

## VI extensions

---

6. května 2019

B4M36PUI/BE4M36PUI — Planning for Artificial Intelligence

- Review of MDP concepts
- Value Iteration algorithm
- VI extensions

## Review of last tutorial

---

## Value function of a policy

Look at the following definition of a value function of a policy for infinite-horizon MDP. It contains multiple mistakes, correct them on a piece of paper:

### **Def: Value function of a policy for infinite-horizon MDP**

Assume infinite horizon MDP with  $\gamma \in [0, 100]$ . Then let Value function of a policy  $\pi$  for every state  $s \in S$  be defined as

$$V^\pi(s) = \sum_{s' \in S} R(s, \pi(s), s')R(s, \pi(s), s') + \gamma\pi(s')$$

## Value function of a policy

Look at the following definition of a value function of a policy for infinite-horizon MDP. It contains multiple mistakes, correct them on a piece of paper:

### Def: Value function of a policy for infinite-horizon MDP

Assume infinite horizon MDP with  $\gamma \in [0, 100]$ . Then let Value function of a policy  $\pi$  for every state  $s \in S$  be defined as

$$V^\pi(s) = \sum_{s' \in S} R(s, \pi(s), s')R(s, \pi(s), s') + \gamma\pi(s')$$

$$\gamma \in [0, 1)$$

$$V^\pi(s) = \sum_{s' \in S} T(s, \pi(s), s')[R(s, \pi(s), s') + \gamma V^\pi(s')]$$

## Value function of a policy

Look at the following definition of a value function of a policy for infinite-horizon MDP. It contains multiple mistakes, correct them on a piece of paper:

### Def: Value function of a policy for infinite-horizon MDP

Assume infinite horizon MDP with  $\gamma \in [0, 100]$ . Then let Value function of a policy  $\pi$  for every state  $s \in S$  be defined as

$$V^\pi(s) = \sum_{s' \in S} R(s, \pi(s), s')R(s, \pi(s), s') + \gamma V^\pi(s')$$

$$\gamma \in [0, 1)$$

$$V^\pi(s) = \sum_{s' \in S} T(s, \pi(s), s')[R(s, \pi(s), s') + \gamma V^\pi(s')]$$

---

Question: Difference to def. of an optimal value function?

# Bellman Equations

Write down equations for finding a value function of a policy  $\pi$ . How would you solve these equations?

$$T(S_0, a_0, S_1) = 0.6$$

$$T(S_0, a_0, S_2) = 0.4$$

•  $T : T(S_1, a_1, S_3) = 1$

$$T(S_2, a_2, S_3) = 0.7$$

$$T(S_2, a_2, S_0) = 0.3$$

$$R(S_0, a_0, S_1) = 5$$

$$R(S_0, a_0, S_2) = 2$$

$$R(S_1, a_1, S_3) = 1$$

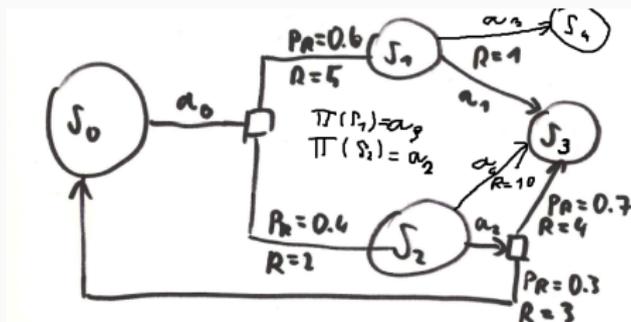
•  $R : R(S_2, a_2, S_3) = 4$

$$R(S_2, a_2, S_0) = 3$$

$$R(S_1, a_3, S_4) = 4$$

$$R(S_2, a_4, S_3) = 10$$

- $S: S_0, S_1, S_2, S_3, S_4$
- $A: a_0, a_1, a_2, a_3, a_4$



## Value Iteration

---

Basic algorithm for finding solution of Bellman Equations iteratively.

1. initialize  $V_0$  arbitrarily for each state, e.g to 0, set  $n = 0$
2. Set  $n = n + 1$ .
3. Compute Bellman Backup, i.e. for each  $s \in S$ :
  - 3.1  $V_n(s) = \max_{a \in A} \sum_{s' \in S} T(s, a, s') [R(s, a, s') + \gamma V_{n-1}(s')]$
4. GOTO 2.

## VI example

Robot Emil-like domain.

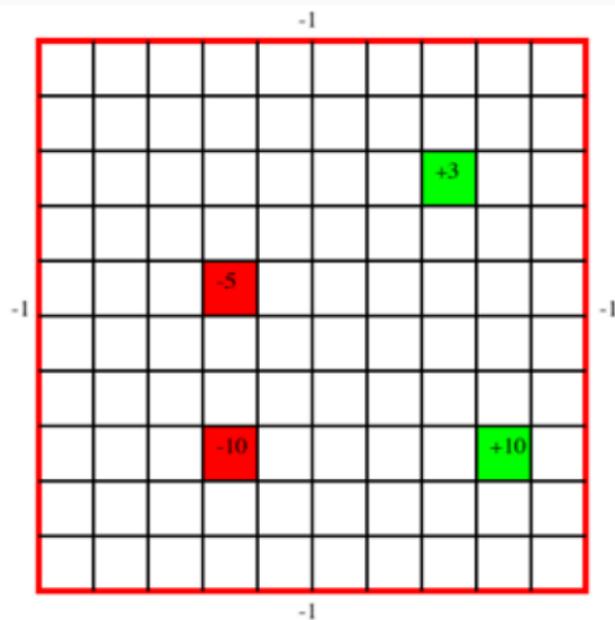
Assuming  $\gamma = 1$ .

Using VI, initializing

$\forall s V_0(s) = 0$ , calculate

$V_1, V_2, V_3$  for the nine states  
around +10 tile.

- Moving into edges gives -1 reward
- Moving onto marked tiles gives corresponding reward



Basic algorithm for finding solution of Bellman Equations iteratively.

1. initialize  $V_0$  arbitrarily for each state, e.g to 0, set  $n = 0$
2. Set  $n = n + 1$ .
3. Compute Bellman Backup, i.e. for each  $s \in S$ :
  - 3.1  $V_n(s) = \max_{a \in A} \sum_{s' \in S} T(s, a, s') [R(s, a, s') + \gamma V_{n-1}(s')]$
4. GOTO 2.

---

Question: Does it converge? How fast? When do we stop?

### Def: Residual

*Residual of value function  $V_n$  from  $V_{n+1}$  at state  $s \in S$  is defined by:*

$$Res^{V_n}(s) = |V_n(s) - V_{n+1}(s)|$$

### Def: Residual

*Residual of value function  $V_n$  from  $V_{n+1}$  at state  $s \in S$  is defined by:*

$$\text{Res}^{V_n}(s) = |V_n(s) - V_{n+1}(s)|$$

*Residual of value function  $V$  from  $V'$  is given by:*

$$\text{Res}^{V_n} = \|V_n - V_{n+1}\|_{\infty} = \max_s |V_n(s) - V_{n+1}(s)|$$

## VI stopping criterion

Stopping criterion: When residual of consecutive value functions is below low value of  $\epsilon$ :

$$\|V_n - V_{n+1}\| < \epsilon$$

However, this does not imply  $\epsilon$  distance of value of greedy policy from optimal value function.

## VI stopping criterion

Stopping criterion: When residual of consecutive value functions is below low value of  $\epsilon$ :

$$\|V_n - V_{n+1}\| < \epsilon$$

However, this does not imply  $\epsilon$  distance of value of greedy policy from optimal value function.

Theorems for general MDP exist of form:

$$V_n, V^* \text{ as above} \implies \forall s \ |V_n(s) - V^*(s)| < \epsilon (\text{Some MDP dependent term})$$

## VI stopping criterion

Stopping criterion: When residual of consecutive value functions is below low value of  $\epsilon$ :

$$\|V_n - V_{n+1}\| < \epsilon$$

However, this does not imply  $\epsilon$  distance of value of greedy policy from optimal value function.

Theorems for general MDP exist of form:

$$V_n, V^* \text{ as above} \implies \forall s |V_n(s) - V^*(s)| < \epsilon (\text{Some MDP dependent term})$$

In case of discounted ( $\gamma < 1$ ) infinite-horizon MDPs:

$$V_n, V^* \text{ as above} \implies \forall s |V_n(s) - V^*(s)| < 2 \frac{\epsilon \gamma}{1 - \gamma}$$

## VI with stopping criterion

1. initialize  $V_0$  arbitrarily for each state, e.g to 0, set  $n = 0$
2. Set  $n = n + 1$ .
3. Compute Bellman Backup, i.e. for each  $s \in S$ :
  - 3.1  $V_n(s) = \max_{a \in A} \sum_{s' \in S} T(s, a, s') [R(s, a, s') + \gamma V_{n-1}(s')]$
  - 3.2 Calculate residual  $Res = \max_{s \in S} |V_n(s) - V_{n-1}(s)|$
4. if  $res > \epsilon$  GOTO 2. else TERMINATE

## VI with stopping criterion

1. initialize  $V_0$  arbitrarily for each state, e.g to 0, set  $n = 0$
  2. Set  $n = n + 1$ .
  3. Compute Bellman Backup, i.e. for each  $s \in S$ :
    - 3.1  $V_n(s) = \max_{a \in A} \sum_{s' \in S} T(s, a, s') [R(s, a, s') + \gamma V_{n-1}(s')]$
    - 3.2 Calculate residual  $Res = \max_{s \in S} |V_n(s) - V_{n-1}(s)|$
  4. if  $res > \epsilon$  GOTO 2. else TERMINATE
- 

Question: What is the policy?

## VI with stopping criterion

1. initialize  $V_0$  arbitrarily for each state, e.g to 0, set  $n = 0$
  2. Set  $n = n + 1$ .
  3. Compute Bellman Backup, i.e. for each  $s \in \mathcal{S}$ :
    - 3.1  $V_n(s) = \max_{a \in A} \sum_{s' \in \mathcal{S}} T(s, a, s') [R(s, a, s') + \gamma V_{n-1}(s')]$
    - 3.2 Calculate residual  $Res = \max_{s \in \mathcal{S}} |V_n(s) - V_{n-1}(s)|$
  4. if  $res > \epsilon$  GOTO 2. else TERMINATE
- 

Question: What is the policy?

- *Greedy policy*  $\pi_n^V$  is the policy given as argmax of  $V_n$ .

- Convergence: VI converges from any initialization (unlike PI)
- Termination: when residual is "small"

- Convergence: VI converges from any initialization (unlike PI)
- Termination: when residual is "small"

---

Question: What are the memory requirements of VI?

- Convergence: VI converges from any initialization (unlike PI)
  - Termination: when residual is "small"
- 

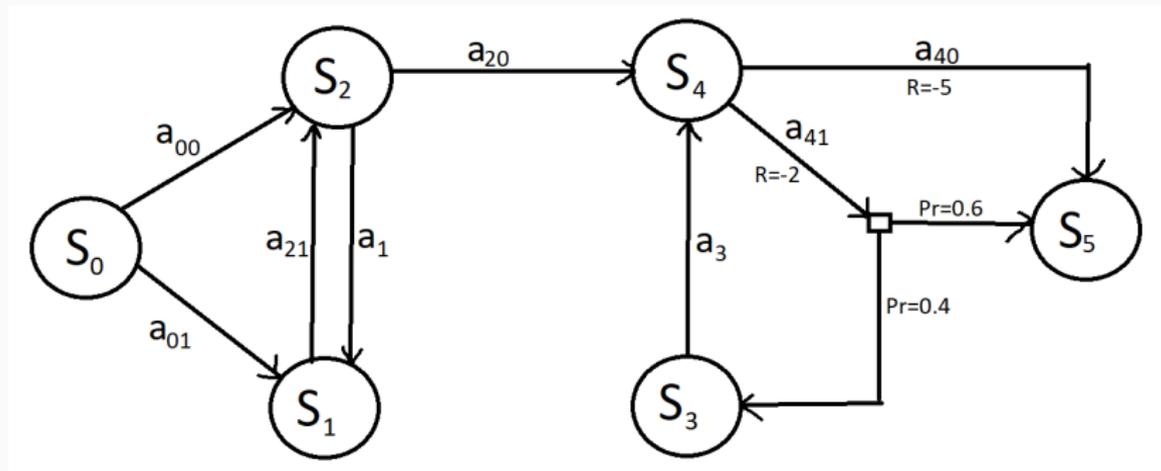
Question: What are the memory requirements of VI?

- Value of each state needs to be stored twice

## VI extensions

---

## Another beautiful MDP example



- All undeclared rewards are -1

**Task:** Initialize VI with negative distance to  $S_5$  and calculate first 3 iterations of VI, with state ordering  $S_0$  to  $S_5$

## Asynchronous VI

1. initialize  $V_0$  arbitrarily for each state, e.g to 0
2. While  $Res^V > \epsilon$ , do:
  - 2.1 pick some state  $s$
  - 2.2 Bellman backup  $V(s) \leftarrow \max_{a \in A} \sum_{s' \in S} T(s, a, s') [R(s, a, s') + \gamma V(s')]$
  - 2.3 Update residual at  $s$   $Res^V(s) = |V_{old}(s) - V_{new}(s)|$

1. initialize  $V_0$  arbitrarily for each state, e.g to 0
  2. While  $Res^V > \epsilon$ , do:
    - 2.1 pick some state  $s$
    - 2.2 Bellman backup  $V(s) \leftarrow \max_{a \in A} \sum_{s' \in S} T(s, a, s') [R(s, a, s') + \gamma V(s')]$
    - 2.3 Update residual at  $s$   $Res^V(s) = |V_{old}(s) - V_{new}(s)|$
- 

Question: Memory requirements compared to VI?

1. initialize  $V_0$  arbitrarily for each state, e.g to 0
  2. While  $Res^V > \epsilon$ , do:
    - 2.1 pick some state  $s$
    - 2.2 Bellman backup  $V(s) \leftarrow \max_{a \in A} \sum_{s' \in S} T(s, a, s') [R(s, a, s') + \gamma V(s')]$
    - 2.3 Update residual at  $s$   $Res^V(s) = |V_{old}(s) - V_{new}(s)|$
- 

Question: Memory requirements compared to VI?

Question: Convergence condition?

- Asymptotic as VI under condition that every state visited  $\infty$  often.

1. initialize  $V_0$  arbitrarily for each state, e.g to 0
  2. While  $Res^V > \epsilon$ , do:
    - 2.1 pick some state  $s$
    - 2.2 Bellman backup  $V(s) \leftarrow \max_{a \in A} \sum_{s' \in S} T(s, a, s') [R(s, a, s') + \gamma V(s')]$
    - 2.3 Update residual at  $s$   $Res^V(s) = |V_{old}(s) - V_{new}(s)|$
- 

Question: Memory requirements compared to VI?

Question: Convergence condition?

- Asymptotic as VI under condition that every state visited  $\infty$  often.

Question: How to pick  $s$  in 2.1?

- Simplest is *Gauss-Seidel VI*, that is run AVI over all states iteratively

How else can we pick states to update? (Ans: by ordering them in clever ways)

- Build priority queue of states to update  $\rightarrow$  *Prioritized Sweeping VI*.  
Update states in the order of the queue. Priority function:

$$\text{priority}_{PS}(s) \leftarrow \max\{\text{priority}_{PS}(s), \max_{a \in A} \{T(s, a, s') \text{Res}^V(s')\}\}$$

How else can we pick states to update? (Ans: by ordering them in clever ways)

- Build priority queue of states to update  $\rightarrow$  *Prioritized Sweeping VI*.  
Update states in the order of the queue. Priority function:

$$\text{priority}_{PS}(s) \leftarrow \max\{\text{priority}_{PS}(s), \max_{a \in A}\{T(s, a, s')Res^V(s')\}\}$$

EXAMPLE ON BOARD

How else can we pick states to update? (Ans: by ordering them in clever ways)

- Build priority queue of states to update  $\rightarrow$  *Prioritized Sweeping VI*.  
Update states in the order of the queue. Priority function:

$$\text{priority}_{PS}(s) \leftarrow \max\{\text{priority}_{PS}(s), \max_{a \in A}\{T(s, a, s')Res^V(s')\}\}$$

EXAMPLE ON BOARD

---

Convergence?

How else can we pick states to update? (Ans: by ordering them in clever ways)

- Build priority queue of states to update  $\rightarrow$  *Prioritized Sweeping VI*.  
Update states in the order of the queue. Priority function:

$$\text{priority}_{PS}(s) \leftarrow \max\{\text{priority}_{PS}(s), \max_{a \in A}\{T(s, a, s')Res^V(s')\}\}$$

EXAMPLE ON BOARD

---

Convergence?

- If all states start with non-zero priority

How else can we pick states to update? (Ans: by ordering them in clever ways)

- Build priority queue of states to update  $\rightarrow$  *Prioritized Sweeping VI*.  
Update states in the order of the queue. Priority function:

$$\text{priority}_{PS}(s) \leftarrow \max\{\text{priority}_{PS}(s), \max_{a \in A}\{T(s, a, s')Res^V(s')\}\}$$

EXAMPLE ON BOARD

---

Convergence?

- If all states start with non-zero priority
- OR If you interleave regular VI sweeps with Prioritized VI

Subdivide state space into partitions. Pre-solve parts independently.

- Example is *Topological VI*

Subdivide state space into partitions. Pre-solve parts independently.

- Example is *Topological VI*

Topological VI:

1. Find acyclic partitioning (by finding strongly connected components in the graph)
2. Run VI in each partition to convergence backward from terminal states

Subdivide state space into partitions. Pre-solve parts independently.

- Example is *Topological VI*

Topological VI:

1. Find acyclic partitioning (by finding strongly connected components in the graph)
2. Run VI in each partition to convergence backward from terminal states

---

Question: Why acyclic partitioning?

Subdivide state space into partitions. Pre-solve parts independently.

- Example is *Topological VI*

Topological VI:

1. Find acyclic partitioning (by finding strongly connected components in the graph)
2. Run VI in each partition to convergence backward from terminal states

---

Question: Why acyclic partitioning?

EXAMPLE ON BOARD