ECE276B: Planning & Learning in Robotics
Lecture 13: Value Function Approximation

Nikolay Atanasov

natanasov@ucsd.edu

UC San Diego

JACOBS SCHOOL OF ENGINEERING

Electrical and Computer Engineering

Outline

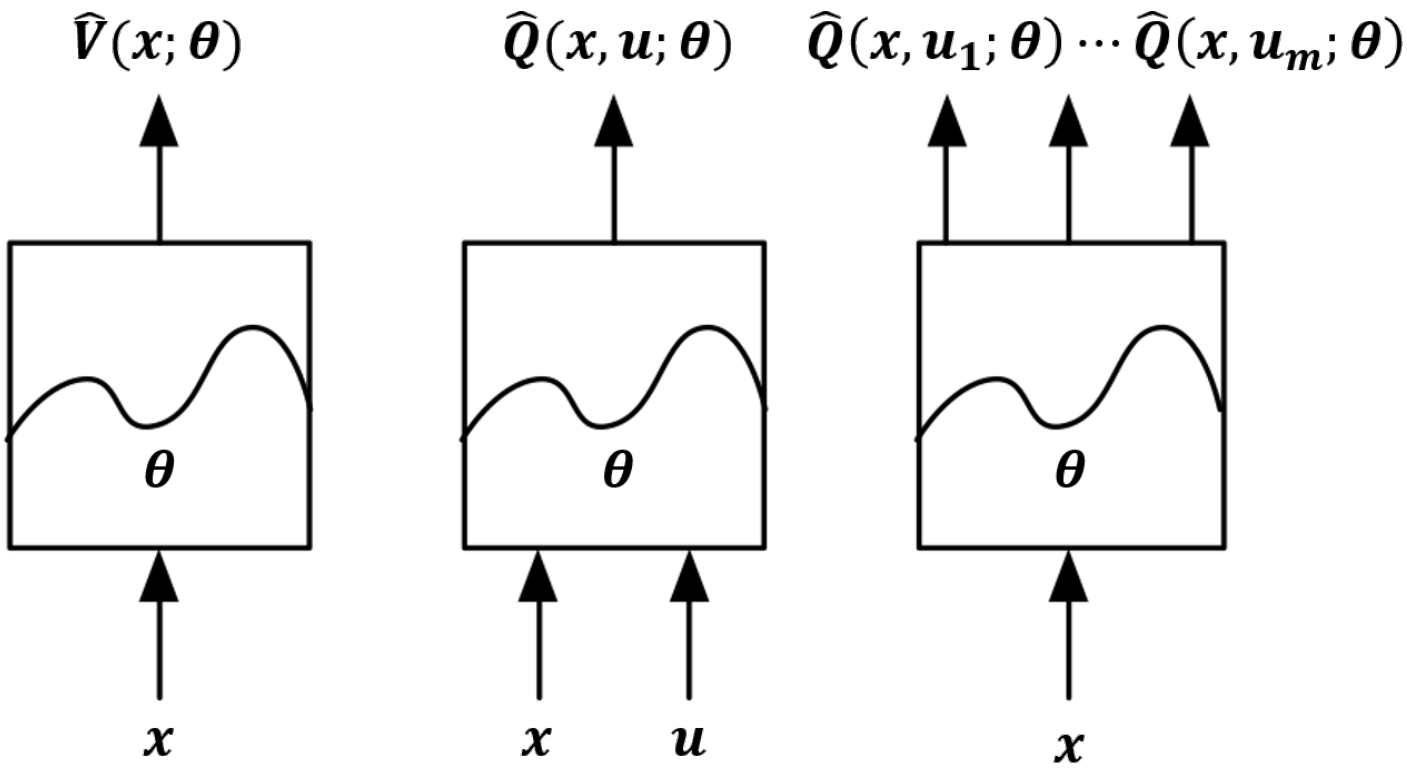
Optimal Control in Large and Infinite Spaces

- So far we have been using a vector to represent the value function:
  - Every state $\mathbf{x}$ has an entry $V^\pi(\mathbf{x})$
  - Every state-control pair $(\mathbf{x}, \mathbf{u})$ has an entry $Q^\pi(\mathbf{x}, \mathbf{u})$
- In very large and continuous state and control spaces:
  - There are too many states and controls to store in memory
  - It is too slow to approximate the value of each state individually
- **Key idea**:
  - Represent the value function using function approximation with parameters $\boldsymbol{\theta}$:

$$V^\pi(\mathbf{x}) \approx \hat{V}(\mathbf{x}; \boldsymbol{\theta}) \qquad Q^\pi(\mathbf{x}, \mathbf{u}) \approx \hat{Q}(\mathbf{x}, \mathbf{u}; \boldsymbol{\theta})$$

  - Update the parameters $\boldsymbol{\theta}$ using MC or TD learning
  - This allows generalization from seen to unseen states and controls

Value Function Approximation



Value Function Approximation

- Many function approximators are possible:
  - Linear combination of features (differentiable)
  - Neural network (differentiable)
  - Fourier / wavelet base (differentiable)
  - Nearest neighbor
  - Decision tree
- A **differentiable** function approximator is necessary to allow parameter updates
- A training method for non-stationary non-iid data is required

Value Approximation via Unconstrained Optimization

- **Main idea**:
  - define a function $J(\boldsymbol{\theta})$ measuring the error between $V^{\pi}(\mathbf{x})$ and $\hat{V}(\mathbf{x};\boldsymbol{\theta})$
  - determine the parameters through an optimization problem:

$$\boldsymbol{\theta}^{*} \in \arg\min_{\boldsymbol{\theta}} J(\boldsymbol{\theta})$$

- Two approaches to solving $\min_{\boldsymbol{\theta}} J(\boldsymbol{\theta})$:
  - **Incremental**: use a (stochastic) descent method:

$$\boldsymbol{\theta}_{k+1} = \boldsymbol{\theta}_k + \alpha_k \delta\boldsymbol{\theta}_k$$

    where $\delta\boldsymbol{\theta}_k$ is a valid descent direction with $\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_k)^{\top} \delta\boldsymbol{\theta}_k < 0$

  - **Batch**: obtain $\boldsymbol{\theta}^{*}$ from the optimality conditions:

$$\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = 0$$

Optimality Conditions

First-order Necessary Condition

Suppose $J(\boldsymbol{\theta})$ is differentiable at $\bar{\boldsymbol{\theta}}$. If $\bar{\boldsymbol{\theta}}$ is a local minimizer, then $\nabla J(\bar{\boldsymbol{\theta}}) = 0$.

Second-order Necessary Condition

Suppose $J(\boldsymbol{\theta})$ is twice-differentiable at $\bar{\boldsymbol{\theta}}$. If $\bar{\boldsymbol{\theta}}$ is a local minimizer, then $\nabla J(\bar{\boldsymbol{\theta}}) = 0$ and $\nabla^2 J(\bar{\boldsymbol{\theta}}) \succeq 0$.

Second-order Sufficient Condition

Suppose $J(\boldsymbol{\theta})$ is twice-differentiable at $\bar{\boldsymbol{\theta}}$. If $\nabla J(\bar{\boldsymbol{\theta}}) = 0$ and $\nabla^2 J(\bar{\boldsymbol{\theta}}) \succ 0$, then $\bar{\boldsymbol{\theta}}$ is a local minimizer.

Necessary and Sufficient Condition

Suppose $J(\boldsymbol{\theta})$ is differentiable at $\bar{\boldsymbol{\theta}}$. If J is **convex**, then $\bar{\boldsymbol{\theta}}$ is a global minimizer **if and only if** $\nabla J(\bar{\boldsymbol{\theta}}) = 0$.

Descent Optimization Methods

Descent Direction Theorem

Suppose $J(\boldsymbol{\theta})$ is differentiable at $\bar{\boldsymbol{\theta}}$. If $\exists\ \delta\boldsymbol{\theta}$ such that $\nabla J(\bar{\boldsymbol{\theta}})^T \delta\boldsymbol{\theta} < 0$, then $\exists\ \epsilon > 0$ such that $J(\bar{\boldsymbol{\theta}} + \alpha\delta\boldsymbol{\theta}) < J(\bar{\boldsymbol{\theta}})$ for all $\alpha \in (0, \epsilon)$.

- The vector $\delta\boldsymbol{\theta}$ is called a **descent direction**
- The theorem states that if a descent direction exists at $\bar{\boldsymbol{\theta}}$, then it is possible to move to a new point that has a lower J value.
- **Descent method**: given an initial guess $\boldsymbol{\theta}_k$, take a step of size $\alpha_k > 0$ along a descent direction $\delta\boldsymbol{\theta}_k$:

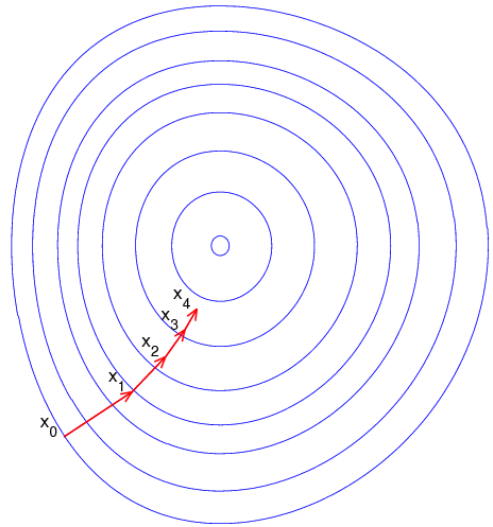
$$\boldsymbol{\theta}_{k+1} = \boldsymbol{\theta}_k + \alpha_k \delta\boldsymbol{\theta}_k$$

Descent Optimization Methods

- Methods differ in the way $\delta\boldsymbol{\theta}_k$ and α_k are chosen:
  - $\delta\boldsymbol{\theta}_k$ should be a descent direction: $\nabla J(\boldsymbol{\theta}_k)^T \delta\boldsymbol{\theta}_k < 0$ for all $\boldsymbol{\theta}_k \neq \boldsymbol{\theta}^*$
  - α_k needs to ensure sufficient decrease in J to guarantee convergence:

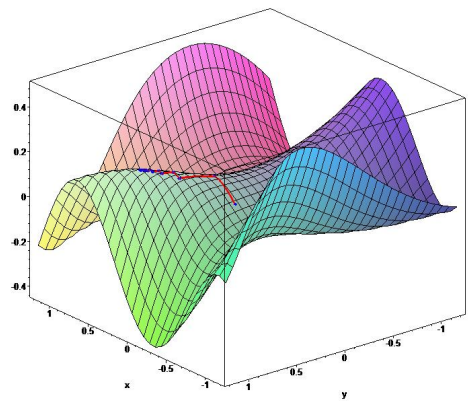
$$\alpha_k^* \in \arg\min_{\alpha>0} J(\boldsymbol{\theta}_k + \alpha\delta\boldsymbol{\theta}_k)$$

    usually obtained via line search



- **Steepest descent direction**: $\delta\boldsymbol{\theta}_k := -\frac{\nabla J(\boldsymbol{\theta}_k)}{\|\nabla J(\boldsymbol{\theta}_k)\|}$
- **Gradient descent**: $\delta\boldsymbol{\theta}_k := -\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_k)$ points in the direction of steepest local descent and we can iterate:

$$\boldsymbol{\theta}_{k+1} = \boldsymbol{\theta}_k - \alpha_k \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}_k)$$



Min Square Error Value Function Approximation

- Find parameters $\boldsymbol{\theta}$ minimizing the mean-square error (MSE) between the true and approximate value function of policy π:

$$J(\boldsymbol{\theta}) = \frac{1}{2}\mathbb{E}\left[\left(V^{\pi}(\mathbf{x}) - \hat{V}(\mathbf{x};\boldsymbol{\theta})\right)^2\right] \quad \text{OR} \quad J(\boldsymbol{\theta}) = \frac{1}{2}\mathbb{E}\left[\left(Q^{\pi}(\mathbf{x},\mathbf{u}) - \hat{Q}(\mathbf{x},\mathbf{u};\boldsymbol{\theta})\right)^2\right]$$

  where the expectation is over the state-control distribution induced by π

- Need to choose:
  - An incremental or batch optimization approach
  - A representation for $\hat{V}(\mathbf{x};\boldsymbol{\theta})$ or $\hat{Q}(\mathbf{x},\mathbf{u};\boldsymbol{\theta})$

Incremental vs Batch optimization

- **Incremental optimization**:
  - **Gradient descent**:

$$\delta\boldsymbol{\theta} = -\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = \mathbb{E}\left[\left(V^{\pi}(\mathbf{x}) - \hat{V}(\mathbf{x};\boldsymbol{\theta})\right)\nabla_{\boldsymbol{\theta}}\hat{V}(\mathbf{x},\boldsymbol{\theta})\right]$$

$$\delta\boldsymbol{\theta} = -\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = \mathbb{E}\left[\left(Q^{\pi}(\mathbf{x},\mathbf{u}) - \hat{Q}(\mathbf{x},\mathbf{u};\boldsymbol{\theta})\right)\nabla_{\boldsymbol{\theta}}\hat{Q}(\mathbf{x},\mathbf{u};\boldsymbol{\theta})\right]$$

  - **Stochastic gradient descent**: uses samples $\mathbf{x}_t, \mathbf{u}_t$ from π rather than computing the exact expectation:

$$\delta\boldsymbol{\theta}_t = \left(V^{\pi}(\mathbf{x}_t) - \hat{V}(\mathbf{x}_t;\boldsymbol{\theta})\right)\nabla_{\boldsymbol{\theta}}\hat{V}(\mathbf{x}_t;\boldsymbol{\theta})$$

$$\delta\boldsymbol{\theta}_t = \left(Q^{\pi}(\mathbf{x}_t,\mathbf{u}_t) - \hat{Q}(\mathbf{x}_t,\mathbf{u}_t;\boldsymbol{\theta})\right)\nabla_{\boldsymbol{\theta}}\hat{Q}(\mathbf{x}_t,\mathbf{u}_t;\boldsymbol{\theta})$$

    The stochastic gradient equals the true gradient in expectation $\mathbb{E}[\delta\boldsymbol{\theta}_t] = \delta\boldsymbol{\theta}$

- **Batch optimization**: the expected update $\mathbb{E}[\delta\boldsymbol{\theta}_t]$ must be zero at the minimizer θ^* of $J(\boldsymbol{\theta})$. Determine $\boldsymbol{\theta}^*$ directly by solving:

$$\mathbb{E}[\delta\boldsymbol{\theta}_t] = 0$$

Linear Value Function Approximation

- Associate state $\mathbf{x}$ with feature vector $\phi(\mathbf{x})$ or state-control pair $(\mathbf{x}, \mathbf{u})$ with feature vector $\phi(\mathbf{x}, \mathbf{u})$, e.g.:
  - kernel distance to n landmarks: $\phi(\mathbf{x}) = [k(\mathbf{x}, \mathbf{x}_1), \ldots, k(\mathbf{x}, \mathbf{x}_n)]^\top$
  - piece and pawn configurations in chess

- Represent the value function by a linear combination of features:

$$\hat{V}(\mathbf{x}; \boldsymbol{\theta}) = \boldsymbol{\theta}^\top \phi(\mathbf{x}) = \sum_j \theta_j \phi_j(\mathbf{x})$$

$$\hat{Q}(\mathbf{x}, \mathbf{u}; \boldsymbol{\theta}) = \boldsymbol{\theta}^\top \phi(\mathbf{x}, \mathbf{u}) = \sum_j \theta_j \phi_j(\mathbf{x}, \mathbf{u})$$

- Example: finite-space representation of $V^\pi(\mathbf{x})$ over $\{\mathbf{x}_1, \ldots, \mathbf{x}_n\}$ is a special case of linear function approximation with $\phi(\mathbf{x}) = [\mathbb{1}_{\{\mathbf{x}=\mathbf{x}_1\}}, \ldots, \mathbb{1}_{\{\mathbf{x}=\mathbf{x}_n\}}]^\top$ and $\boldsymbol{\theta}$ stores the values of the n points: $\hat{V}(\mathbf{x}; \boldsymbol{\theta}) = \sum_j \theta_j \mathbb{1}_{\{\mathbf{x}=\mathbf{x}_j\}}$

Outline

Value Function Approximation

Incremental Methods

Batch Methods

Incremental Prediction for Linear Approximation

- When the value function is represented by a linear combination of features, the objective function $J(\boldsymbol{\theta})$ is quadratic in $\boldsymbol{\theta}$:

$$J(\boldsymbol{\theta}) = \frac{1}{2}\mathbb{E}\left[\left(V^{\pi}(\mathbf{x}) - \boldsymbol{\theta}^{\top}\phi(\mathbf{x})\right)^2\right] \qquad J(\boldsymbol{\theta}) = \frac{1}{2}\mathbb{E}\left[\left(Q^{\pi}(\mathbf{x},\mathbf{u}) - \boldsymbol{\theta}^{\top}\phi(\mathbf{x},\mathbf{u})\right)^2\right]$$

- Stochastic gradient descent converges to a *global* optimum
- A descent direction $\delta\boldsymbol{\theta}_t$ is easy to obtain:

$$\delta\boldsymbol{\theta}_t = \underbrace{\left(V^{\pi}(\mathbf{x}_t) - \hat{V}(\mathbf{x}_t;\boldsymbol{\theta})\right)}_{\text{prediction error}} \underbrace{\phi(\mathbf{x}_t)}_{\text{feature value}}$$

$$\delta\boldsymbol{\theta}_t = \underbrace{\left(Q^{\pi}(\mathbf{x}_t,\mathbf{u}_t) - \hat{Q}(\mathbf{x}_t,\mathbf{u}_t;\boldsymbol{\theta})\right)}_{\text{prediction error}} \underbrace{\phi(\mathbf{x}_t,\mathbf{u}_t)}_{\text{feature value}}$$

Incremental Prediction Algorithms

- The (stochastic) gradient descent for optimizing $\boldsymbol{\theta}$ can be performed only if $V^{\pi}(\mathbf{x})$ is available to compute the prediction error
- In practice, we substitute a *target* for $V^{\pi}(\mathbf{x})$ obtained from noisy samples along an episode $\rho = \mathbf{x}_0, \mathbf{u}_0, \mathbf{x}_1, \mathbf{u}_1, \ldots \sim \pi$:
  - MC: uses a dataset $\mathcal{D} := \{(\mathbf{x}_t, L_t(\rho_t))\}$
  - TD: uses a dataset $\mathcal{D} := \left\{(\mathbf{x}_t, \ell(\mathbf{x}_t, \mathbf{u}_t) + \gamma \hat{V}(\mathbf{x}_{t+1}; \boldsymbol{\theta})\right\}$
  - TD(λ): uses a dataset $\mathcal{D} := \left\{(\mathbf{x}_t, L_t^{\lambda}(\rho_t))\right\}$

Incremental Prediction Algorithms

- **MC**: the target is the return $L_t(\rho_t)$:

$$\delta\boldsymbol{\theta}_t = \Big(L_t(\rho_t) - \hat{V}(\mathbf{x}_t;\boldsymbol{\theta})\Big)\,\nabla_{\boldsymbol{\theta}}\hat{V}(\mathbf{x}_t;\boldsymbol{\theta})$$

- **TD**: the target is the TD target:

$$\delta\boldsymbol{\theta}_t = \Big(\ell(\mathbf{x}_t,\mathbf{u}_t) + \gamma\hat{V}(\mathbf{x}_{t+1};\boldsymbol{\theta}) - \hat{V}(\mathbf{x}_t;\boldsymbol{\theta})\Big)\,\nabla_{\boldsymbol{\theta}}\hat{V}(\mathbf{x}_t;\boldsymbol{\theta})$$

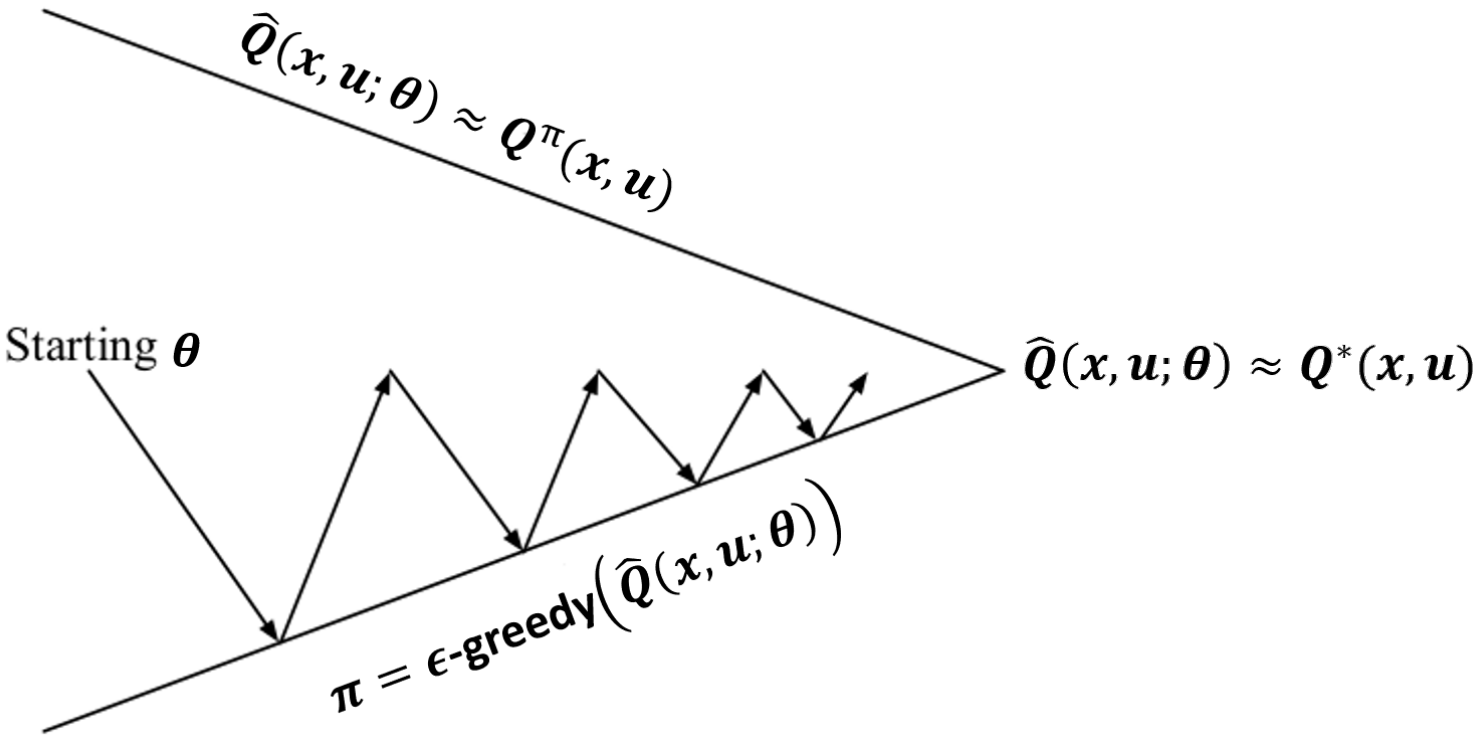
- **Forward-view TD(λ)**: the target is the λ-return $L_t^\lambda(\rho_t)$:

$$\delta\boldsymbol{\theta}_t = \Big(L_t^\lambda(\rho_t) - \hat{V}(\mathbf{x}_t;\boldsymbol{\theta})\Big)\,\nabla_{\boldsymbol{\theta}}\hat{V}(\mathbf{x}_t;\boldsymbol{\theta})$$

- **Backward-view TD(λ)**:

$$\begin{aligned}\delta_t &= \ell(\mathbf{x}_t,\mathbf{u}_t) + \gamma\hat{V}(\mathbf{x}_{t+1};\boldsymbol{\theta}) - \hat{V}(\mathbf{x}_t;\boldsymbol{\theta})\\ \mathbf{e}_t &= \gamma\lambda\mathbf{e}_{t-1} + \nabla_{\boldsymbol{\theta}}\hat{V}(\mathbf{x}_t;\boldsymbol{\theta})\\ \delta\boldsymbol{\theta}_t &= \delta_t\mathbf{e}_t\end{aligned}$$

Control with Value Function Approximation



- **Policy Evaluation**: approximate $Q^{\pi}(\mathbf{x}, \mathbf{u}) \approx \hat{Q}(\mathbf{x}, \mathbf{u}; \theta)$ via stochastic gradient descent
- **Policy Improvement**: ϵ-greedy policy improvement based on $\hat{Q}(\mathbf{x}, \mathbf{u}; \theta)$

Incremental Control Algorithms

- Q-Prediction: we must substitute a *target* for $Q^\pi(\mathbf{x}, \mathbf{u})$
- **MC**:

$$\delta\boldsymbol{\theta}_t = \Big(L_t(\rho) - \hat{Q}(\mathbf{x}_t, \mathbf{u}_t; \boldsymbol{\theta})\Big) \nabla_{\boldsymbol{\theta}} \hat{Q}(\mathbf{x}_t, \mathbf{u}_t; \boldsymbol{\theta})$$

- **TD**:

$$\delta\boldsymbol{\theta}_t = \Big(\ell(\mathbf{x}_t, \mathbf{u}_t) + \gamma \hat{Q}(\mathbf{x}_{t+1}, \mathbf{u}_{t+1}; \boldsymbol{\theta}) - \hat{Q}(\mathbf{x}_t, \mathbf{u}_t; \boldsymbol{\theta})\Big) \nabla_{\boldsymbol{\theta}} \hat{Q}(\mathbf{x}_t, \mathbf{u}_t; \boldsymbol{\theta})$$

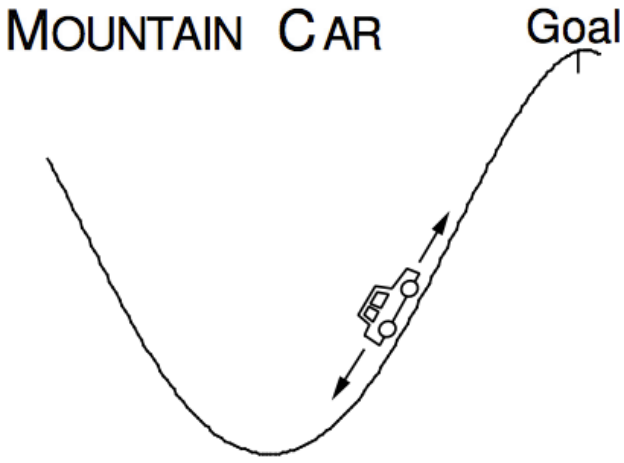
- **Forward-view TD(λ)**:

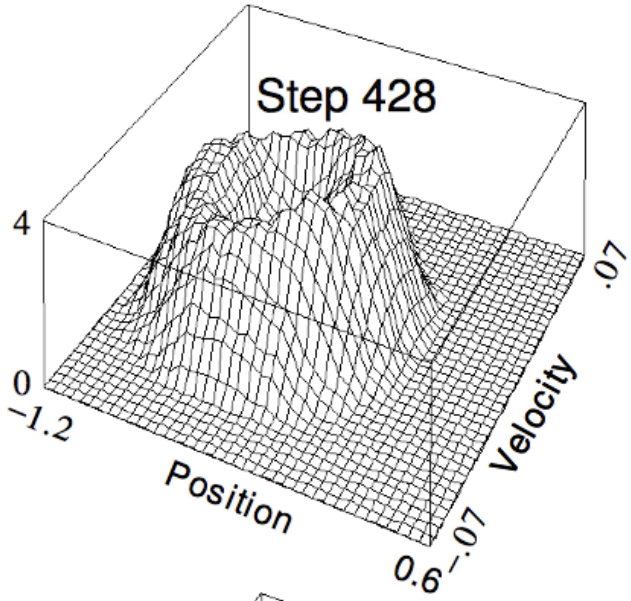
$$\delta\boldsymbol{\theta}_t = \Big(L_t^\lambda(\rho) - \hat{Q}(\mathbf{x}_t, \mathbf{u}_t; \boldsymbol{\theta})\Big) \nabla_{\boldsymbol{\theta}} \hat{Q}(\mathbf{x}_t, \mathbf{u}_t; \boldsymbol{\theta})$$

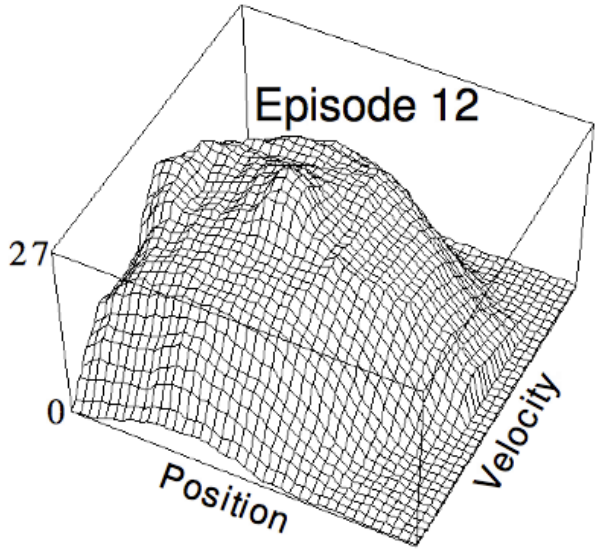
- **Backward-view TD(λ)**:

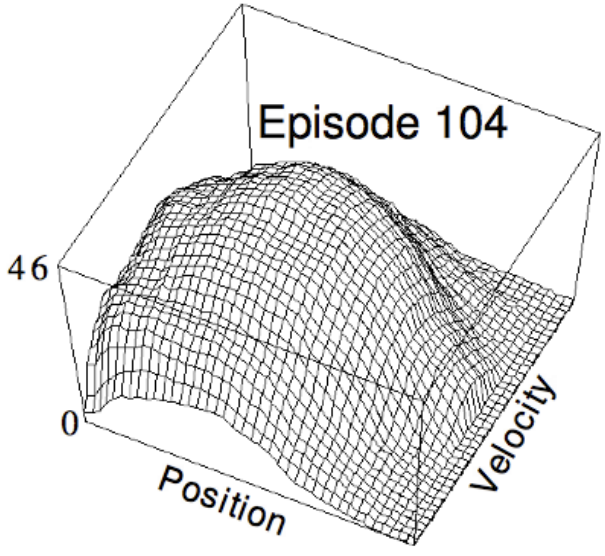
$$\begin{aligned}
\delta_t &= \ell(\mathbf{x}_t, \mathbf{u}_t) + \gamma \hat{Q}(\mathbf{x}_{t+1}, \mathbf{u}_{t+1}; \boldsymbol{\theta}) - \hat{Q}(\mathbf{x}_t, \mathbf{u}_t; \boldsymbol{\theta}) \\
\mathbf{e}_t &= \gamma\lambda \mathbf{e}_{t-1} + \nabla_{\boldsymbol{\theta}} \hat{Q}(\mathbf{x}_t, \mathbf{u}_t; \boldsymbol{\theta}) \\
\delta\boldsymbol{\theta}_t &= \delta_t \mathbf{e}_t
\end{aligned}$$

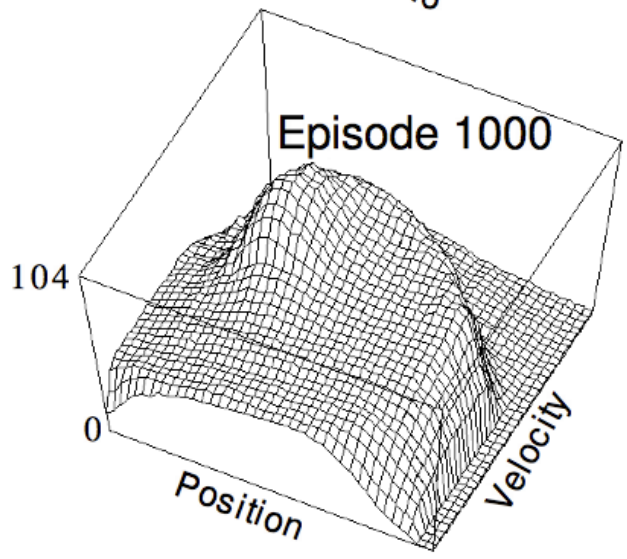
Linear SARSA with Coarse Coding in Mountain Car

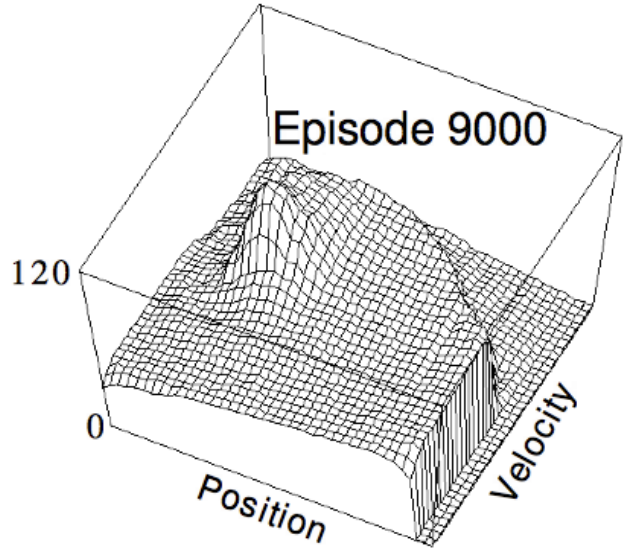












Convergence of Prediction and Control Algorithms

- Model-free Prediction:

Algorithm	Finite Space	Linear	Non-Linear
On-Policy MC	✓	✓	✓
On-Policy TD	✓	✓	✗
Off-Policy MC	✓	✓	✓
Off-Policy TD	✓	✗	✗

  - There is a version of TD that follows the gradient of the projected Bellman error and converges in all cases

- Model-free Control:

Algorithm	Finite Space	Linear	Non-Linear
MC Control	✓	(✓)	✗
SARSA	✓	(✓)	✗
Q-learning	✓	✗	✗

  - (✓) = chatters around a near-optimal value function
  - There is a gradient Q-learning version that converges in the linear case

Outline

Batch Prediction

- **Given**:
  - Value function approximation $\hat{V}(\mathbf{x};\boldsymbol{\theta}) \approx V^{\pi}(\mathbf{x})$
  - Experience $\mathcal{D} := \{(\mathbf{x}_t, V^{\pi}(\mathbf{x}_t))\}$
- **Goal**: find the best fitting value function approximation:

$$\min_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) := \frac{1}{2}\mathbb{E}\left[\left(V^{\pi}(\mathbf{x}) - \hat{V}(\mathbf{x};\boldsymbol{\theta})\right)^2\right] \approx \frac{1}{2}\sum_{\mathbf{x}_t \in \mathcal{D}}\left(V^{\pi}(\mathbf{x}_t) - \hat{V}(\mathbf{x}_t;\boldsymbol{\theta})\right)^2$$

- **Stochastic gradient descent (SGD) with experience replay**:
  1. Sample: $(\mathbf{x}_t, V^{\pi}(\mathbf{x}_t)) \sim \mathcal{D}$
  2. Apply SGD update with $\delta\boldsymbol{\theta}_t = \left(V^{\pi}(\mathbf{x}_t) - \hat{V}(\mathbf{x}_t;\boldsymbol{\theta})\right)\nabla_{\boldsymbol{\theta}}\hat{V}(\mathbf{x}_t,\boldsymbol{\theta})$
  - SGD with experience replay finds the least-squares solution but it may take many iterations
- **Batch method**: the expected update must be zero at the min of $J(\boldsymbol{\theta})$:

$$0 = \mathbb{E}[\delta\boldsymbol{\theta}_t] \approx \sum_{\mathbf{x}_t \in \mathcal{D}}\left(V^{\pi}(\mathbf{x}_t) - \hat{V}(\mathbf{x}_t;\boldsymbol{\theta})\right)\nabla_{\boldsymbol{\theta}}\hat{V}(\mathbf{x}_t,\boldsymbol{\theta})$$

  - Obtain $\boldsymbol{\theta}^*$ directly by solving the above equation

Batch Prediction for Linear Approximation

- When the value function is represented by a linear combination of features $\hat{V}(\mathbf{x};\boldsymbol{\theta}) = \boldsymbol{\theta}^\top \phi(\mathbf{x})$, the function $J(\boldsymbol{\theta})$ is quadratic in $\boldsymbol{\theta}$:

$$J(\boldsymbol{\theta}) = \frac{1}{2}\mathbb{E}\left[\left(V^\pi(\mathbf{x}) - \boldsymbol{\theta}^\top \phi(\mathbf{x})\right)^2\right] \approx \frac{1}{2}\sum_{\mathbf{x}_t \in \mathcal{D}}\left(V^\pi(\mathbf{x}_t) - \boldsymbol{\theta}^\top \phi(\mathbf{x}_t)\right)^2$$

- We can obtain the least squares solution $\boldsymbol{\theta}^*$ directly:

$$0 = \mathbb{E}\left[\delta\boldsymbol{\theta}_t\right] = \sum_{\mathbf{x}_t \in \mathcal{D}}(V^\pi(\mathbf{x}_t) - \boldsymbol{\theta}^\top \phi(\mathbf{x}_t))\phi(\mathbf{x}_t)$$

$$\left(\sum_{\mathbf{x}_t \in \mathcal{D}} \phi(\mathbf{x}_t)\phi(\mathbf{x}_t)^\top\right)\boldsymbol{\theta} = \sum_{\mathbf{x}_t \in \mathcal{D}} V^\pi(\mathbf{x}_t)\phi(\mathbf{x}_t)$$

Linear Least Squares Prediction Algorithms

- We do not know the true values $V^{\pi}(\mathbf{x}_t)$ and must use noisy samples instead
- **Least-squares Monte Carlo**:

$$V^{\pi}(\mathbf{x}_t) \approx L_t(\rho)$$

- **Least-squares Temporal Difference**:

$$V^{\pi}(\mathbf{x}_t) \approx \ell(\mathbf{x}_t, \mathbf{u}_t) + \gamma \hat{V}(\mathbf{x}_{t+1}; \boldsymbol{\theta})$$

- **Least-squares TD**(λ):

$$V^{\pi}(\mathbf{x}_t) \approx L_t^{\lambda}(\rho)$$

- In each case, we can solve directly for the fixed point $\boldsymbol{\theta}^*$

Linear Least-Squares Prediction Algorithms

$$0 = \sum_{t=0}^{T} \alpha \left(L_t(\rho) - \hat{V}(\mathbf{x}_t; \boldsymbol{\theta}) \right) \phi(\mathbf{x}_t)$$

- **LSMC**:

$$\boldsymbol{\theta}^* = \left(\sum_{t=0}^{T} \phi(\mathbf{x}_t) \phi(\mathbf{x}_t)^T \right)^{-1} \sum_{t=0}^{T} \phi(\mathbf{x}_t) L_t(\rho)$$

$$0 = \sum_{t=0}^{T} \alpha \left(\ell(\mathbf{x}_t, \mathbf{u}_t) + \gamma \hat{V}(\mathbf{x}_{t+1}; \boldsymbol{\theta}) - \hat{V}(\mathbf{x}_t; \boldsymbol{\theta}) \right) \phi(\mathbf{x}_t)$$

- **LSTD**:

$$\boldsymbol{\theta}^* = \left(\sum_{t=0}^{T} \phi(\mathbf{x}_t) \left(\phi(\mathbf{x}_t) - \gamma \phi(\mathbf{x}_{t+1}) \right)^\top \right)^{-1} \sum_{t=0}^{T} \phi(\mathbf{x}_t) \ell(\mathbf{x}_t, \mathbf{u}_t)$$

$$0 = \sum_{t=0}^{T} \alpha \left(\ell(\mathbf{x}_t, \mathbf{u}_t) + \gamma \hat{V}(\mathbf{x}_{t+1}; \boldsymbol{\theta}) - \hat{V}(\mathbf{x}_t; \boldsymbol{\theta}) \right) \mathbf{e}_t$$

- **LSTD**(λ):

$$\boldsymbol{\theta}^* = \left(\sum_{t=0}^{T} \mathbf{e}_t \left(\phi(\mathbf{x}_t) - \gamma \phi(\mathbf{x}_{t+1}) \right)^\top \right)^{-1} \sum_{t=0}^{T} \mathbf{e}_t \ell(\mathbf{x}_t, \mathbf{u}_t)$$

Convergence of Linear-Least Squares Prediction Algorithms

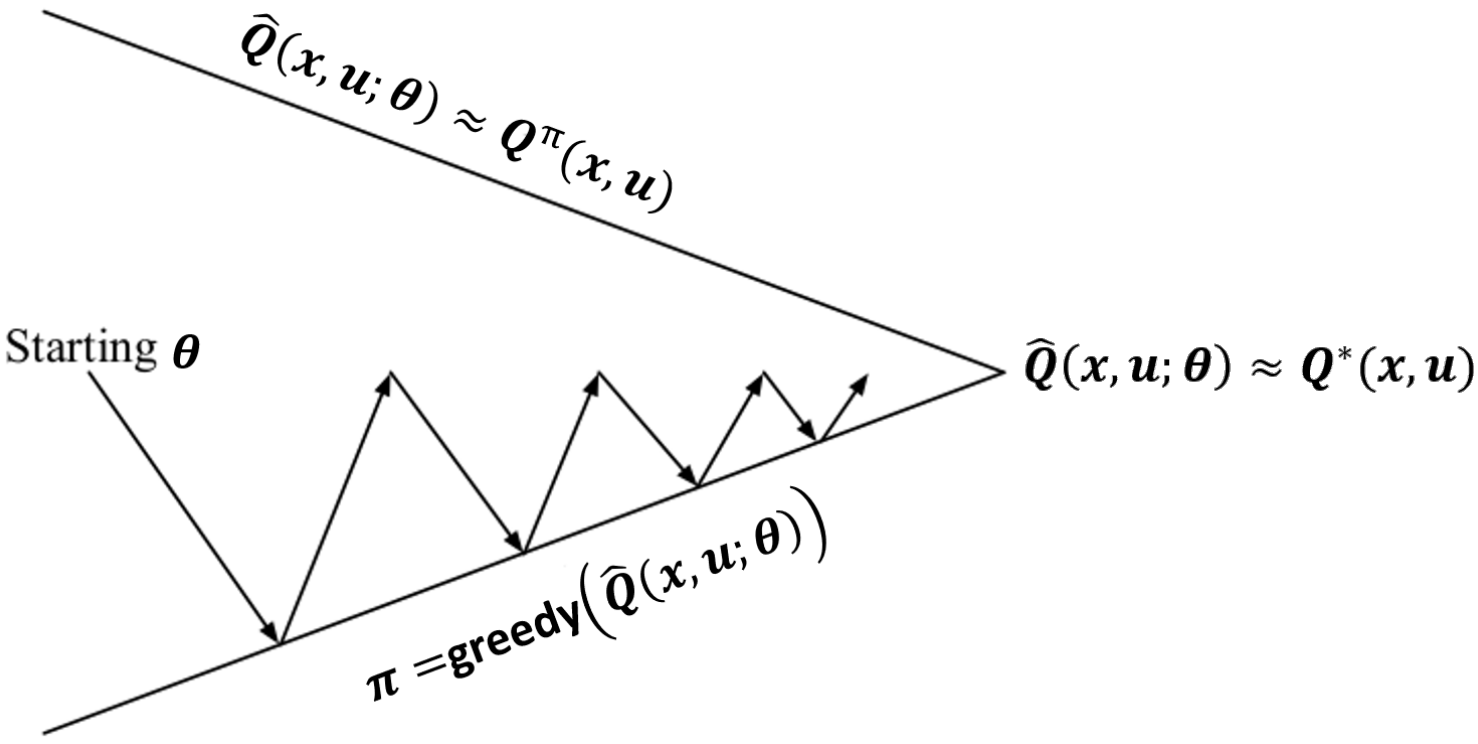
- On-Policy:

Algorithm	Finite Space	Linear	Non-Linear
MC	✓	✓	✓
LSMC	✓	✓	–
TD	✓	✓	✗
LSTD	✓	✓	–

- Off-Policy:

Algorithm	Finite Space	Linear	Non-Linear
MC	✓	✓	✓
LSMC	✓	✓	–
TD	✓	✗	✗
LSTD	✓	✓	–

Least Squares Policy Iteration



- **Policy Evaluation**: least-squares Q estimation using data from old policies
- **Policy Improvement**: does not have to be ϵ-greedy since data from old policies is stored

Least Squares Policy Iteration

- **Policy Evaluation**: efficiently use all experience $\mathcal{D} := \{(\mathbf{x}_t, \mathbf{u}_t, V^\pi(\mathbf{x}_t))\}$ to compute $\hat{Q}(\mathbf{x}, \mathbf{u}; \boldsymbol{\theta}) = \boldsymbol{\theta}^\top \phi(\mathbf{x}, \mathbf{u})$
- Since the policy in PI is changing, the experience is generated from many different policies and we must approximate Q^π using **off-policy** learning
- Instead of importance sampling, use an idea from Q-learning:
  - Use experience: $\mathbf{x}_t, \mathbf{u}_t, \ell(\mathbf{x}_t, \mathbf{u}_t), \mathbf{x}_{t+1} \sim \pi_{old}$
  - With new action: $\mathbf{u}_{t+1} = \pi_{new}(\mathbf{x}_{t+1})$
  - Update $\hat{Q}(\mathbf{x}_t, \mathbf{u}_t; \boldsymbol{\theta})$ towards new action value: $\ell(\mathbf{x}_t, \mathbf{u}_t) + \gamma \hat{Q}(\mathbf{x}_t, \mathbf{u}_{t+1}; \boldsymbol{\theta})$

Least Squares Policy Iteration

- Experience: $\mathbf{x}_t, \mathbf{u}_t, \ell(\mathbf{x}_t, \mathbf{u}_t), \mathbf{x}_{t+1} \sim \pi_{old}$
- Incremental update:

$$\delta\boldsymbol{\theta}_t = \left(\ell(\mathbf{x}_t, \mathbf{u}_t) + \gamma \hat{Q}(\mathbf{x}_{t+1}, \pi(\mathbf{x}_{t+1}); \theta) - \hat{Q}(\mathbf{x}_t, \mathbf{u}_t; \boldsymbol{\theta})\right) \phi(\mathbf{x}_t, \mathbf{u}_t)$$

- **LSTDQ**: least-squares TD Q estimation algorithm using the fact that the expected update must be zero at the minimum of $J(\boldsymbol{\theta})$:

$$0 = \sum_{t=0}^{T} \alpha \left(\ell(\mathbf{x}_t, \mathbf{u}_t) + \gamma \hat{Q}(\mathbf{x}_{t+1}, \pi(\mathbf{x}_{t+1}); \boldsymbol{\theta}) - \hat{Q}(\mathbf{x}_t, \mathbf{u}_t; \boldsymbol{\theta})\right) \phi(\mathbf{x}_t, \mathbf{u}_t)$$

$$\boldsymbol{\theta}^* = \left(\sum_{t=0}^{T} \phi(\mathbf{x}_t, \mathbf{u}_t) \left(\phi(\mathbf{x}_t, \mathbf{u}_t) - \gamma \phi(\mathbf{x}_{t+1}, \pi(\mathbf{x}_{t+1}))\right)^T\right)^{-1} \sum_{t=0}^{T} \phi(\mathbf{x}_t, \mathbf{u}_t) \ell(\mathbf{x}_t, \mathbf{u}_t)$$

Algorithm 1 LSPI-TD

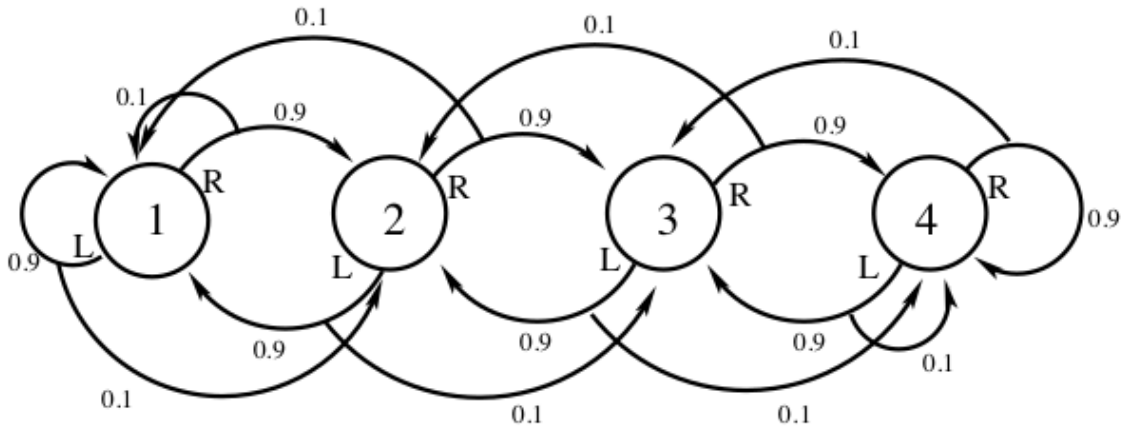
1: **Input**: experience $\mathcal{D}$ and base policy π
2: **loop**
3: $\quad \boldsymbol{\theta}^* \leftarrow$ **LSTDQ**$(\pi, \mathcal{D})$
4: $\quad \pi(\mathbf{x}) \leftarrow \underset{\mathbf{u} \in \mathcal{U}(\mathbf{x})}{\arg\min}\, \hat{Q}(\mathbf{x}, \mathbf{u}; \theta^*)$

Convergence of Control Algorithms

Algorithm	Finite Space	Linear	Non-Linear
MC Control	✓	(✓)	✗
SARSA	✓	(✓)	✗
Q-learning	✓	✗	✗
LSPI-TD	✓	(✓)	–

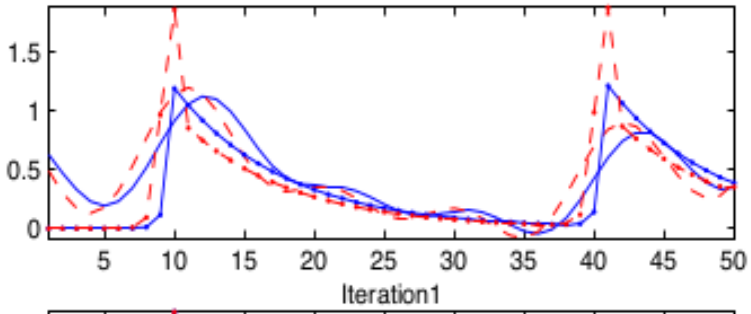
- (✓) = chatters around a near-optimal value function

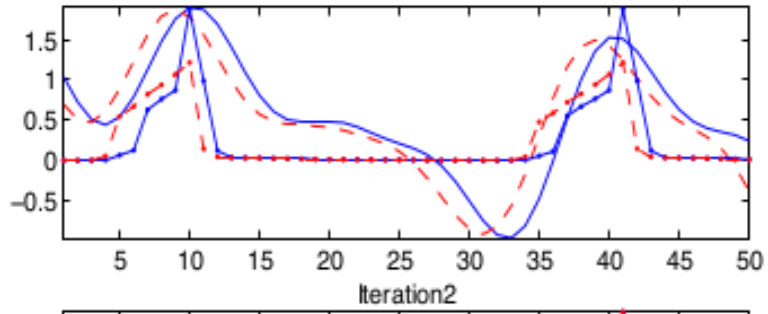
Example: Chain Walk

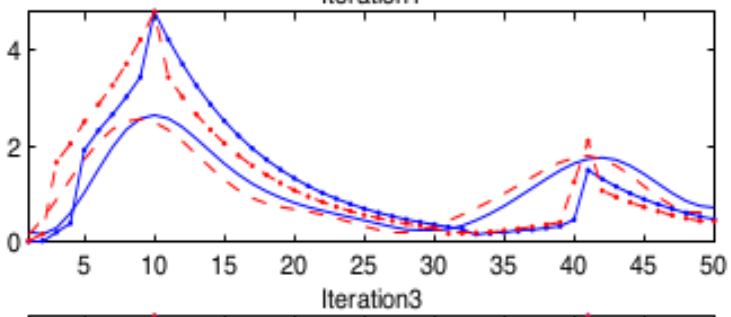


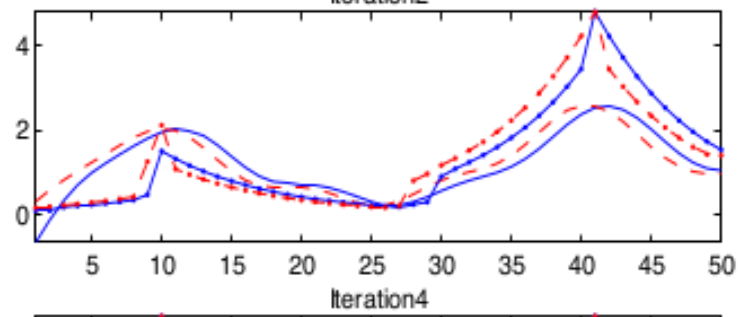
- Consider a 50 state version of the problem
- Cost: -1 in states 10 and 41 and 0 elsewhere
- Optimal policy: $\pi(x) = \begin{cases} R & \text{if } x \in \{1, \ldots, 9\} \cup \{26, \ldots, 41\} \\ L & \text{if } x \in \{10, \ldots, 25\} \cup \{42, \ldots, 50\} \end{cases}$
- Features: 10 evenly spaced Gaussians ($\sigma = 4$) for each control
- Experience: $10,000$ steps from a random walk policy

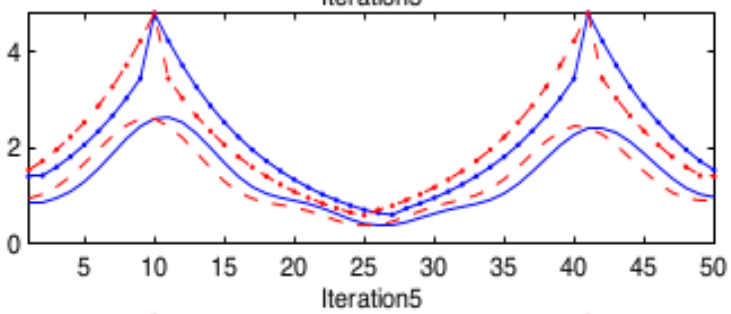
Chain Walk LSPI: Action-Value Function

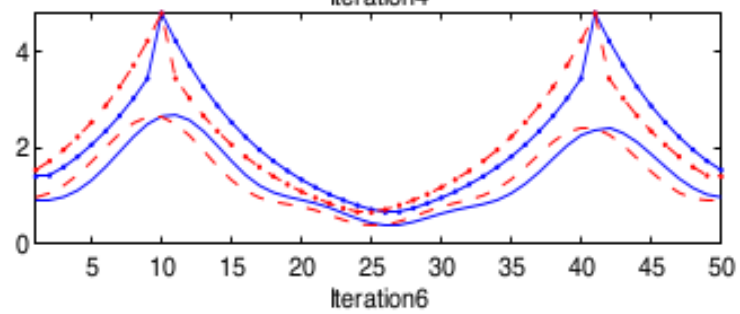


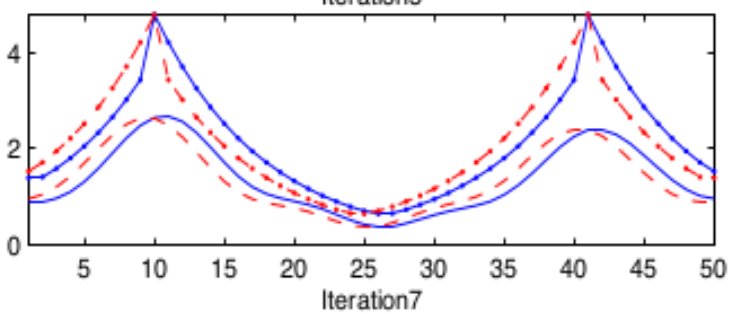






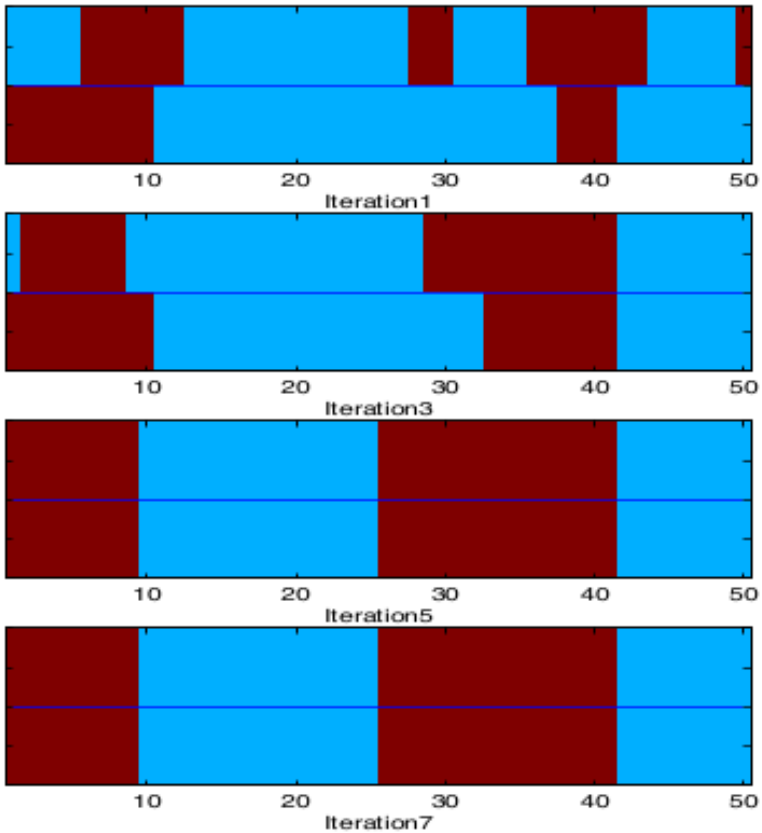


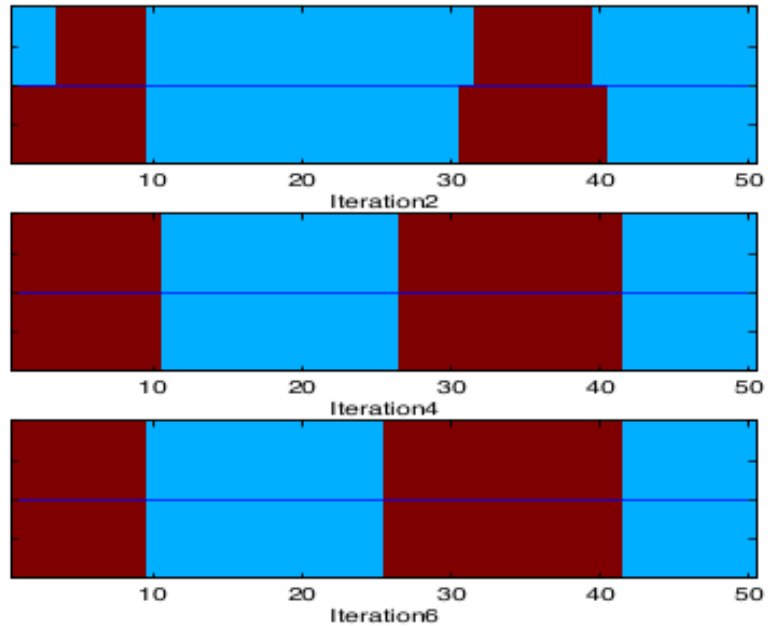




- True (dotted) and approximate (smooth) action-value function
- Left (blue) and right (red) control

Chain Walk LSPI: Policy





- Left (blue) and right (red) control