This handout includes space for every question that requires a written response. Please feel free to use it to handwrite your solutions (legibly, please). If you choose to typeset your solutions, the `README.md` for this assignment includes instructions to regenerate this handout with your typeset LaTeX solutions.

1.a

(2.14)

Via value iteration

$$V_{opt}(s) = \begin{cases} 0 & (\text{if } \text{isEnd}(s)) \\ \max_{a \in \text{Actions}(s)} Q_{opt}(s,a) & \end{cases}$$

$$Q_{opt}(s,a) = \sum_{s'} T(s,a,s')\left[r + \gamma V_{opt}^{(t-1)}(s')\right]$$

$\gamma = 1$

$$r = \begin{cases} -5 & \\ 20 & s=-2 \\ 100 & s=2 \end{cases}$$

	state s				
	-2	-1	0	1	2
$V_{opt}^{(0)}(s)$	0	0	0	0	0
$V_{opt}^{(1)}(s)$	0	15	-5	26.5	0
$V_{opt}^{(2)}(s)$	0	14	13.45	23	0
$\pi_{opt}(s)$	-	-1	+1	+1	-

1.a

1.b

s	a	s'	T(s,a,s')	r
0	+1	1	.3	-5
0	+1	-1	.7	-5
0	-1	1	.2	-5
0	-1	-1	.8	-5
1	+1	2	.3	100
1	+1	0	.7	-5
1	-1	2	.2	100
1	-1	0	.8	-5
-1	+1	-2	.7	20
-1	+1	0	.3	-5
-1	-1	-2	.8	20
-1	-1	0	.2	-5

$\gamma = 1$

$\text{Actions}(s) = \{-1, +1\}$

$$V_{opt}^{(t)}(s) = \max_{a \in \text{Actions}(s)} \left[\sum_{s'} T(s,a,s') \left[r + \gamma V_{opt}^{(t+1)}(s') \right] \right]$$

keep the action options

keep $\sum_{s'} T(s,a,s') = 1$ for $\sum_{s'}$

$$V_{opt}^{(1)}(0) = .3\left[-5 + (1)(0)\right] + .7\left[-5 + (1)(0)\right]$$

$$= -5$$

$$V_{opt}^{(2)}(0) = .3\left[-5 + (1)(2.5)\right] + .7\left[-5 + (1)(15)\right]$$

$$V_{opt}^{(1)}(1) = .3\left[100 + (1)(0)\right] + .7\left[-5 + (1)(0)\right]$$

$$V_{opt}^{(2)}(1) = .3\left[100 + (1)(0)\right] + .7\left[-5 + (1)(-5)\right]$$

$$V_{opt}^{(1)}(-1) = .8\left[20 + (1)(0)\right] + .2\left[-5 + (1)(0)\right]$$

See
214
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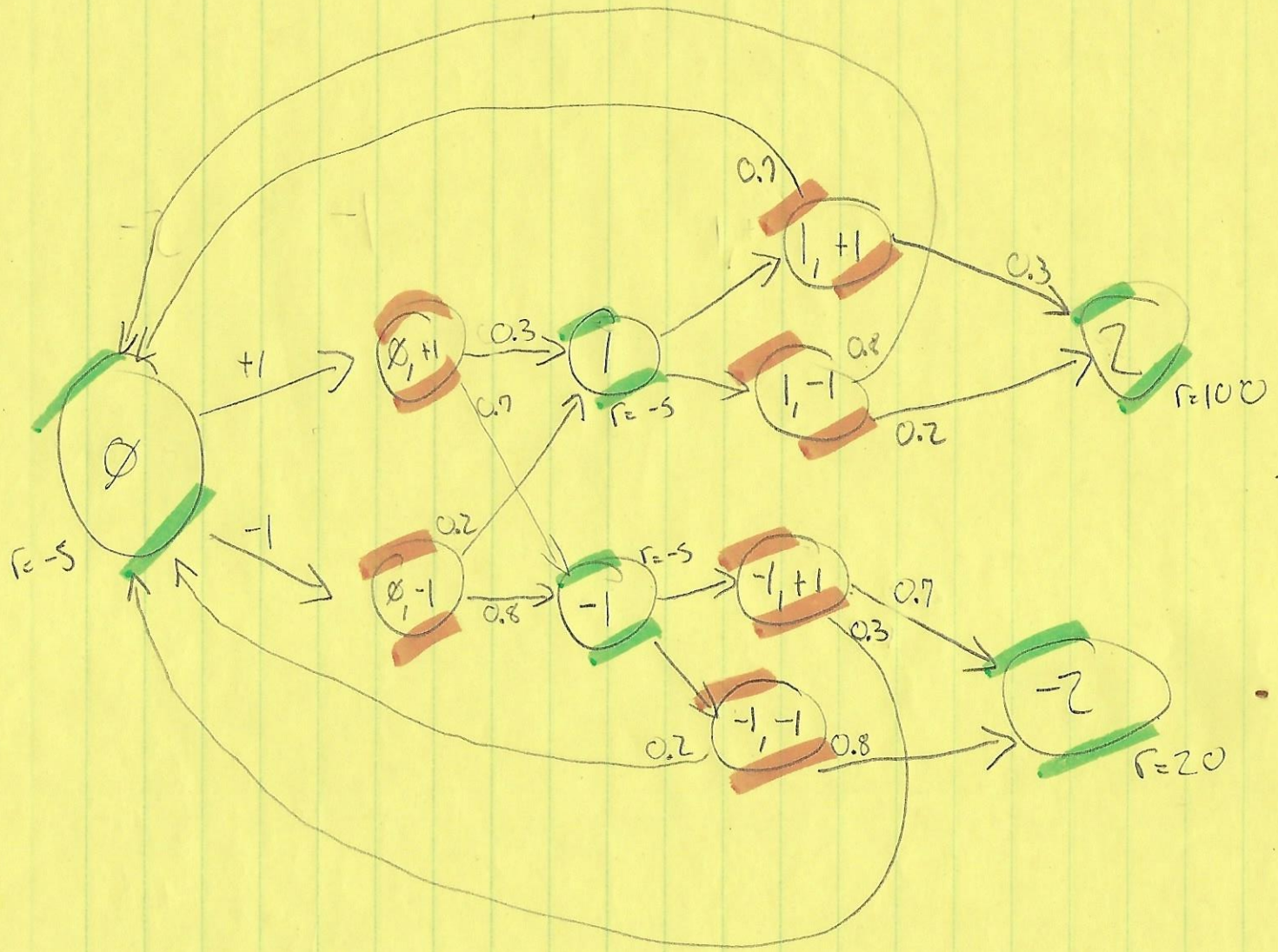
∅
r=-5
+1
∅, +1
0.3
0.7
1
r=-5
1, +1
0.7
0.3
1, -1
0.8
0.2
2
r=100
-1
∅, -1
0.2
0.8
-1
r=-5
-1, +1
0.7
0.3
-1, -1
0.2
0.8
-2
r=20

2.a

MDP graph needs to be acyclic because convergence can't occur otherwise with $\lambda' = 1$

Or

we can introduce convergence with the introduction of a new end state that any of the prior states can end at. to integrate this the previous transition probabilities need to be slightly diminished to make room for the new state since the sum of T between s and s' must equal 1 one approach to do this and include the original λ of the original MDP is:

$\lambda' = 1$ $\quad A'(s) = A(s)$ $\quad S' = S \cup \{0\}$ $\quad 0$ = new end state

$R'(s,a,s') = R(s,a,s')$ since 0 is a end state we can make $R(s,a,0) = R_{opt}(s,a,s')$ for s or their reward for the optimal action for each state

$T'(s,a,s') = T(s,a,s') * \lambda \cup T(s,a,0) = (1-\lambda)$