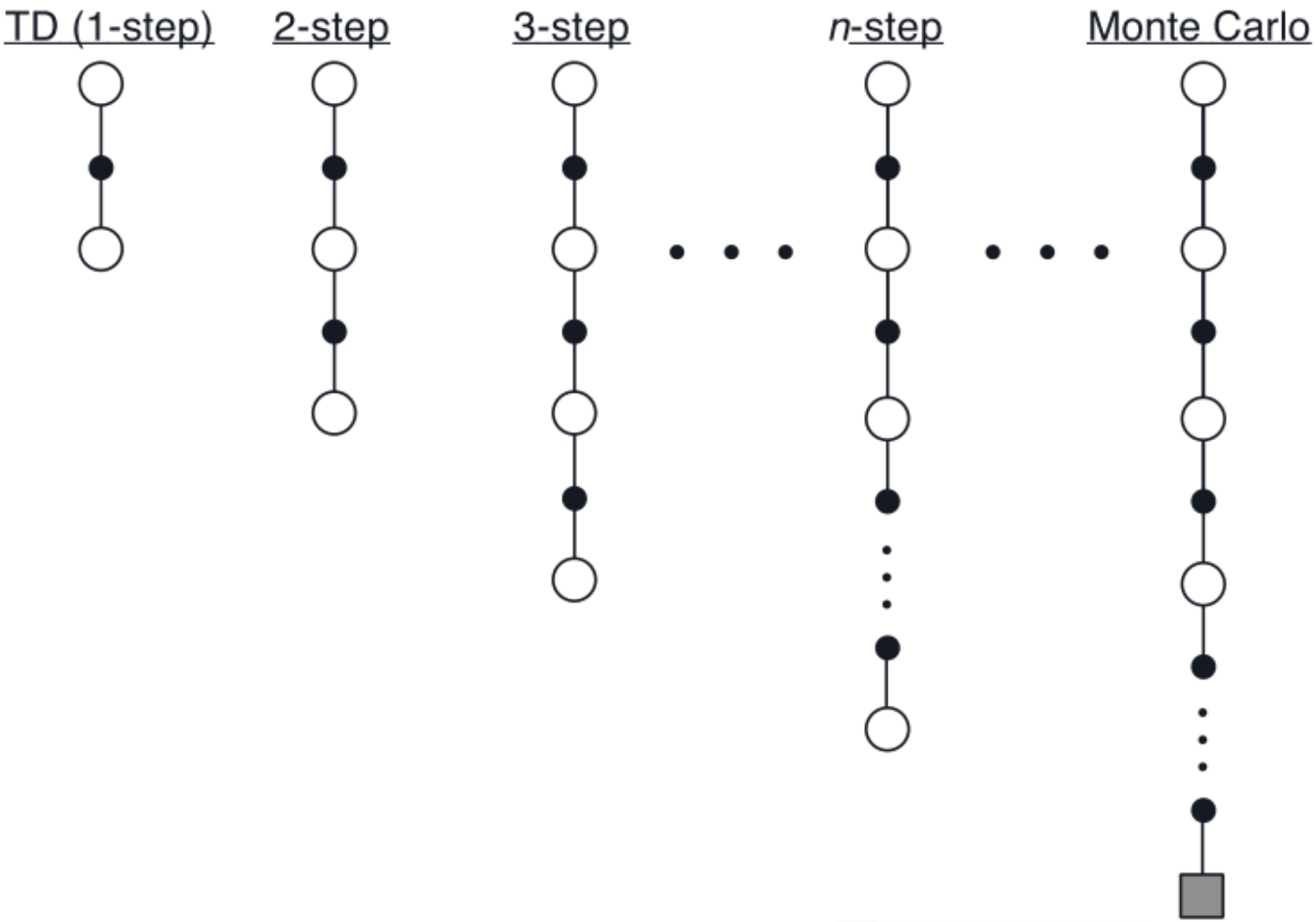
$$G_t^n = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots \gamma^n V(s_{t+n})$$

In this above expression G_t^n is the full reward, *truncated* at n steps, at time t. The basic idea is that we do not update the Q-value immediately after executing an action: we wait n steps and update it based on the n-step return.

If T is the termination step and $t + n > T$, then we just use the full reward.

In Monte-Carlo methods, we go all the way to the end of an episode. Monte-Carlo Tree Search is one such Monte-Carlo method, but there are others that we do not cover.

Different Levels Truncated Rewards



Updating the Q-function

The update rule for the Q-function is then different. First, we need to calculate the truncated reward for n steps, in which τ is the time step that we are updating for:

$$G \leftarrow \sum_{i=\tau+1}^{\min(\tau+n,T)} \gamma^{i-\tau-1} r_i$$

This just sums the rewards from time step $\tau + 1$ until either n steps ($\tau + n$) or termination of the episode (T), whichever comes first. For n-step SARSA, we have:

Then update:

$$\text{If } \tau + n < T \text{ then } G \leftarrow G + \gamma^n Q(S_{\tau+n}, A_{\tau+n})$$
$$Q(S_\tau, A_\tau) \leftarrow Q(S_\tau, A_\tau) + \alpha[G - Q(S_\tau, A_\tau)]$$

The first line just adds the future expect reward if we are not at the end of the episode (if $\tau + n < T$).

But! It's not so simple

While conceptually this is not so difficult, we have to modify our algorithms quite a bit, because at each step, n-step return uses a reward from the future.

For the first $n-1$ steps of the any episode, we do not update Q at all.

Also, we have to continue updating $n-1$ steps after the end of the episode.

This leads to the algorithm on the following slide. All of the changes, except for the three lines immediately after 'if $\tau \geq 0$', just manage the n-steps.

Computationally, this is not much worse than 1-step learning. We need to store the last n states, but the per-step computation is small and uniform for n-step, just as for 1-step.

n-step SARSA

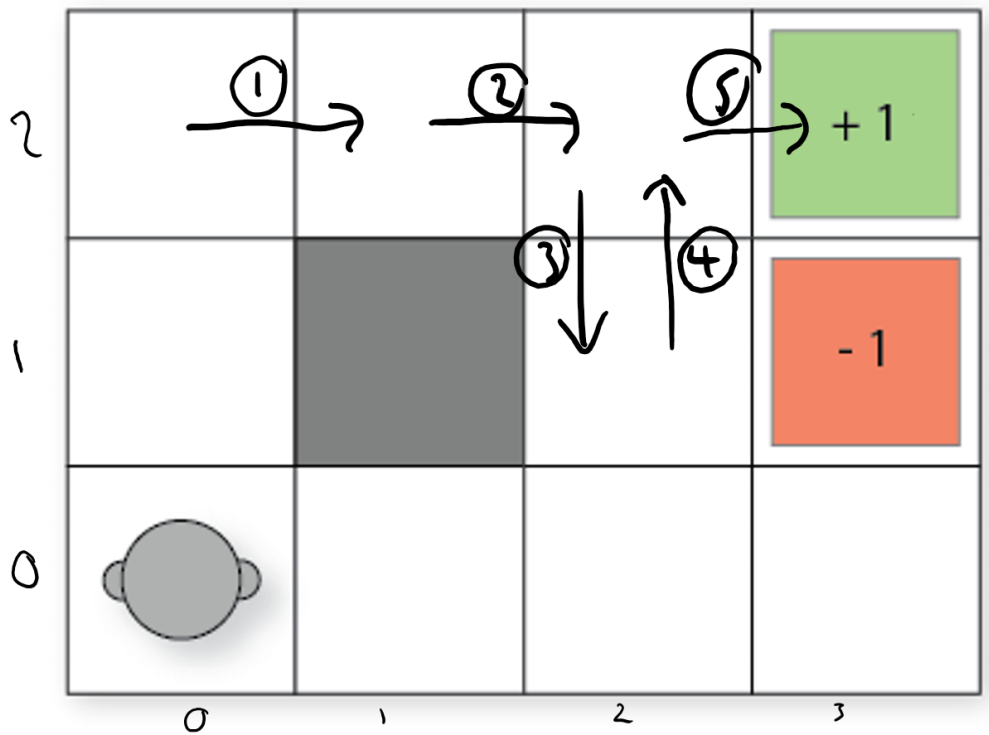
n-step Sarsa for estimating $Q \approx q_*$, or $Q \approx q_\pi$ for a given π

Initialize $Q(s, a)$ arbitrarily, for all $s \in \mathcal{S}, a \in \mathcal{A}$
Initialize π to be ε-greedy with respect to Q, or to a fixed given policy
Parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$, a positive integer n
All store and access operations (for S_t, A_t, and R_t) can take their index mod n

Repeat (for each episode):
  Initialize and store $S_0 \neq$ terminal
  Select and store an action $A_0 \sim \pi(\cdot|S_0)$
  $T \leftarrow \infty$
  For $t = 0, 1, 2, \ldots$:
  | If $t < T$, then:
  | Take action A_t
  | Observe and store the next reward as R_{t+1} and the next state as S_{t+1}
  | If S_{t+1} is terminal, then:
  | $T \leftarrow t + 1$
  | else:
  | Select and store an action $A_{t+1} \sim \pi(\cdot|S_{t+1})$
  | $\tau \leftarrow t - n + 1$ (τ is the time whose estimate is being updated)
  | If $\tau \geq 0$:
  | $G \leftarrow \sum_{i=\tau+1}^{\min(\tau+n,T)} \gamma^{i-\tau-1} R_i$
  | If $\tau + n < T$, then $G \leftarrow G + \gamma^n Q(S_{\tau+n}, A_{\tau+n})$ $(G_{\tau:\tau+n})$
  | $Q(S_\tau, A_\tau) \leftarrow Q(S_\tau, A_\tau) + \alpha [G - Q(S_\tau, A_\tau)]$
  | If π is being learned, then ensure that $\pi(\cdot|S_\tau)$ is ε-greedy wrt Q
  Until $\tau = T - 1$

Exercise

Consider our simple 2D navigation task, in which we do not know the probability transitions nor the rewards. Initially, the reinforcement learning algorithm will be required to search randomly until it finds a reward. Propagated this reward back n-steps will be helpful.



Assuming $Q(s, a) = 0$ for all s and a, if we (finally) traverse the episode the labelled episode, what will our Q-function look like for a 5-step update with $\alpha = 0.5$ and $\gamma = 0.9$?

Exercise (continued)

$$
\begin{aligned}
G &\leftarrow \sum_{i=\tau+1}^{\min(\tau+n,T)} \gamma^{i-\tau-1} r_i \\
G_5 &\leftarrow \gamma^1 \cdot 1 \\
G_4 &\leftarrow \gamma^2 \cdot 1 \\
&\dots \\
G_1 &\leftarrow \gamma^5 \cdot 1
\end{aligned}
$$

$$
\begin{aligned}
Q((2,2),E) &\leftarrow Q((2,2),E) + \alpha[G_5 - Q((2,2),E)] \\
&\leftarrow 0 + 0.5[0.9 - 0] \\
&\leftarrow 0.45
\end{aligned}
$$

$$
\begin{aligned}
Q((2,1),N) &\leftarrow Q((1,2),N) + \alpha[G_4 - Q((1,2),N)] \\
&\leftarrow 0 + 0.5[0.81 - 0] \\
&\leftarrow 0.405
\end{aligned}
$$

$$\dots$$

$$
\begin{aligned}
Q((1,2),E) &\leftarrow Q((2,1),E) + \alpha[G_2 - Q((2,1),E)] \\
&\leftarrow 0 + 0.5[0.6551 - 0] \\
&\leftarrow 0.3281
\end{aligned}
$$

Exercise (continued)

The table below compares 1-step vs. 5-step SARSA for the trace above. In 1-step SARSA, reaching the reward only informs the state from which it is reached. Whereas for 5-step, it informs the previous five steps. Then, in the next episode, there is more chance of encountering a non-zero state, so which will again inform the five steps instead of just one. The rewards 'spread' throughout the Q-table faster.

With 1-step learning

State	Action			
	North	South	East	West
(0,0)	0	0	0	0
(0,1)	0	0	0	0
(0,2)	0	0	0	0
...				
(1,2)	0	0	0	0
(2,1)	0	0	0	0
(2,2)	0	0	0.45	0
(2,3)	0	0	0	0
...				

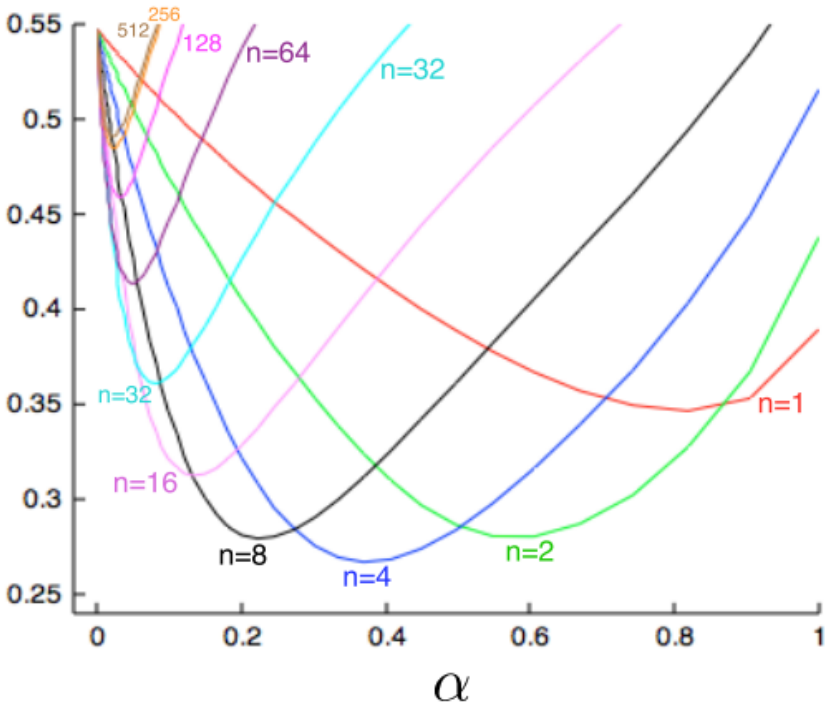
With 5-step learning

State	Action			
	North	South	East	West
(0,0)	0	0	0	0
(0,1)	0	0	0	0
(0,2)	0	0	0.2953	0
...				
(1,2)	0	0	0.3281	0
(2,1)	0.405	0	0	0
(2,2)	0	0.3645	0.45	0
(2,3)	0	0	0	0
...				

Simple experiment: Random Walk

Consider the following simple deterministic Markov reward process:

The following shows results from a series of experiments in varying α and n. The y-axis shows the root mean-squared error:



$n = 1$ is TD(0), while larger n are closer to Monte-Carlo methods. Note that the 'in between' parameters perform best in this example.

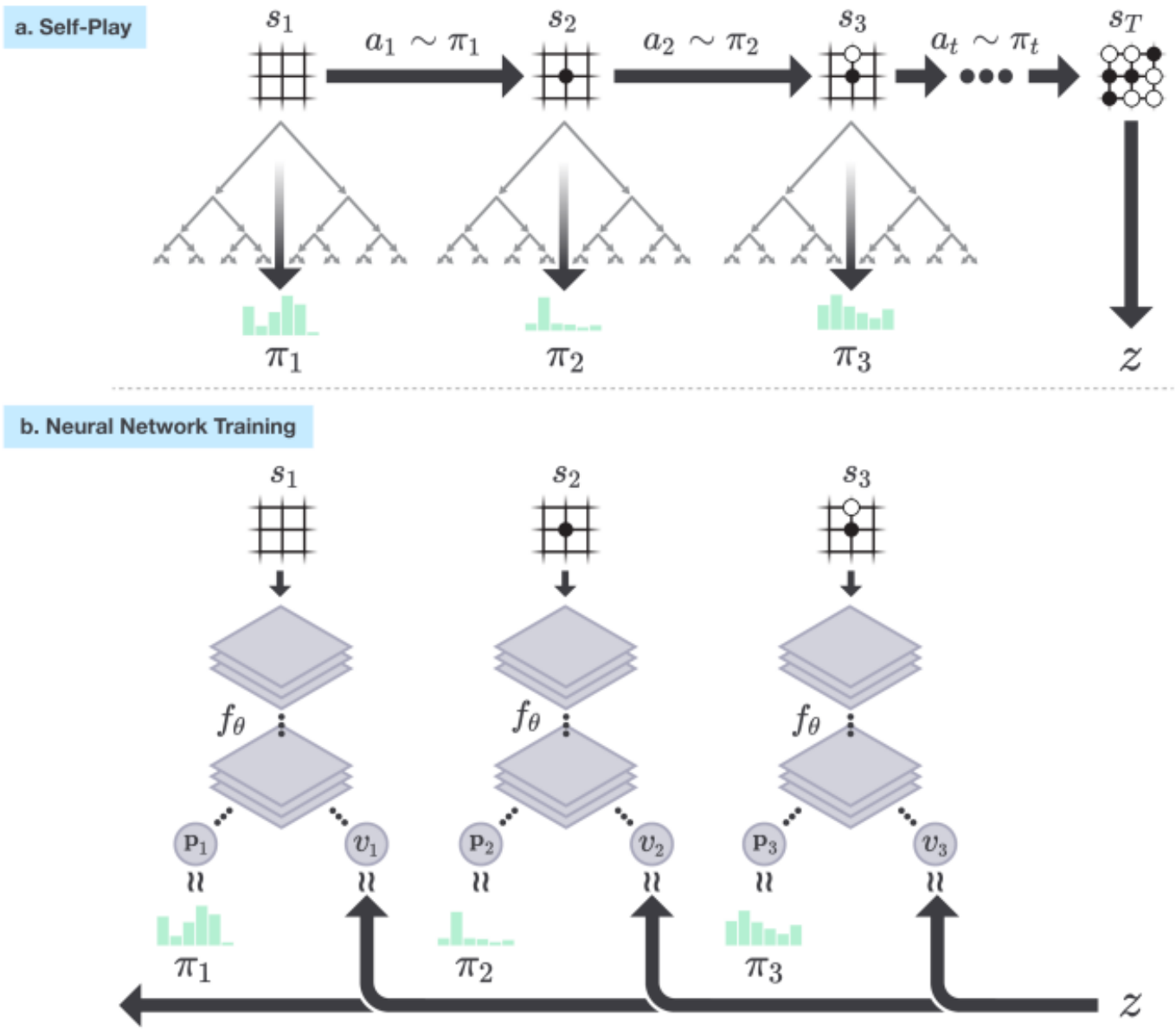
Agenda

Combining MCTS and Reinforcement Learning: AlphaGo Zero (Not examinable)

AlphaGo Zero (or more accurately its predecessor AlphaGo) made headlines when it beat Go world champion Lee Sodol in 2016. It uses a combination of MCTS and (deep) reinforcement learning to learn a policy. A simple overview:

1. It uses a deep neural network to estimate the Q-function. More accurately, it gives an estimate of the probability of selecting action a in state s ($P(a|s)$), and the *value* of the state ($V(s)$), which represents the probability of the player winning from s.
2. It is trained via *self-play*.
3. At each move, AlphaGo Zero:
   1. Executes an MCTS search using UCB $Q(s,a) + P(s,a)/1 + N(s,a)$, which returns the probabilities of playing each move.
   2. The neural network is used to guide the MCTS by influencing $Q(s,a)$.
   3. The final result of a simulated game is used as the reward for each simulation.
   4. After a set number of MCTS simulations, the best move is chosen for self-play.
   5. Repeat steps 1-4 for each move until the self-play game ends.
   6. Then, feedback the result of the self-play game to update the Q function for each move.

AlphaGo is Best Summarised Using This Figure



Reading

- Chapter 7 of *Introduction to Reinforcement Learning* [*Sutton and Barto*]
  Available at:
  `https://webdocs.cs.ualberta.ca/~sutton/book/the-book.html`
- *Mastering the Game of Go without Human Knowledge* from DeepMind.
  Available at:
  `https://deepmind.com/documents/119/agz_unformatted_nature.pdf`