EEE598 Fall 2021 HW3 Jacob Sindorf

Homework 3

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In your submission, please include:

• printout of Matlab scripts (pdf) that you created and .m files

• printout of figures

• discussion and steps as requested

• all printouts (solutions, coding parts, figures and discussions) should be in-

cluded in a SINGLE pdf file.

descriptions to help me follow your reasoning.

Please, be clear, concise and organized, and make sure your hand-writing is readable. Make sure that your Matlab code is clearly organized, and provide sufficient

actor frame sure that your frames could be clearly organized, and provide

10 points total

November 3, 2021 DRAFT

I. INVENTORY CONTROL PROBLEM WITH INFINITE HORIZON DISCOUNTED COST

Consider the same inventory management problem of HW1:

A company needs to manage its inventory levels of a certain product in a warehouse. Assume that the control problem operates at discrete stages $k = 0, 1, 2, \ldots$ For instance, each stage may represent a month, or a year (depends on the application).

At stage k, let $S_k \in \{0, ..., M\}$ be the current inventory level at the warehouse, and M be the maximum amount of products that can be stocked at the warehouse.

The company refills its inventory only when its inventory level reaches 0.

During stage k, D_k items are purchased from customers (demand). It follows a probability distribution $P(\cdot)$, independent and identically distributed (i.i.d.) over stages, so that P(d) is the probability that $D_k = d$ items are purchased by costumers in stage k.

The cost for the company to purchase each unit is c. The revenue to the company for each unit sold is r. However, due to finite inventory, some of the requests may not be met. In this case, each unit of unsatisfied requests incur a penalty of p. Finally, the cost of maintaining the inventory is m per unit per stage.

Assumptions on the sequence of events:

- 1 The stock level is S_k at the beginning of stage k
- 2 Then, the maintenance cost is incurred
- 3 Then, U_k new units are purchased, if necessary (based on the policy outlined earlier)
- 4 Then, D_k units of demand occur. We assume that D_k is uniform in $\{0, \ldots, M\}$, so that $P(D_k = d) = 1/(M+1), \ \forall d = 0, 1, \ldots, M$.
 - 5 After the demand is processed, stage k terminates and the new one begins.

November 3, 2021 DRAFT

Do the following with Matlab, for a scenario with $M=20,\,c=1,\,r=2,\,p=1,$ m = 0.5 (same as HW1):

1) [4 points] Implement an algorithm to compute the infinite horizon discounted expected profit:

$$V(i) \triangleq \mathbb{E}\left[\left(\sum_{k=0}^{\infty} \gamma^k p_k\right) | S_0 = i\right],$$

where p_k is the profit at the kth stage (function of current state S_k , action U_k , and demand D_k), $\gamma = 0.9$ is the discount factor. Either policy iteration or (wed in this value iteration are fine, it is up to you. report)

Plot the optimal policy as a function of the state, and the optimal value function (two distinct plots).

Code Losic

Polity iteration

-: newalize
$$\mu^{(o)}$$
 as lazy policy $\mu(o) = M$
 $\mu(i) = M$

Polity Evaluation

 $V_{\mu(i)} = \overline{C(i_{\mu}(i))} + \overline{Y} \in P_{i_{\mu}(i_{\mu})} V_{\mu(i_{\mu})}; \forall i$
 $\overline{C(i_{\mu}(i))} = \frac{1}{M+1} \underbrace{\sum_{i=0}^{M} Cost(i_{i_{\mu}}u_{i_{i_{\mu}}})}_{C(i_{\mu}u_{i_{\mu}})} (from HW1)$

Shord in a struct

 $Clinevals(i)$, $C(\mu(i))$
 $i \xrightarrow{i}$

Prob. Matrix in Sharet, (from HW1)

pmat (His). m(ij)

-) pulls apprepriate value sives action and state

· Polis Improvement

·Check

Mnew = Moid?

yes, openal solution found

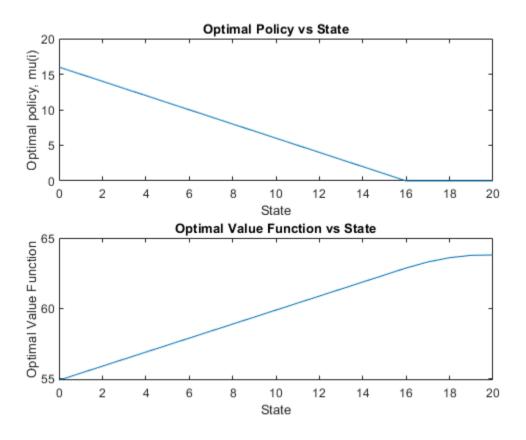
No

Mold = Mach, loop aga:n

```
%Constants
M = 20:
c = 1; r = 2; p = 1; m = .5;
qamma = .9;
%Initial Policy = Lazy Policy
mu = zeros(1,M+1);
mu(1) = M;
%Get all possible Pj|i,u and cline values
pmat = pmatcalc(M);
clinevals = clinecalc(M);
%Policy Evaluation
%Policy Evaluation
Vmu(i) = cline(i, mu(i)) + qamma*(sumj (Pj|i, mu(i)) * Vmu(j))
%Simplify to Vmu = (I - gamma*Pmu)^-1 * Clinemu
          %iteration count
converge = 0; %once optimal is found, break the policy eval/improve
while converge == 0
   %Build Pmu and clinemu
   %Need to build Pmu/clinemu based on optimal policy.
   %Per i and mu(i), take the entire row corresponding to it from
pmat
   %take the value for clinevals
   for i = 1:M+1
      Pmu(i,:) = pmat(mu(i)+1).m(i,:); %to idex the actions, have
to add one
      %0-20 or 1-21.
      clinemu(i) = clinevals(i).c(mu(i)+1);
   end
   Vmu = inv(eye(M+1) - gamma.*Pmu);
   Vmu = Vmu*clinemu';
   %Policy Improvement
   %iloop
   for i = 0:M
      %u loop
      %get max value over all actions
      for u = 0:(M-i) %can't do every action with every state
         %j loop
         %get sum Pj|i,u Vmu(j)
         for j = 1:M+1
```

```
jloop(j) = pmat(u+1).m(i+1,j)*Vmu(j);
          %end jloop
          end
          uloop(u+1) = clinevals(i+1).c(u+1) + gamma*sum(jloop);
          %end u loop
       end
       [Vmunew(i+1), munew(i+1)] = max(uloop);
       %end i loop
   end
   munew = munew - 1; %Take care of 1 index
   %Policy check
   if munew == mu
       converge = 1; %break while loop
   else
       %didn't converge, go again
       mu = munew;
       iter = iter + 1;
   end
end
fprintf('optimal policy: \n');
states = [0:1:M];
subplot(2,1,1)
plot(states, mu);
xlabel('State')
ylabel('Optimal policy, mu(i)')
title('Optimal Policy vs State')
subplot(2,1,2)
plot(states, Vmunew);
xlabel('State')
ylabel('Optimal Value Function')
title('Optimal Value Function vs State')
optimal policy:
mu =
 Columns 1 through 13
                                                   7
                                               8
   16
         15
              14
                   13
                        12
                              11
                                   10
 5
 Columns 14 through 21
```

3 2 1 0 0 0 0 0



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```
%Generate Pmatrix based on action
%store in a struct
%FROM HW1
function [pmat] = pmatcalc(M)
delta = .00001;
pmat = struct('m',{}); %structre to hold possible Prob matricies
%matrix based on action, so go from 0 to M for action (1 to M+1 index)
for a = 1:M+1 %(0 to M), go through all possble actions to make M prob
matricies
   Probmat = zeros(M+1-(a-1),M+1); %initalize based on action
     %note, i goes from 0 to M, but action cannot exceed next state.
     %thus limit i based on action as we technically look at i+a to
용
get j
용
     %so this excludes impossible actions
용
     (ex: M=3, a=1, i\sim=3 as i + a > M, so exlude row M (3),
용
     giving an (3+1-1,3+1) or (3,4) matrix
   for i = 1:size(Probmat,1)
       for j = 1:M+1
           if j > i
             if (j-1) > (i+a-2)% matlab is 1 index so scale
                 Probmat(i,j) = 0;
             else \%j <= (i-1) + (a-1)
                 Probmat(i,j) = (1/(M+1));
             end
           else %j<=i
               if j ~= 1
                  Probmat(i,j) = (1/(M+1));
              else %j == 1
                  Probmat(i,j) = ((M+1-(i-1)-(a-1))/(M+1));
               end
           end
       end
   end
     if abs(sum(Probmat(i,:)) - 1) > delta %make sure row sums to 1
           fprintf('error'); %if not show where it messed up
     end
   pmat(a).m = Probmat;
end
end
```

```
%Generate expected cost cline(i,u)
%store in a struct
%FROM HW1
function [clinevals] = clinecalc(M)
clinevals = struct('c',{});
%constants
c = 1; r = 2; p = 1; m = .5;
for j=0:M
               clinetemp = zeros(1,(M+1-j));
               for a = 0:M-j
                              costpk = zeros(1,a+1);
                              for d = 0:M
                                                                                       %find cost based on demand d, state j, and
    action a
                                              if d > (j+a)
                                                            costpk(1,d+1) = -(j)*m -c*a + (j+a)*r - p*(d - (j+a)*r - 
+a));
                                              else
                                                             costpk(1,d+1) = -(j)*m - c*a + d*r;
                                              end
                              end
                              costpksum = sum(costpk); %sum each row and multiply by prob
                              cline = (1/(M+1))*costpksum;
                              clinetemp(1,a+1) = cline;
               end
               clinevals(j+1).c = clinetemp;
end
end
```

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2) [3 point] For the optimal policy you have just found, implement a *direct approximation algorithm* to compute an approximate value function. One way to generate features is to use polynomials. So, for instance, $\phi(i) = [1, i, i^2, \dots, i^{F-1}]^{\top}$ may be used as the feature vector for the inventory level i, where F is the number of features. For our problem, we are going to use only two features, that is, the following feature vector

$$\boldsymbol{\phi}(i) = [1, i]^{\top}.$$

Recall that the approximated value function is expressed in state i as

$$\tilde{V}(i) = \boldsymbol{\phi}(i)^{\top} \cdot \mathbf{r}^*$$

where in direct approximation \mathbf{r}^* is found by minimizing the squared error between the true value function and its approximation, and is obtained as

$$\mathbf{r}^* = (\Phi \cdot \Pi \cdot \Phi^\top)^{-1} \cdot \Phi \cdot \Pi \cdot \mathbf{V}$$

where V is the true value function vector (under the optimal policy); Φ is the feature matrix; Π is a diagonal matrix with diagonal elements $[\Pi]_{i,i} = \pi(i)$ (the steady-state distribution of state i).

The algorithm should return both \mathbf{r}^* and the approximated value function vector \tilde{V}

Code Logic

$$\mathbf{A} \big) \qquad \mathbf{r}^* = (\boldsymbol{\Phi} \cdot \boldsymbol{\Pi} \cdot \boldsymbol{\Phi}^\top)^{-1} \cdot \boldsymbol{\Phi} \cdot \boldsymbol{\Pi} \cdot \mathbf{V}$$

$$\tilde{V}(i) = \boldsymbol{\phi}(i)^{\top} \cdot \mathbf{r}^*$$

```
%Constants
M = 20:
c = 1; r = 2; p = 1; m = .5;
qamma = .9;
%Get all possible Pj|i,u and cline values
pmat = pmatcalc(M);
clinevals = clinecalc(M);
%Optimal policy from question 1
\texttt{mustar} = [16 \ 15 \ 14 \ 13 \ 12 \ 11 \ 10 \ 9 \ 8 \ 7 \ 6 \ 5 \ 4 \ 3 \ 2 \ 1 \ 0 \ 0 \ 0 \ 0
 01;
%Get Phi
phi = ones(2,M+1);
for i = 0:M
  phi(2,i+1) = i;
end
%Build Pmu and clinemu
%Need to build Pmu/clinemu based on optimal policy.
%Per i and mu(i), take the entire row corresponding to it from pmat
%take the value for clinevals
for i = 1:M+1
  Pmu(i,:) = pmat(mustar(i)+1).m(i,:); %to idex the actions, have
to add one
     %0-20 or 1-21.
  clinemu(i) = clinevals(i).c(mustar(i)+1);
end
%Get V
V = inv(eye(M+1) - gamma.*Pmu)*clinemu';
%Get PI
onerow = ones(M+1,1);
w = [(eye(M+1) - Pmu) onerow];
pivals = onerow' *inv(w*w');
PI = diag(pivals);
%Get rstar
rstar = inv(phi*PI*phi')*phi*PI*V;
```

```
%Get Vtil
for i = 1:M+1
  Vtil(i) = phi(:,i)'*rstar;
end
fprintf('r and Vtilda values: \n');
rstar
Vtil
r and Vtilda values:
rstar =
  54.8571
   0.5000
Vtil =
 Columns 1 through 7
  54.8571 55.3571 55.8571 56.3571 56.8571 57.3571 57.8571
 Columns 8 through 14
  58.3571 58.8571 59.3571 59.8571
                               60.3571
                                       60.8571
                                              61.3571
 Columns 15 through 21
  61.8571 62.3571 62.8571 63.3571 63.8571
                                       64.3571
                                              64.8571
```

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- 3) [3 point] Note that, to compute r*, we need to have the steady-state distribution (Π) and the value function (V), which defeats the purpose of approximation methods! To solve this issue, implement a Monte-Carlo method to estimate r*, without the need to know Π nor V, and without the need to operate with large dimensional vectors. Specifically, implement the online algorithm specified in the class notes (to do so, you will need to simulate the dynamics of the systems, i.e., a sequence of states, controls, demands, and profits, as already done in HW1):
 - 0 Initialize $S_0=0,\,k=0;\,\mathbf{y}_{-1}=\mathbf{0},\,\mathbf{B}_0=\mathbf{0},\,\mathbf{w}_0=\mathbf{0}.$ Then, for $k\geq 0$ do:
 - 1 Collect the state sample S_k , generate the action U_k (based on the optimal policy), the demand D_k randomly, and profit p_k (function of S_k, U_k, D_k);
 - 2 Compute the feature vector $\phi(S_k)$
 - 3 Update

$$\mathbf{y}_k = \gamma \mathbf{y}_{k-1} + \boldsymbol{\phi}(S_k).$$

$$\mathbf{B}_{k+1} = \left(1 - \frac{1}{k+1}\right) \mathbf{B}_k + \frac{1}{k+1} \boldsymbol{\phi}(S_k) \boldsymbol{\phi}(S_k)^{\top}$$

$$\mathbf{w}_{k+1} = \left(1 - \frac{1}{k+1}\right) \mathbf{w}_k + \frac{1}{k+1} \mathbf{y}_k C_k$$

Estimate r* as

$$\mathbf{r}_{k+1}^{(est)} = \mathbf{B}_{k+1}^{-1} \mathbf{w}_{k+1}$$

4 – Update the state and proceed to the next stage k+1

Do this process for $K = 10^5$ timesteps. At each k, compute the error metric

$$\operatorname{error}(k) = \frac{\|\mathbf{r}_{k+1}^{(est)} - \mathbf{r}^*\|_2^2}{\|\mathbf{r}^*\|_2^2}$$

(for a vector \mathbf{x} , $\|\mathbf{x}\|_2^2 = \sum_i \mathbf{x}_i^2$, i.e, the sum of the square of all its elements).

Plot error(k) versus k, and discuss what you observe.

Plot the true value function V(i), the approximated value function $\tilde{V}(i) = \phi(i)^{\top} \cdot \mathbf{r}^{*}$, and the one approximated via Monte-Carlo method, $\phi(i)^{\top} \cdot \mathbf{r}^{(est)}_{K}$ (at termination of the Monte-Carlo simulation), vs i. Discuss what you observe. In particular, discuss the quality of the approximation in states 17-20. How can you explain what you see? *Hint:* think about the error metric that is used to find \mathbf{r}^{*} :

$$\mathbf{r}^* = \arg\min_{\mathbf{r}} \sum_{i \in \mathcal{S}} \pi(i) (\mathbf{V}(i) - \boldsymbol{\phi}(i)^{\top} \mathbf{r})^2$$

Code Logic

O- Simulate States, costs, durands (for W=10⁵)

with So=0 143ing M*

initiative y=0 Bo=0 wo=0

$$\Gamma_0=0 \quad (B_0^{-1}w_0=0)$$

for
$$K\ge0$$

1- Jet Su, Uu, Du, Cu from calculated sequence
2- Compute $\Phi(\operatorname{Su})$ $\phi(i)=[1,i]^{\top}$. (with $\dot{i}=\operatorname{Su}$)

$$\mathbf{3} - \mathbf{u} \rho \mathbf{d} \mathbf{q} \mathbf{f} \mathbf{c}$$

$$\mathbf{y}_k = \gamma \mathbf{y}_{k-1} + \phi(S_k).$$

$$\mathbf{B}_{k+1} = \left(1 - \frac{1}{k+1}\right) \mathbf{B}_k + \frac{1}{k+1} \phi(S_k) \phi(S_k)^{\top}$$

$$\mathbf{w}_{k+1} = \left(1 - \frac{1}{k+1}\right) \mathbf{w}_k + \frac{1}{k+1} \mathbf{y}_k C_k$$

Y- Jet new dext
$$\mathbf{r}_{k+1}^{(est)} = \mathbf{B}_{k+1}^{-1}\mathbf{w}_{k+1}$$

$$\operatorname{error}(k) = \frac{\|\mathbf{r}_{k+1}^{(est)} - \mathbf{r}^*\|_2^2}{\|\mathbf{r}^*\|_2^2} \quad - \quad \text{ for error}$$

(for a vector \mathbf{x} , $\|\mathbf{x}\|_2^2 = \sum_i \mathbf{x}_i^2$, i.e, the sum of the square of all its elements).

5- Now
$$g_{k} = g_{k+1}$$
 old = new (updak homs)

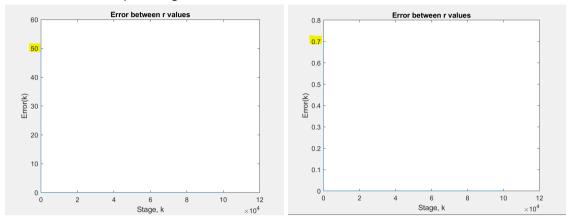
 $g_{k} = g_{k}$
 g_{k+1}

6- loop h= 105 times

$$\bigvee_{MC} (i) = \phi(i)^{\top} \cdot \mathbf{r}_{K}^{(est)}$$

Error Discussion

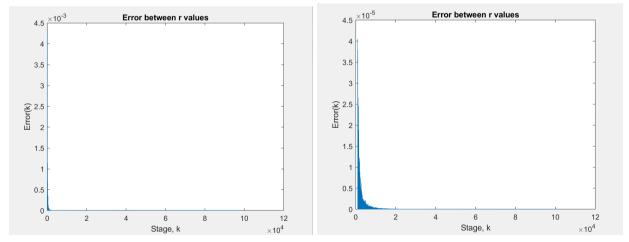
We can see that the range of error is very high within the first very few timesteps. That being within the first 10-20 timesteps, the error is much much higher than the rest of the runs. Sometimes the error was as high as 50, other times it was around .7 at max. This is due to the randomness in sequence generation.



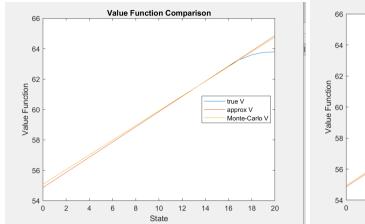
Results show That usually within the first four steps, the error calculation usually has issues. With values of inf and NaN due to singular inverse of Bk. So to fix this I just set the first four to zero.

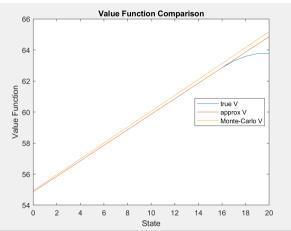


Error is easier to see when we skip the beginning. This graph shows errors after 100 timesteps. It is already to the -3 power in size and still decreases to a very very small number. The graph next to it is after 1e3 timesteps and still continues to decrease to basically zero.



The error has issues in the beginning but quickly converges to around zero.

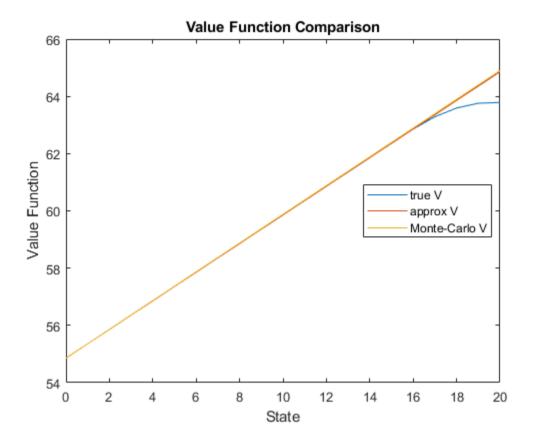




Due to randomness, the Monte Carlo simulation sometimes was about the same as the approximate V, and other times it was either just higher or lower than the approximate. Both however follow the same trend of a linear line from around 55 to 65. Both also diverge from the true V around 17, as this value slopes to a constant. Essentially, we are approximating V with a linear approximation, which is why it keeps a linear trend. It would be difficult for it to follow the quick convergence onto a number as the true value does around 17-20.

```
%Constants
M = 20:
c = 1; r = 2; p = 1; m = .5;
qamma = .9;
%Stages to simulate
K = 1e5:
%Optimal policy from question 1
mustar = [16 15 14 13 12 11 10 9 8 7 6 5 4 3 2 1 0 0 0 0
 0];
%Generate sequences
[dseq, Useq, Sseq, cseq] = generateseq(K,M,mustar);
%Initialize
yk = [0;0]; Bk = zeros(2); wk = [0;0];
rest = [0;0];
%k loop K>0 (here 1) so start at 2
for k = 2:K+1
%Compute phi
phi = [1, Sseq(k)]';
%Update
yknew = gamma*yk + phi;
Bknew = (1 - (1/(k+1))).*Bk + (1/(k+1)).*(phi*phi');
wknew = (1 - (1/(k+1))).*wk + (1/(k+1)).*yknew*cseq(k);
%r est and error
restnew = inv(Bknew)*wknew;
%a lot of issues are happening around k = 2,3
%so we will exclude these in the final plot
%due to randomness in sequence generation it changes each run
%sometimes NaN, sometimes inf. So skip k=1:3
if k > 4
  rdiff = (restnew - rest);
  error(k) = (rdiff'*rdiff)/(rest'*rest);
end
%old = new
```

```
Bk = Bknew; wk = wknew; rest = restnew; yk = yknew;
%loop
end
%plot error vs k
%This is commented out, uncomment to plot
%Plots and description shown in report.
% Ks = [1:1:K+1];
% plot(Ks(1e3:end),error(1e3:end));
% xlabel('Stage, k')
% ylabel('Error(k)')
% title('Error between r values')
%Compare V vals
phivals = ones(2,M+1);
for i = 0:M
    phivals(2,i+1) = i;
end
for i = 1:M+1
    VMC(i) = phivals(:,i)'*rest;
end
load('Vmunew.mat')%true val fcn from p1
load('Vtil.mat')%approx val fcn from p2
states = [0:1:M];
%NOTE: due to randomness, MC changes each time
%discuss values.....
plot(states, Vmunew, states, Vtil, states, VMC);
xlabel('State')
ylabel('Value Function')
title('Value Function Comparison')
legend('true V', 'approx V', 'Monte-Carlo V', 'Location', 'best');
Warning: Matrix is singular to working precision.
```



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```
%Generates and returns a sequence of demand, actions(based on opt
policy)
% sequences, and costs
%Inputs: K (stages), M (max inventory level), Muinf (optimal policy)
function [dseq, Useqstar, Sseqstar, cseqstar] = generateseq(K,M,Muinf)
%Constants
c = 1; r = 2; p = 1; m = .5;
So = 0:
% Generate sequence of demands
dseq = zeros(1,K+1); %initialize vector for demand sequence
for i = 1:K+1
   dseq(i) = randi([0 M]); %random gumbel
end
% Generate sequence of states
%Generate state, action = Mustar(state), using same sequence of
demands
%generated earlier
Sseqstar = zeros(1,K+1); %initialize vector for state sequence
Useqstar = zeros(1,K+1);
%initial state = 0, and demand
Sseqstar(1) = So;
Usegstar(1) = Muinf(Ssegstar(1) + 1);
for i = 2:K+1
   %becomes value less than 0, gets a penatly, new state must be 0
   if dseq(i-1) > (Sseqstar(i-1) + Useqstar(i-1))
      Ssegstar(i) = 0;
      Usegstar(i) = Muinf(Ssegstar(i) + 1);
   else %new state is action + current - demand
      Sseqstar(i) = (Sseqstar(i-1) + Useqstar(i-1)) - dseq(i-1);
      Useqstar(i) = Muinf(Sseqstar(i) + 1);
   end
end
% Generate sequence of costs
%must follow maintenance on current state, buy based on action
% sold demand based on current state + action if too much demand
%otherwise just sell based on demand
cseqstar = zeros(1,K+1); %initialize vector for cost sequence
```

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