

# A Guided Tour of Chapter 11: Batch RL: Experience Replay, DQN, LSPI

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# Incremental RL makes inefficient use of training data

- Incremental versus Batch RL in the context of fixed finite data
- Let's understand the difference for the simple case of MC Prediction
- Given fixed finite sequence of trace experiences yielding training data:

$$\mathcal{D} = [(S_i, G_i) | 1 \leq i \leq n]$$

- Incremental MC estimates  $V(s; \mathbf{w})$  using  $\nabla_{\mathbf{w}} \mathcal{L}(\mathbf{w})$  for each data pair:

$$\mathcal{L}_{(S_i, G_i)}(\mathbf{w}) = \frac{1}{2} \cdot (V(S_i; \mathbf{w}) - G_i)^2$$

$$\nabla_{\mathbf{w}} \mathcal{L}_{(S_i, G_i)}(\mathbf{w}) = (V(S_i; \mathbf{w}) - G_i) \cdot \nabla_{\mathbf{w}} V(S_i; \mathbf{w})$$

$$\Delta \mathbf{w} = \alpha \cdot (G_i - V(S_i; \mathbf{w})) \cdot \nabla_{\mathbf{w}} V(S_i; \mathbf{w})$$

- $n$  updates are performed in sequence for  $i = 1, 2, \dots, n$
- Uses update method of FunctionApprox for each data pair  $(S_i, G_i)$
- Incremental RL makes inefficient use of available training data  $\mathcal{D}$
- Essentially each data point is “discarded” after being used for update

# Batch MC Prediction makes efficient use of training data

- Instead we'd like to estimate the Value Function  $V(s; \mathbf{w}^*)$  such that

$$\begin{aligned} \mathbf{w}^* &= \arg \min_{\mathbf{w}} \frac{1}{n} \cdot \sum_{i=1}^n \frac{1}{2} \cdot (V(S_i; \mathbf{w}) - G_i)^2 \\ &= \arg \min_{\mathbf{w}} \mathbb{E}_{(S,G) \sim \mathcal{D}} \left[ \frac{1}{2} \cdot (V(S; \mathbf{w}) - G)^2 \right] \end{aligned}$$

- This is the solve method of FunctionApprox on training data  $\mathcal{D}$
- This approach to RL is known as *Batch RL*
- solve by doing updates with repeated use of available data pairs
- Each update using random data pair  $(S, G) \sim \mathcal{D}$

$$\Delta \mathbf{w} = \alpha \cdot (G - V(S; \mathbf{w})) \cdot \nabla_{\mathbf{w}} V(S; \mathbf{w})$$

- This will ultimately converge to desired value function  $V(s; \mathbf{w}^*)$
- Repeated use of available data known as *Experience Replay*
- This makes more efficient use of available training data  $\mathcal{D}$

# Batch TD Prediction makes efficient use of *Experience*

- In Batch TD Prediction, we have experience  $\mathcal{D}$  available as:

$$\mathcal{D} = [(S_i, R_i, S'_i) | 1 \leq i \leq n]$$

- Where  $(R_i, S'_i)$  is the pair of reward and next state from a state  $S_i$
- So, Experience  $\mathcal{D}$  in the form of finite number of atomic experiences
- This is represented in code as an Iterable [ TransitionStep [S]]
- Parameters updated with repeated use of these atomic experiences
- Each update using random data pair  $(S, R, S') \sim \mathcal{D}$

$$\Delta \mathbf{w} = \alpha \cdot (R + \gamma \cdot V(S'; \mathbf{w}) - V(S; \mathbf{w})) \cdot \nabla_{\mathbf{w}} V(S; \mathbf{w})$$

- This is TD Prediction with Experience Replay on Finite Experience  $\mathcal{D}$

# Batch TD( $\lambda$ ) Prediction

- In Batch TD( $\lambda$ ) Prediction, given finite number of trace experiences

$$\mathcal{D} = [(S_{i,0}, R_{i,1}, S_{i,1}, R_{i,2}, S_{i,2}, \dots, R_{i,T_i}, S_{i,T_i}) | 1 \leq i \leq n]$$

- Parameters updated with repeated use of these trace experiences
- Randomly pick trace experience (say indexed  $i$ )  $\sim \mathcal{D}$
- For trace experience  $i$ , parameters updated at each time step  $t$ :

$$\mathbf{E}_t = \gamma \lambda \cdot \mathbf{E}_{t-1} + \nabla_{\mathbf{w}} V(S_{i,t}; \mathbf{w})$$

$$\Delta \mathbf{w} = \alpha \cdot (R_{i,t+1} + \gamma \cdot V(S_{i,t+1}; \mathbf{w}) - V(S_{i,t}; \mathbf{w})) \cdot \mathbf{E}_t$$

# The Deep Q-Networks (DQN) Control Algorithm

DQN uses **Experience Replay** and **fixed Q-learning targets**.

At each time  $t$  for each episode:

- Given state  $S_t$ , take action  $A_t$  according to  $\epsilon$ -greedy policy extracted from Q-network values  $Q(S_t, a; \mathbf{w})$
- Given state  $S_t$  and action  $A_t$ , obtain reward  $R_{t+1}$  and next state  $S_{t+1}$
- Store atomic experience  $(S_t, A_t, R_{t+1}, S_{t+1})$  in replay memory  $\mathcal{D}$
- Sample random mini-batch of atomic experiences  $(s_i, a_i, r_i, s'_i) \sim \mathcal{D}$
- Update Q-network parameters  $\mathbf{w}$  using Q-learning targets based on “frozen” parameters  $\mathbf{w}^-$  of *target network*

$$\Delta \mathbf{w} = \alpha \cdot \sum_i (r_i + \gamma \cdot \max_{a'_i} Q(s'_i, a'_i; \mathbf{w}^-) - Q(s_i, a_i; \mathbf{w})) \cdot \nabla_{\mathbf{w}} Q(s_i, a_i; \mathbf{w})$$

- $S_t \leftarrow S_{t+1}$

Parameters  $\mathbf{w}^-$  of target network infrequently updated to values of Q-network parameters  $\mathbf{w}$  (hence, Q-learning targets treated as “frozen”)

# Least-Squares RL Prediction

- Batch RL Prediction for general function approximation is iterative
- Uses experience replay and gradient descent
- We can solve directly (without gradient) for linear function approx
- Define a sequence of feature functions  $\phi_j : \mathcal{X} \rightarrow \mathbb{R}, j = 1, 2, \dots, m$
- Parameters  $w$  is a weights vector  $\mathbf{w} = (w_1, w_2, \dots, w_m) \in \mathbb{R}^m$
- Value Function is approximated as:

$$V(s; \mathbf{w}) = \sum_{j=1}^m \phi_j(s) \cdot w_j = \phi(s) \cdot \mathbf{w}$$

where  $\phi(s) \in \mathbb{R}^m$  is the feature vector for state  $s$

# Least-Squares Monte-Carlo (LSMC)

- Loss function for Batch MC Prediction with data  $[(S_i, G_i) | 1 \leq i \leq n]$ :

$$\mathcal{L}(\mathbf{w}) = \frac{1}{2n} \cdot \sum_{i=1}^n \left( \sum_{j=1}^m \phi_j(S_i) \cdot w_j - G_i \right)^2 = \frac{1}{2n} \cdot \sum_{i=1}^n (\phi(S_i) \cdot \mathbf{w} - G_i)^2$$

- The gradient of this Loss function is set to 0 to solve for  $\mathbf{w}^*$

$$\sum_{i=1}^n \phi(S_i) \cdot (\phi(S_i) \cdot \mathbf{w}^* - G_i) = 0$$

- $\mathbf{w}^*$  is solved as  $\mathbf{A}^{-1} \cdot \mathbf{b}$
- $m \times m$  Matrix  $\mathbf{A}$  is accumulated at each data pair  $(S_i, G_i)$  as:

$$\mathbf{A} \leftarrow \mathbf{A} + \phi(S_i) \otimes \phi(S_i) \text{ (note: } \otimes \text{ means Outer-Product)}$$

- $m$ -Vector  $\mathbf{b}$  is accumulated at each data pair  $(S_i, G_i)$  as:

$$\mathbf{b} \leftarrow \mathbf{b} + \phi(S_i) \cdot G_i$$

- Sherman-Morrison incremental inverse can be done in  $O(m^2)$



# Least-Squares Temporal-Difference (LSTD)

- Loss func for Batch TD Prediction with data  $[(s_i, r_i, s'_i) | 1 \leq i \leq n]$ :

$$\mathcal{L}(\mathbf{w}) = \frac{1}{2n} \cdot \sum_{i=1}^n (\phi(s_i) \cdot \mathbf{w} - (r_i + \gamma \cdot \phi(s'_i) \cdot \mathbf{w}))^2$$

- The semi-gradient of this Loss function is set to 0 to solve for  $\mathbf{w}^*$

$$\sum_{i=1}^n \phi(s_i) \cdot (\phi(s_i) \cdot \mathbf{w}^* - (r_i + \gamma \cdot \phi(s'_i) \cdot \mathbf{w}^*)) = 0$$

- $\mathbf{w}^*$  is solved as  $\mathbf{A}^{-1} \cdot \mathbf{b}$
- $m \times m$  Matrix  $\mathbf{A}$  is accumulated at each atomic experience  $(s_i, r_i, s'_i)$ :  
 $\mathbf{A} \leftarrow \mathbf{A} + \phi(s_i) \otimes (\phi(s_i) - \gamma \cdot \phi(s'_i))$  (note:  $\otimes$  means Outer-Product)
- $m$ -Vector  $\mathbf{b}$  is accumulated at each atomic experience  $(s_i, r_i, s'_i)$ :

$$\mathbf{b} \leftarrow \mathbf{b} + \phi(s_i) \cdot r_i$$

- Shermann-Morrison incremental inverse can be done in  $O(m^2)$

# LSTD( $\lambda$ )

- Likewise, we can do LSTD( $\lambda$ ) using Eligibility Traces
- Denote the Eligibility Trace of atomic experience  $i$  as  $\mathbf{E}_i$
- Note:  $\mathbf{E}_i$  accumulates  $\nabla_{\mathbf{w}} V(s; \mathbf{w}) = \phi(s)$  in each trace experience
- When accumulating, previous step's eligibility trace discounted by  $\lambda\gamma$

$$\sum_{i=1}^n \mathbf{E}_i \cdot (\phi(s_i) \cdot \mathbf{w}^* - (r_i + \gamma \cdot \phi(s'_i) \cdot \mathbf{w}^*)) = 0$$

- $\mathbf{w}^*$  is solved as  $\mathbf{A}^{-1} \cdot \mathbf{b}$
- $m \times m$  Matrix  $\mathbf{A}$  is accumulated at each atomic experience  $i$ :

$$\mathbf{A} \leftarrow \mathbf{A} + \mathbf{E}_i \otimes (\phi(s_i) - \gamma \cdot \phi(s'_i)) \quad (\text{note: } \otimes \text{ means Outer-Product})$$

- $m$ -Vector  $\mathbf{b}$  is accumulated at each atomic experience  $(s_i, r_i, s'_i)$  as:

$$\mathbf{b} \leftarrow \mathbf{b} + \mathbf{E}_i \cdot r_i$$

- Sherman-Morrison incremental inverse can be done in  $O(m^2)$

# Convergence of Least Squares Prediction Algorithms

On/Off Policy	Algorithm	Tabular	Linear	Non-Linear
On-Policy	MC	✓	✓	✓
	<b>LSMC</b>	✓	✓	-
	TD	✓	✓	✗
	<b>LSTD</b>	✓	✓	-
Off-Policy	MC	✓	✓	✓
	<b>LSMC</b>	✓	✗	-
	TD	✓	✗	✗
	<b>LSTD</b>	✓	✗	-

# Least Squares RL Control

- To perform Least Squares RL Control, we do GPI with:
  - Policy Evaluation as Least-Squares Q-Value Prediction
  - Greedy Policy Improvement
- For MC or On-Policy TD Control, Q-Value Prediction (for policy  $\pi$ ):

$$Q^\pi(s, a) \approx Q(s, a; \mathbf{w}^*) = \phi(s, a) \cdot \mathbf{w}^*$$

- Direct solve for  $\mathbf{w}^*$  using experience data generated using policy  $\pi$
- We are interested in Off-Policy Control with Least-Squares TD
- Using the same idea as Q-Learning and with Experience Replay
- This technique is known as Least Squares Policy Iteration (LSPI)

# Least Squares Policy Iteration (LSPI)

- Each iteration of GPI starts with a function approximation

$$Q(s, a; \mathbf{w}) = \phi(s, a) \cdot \mathbf{w} = \sum_{j=1}^m \phi_j(s, a) \cdot w_j$$

- Deterministic policy  $\pi_D$  (*target policy* for this iteration) is given by:

$$\pi_D(s) = \arg \max_a Q(s, a; \mathbf{w})$$

- Sample mini-batch of experiences  $(s_i, a_i, r_i, s'_i)$  from replay memory  $\mathcal{D}$
- Goal of the iteration is to solve for weights  $\mathbf{w}^*$  to minimize:

$$\begin{aligned} \mathcal{L}(\mathbf{w}) &= \sum_i (Q(s_i, a_i; \mathbf{w}) - (r_i + \gamma \cdot Q(s'_i, \pi_D(s'_i); \mathbf{w})))^2 \\ &= \sum_i (\phi(s_i, a_i) \cdot \mathbf{w} - (r_i + \gamma \cdot \phi(s'_i, \pi_D(s'_i)) \cdot \mathbf{w}))^2 \end{aligned}$$

- Iteration ends by setting the next iteration's start parameters  $\mathbf{w}$  to  $\mathbf{w}^*$

# Least Squares Policy Iteration (LSPI)

- We set the semi-gradient of  $\mathcal{L}(\mathbf{w}^*)$  to 0

$$\sum_i \phi(s_i, a_i) \cdot (\phi(s_i, a_i) \cdot \mathbf{w}^* - (r_i + \gamma \cdot \phi(s'_i, \pi_D(s'_i)) \cdot \mathbf{w}^*)) = 0 \quad (1)$$

- $\mathbf{w}^*$  is solved as  $\mathbf{A}^{-1} \cdot \mathbf{b}$
- $m \times m$  Matrix  $\mathbf{A}$  is accumulated at each experience  $(s_i, a_i, r_i, s'_i)$ :

$$\mathbf{A} \leftarrow \mathbf{A} + \phi(s_i, a_i) \otimes (\phi(s_i, a_i) - \gamma \cdot \phi(s'_i, \pi_D(s'_i)))$$

- $m$ -Vector  $\mathbf{b}$  is accumulated at each experience  $(s_i, a_i, r_i, s'_i)$  as:

$$\mathbf{b} \leftarrow \mathbf{b} + \phi(s_i, a_i) \cdot r_i$$

- Shermann-Morrison incremental inverse can be done in  $O(m^2)$
- This least-squares solution of  $\mathbf{w}^*$  (Prediction) is known as *LSTDQ*
- GPI with LSTDQ and greedy policy improvement known as *LSPI*

# Convergence of Control Algorithms

Algorithm	Tabular	Linear	Non-Linear
MC Control	✓	( ✓ )	✗
SARSA	✓	( ✓ )	✗
Q-Learning	✓	✗	✗
<b>LSPI</b>	✓	( ✓ )	-

( ✓ ) means it chatters around near-optimal Value Function

# LSPI for Optimal Exercise of American Options

- American Option Pricing is Optimal Stopping, and hence an MDP
- So can be tackled with Dynamic Programming or RL algorithms
- But let us first review the mainstream approaches
- For some American options, just price the European, eg: vanilla call
- When payoff is not path-dependent and state dimension is not large, we can do backward induction on a binomial/trinomial tree/grid
- Otherwise, the standard approach is [Longstaff-Schwartz algorithm](#)
- Longstaff-Schwartz algorithm combines 3 ideas:
  - Valuation based on Monte-Carlo simulation
  - Function approximation of continuation value for in-the-money states
  - Backward-recursive determination of early exercise states
- We consider LSPI as an alternative approach for American Pricing



# LSPI as an alternative to Longstaff-Schwartz

- RL is straightforward if we clearly define the MDP
- *State* is [Current Time, History of Underlying Security Prices]
- *Action* is Boolean: Exercise (i.e., Stop) or Continue
- *Reward* always 0, except upon Exercise (= Payoff)
- *State*-transitions based on Underlying Security's Risk-Neutral Process
- Key is function approximation of state-conditioned continuation value
- Continuation Value  $\Rightarrow$  Optimal Stopping  $\Rightarrow$  Option Price
- We customize LSPI to Optimal Exercise of American Options
- Based on [this paper by Li, Szepesvari, Schuurmans](#)

# LSPI customized for American Options Pricing

- 2 actions:  $a = c$  (continue the option) and  $a = e$  (exercise the option)
- Create function approx representation for  $Q(s, a)$  only for  $a = c$  since we know option payoff  $g(s)$  for  $a = e$ , i.e.,  $Q(s, a) = g(s)$

$$\hat{Q}(s, a; \mathbf{w}) = \begin{cases} \phi(s) \cdot \mathbf{w} & \text{if } a = c \\ g(s) & \text{if } a = e \end{cases}$$

for feature funcs  $\phi(\cdot) = [\phi_i(\cdot) | i = 1, \dots, m]$  of only state & not action

- Each iteration starts with  $\mathbf{w}$  defining  $\hat{Q}$  (and it's greedy policy  $\pi_D$ ), and ends by solving for  $\mathbf{w}^*$  setting next iteration's  $\mathbf{w}$  to  $\mathbf{w}^*$
- Since we learn Q-Value function for only  $a = c$ , experience policy  $\mu$  generating experience data for training is a constant function  $\mu(s) = c$
- Also, for American Options, the reward for  $a = c$  is 0
- So each atomic experiences for training is of the form  $(s, c, 0, s')$
- So we represent each atomic experience for training as a 2-tuple  $(s, s')$

# LSPI customized for American Options Pricing

- This reduces LSPI Semi-Gradient Equation (1) to:

$$\sum_i \phi(s_i) \cdot (\phi(s_i) \cdot \mathbf{w}^* - \gamma \cdot \hat{Q}(s'_i, \pi_D(s'_i); \mathbf{w}^*)) = 0 \quad (2)$$

- We need to consider two cases for the term  $\hat{Q}(s'_i, \pi_D(s'_i); \mathbf{w}^*)$ 
  - C1: If  $s'_i$  is non-terminal and  $\pi_D(s'_i) = c$  (i.e.,  $\phi(s'_i) \cdot \mathbf{w} \geq g(s'_i)$ ):  
Substitute  $\phi(s'_i) \cdot \mathbf{w}^*$  for  $\hat{Q}(s'_i, \pi_D(s'_i); \mathbf{w}^*)$  in Equation (2)
  - C2: If  $s'_i$  is a terminal state or  $\pi_D(s'_i) = e$  (i.e.,  $g(s'_i) > \phi(s'_i) \cdot \mathbf{w}$ ):  
Substitute  $g(s'_i)$  for  $\hat{Q}(s'_i, \pi_D(s'_i); \mathbf{w}^*)$  in Equation (2)
- So we can rewrite Equation (2) as:

$$\sum_{i|C1} \phi(s_i) \cdot (\phi(s_i) \cdot \mathbf{w}^* - \gamma \cdot \phi(s'_i) \cdot \mathbf{w}^*) + \sum_{i|C2} \phi(s_i) \cdot (\phi(s_i) \cdot \mathbf{w}^* - \gamma \cdot g(s'_i)) = 0$$

- Factoring out  $\mathbf{w}^*$  and using indicator notation for cases C1, C2:

$$\left( \sum_i \phi(s_i) \otimes (\phi(s_i) - \mathbb{I}_{C1} \cdot \gamma \cdot \phi(s'_i)) \right) \cdot \mathbf{w}^* = \gamma \cdot \sum_i \mathbb{I}_{C2} \cdot \phi(s_i) \cdot g(s'_i)$$

# LSPI customized for American Options Pricing

- This can be written in the familiar vector-matrix notation:  $\mathbf{A} \cdot \mathbf{w}^* = \mathbf{b}$

$$\mathbf{A} = \sum_i \phi(s_i) \otimes (\phi(s_i) - \mathbb{I}_{\phi(s'_i) \cdot \mathbf{w} \geq g(s'_i)} \cdot \gamma \cdot \phi(s'_i))$$

$$\mathbf{b} = \gamma \cdot \sum_i \mathbb{I}_{g(s'_i) > \phi(s'_i) \cdot \mathbf{w}} \cdot \phi(s_i) \cdot g(s'_i)$$

- $m \times m$  Matrix  $\mathbf{A}$  is accumulated at each atomic experience  $(s_i, s'_i)$  as:

$$\mathbf{A} \leftarrow \mathbf{A} + \phi(s_i) \otimes (\phi(s_i) - \mathbb{I}_{\phi(s'_i) \cdot \mathbf{w} \geq g(s'_i)} \cdot \gamma \cdot \phi(s'_i))$$

- $m$ -Vector  $\mathbf{b}$  is accumulated at each atomic experience  $(s_i, s'_i)$  as:

$$\mathbf{b} \leftarrow \mathbf{b} + \gamma \cdot \mathbb{I}_{g(s'_i) > \phi(s'_i) \cdot \mathbf{w}} \cdot \phi(s_i) \cdot g(s'_i)$$

- Sherman-Morrison incremental inverse of  $\mathbf{A}$  can be done in  $O(m^2)$

# Feature functions

- Li, Szepesvari, Schuurmans recommend Laguerre polynomials (first 3)
- Over  $S' = S_t/K$  where  $S_t$  is underlying price and  $K$  is strike
- $\phi_0(S_t) = 1, \phi_1(S_t) = e^{-\frac{S'}{2}}, \phi_2(S_t) = e^{-\frac{S'}{2}} \cdot (1 - S'), \phi_3(S_t) = e^{-\frac{S'}{2}} \cdot (1 - 2S' + S'^2/2)$
- They used these for Longstaff-Schwartz as well as for LSPI
- For LSPI, we also need feature functions for time
- They recommend  
 $\phi_0^{(t)}(t) = \sin(\frac{\pi(T-t)}{2T}), \phi_1^{(t)}(t) = \log(T - t), \phi_2^{(t)}(t) = (\frac{t}{T})^2$

# Deep Q-Learning for American Pricing

- LSPI is data-efficient/compute-efficient, but linearity is a limitation
- Alternative is (incremental) Q-Learning with neural network approx
- We employ the same set up as LSPI (including Experience Replay)

$$\hat{Q}(s, a; \mathbf{w}) = \begin{cases} f(s; \mathbf{w}) & \text{if } a = c \\ g(s) & \text{if } a = e \end{cases}$$

where  $f(s; \mathbf{w})$  is the deep neural network function approximation

- Q-Learning update for each atomic experience  $(s_i, s'_i)$

$$\Delta \mathbf{w} = \alpha \cdot (\gamma \cdot \hat{Q}(s'_i, \pi(s'_i); \mathbf{w}) - f(s_i; \mathbf{w})) \cdot \nabla_{\mathbf{w}} f(s_i; \mathbf{w})$$

- When  $s'_i$  is a non-terminal state, the update is:

$$\Delta \mathbf{w} = \alpha \cdot (\gamma \cdot \max(g(s'_i), f(s'_i; \mathbf{w})) - f(s_i; \mathbf{w})) \cdot \nabla_{\mathbf{w}} f(s_i; \mathbf{w})$$

- When  $s'_i$  is a terminal state, the update is:

$$\Delta \mathbf{w} = \alpha \cdot (\gamma \cdot g(s'_i) - f(s_i; \mathbf{w})) \cdot \nabla_{\mathbf{w}} f(s_i; \mathbf{w})$$

# Key Takeaways from this Chapter

- Batch RL makes efficient use of data
- DQN uses experience replay and fixed Q-learning targets, avoiding the pitfalls of time-correlation and semi-gradient
- LSTD is a direct (gradient-free) solution of Batch TD Prediction
- LSPI is an off-policy, experience-replay Control Algorithm using LSTDQ for Policy Evaluation
- Optimal Exercise of American Options can be tackled with LSPI and Deep Q-Learning algorithms