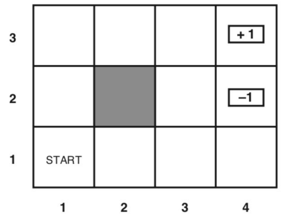
CS4246 / CS5446

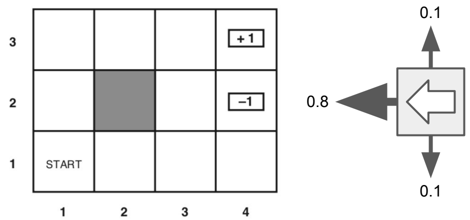
Tutorial Week 11

Muhammad **Rizki** Maulana
rizki@u.nus.edu

First



(a)



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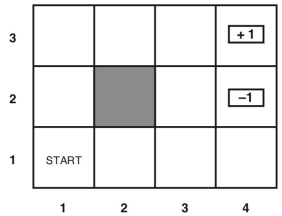

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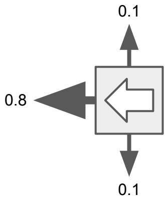

Detect adjacent wall

Noisy sensor:

- Correct : 0.9
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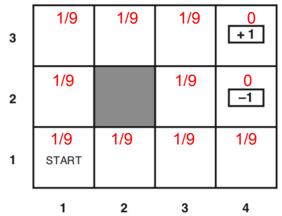

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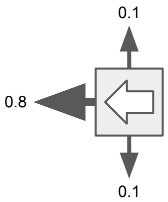

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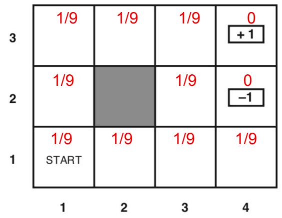

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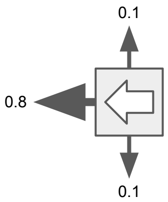

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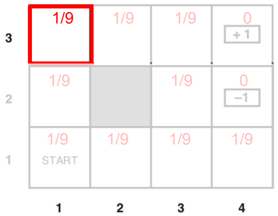
Question



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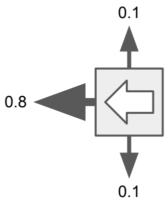

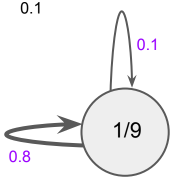

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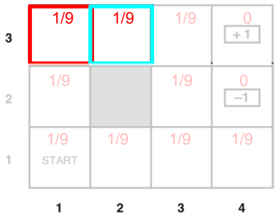

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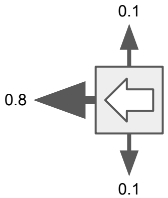

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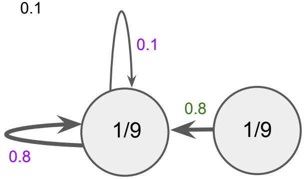

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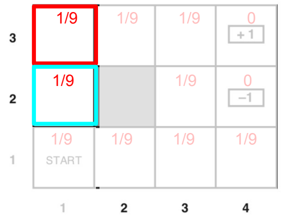

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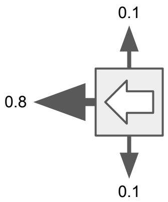

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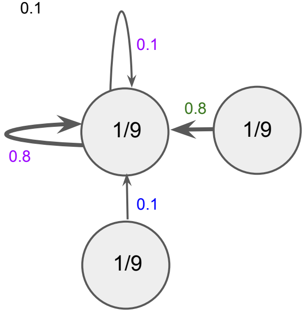

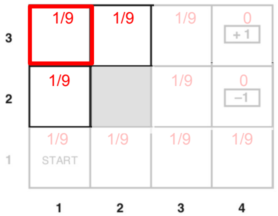

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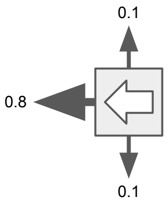

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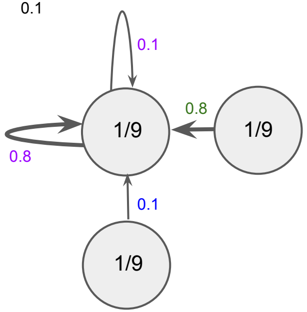
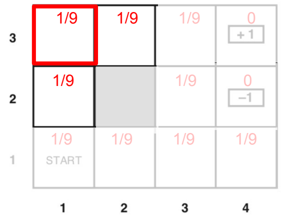


$$P(x'|Left, b_0) = \sum_x P(x'|Left, x) b_0(x)$$



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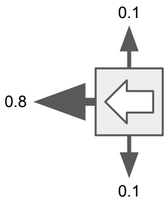

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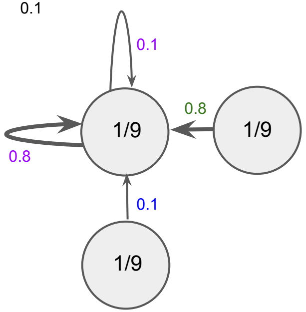
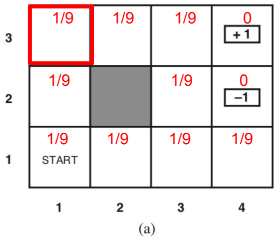
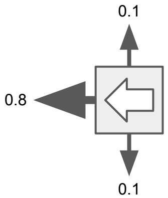


$$P(x'|Left, b_0) = \sum_x P(x'|Left, x) b_0(x)$$

$$0.9(1/9) + 0.8(1/9) + 0.1(1/9) = 0.2$$





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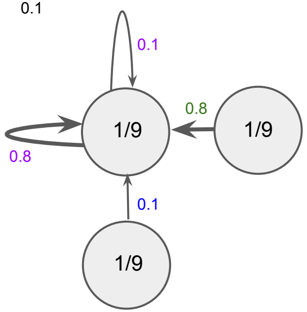

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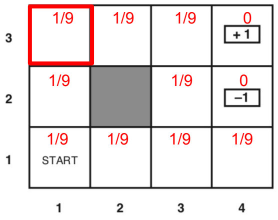
0.2	$\frac{1}{9}$	$\frac{0.2}{9}$	0
$\frac{1}{9}$	×	$\frac{1}{9}$	$\frac{0.1}{9}$
0.2	$\frac{1}{9}$	$\frac{1}{9}$	$\frac{0.1}{9}$



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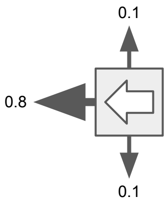

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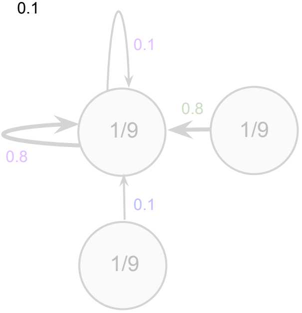

$$P(x'|Left, b_0) = \sum_x P(x'|Left, x)b_0(x)$$

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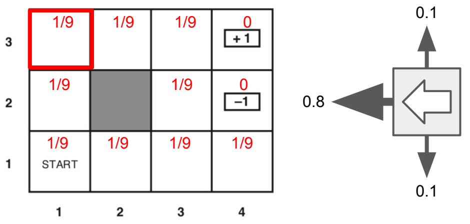
0.2	$\frac{1}{9}$	$\frac{0.2}{9}$	0
$\frac{1}{9}$	×	$\frac{1}{9}$	$\frac{0.1}{9}$
0.2	$\frac{1}{9}$	$\frac{1}{9}$	$\frac{0.1}{9}$

Now, we update these estimates with the sensor data, which says there is one adjacent wall (i.e., multiply by $P(z = \text{‘1 adjacent wall’}|x')$):



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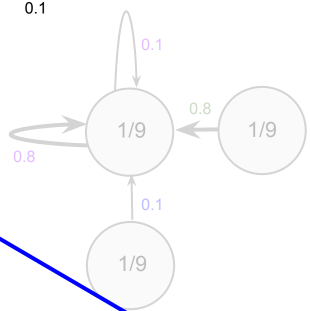

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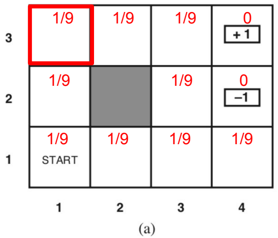
0.1×0.2	$0.1 \times \frac{1}{9}$	$0.9 \times \frac{0.2}{9}$	0
$0.1 \times \frac{1}{9}$	$\times$	$0.9 \times \frac{1}{9}$	$0.9 \times \frac{0.1}{9}$
0.1×0.2	$0.1 \times \frac{1}{9}$	$0.9 \times \frac{1}{9}$	$0.1 \times \frac{0.1}{9}$

1 adj wall

2 adj wall



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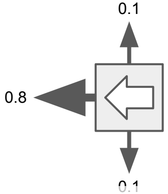

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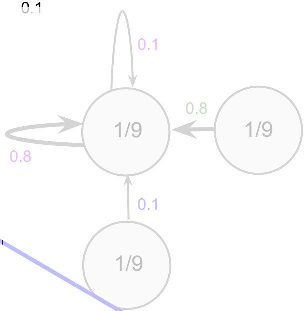

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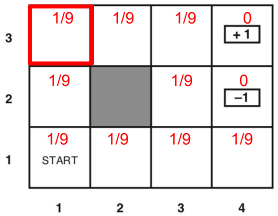
$0.1 \times \frac{1}{9}$	×	$0.9 \times \frac{1}{9}$	$0.9 \times \frac{0.1}{9}$
0.1×0.2	$0.1 \times \frac{1}{9}$	$0.9 \times \frac{1}{9}$	$0.1 \times \frac{0.1}{9}$

1 adj wall

2 adj wall

and renormalize to get b_1:

0.06569	0.03650	0.06569	0
0.03650	×	0.32847	0.03285
0.06569	0.03650	0.32847	0.00365



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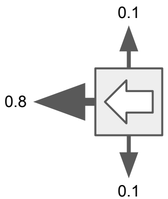

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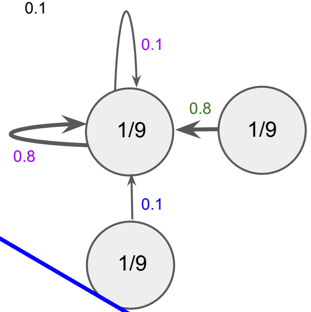

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Second

[Modified from RN 3e 17.14] What is the time complexity of d steps of POMDP value iteration for a sensorless environment? Give an upper bound on the number of α-vectors generated in the process.

Question

[Modified from RN 3e 17.14] What is the time complexity of d steps of POMDP value iteration for a sensorless environment? Give an upper bound on the number of α-vectors generated in the process.

$$\alpha_p(s) = \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma \sum_{e'} P(e'|s')\alpha_{p.e'}(s')]$$

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sensorless

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conditional plans

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Sensorless Vacuum Cleaner World

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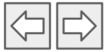

2

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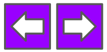

2

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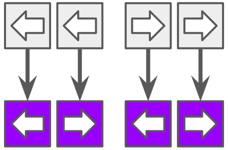

2^2

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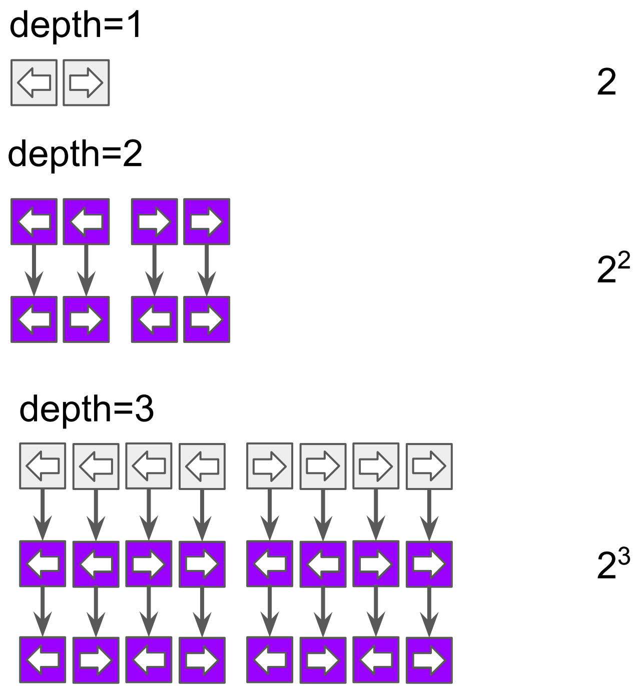
$$V(b) = \max_p b \cdot \alpha_p$$

conditional plans

Sensorless Vacuum Cleaner World



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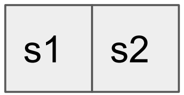

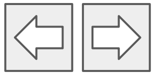

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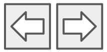

2

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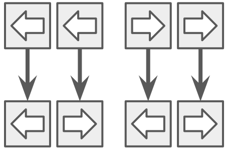
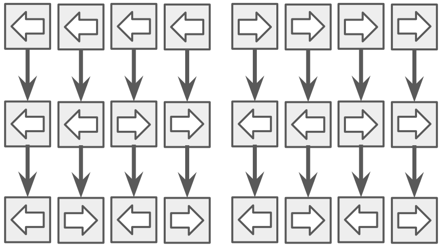


2^2

depth=3



2^3

depth=d,
|A| actions

$|A|^d$

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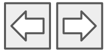
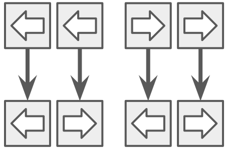
Number of alpha vectors at depth d

depth=1



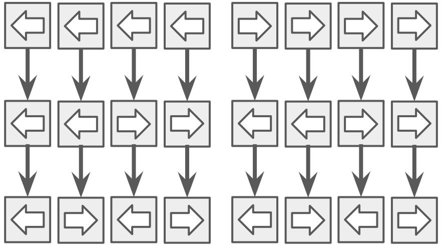
2

depth=2



$+2^2$

depth=3



$+2^3$

depth=d,
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$+|A|^d$

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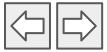
conditional plans

Sensorless Vacuum Cleaner World

Number of alpha vectors at depth d

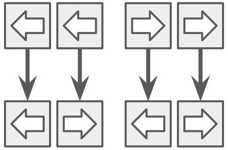
$$\sum_d |A|^d = O(|A|^d)$$

depth=1



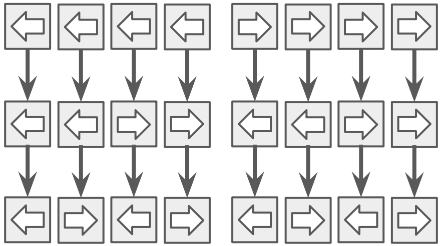
2

depth=2



$+2^2$

depth=3

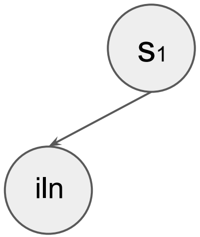


$+2^3$

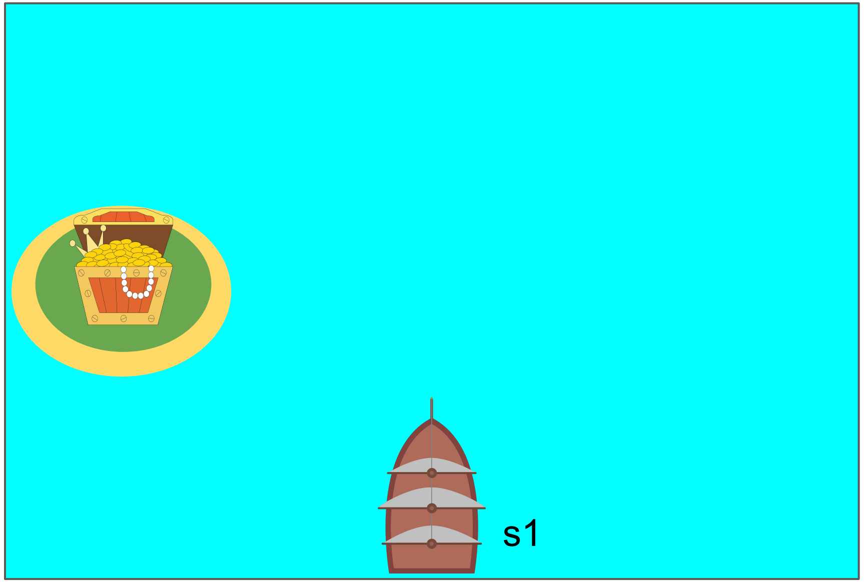
depth=d,
|A| actions

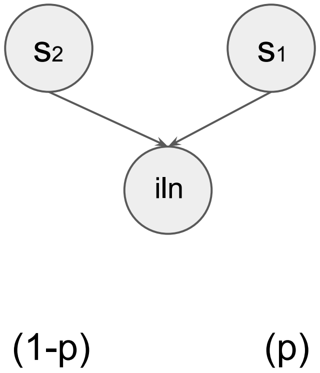
$+|A|^d$

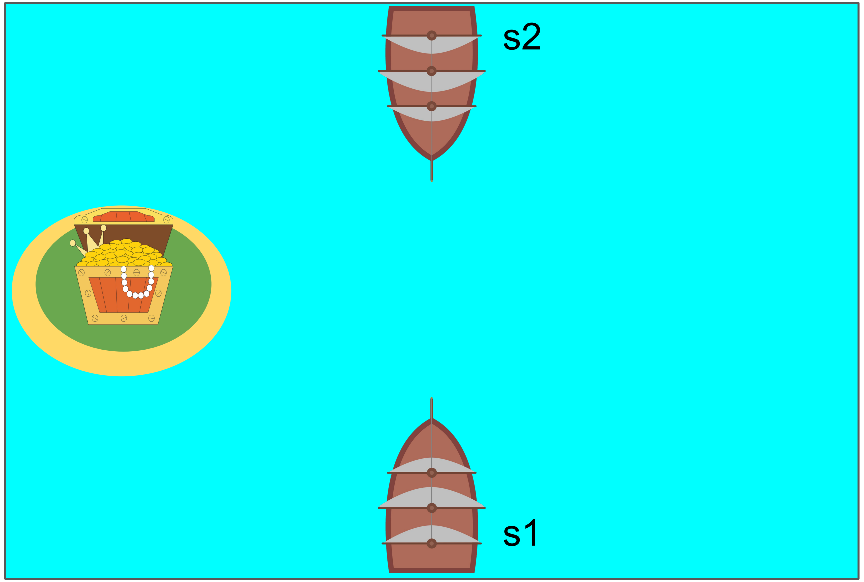
Third

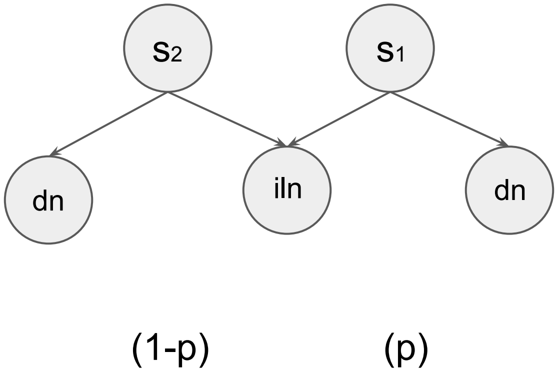


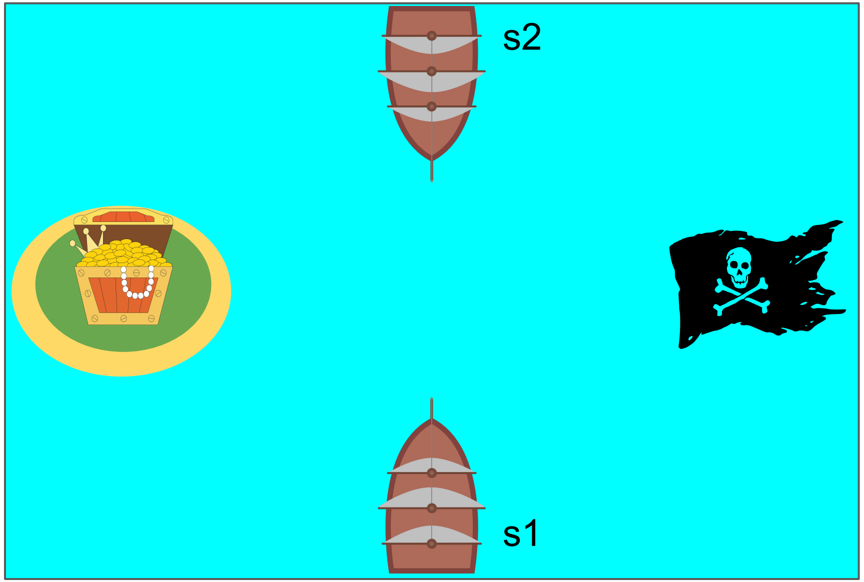
(p)

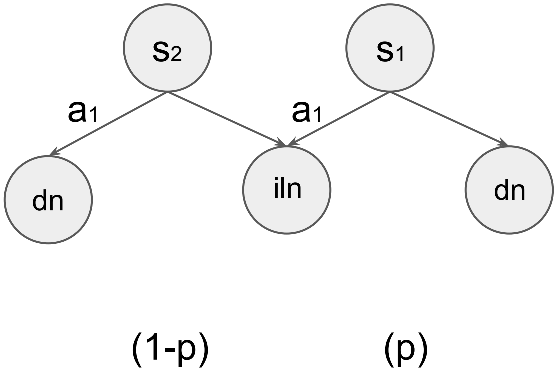


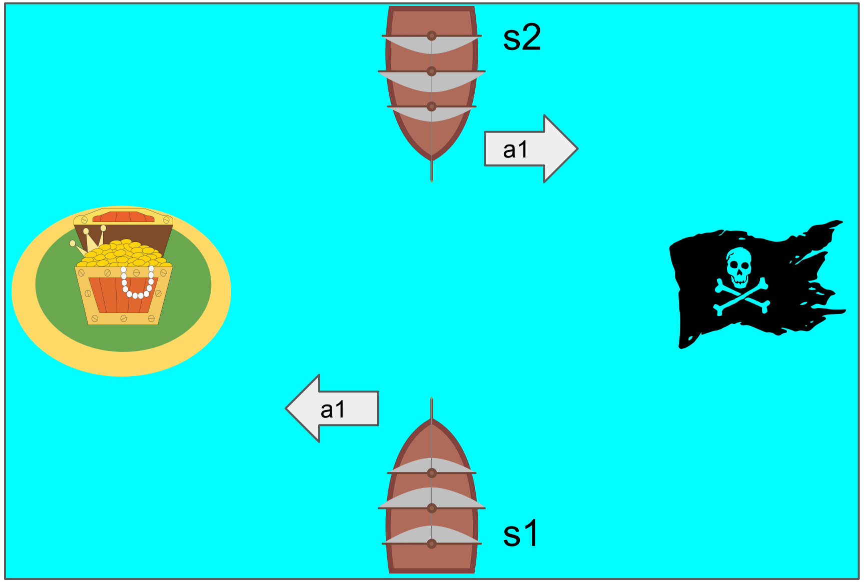

s2
s1
iln
(1-p)
(p)

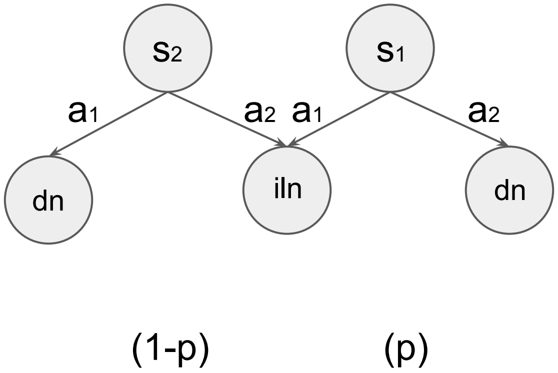

s2
s1


s2
s1
dn
iln
dn
(1-p)
(p)

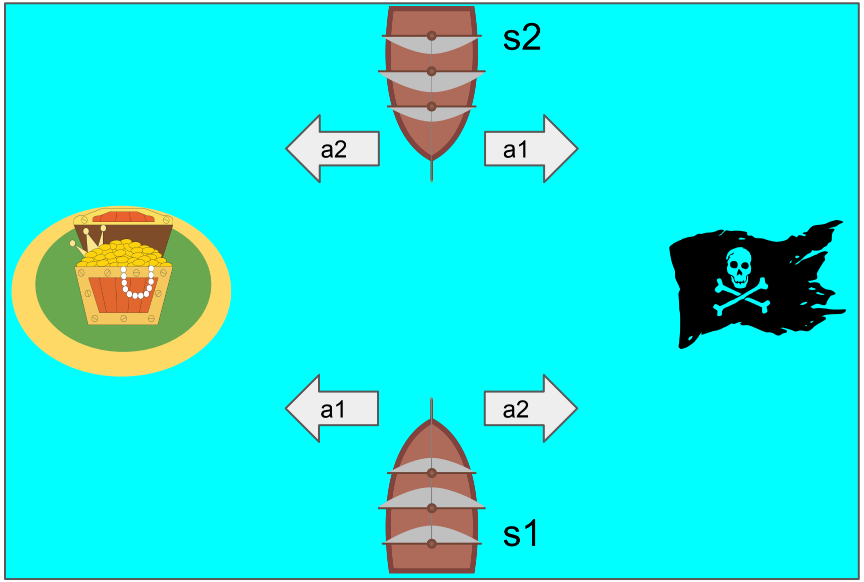

s2
s1


s_2
s_1
a_1
a_1
dn
iln
dn
(1-p)
(p)

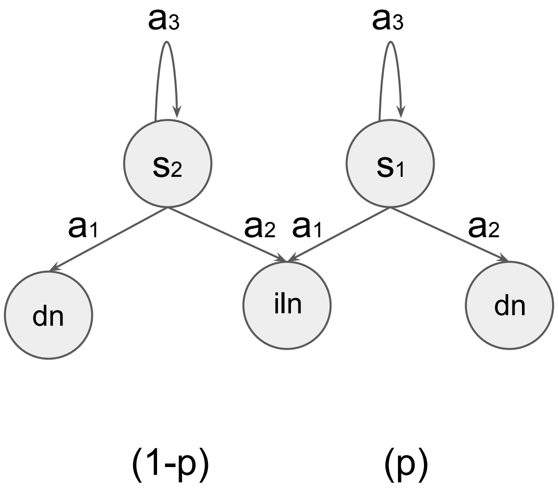

s2
a1
a1
s1



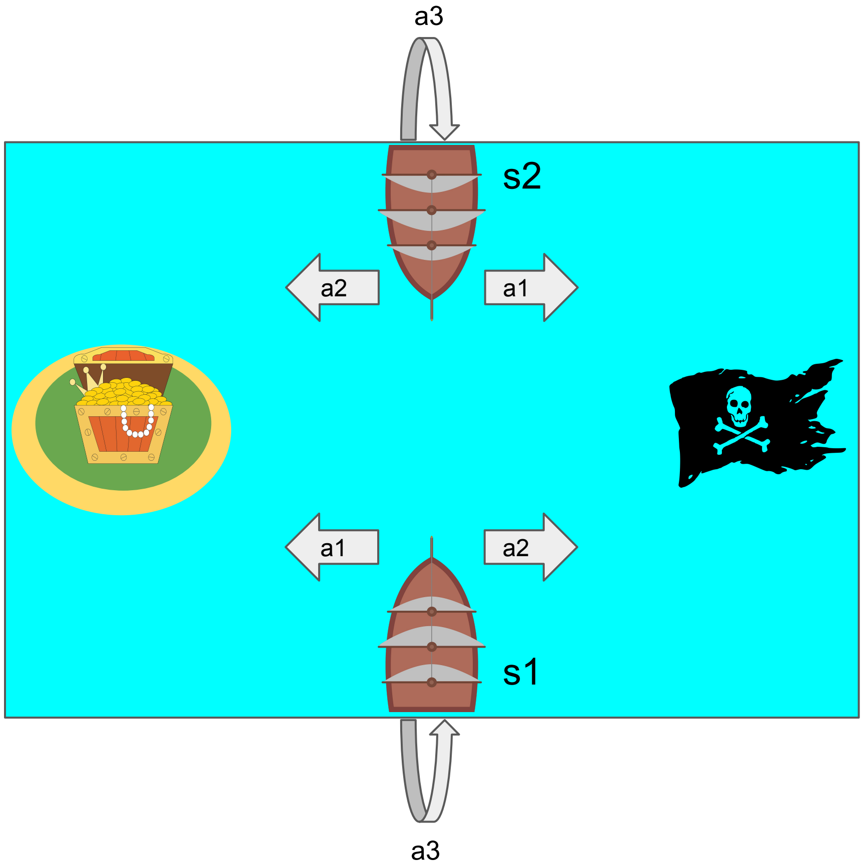
s_2
s_1
a_1
a_2
a_1
a_2
dn
iln
dn
(1-p)
(p)

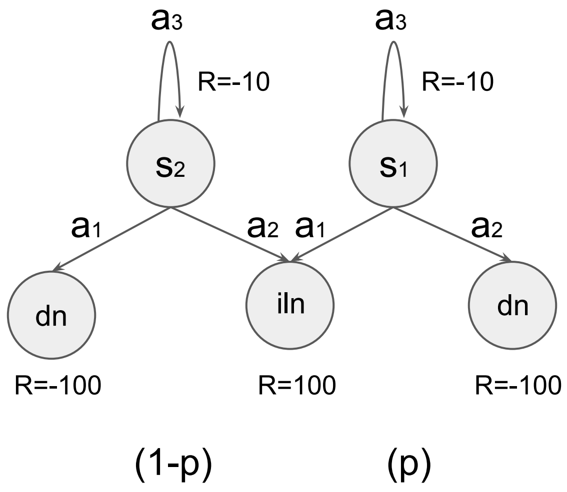


s2
a2
a1
a1
a2
s1

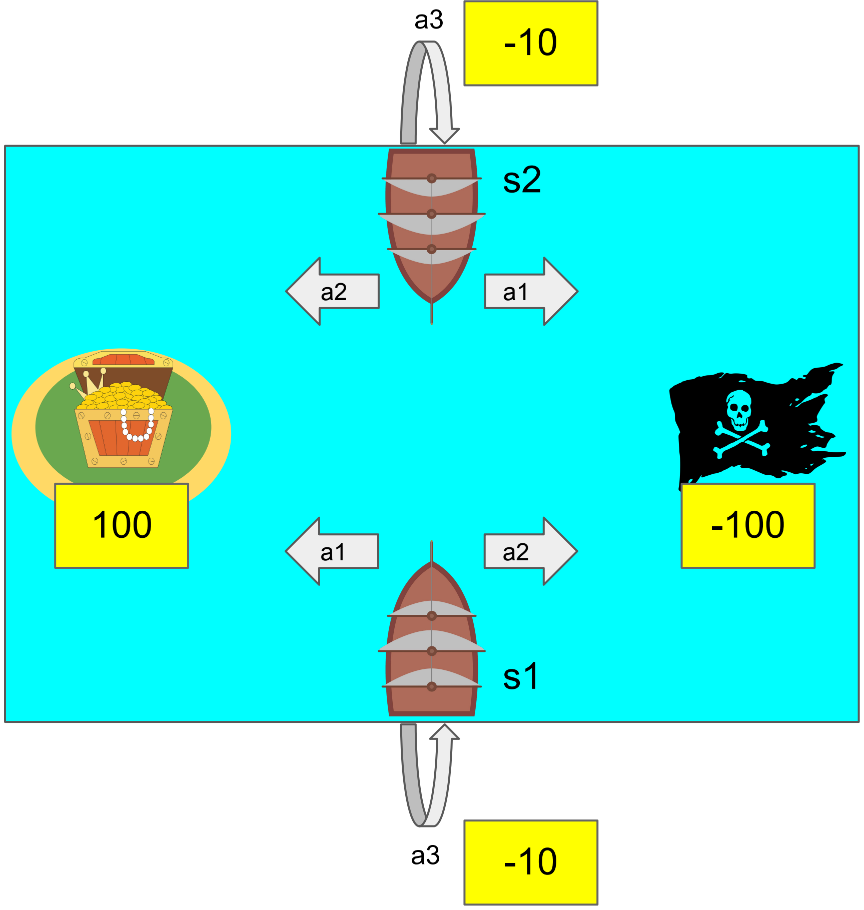


Ask Keeper

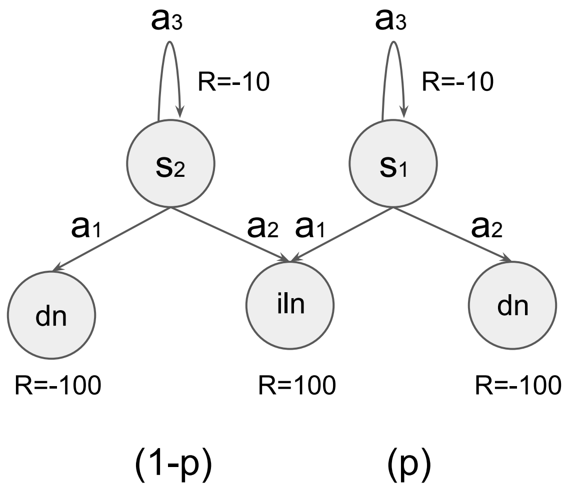




a_3
R=-10
s_2
a_1
a_2
dn
R=-100
iln
R=100
(1-p)
a_3
R=-10
s_1
a_1
a_2
dn
R=-100
(p)



a3
-10
s2
a2
a1
100
-100
a1
a2
s1
a3
-10



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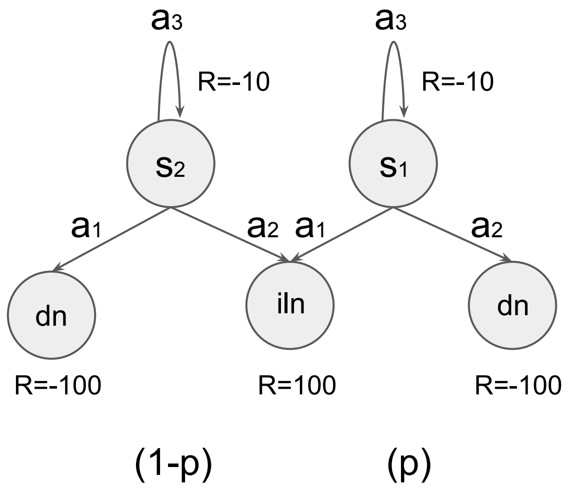

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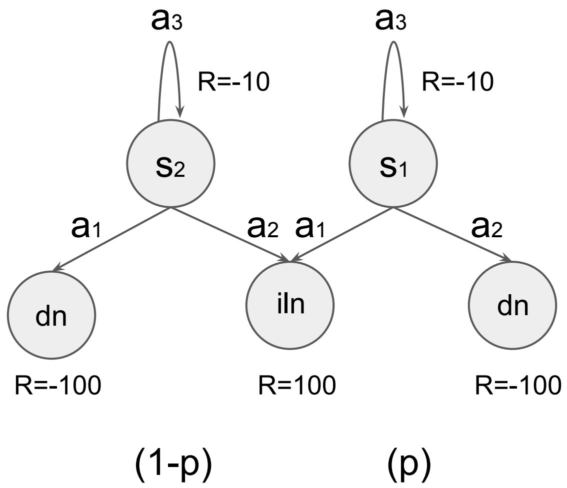
Question



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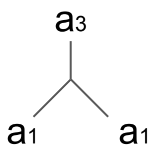

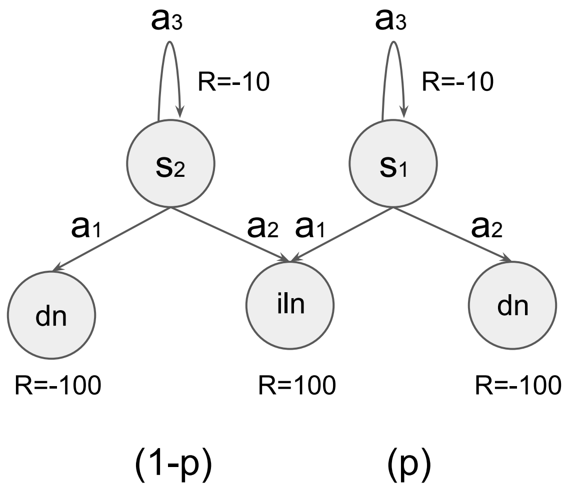

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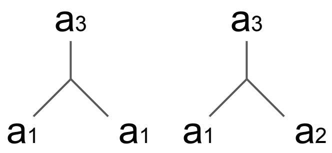

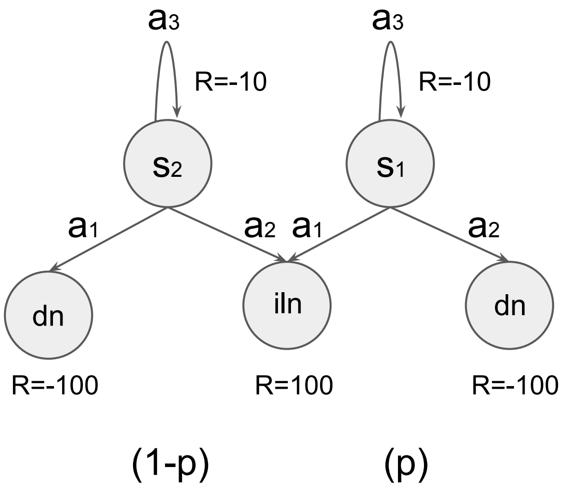

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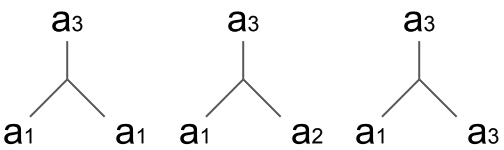

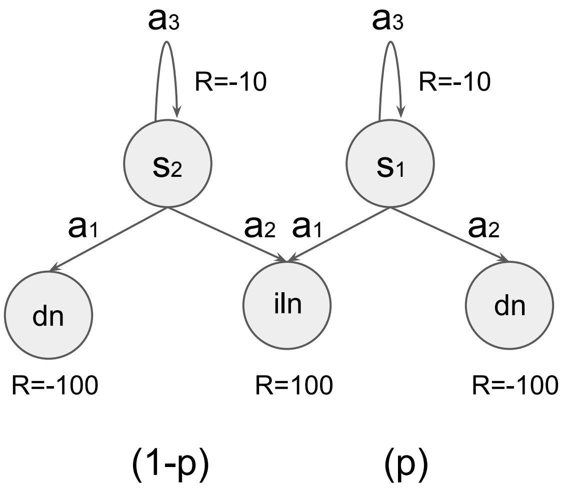

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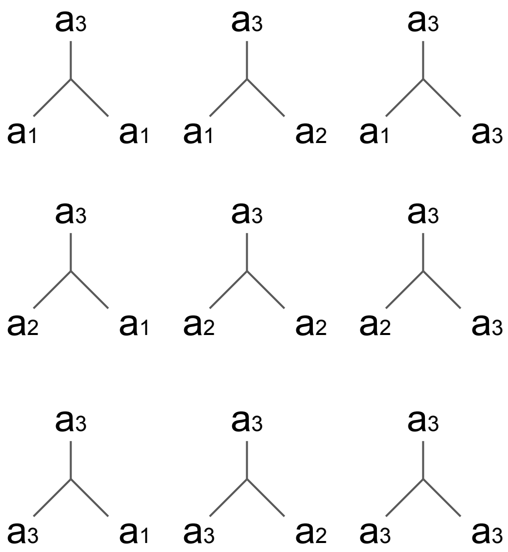

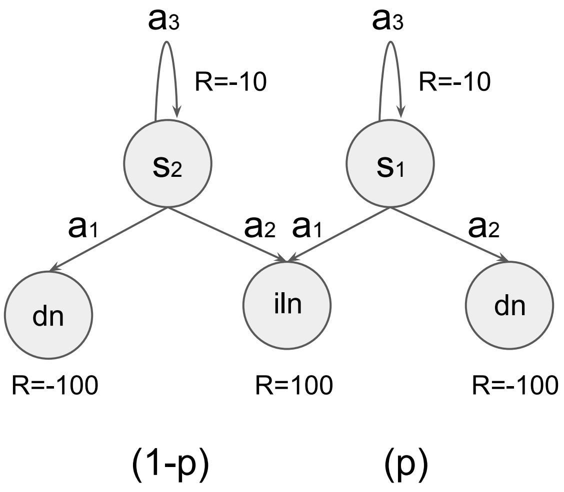

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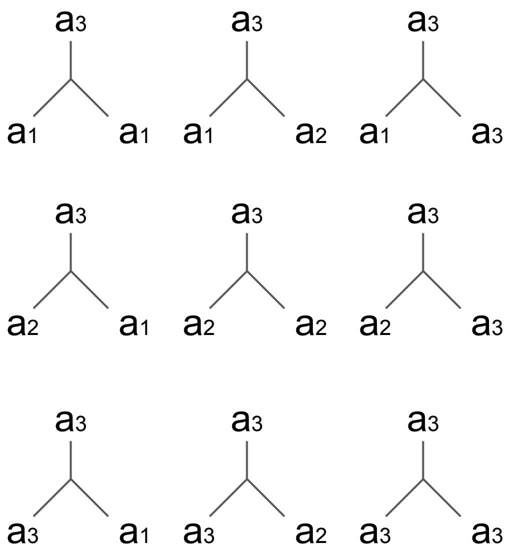

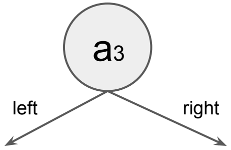

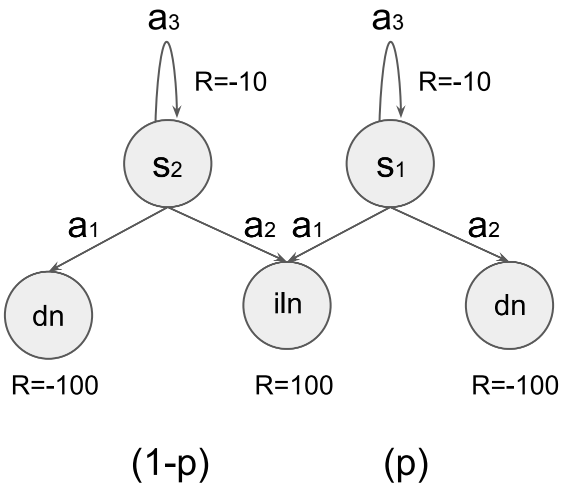

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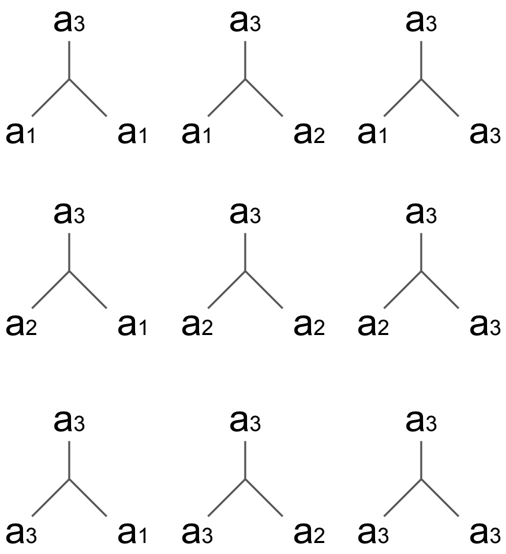

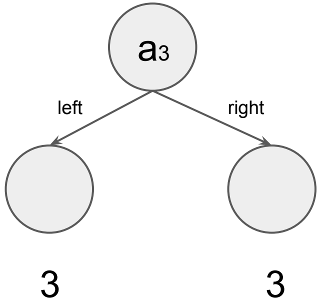

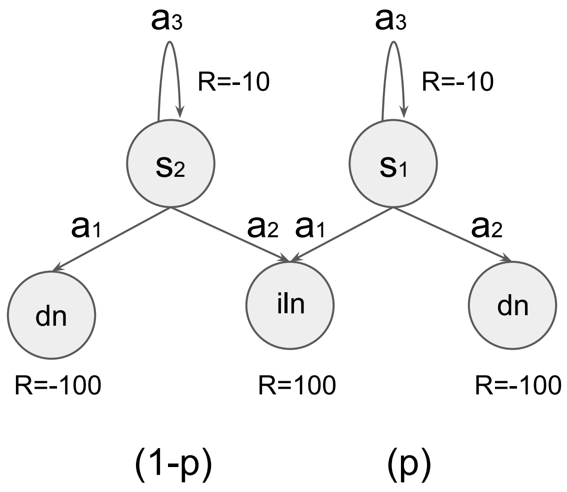

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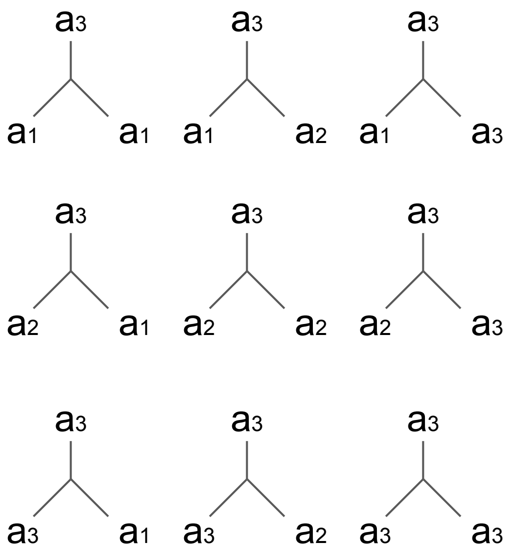
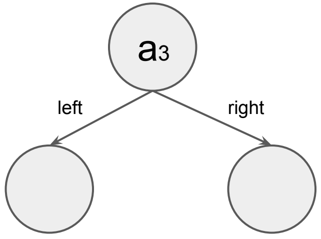
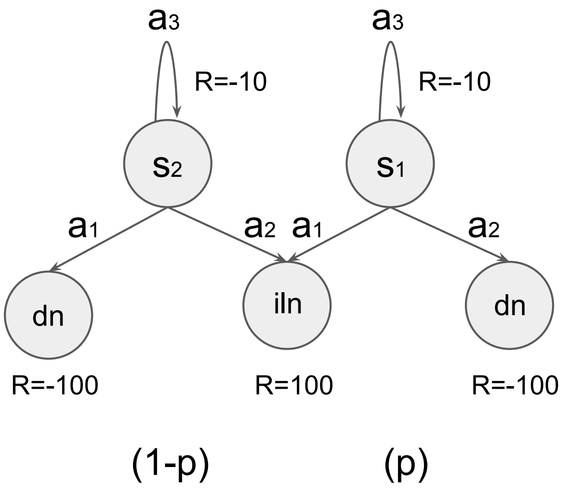




3 x 3 = 9



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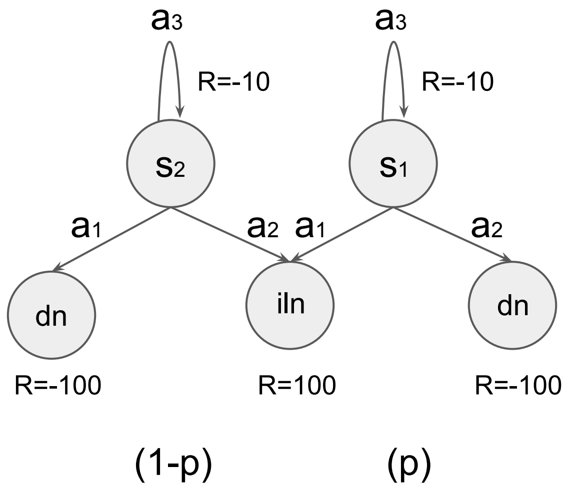

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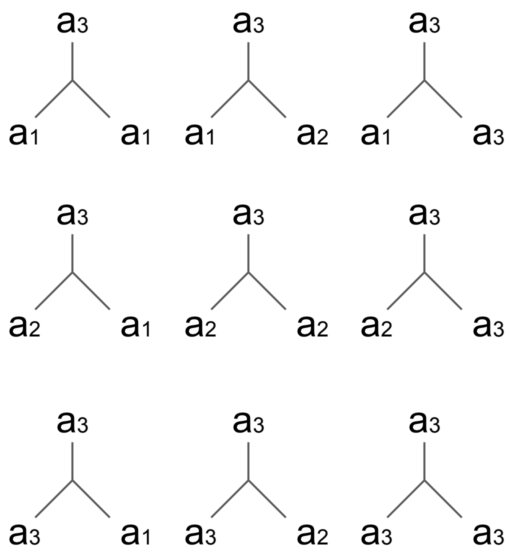
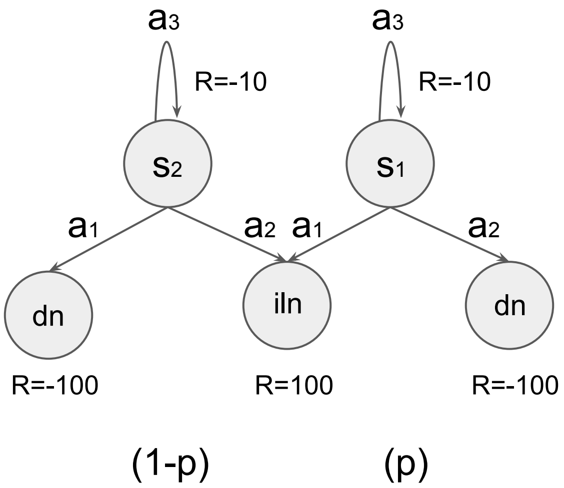


Question



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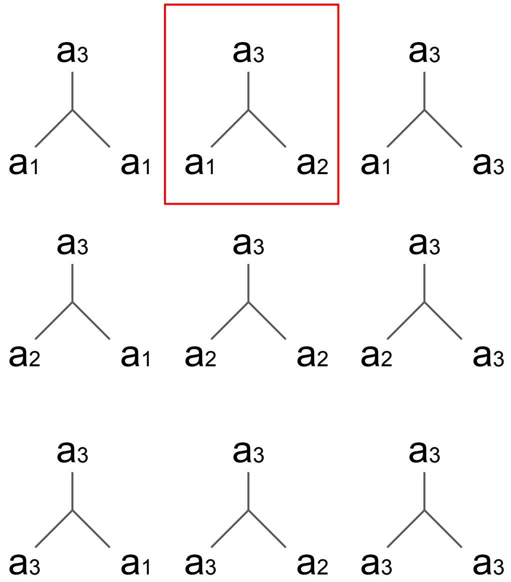

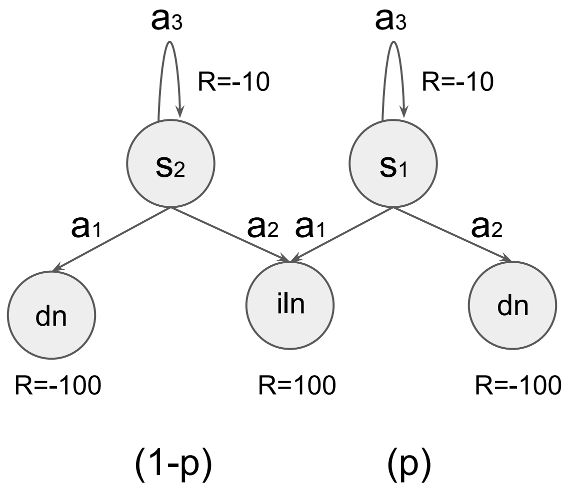

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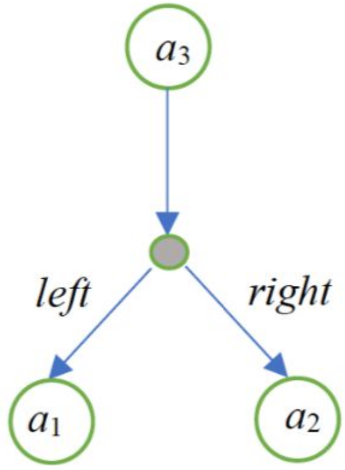
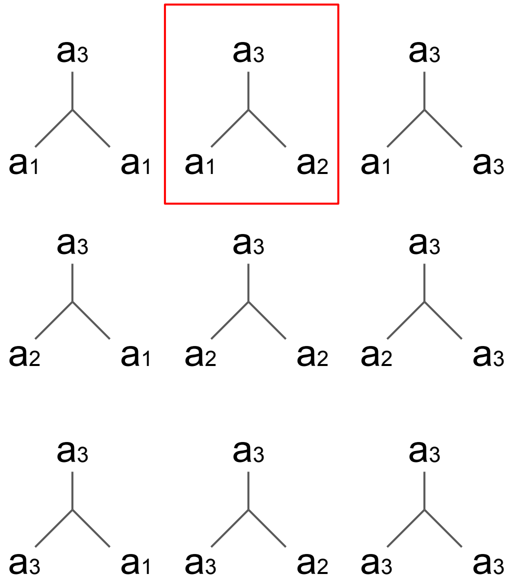
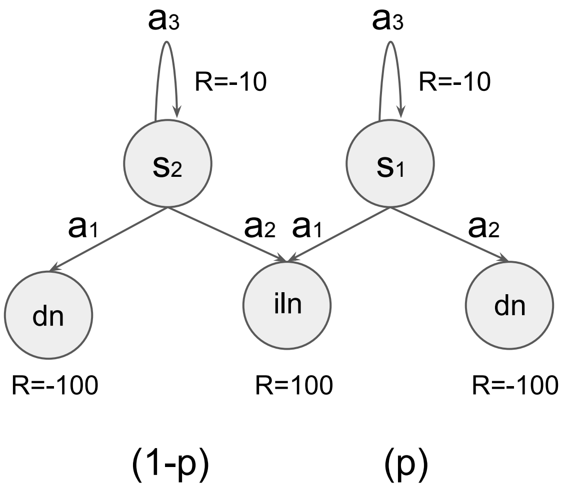
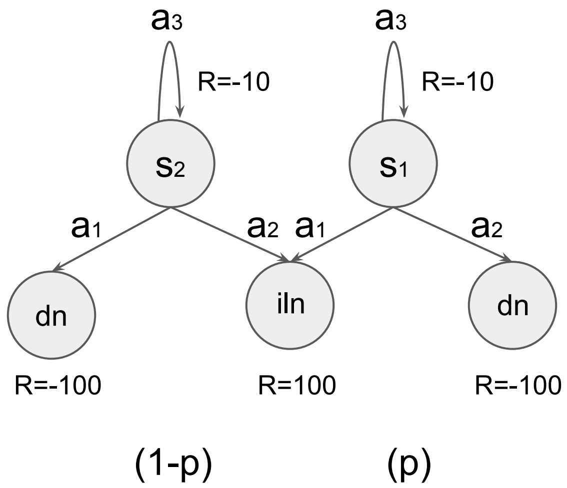
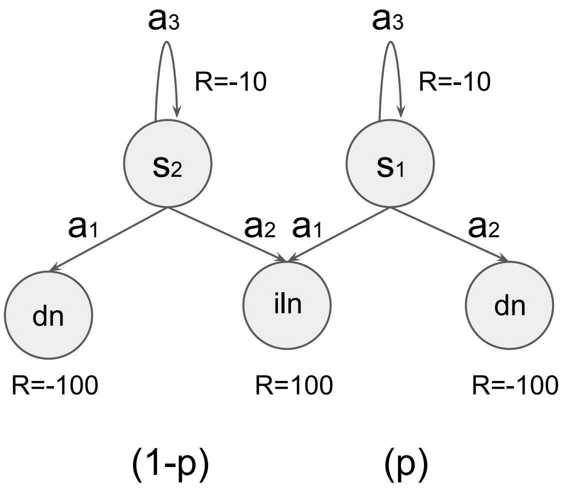





a3
R=-10
s2
a1
a2
dn
R=-100
iln
R=100
a3
R=-10
s1
a1
a2
dn
R=-100
(1-p)
(p)



(b) The one-step plan consisting of asking the Keeper cannot be optimal. Hence there can be at most two non-dominated one-step plans. From part (a) of this question, we know that there is only one non-dominated two-step conditional plan, giving a total of 3 non-dominated one and two step plans.



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i. Give the three α-vectors corresponding to the three non-dominated plans. Assume that the discount factor is $\gamma = 1$ (not discounted).

Question

(b) The one-step plan consisting of asking the Keeper cannot be optimal. Hence there can be at most two non-dominated one-step plans. From part (a) of this question, we know that there is only one non-dominated two-step conditional plan, giving a total of 3 non-dominated one and two step plans.

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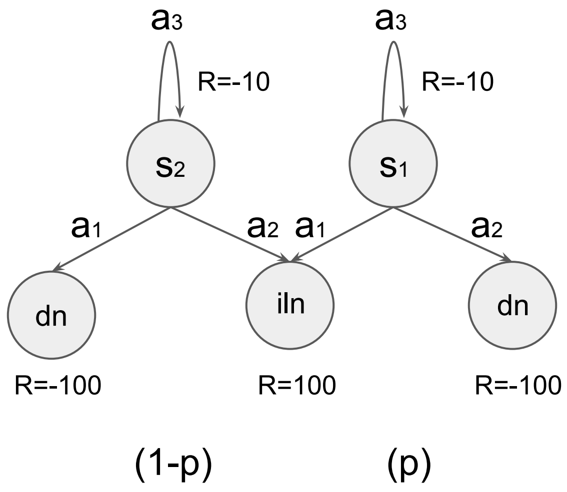

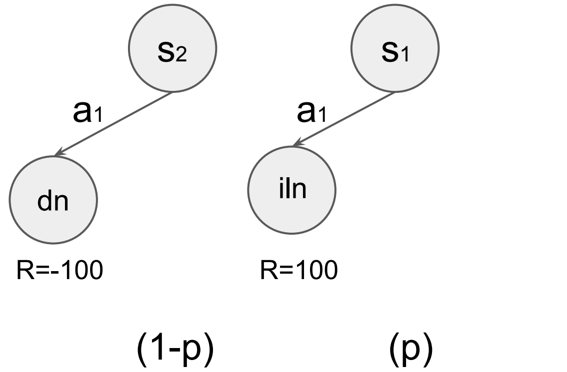

Action left: $\alpha_l(s_1) = R(s_1, a_1) = 100,$

$\alpha_l(s_2) = R(s_2, a_1) = -100$

(b) The one-step plan consisting of asking the Keeper cannot be optimal. Hence there can be at most two non-dominated one-step plans. From part (a) of this question, we know that there is only one non-dominated two-step conditional plan, giving a total of 3 non-dominated one and two step plans.

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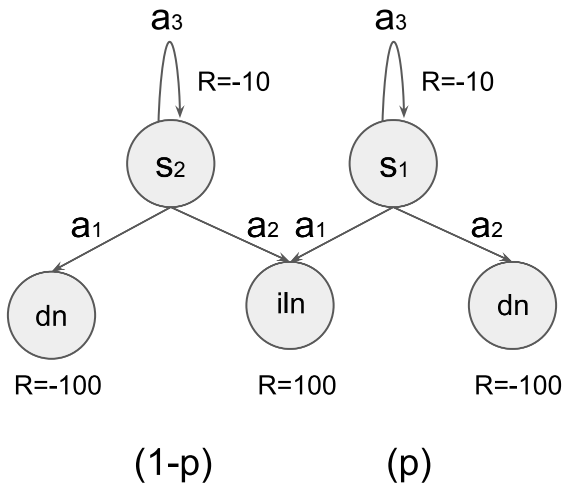

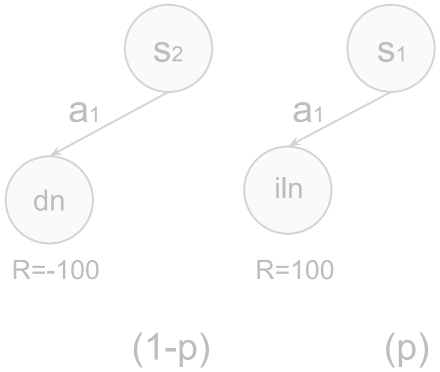

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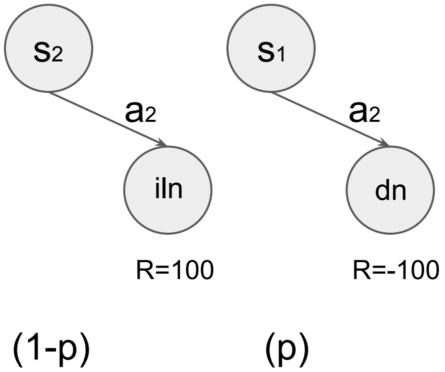

Action right: $\alpha_r(s_1) = R(s_1, a_2) = -100$

$\alpha_l(s_2) = R(s_2, a_2) = 100$

(b) The one-step plan consisting of asking the Keeper cannot be optimal. Hence there can be at most two non-dominated one-step plans. From part (a) of this question, we know that there is only one non-dominated two-step conditional plan, giving a total of 3 non-dominated one and two step plans.

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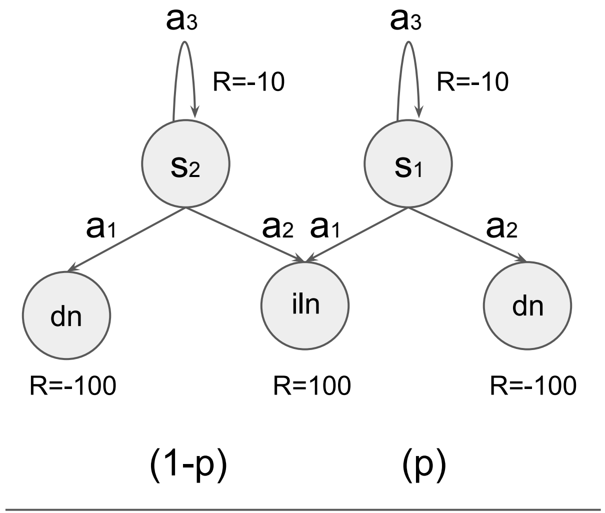

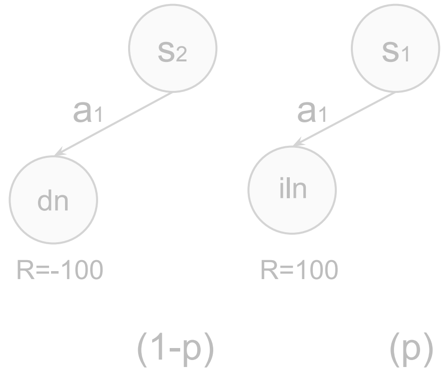

Action left: $\alpha_l(s_1) = R(s_1, a_1) = 100,$

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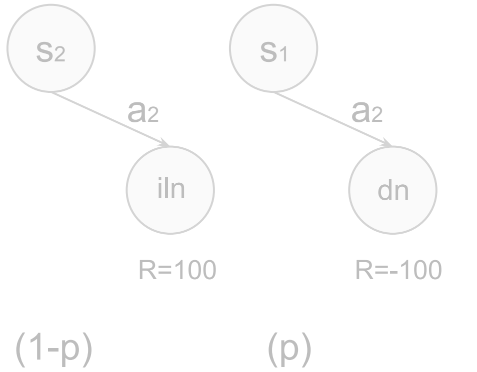

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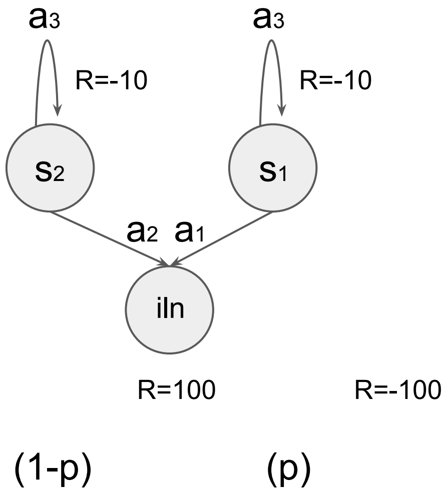
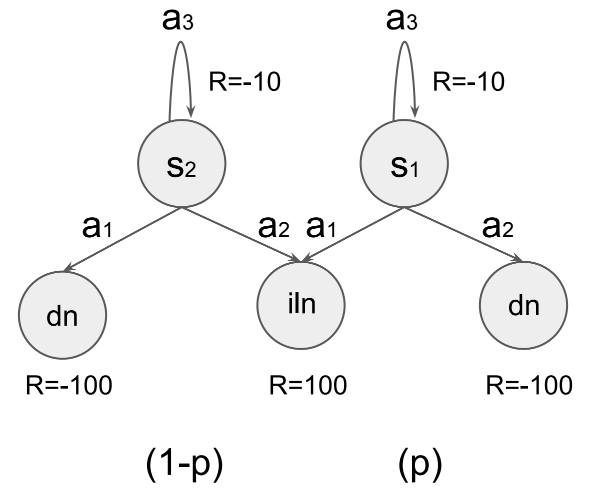
$\alpha_l(s_2) = R(s_2, a_2) = 100$



Two-step plan:

$\alpha_p(s_1) = \alpha_p(s_2) = -10 + 100 = 90$



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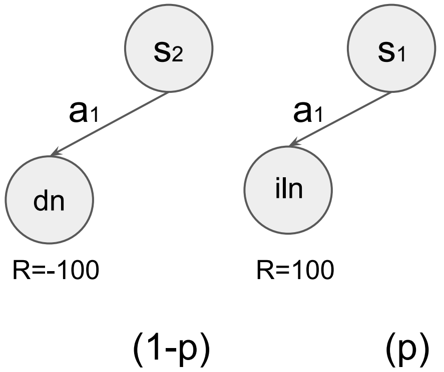

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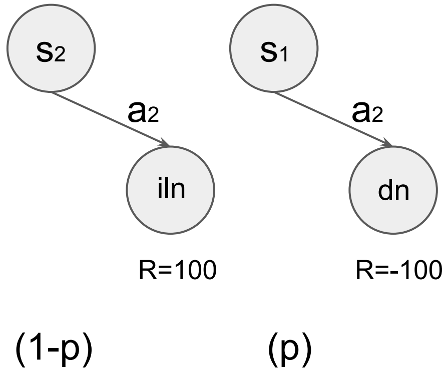
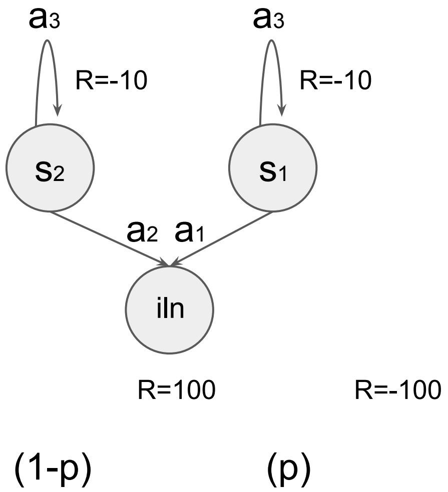


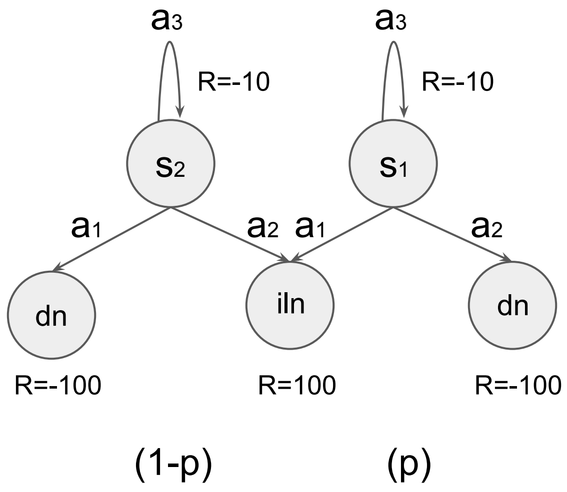
Action right: $\alpha_r(s_1) = R(s_1, a_2) = -100$

$\alpha_l(s_2) = R(s_2, a_2) = 100$



Two-step plan:

$\alpha_p(s_1) = \alpha_p(s_2) = -10 + 100 = 90$



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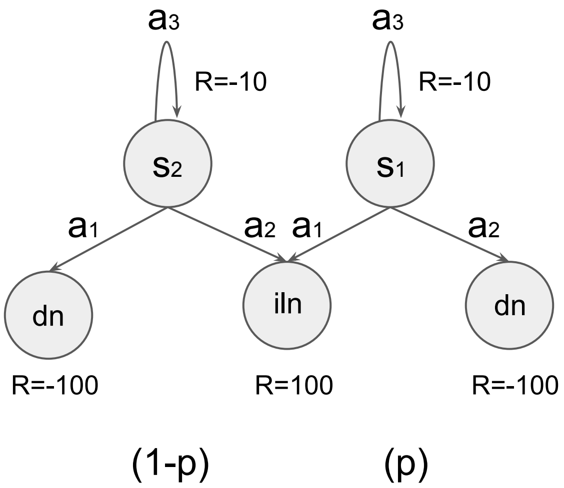

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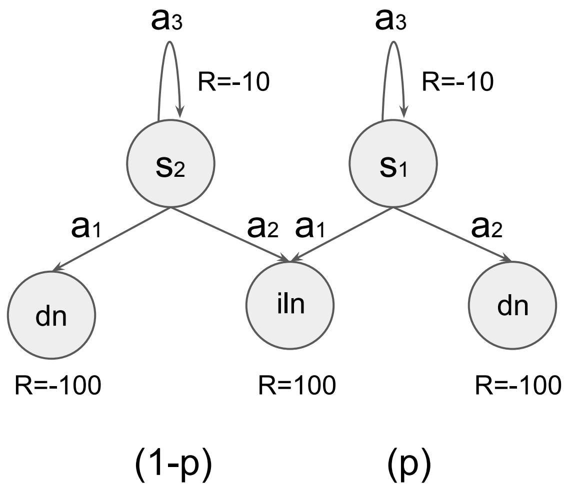
ii. Partition the beliefs into regions where each plan is optimal. Describe the regions.

Question



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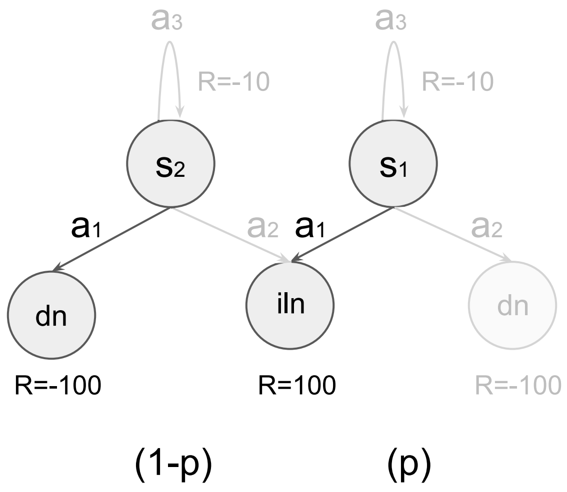

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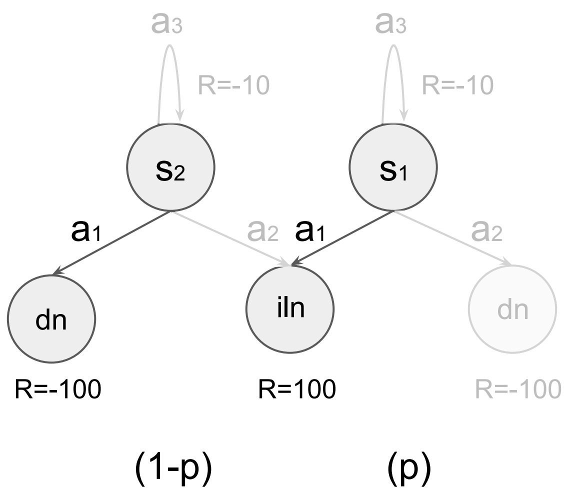
Left is optimal:

$$E[\alpha_l] \geq E[\alpha_p]$$



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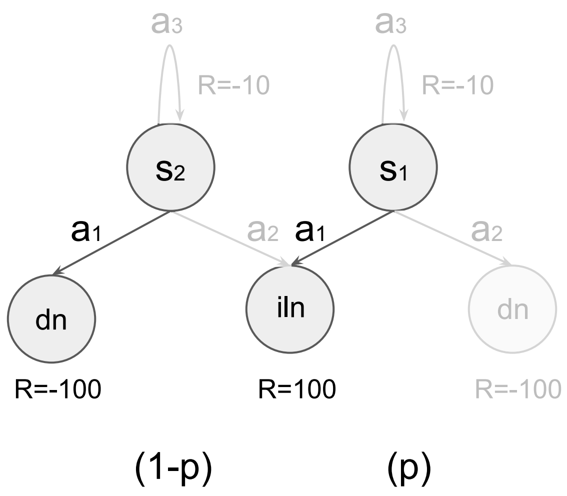

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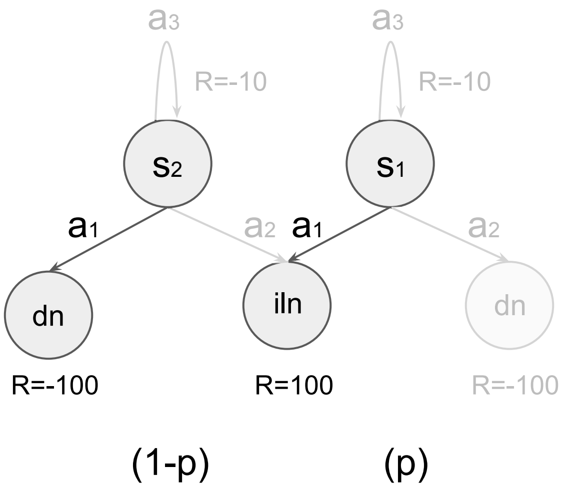

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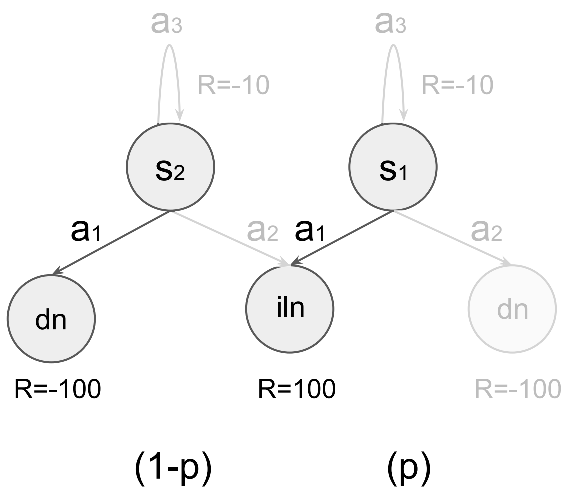

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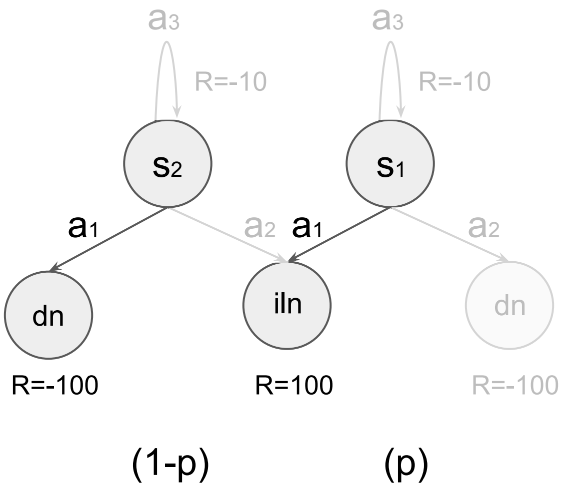
p \times 100 + (1-p) \times -100 &\geq 90 \\
100p - 100 + 100p &\geq 90 \\
200p &\geq 190
\end{aligned}
$$



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200p &\geq 190 \\
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\end{aligned}
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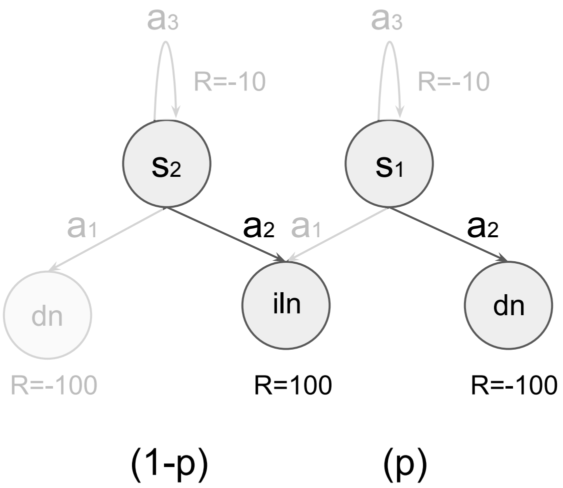

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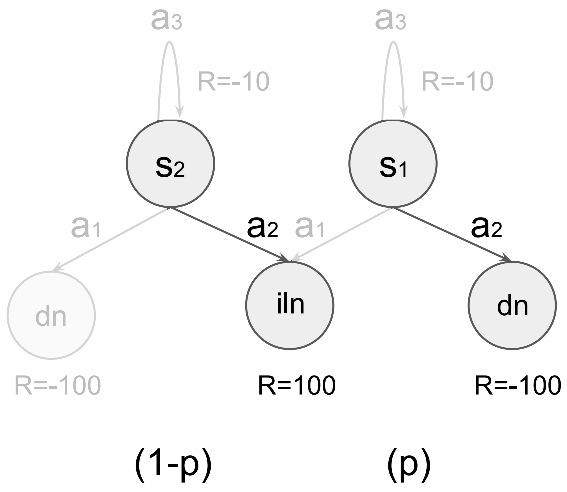

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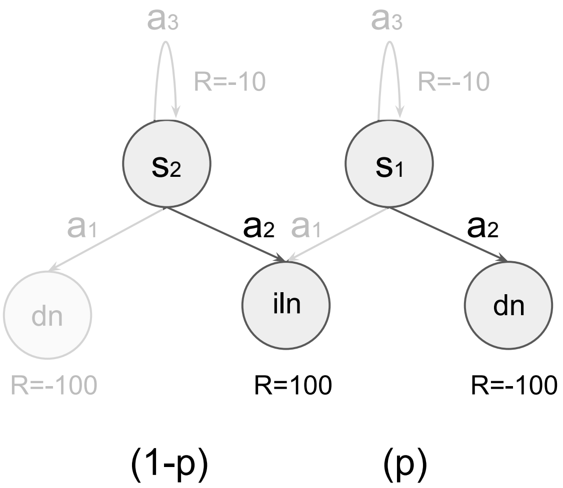
Right is optimal:

$$E[\alpha_r] \geq E[\alpha_p]$$



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E[\alpha_l] &\geq E[\alpha_p] \\
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p \times 100 + (1-p) \times -100 &\geq 90 \\
100p - 100 + 100p &\geq 90 \\
200p &\geq 190 \\
p &\geq \frac{19}{20}
\end{aligned}
$$

Right is optimal:

$$
\begin{aligned}
E[\alpha_r] &\geq E[\alpha_p] \\
p \times \alpha_r(s_1) + (1-p) \times \alpha_r(s_2) &\geq 90
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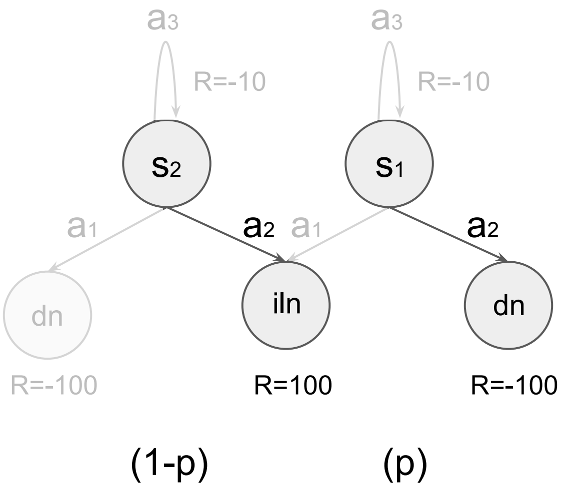

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Right is optimal:

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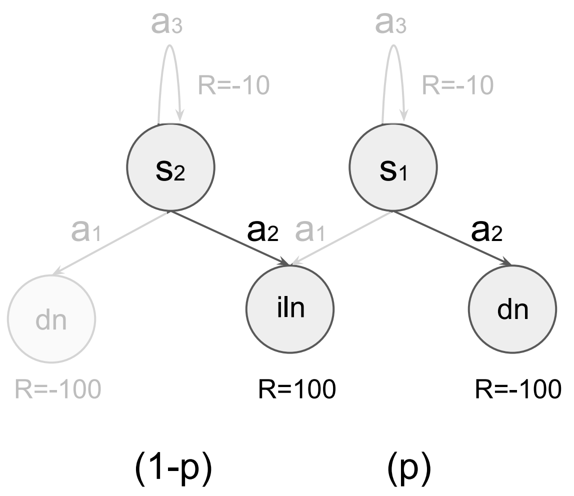

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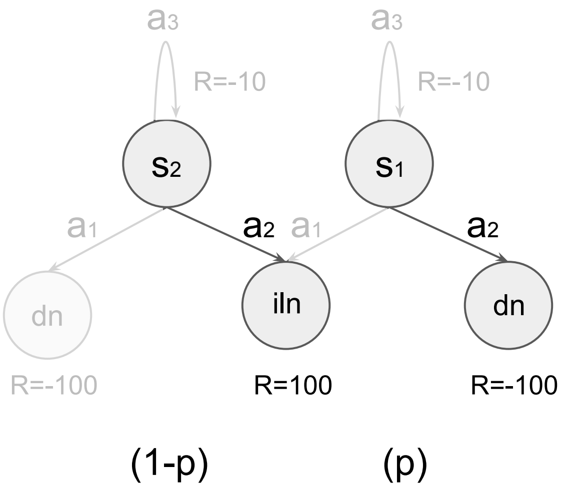
p \times -100 + (1-p) \times 100 &\geq 90 \\
-100p + 100 - 100p &\geq 90
\end{aligned}
$$



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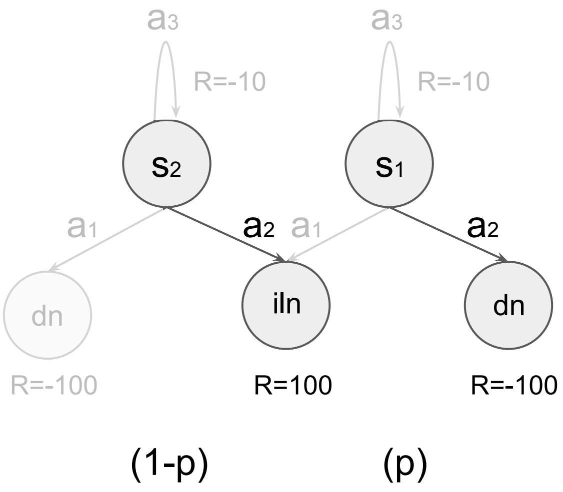

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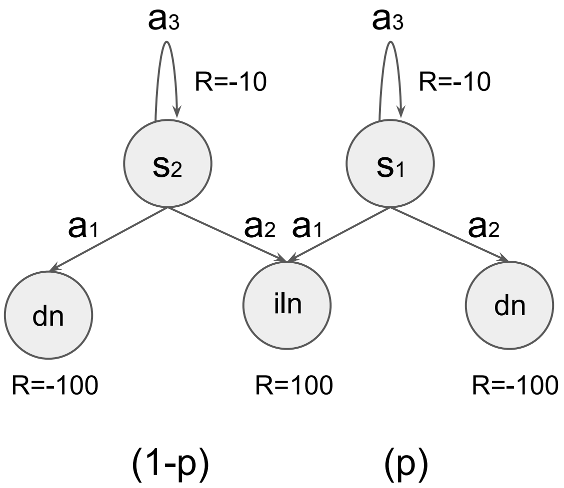

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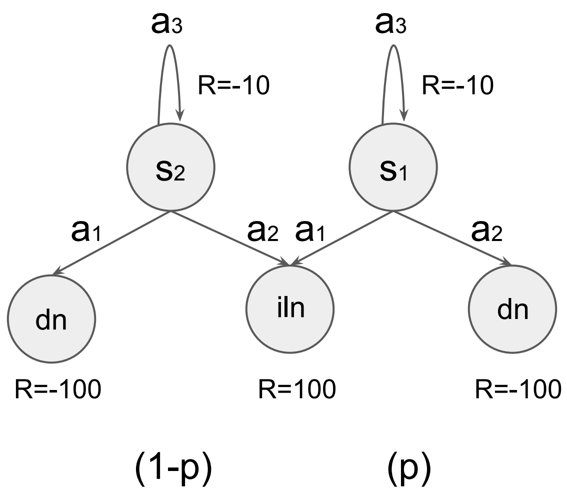
Two-step is optimal:

$$\frac{1}{20} \leq p \leq \frac{19}{20}$$
$$0.05 \leq p \leq 0.95$$

Right is optimal:

$$\begin{aligned} E[\alpha_r] &\geq E[\alpha_p] \\ p \times \alpha_r(s_1) + (1-p) \times \alpha_r(s_2) &\geq 90 \\ p \times -100 + (1-p) \times 100 &\geq 90 \\ -100p + 100 - 100p &\geq 90 \\ -200p &\geq -10 \\ p &\leq \frac{1}{20} \end{aligned}$$



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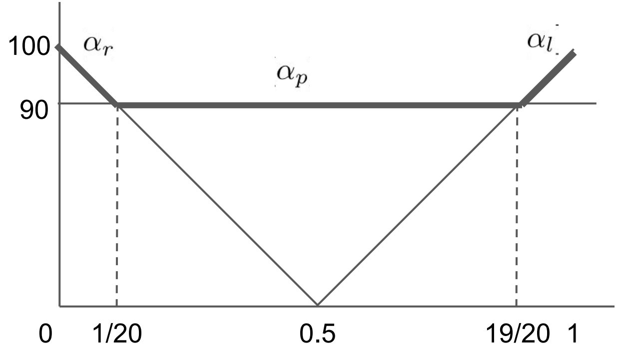

Question?

<EOF>

Credits

Images are taken from pixabay.com