

Exploration under Function Approximation

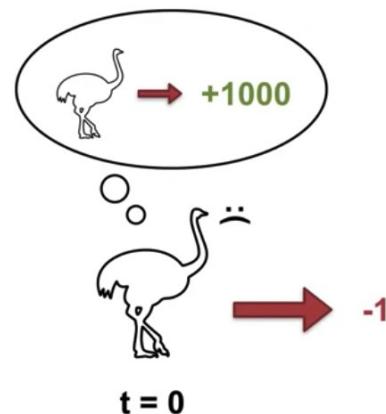
Objectives

- Describe how optimistic initial values can be used with function approximation
- Understand how Epsilon greedy can be used with function approximation

Optimistic Initial Values in the Tabular

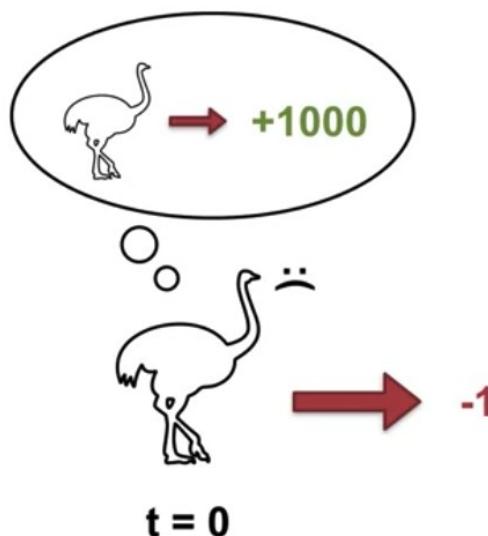
- We initialize our values to be greater than the true values.
- This is like the agent imagining that it can get more reward by taking that action than it actually

car



Optimistic Initial Values in the Tabular

- This is straightforward to implement in a tabular setting where the update to each state action pair is independent of all the other state action pairs



$$Q(s, a) \leftarrow 1000 \quad \forall s, a$$

Optimistic Initial Values in the Tabular

- How to initialize values optimistically under function approximation:
 - In function approximation, optimistic initial values corresponds to initializing the weights such that the resulting values are optimistic.
 - In some cases this is straightforward, for example, when the features are binary, we simply initialize each weight to be the largest possible return.
 - Then, as long as each state has at least one feature active, the value will be optimistic and likely overly so.

Optimistic Initial Values in the Tabular

- How to initialize values optimistically under function approximation:
 - Non-linear: the relationship between the final values and the features can be quite complicated.

Linear

$$q_{\pi}(s, a) \approx \hat{q}(s, a, \mathbf{w}) = \mathbf{w}^T \mathbf{x}(s, a)$$

Non-linear

$$q_{\pi}(s, a) \approx \hat{q}(s, a, \mathbf{w}) = \mathbf{NN}(s, a, \mathbf{w})$$

$$\mathbf{w} \leftarrow \begin{bmatrix} 100 \\ 100 \\ 100 \\ 100 \\ \vdots \end{bmatrix}$$

$$\mathbf{w} \leftarrow ???$$

Optimistic Initial Values in the Tabular

- Depending on how our features generalize, optimistic initial values may not result in the same kind of systematic exploration we see in the tabular case.
- Consider an extreme example, where we have only one feature that is always one.
 - We can initialize optimistically but every update will change the value for all states.
 - This means that before some states are even visited, the value will already have decreased such that it is no longer optimistic.

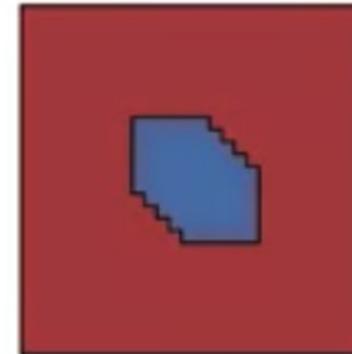
Optimistic Initial Values in the Tabular

- Function approximation with tile coding can produce such localized updates.
- Neural networks also provide local updates, but neural networks may also generalize

age



Single feature



Tile coding



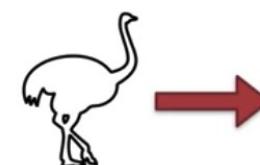
Neural network

Epsilon Greedy

- Epsilon greedy is generally applicable and easy to use even in cases with non-linear function approximation.
- The only thing Epsilon greedy needs are the action value estimates, initialized or appr

$$1 - \epsilon$$

✓ they are



$$A_t = \underset{a}{\operatorname{argmax}} \hat{q}(S_t, a, \mathbf{w})$$

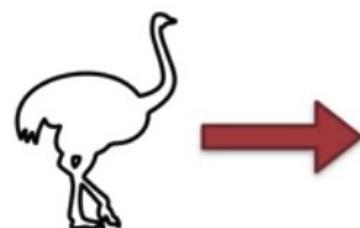
Epsilon Greedy

- However, Epsilon greedy is not a directed exploration method.
- It relies on randomness to discover better actions near states followed by the current policy.
- It is therefore not as systematic as exploration methods that rely on optimism.

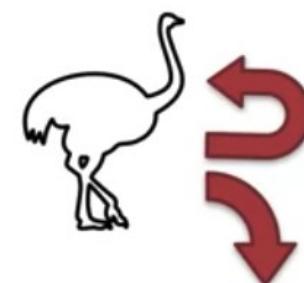
Epsilon Greedy

ϵ -greedy

$1 - \epsilon$



ϵ



$A_t = \underset{a}{\operatorname{argmax}} \hat{q}(S_t, a, \mathbf{w})$

$A_t = \text{Random action}$

Exploration under Function
Approximation

Summary

- Describe how optimistic initial values can be used with function approximation
- Understand how Epsilon greedy can be used with function approximation

Q & A