$$Q_1: (a) V_{A}(4) = mon Q_A(s,a)$$

$$(b) Q_A(s,a) = \frac{1}{s',r} P(s',r|s,a) (f+iV_A(s'))$$

$$(c) V_A(4) = arg_{mon} Q_A(s,a)$$

$$(d) V_A(4) = arg_{mon} \frac{1}{s',r} P(s',r|s,a) (f+iV_A(s'))$$

$$(e) \begin{cases} P(s'|s,a) = \frac{1}{r} P(s',r|s,a) \\ F(s,a) = \frac{1}{s',r} P(s',r|s,a) \\ F(s,a) = \frac{1}{s',r} P(s',r|s,a) + \frac{1}{s'} P(s'|s,a) \times iV_A(s') \end{cases}$$

$$V_{A}(s) = \max_{a} \left[ \frac{1}{r} (s,a) + \frac{1}{s'} P(s'|s,a) \times iV_A(s') \right]$$

$$Q_{A}(s,a) = \Gamma(s,a) + \frac{1}{s'} P(s'|s,a) \times iV_A(s')$$

$$Q_{A}(s,a) = \Gamma(s,a) + \frac{1}{s'} P(s'|s,a) \times mon Q_{A}(s',a')$$

Q2: . a. Since the condition for the policy iteration algorithm to stop optimizing is that the policy 7014) no longer changes (meaning that the optimal policy is obtained), but for real use we care more about the results rather than the policy, once we got a result that is good enough for use to use (even if the policy is different but the result no longer changes), we can stop optimizing the policy.

Therefore, we need to change the judgment condition in the pseudocode to determine whether the policy should be optimized

by the result obtained from different policies:

3. Policy Improvement  $policy\text{-stable} \leftarrow true$  For each  $s \in \mathcal{S}$ :  $old\text{-action} \leftarrow \pi(s)$   $\pi(s) \leftarrow \operatorname{argmax}_a \sum_{s',r} p(s',r|s,a) \big[ r + \gamma V(s') \big]$  If  $old\text{-action} \neq \pi(s)$ , then  $policy\text{-stable} \leftarrow false$  If policy-stable, then stop and return  $V \approx v_*$  and  $\pi \approx \pi_*$ ; else go to 2

Change the yellow part to: 9 old-action (s.a) \$ 92 (s.a)

(b) Value iteration does not have similiar problems, because value iteration does not only focus on the policy like the policy iteration, but on the value. The policy is optimal as long as the result is optimal.

Q3. (a). 1. Initialization:

Q14,a)  $\in$  R and  $\pi_{14}$   $\in$  A14) orbitrarily for all  $s \in S$ .

2. Policy Evaluation:

Loop:  $\Delta \leftarrow 0$ Loop for each  $s \in S$   $\alpha \leftarrow \pi_{16}$ )  $q \leftarrow Q_{15,a}$   $Q_{16,a} \leftarrow \frac{1}{2} \Gamma_{16} \Gamma_{1$ 

3. Policy Improvement:

policy - stable - True

For each s & S:

old - action - 70(5)

10 (5) - argmax 9 (6.a)

If = p(5',r|5,7(5))[r+i=170(a'|5)9(a',4') +

Then policy-stable - False

If policy-stable, then stop and return Q = 9x, and \$ = 1x; else. go to 2.

(b). 8>0

Initialize Q16,0), for all 5 & St. arbitrarily except that Q(terminal, a).

Loop:

∆ ← o

Loop for each SES:

a - argmox 9 (4.a)

9 6 12 15.0)

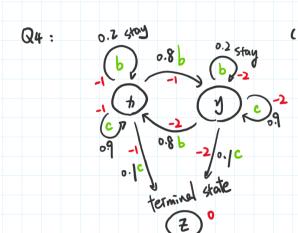
Q15,0) = I P16, + |5.0) [++ 1 max 9 15,0')]

1 = max (D, 19-015,0)

Until DC 9

Output a deterministic policy, 70 2 74, such that

7/15) = argmax 5/17 p (5', r | 5, a) [ r + x 9 (6', 20 (5'))]



(a) I think we can be sure that moving to z is the best action for both states to and y. But for state y. moving to to is also a better action than staying, because it reduces the amount of negative future reward gained. Although policy b

reduces negative future reward by a smaller amount shown policy c for y, it makes it more likely than policy c that negative future reward will be reduced. Therefore, I think policy c should be the optimal policy for state x, and policy b may be the optimal policy for state y.

(b). O Policy evaluation.

$$V_{2}(s) = \frac{1}{a} \pi (a|s) \left[ \frac{1}{s',r} p(s,r|s,a)(r+ x V_{2}(s')) \right]$$
  
Initial policy has action c in both states:

$$7v(x) = C \cdot 7v(y) = C$$

$$\begin{cases} V_{7v}(x) = 0. | x(-1+0) + 0.9 \times (-1+x) V_{7v}(x) \\ V_{7v}(y) = 0. | x(-2+0) + 0.9 \times (-2+x) V_{7v}(y) \end{cases}$$

$$\frac{1}{\sqrt{2}v(x)} = \frac{1}{1-0.9x}$$

$$\Rightarrow \begin{cases} \sqrt{2} c(x) = -\frac{1}{1 - 0.98} \\ \sqrt{2} c(y) = -\frac{2}{1 - 0.98} \end{cases}$$

Paicy improvement.

When we capply policy b.

{ Vab(x) = 0.2 x(-1+ & Vac(x)) + 0.8 x(-1+ & Vac(y)) Vab(y) = 0.2 x(-2+ & Vac(y)) + 0.8 x(-2+ & Vac(x))

=) For 8=1 { V2b(x) = -19 < V2c(x) = -10 V2bcy = -14 > V2ccy) = -20.

Thus. N'(x) > c, N'(y) > b.

n'(x) ≠ n(x). n'(y) ≠ n(y). It doesn't meet the condition of policy-stable, so return to policy evaluation.

Policy evaluation.

When we apply policy as lost improvement.

{Vac(x) = 0. |x(-1+0) + 0.9x(-1+ Vac(x)) Vabcy) = 0.2x(-1+ YVab(y)) + 0.8x(-2+ 8V2c (x))

=) For r=1 { Vac cx) = -10 Vab (4) = -12.5

Policy improvement

When we apply different policy again.  $\begin{cases}
Vab(x) = 0.2 \times (-1+\delta Vac(x)) + 0.8 \times (-1+\delta Vab(y)) \\
Vac(y) = 0.1 \times (-2+0) + 0.9 \times (-2+\delta Vab(y))
\end{cases}$ Tor Y = 1.  $\begin{cases}
Vab(x) = -13 < Vac(x) = -10 \\
Vac(y) = -13.25 < Vab(y) = -12.5
\end{cases}$ Thus,  $\pi'(x) \rightarrow c$ ,  $\pi'(y) \rightarrow b$ .

 $7\sqrt[3]{cx} = 7\sqrt[3]{cx}$ ,  $7\sqrt[3]{cy} = 7\sqrt[3]{cy}$ , it meets the condition of policy-stable, so stop and return:  $\begin{cases}
V_{+}(x) = -10 & \text{if } T_{+}(x) = C \\
V_{+}(y) = -12.5 & \text{if } T_{+}(y) = b.
\end{cases}$ 

Initial policy how action b in both states:

$$\begin{cases} V_{20}b(x) = 0.2 \times (-1 + V_{20}b(x)) + 0.8 \times (-1 + V_{20}b(y)) \\ V_{20}b(y) = 0.2 \times (-2 + V_{20}b(y)) + 0.8 \times (-2 + V_{20}b(x)) \end{cases}$$

For r=1: The equation does not hold and the

result cannot be caculated.

For 
$$r \neq 1$$
:  $\begin{cases} V_{xb}(y) = \frac{-2+0.4r}{1-0.4r-0.6r^2} \\ V_{xb}(x) = \frac{-1+0.8r}{1-0.2r} \times \frac{-2+0.4r}{1+0.4r-0.6r^2} \end{cases}$ 

Thus. I think discounting may have impact on the results, depending on the different discount factors. We need to analyze the optimal policy according to the specific discount factor.

```
Vs(a) = [[-1.85380443 -1.34185832 -1.22622928 -1.42007309 -1.97241846]
[-0.96965064 -0.43208514 -0.35180898 -0.58272448 -1.18027658]
[ 0.05486787  0.74165922  0.67626363  0.36114423  -0.40025498]
[ 3.31359559 8.79292942 4.43113177 5.32556099 1.4955287 ]]
Vs(b) =
[[21.9764967 24.41877948 21.97690153 19.41877948 17.47690153]
[19.77884703 21.97690153 19.77921138 17.80129024 16.02116122]
[17.80096232 19.77921138 17.80129024 16.02116122 14.4190451 ]
[16.02086609 17.80129024 16.02116122 14.4190451 12.97714059]
[14.41877948 16.02116122 14.4190451 12.97714059 11.67942653]]
pi(s)_b =
[['right' 'up' 'left' 'up' 'left']
['up' 'up' 'up' 'left' 'left']
['up' 'up' 'up' 'up' 'up']
['up' 'up' 'up' 'up' 'up']
['up' 'up' 'up' 'up' 'up']]
Vs(c) =
[[21.97748529 24.4194281 21.97748529 18.45018449 16.60516604]
[19.77973676 21.97748529 19.77973676 17.80176308 16.02158677]
[17.80176308 19.77973676 17.80176308 16.02158677 14.4194281 ]
[16.02158677 17.80176308 16.02158677 14.4194281 12.97748529]
pi(s)_c =
[['right' 'up' 'left' 'up' 'left']
['up' 'up' 'up' 'left' 'left']
['up' 'up' 'up' 'up' 'up']
['up' 'up' 'up' 'up' 'up']
['up' 'up' 'up' 'up' 'up']]
```