

Markov Decision Processes

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Sequence of Actions

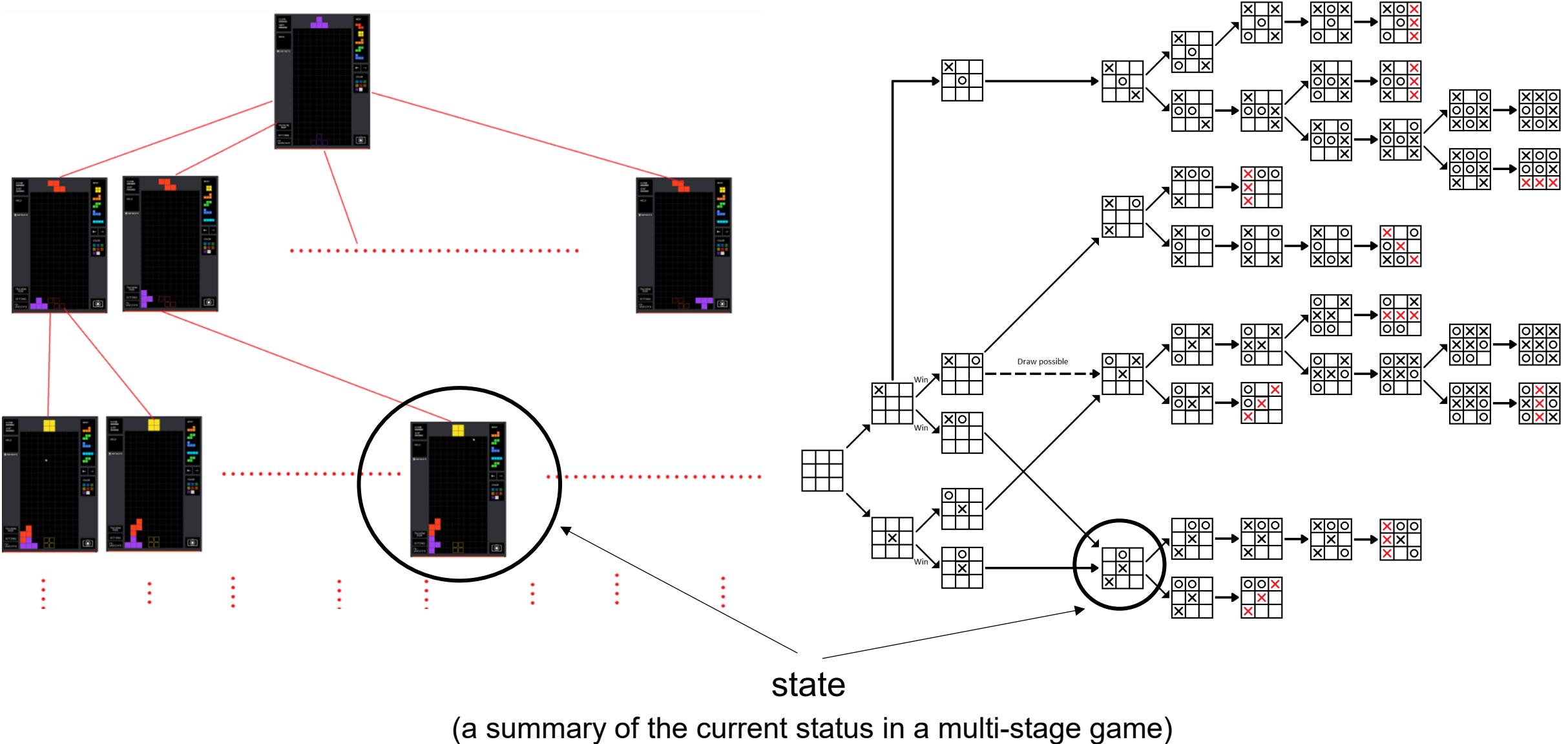


To win the game, the learner has to take a sequence of actions $a_1 \rightarrow a_2 \rightarrow \dots \rightarrow a_H$.

The effect of a particular action may not be revealed instantaneously.

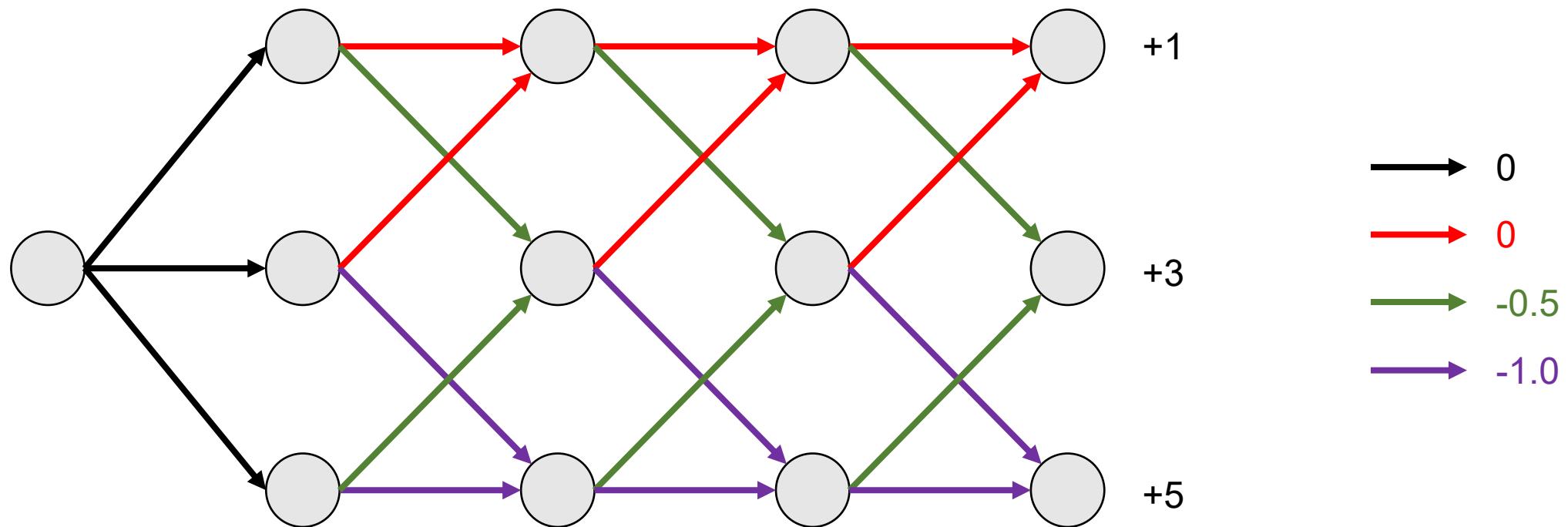
- Some effect may be revealed instantaneously
- Some may be revealed later

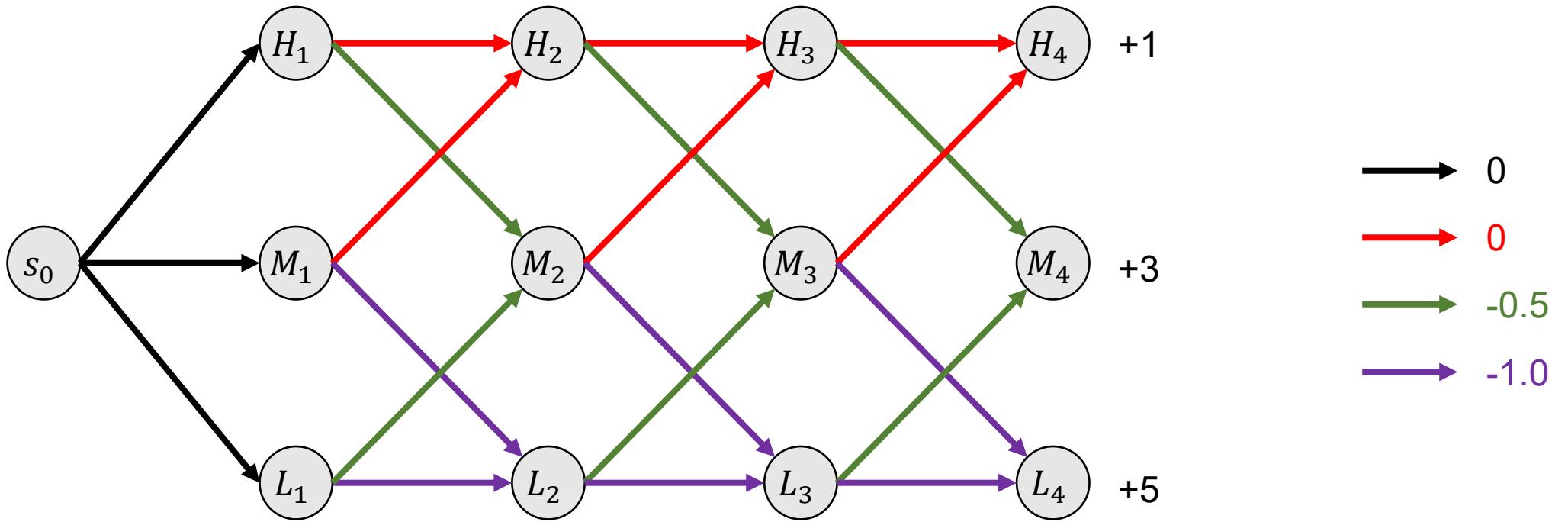
Sequence of Actions



Warm-Up: Deterministic World

Which path gives us the highest **total reward**?

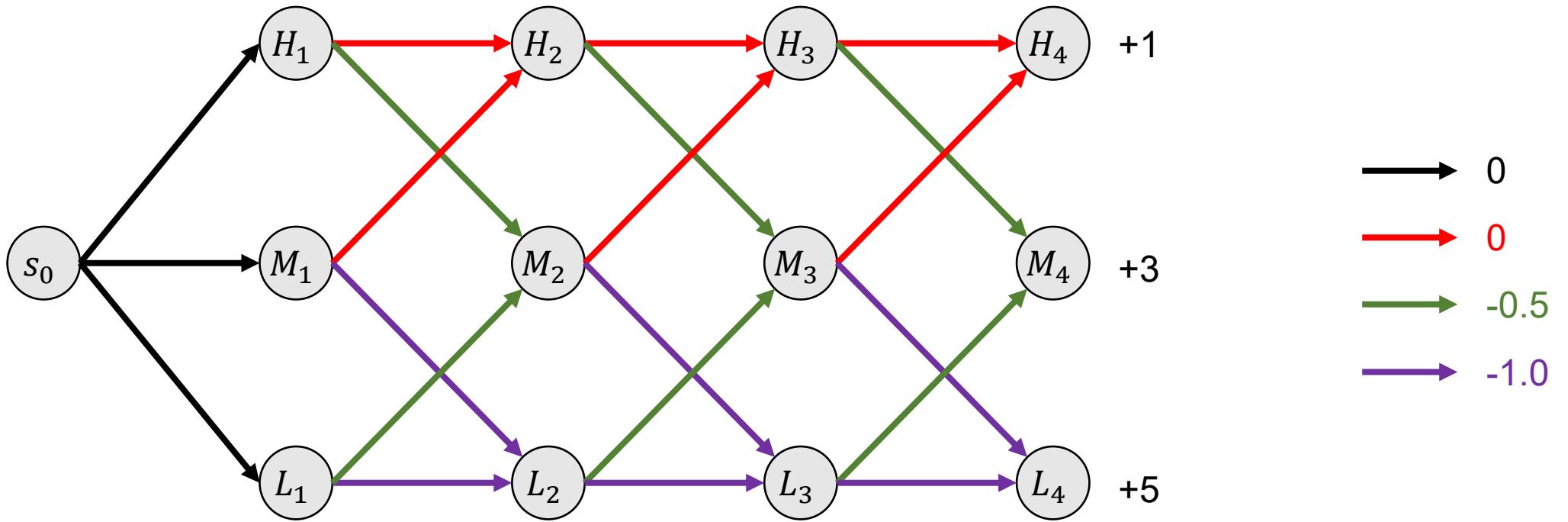




$V^*(s) :=$ maximum total reward starting from state s

$Q^*(s, a) :=$ maximum total reward starting from state s and taking action a **for one step**, and then following the optimal strategy

$\pi^*(s) :=$ optimal decision on state s



$$V^*(H_4) =$$

$$Q^*(H_3, \textcolor{red}{R}) =$$

$$V^*(H_3) =$$

$$Q^*(H_2, \textcolor{red}{R}) =$$

$$V^*(H_2) =$$

$$Q^*(H_3, \textcolor{green}{G}) =$$

$$Q^*(H_2, \textcolor{green}{G}) =$$

$$V^*(M_4) =$$

$$Q^*(M_3, \textcolor{red}{R}) =$$

$$V^*(M_3) =$$

$$Q^*(M_2, \textcolor{red}{R}) =$$

$$V^*(M_2) =$$

$$Q^*(M_3, \textcolor{purple}{P}) =$$

$$Q^*(M_2, \textcolor{purple}{P}) =$$

$$V^*(L_4) =$$

$$Q^*(L_3, \textcolor{green}{G}) =$$

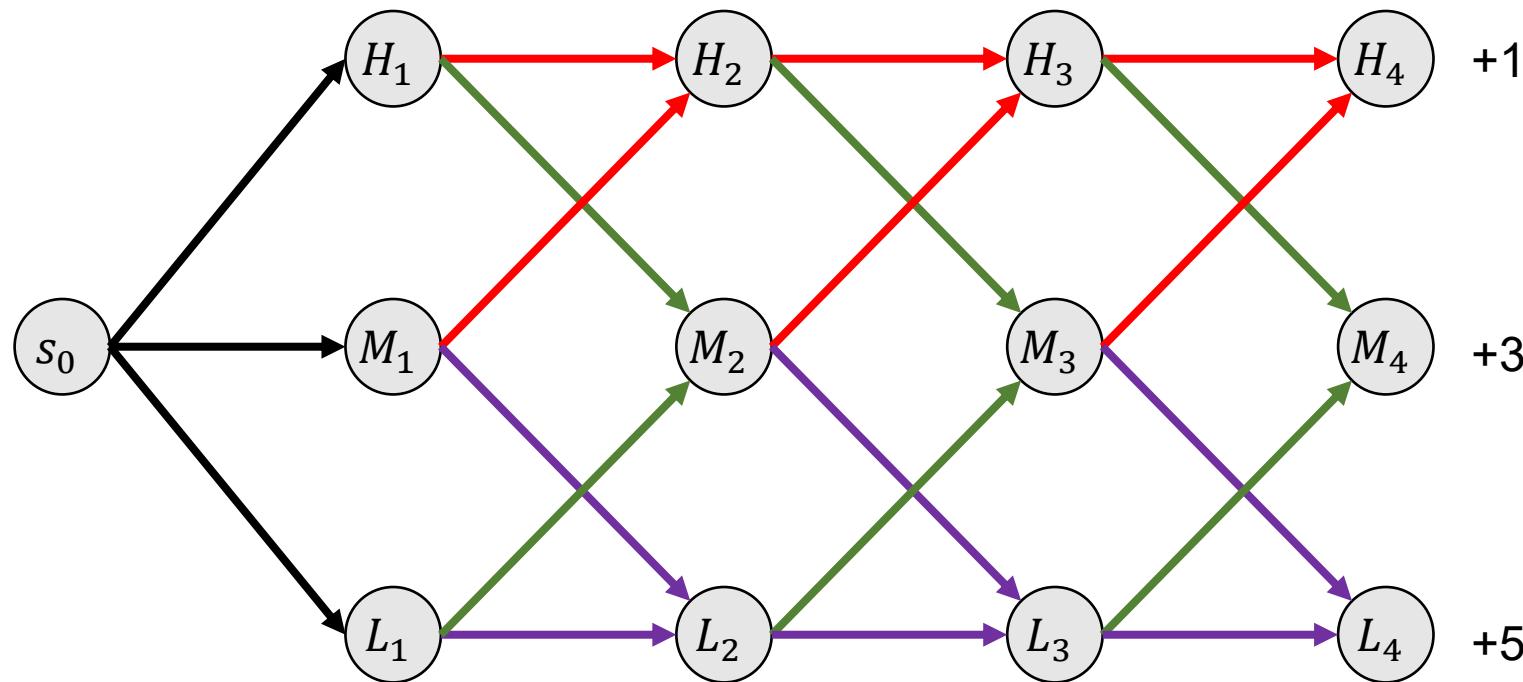
$$V^*(L_3) =$$

$$Q^*(L_2, \textcolor{green}{G}) =$$

$$V^*(L_2) =$$

$$Q^*(L_3, \textcolor{purple}{P}) =$$

$$Q^*(L_2, \textcolor{purple}{P}) =$$



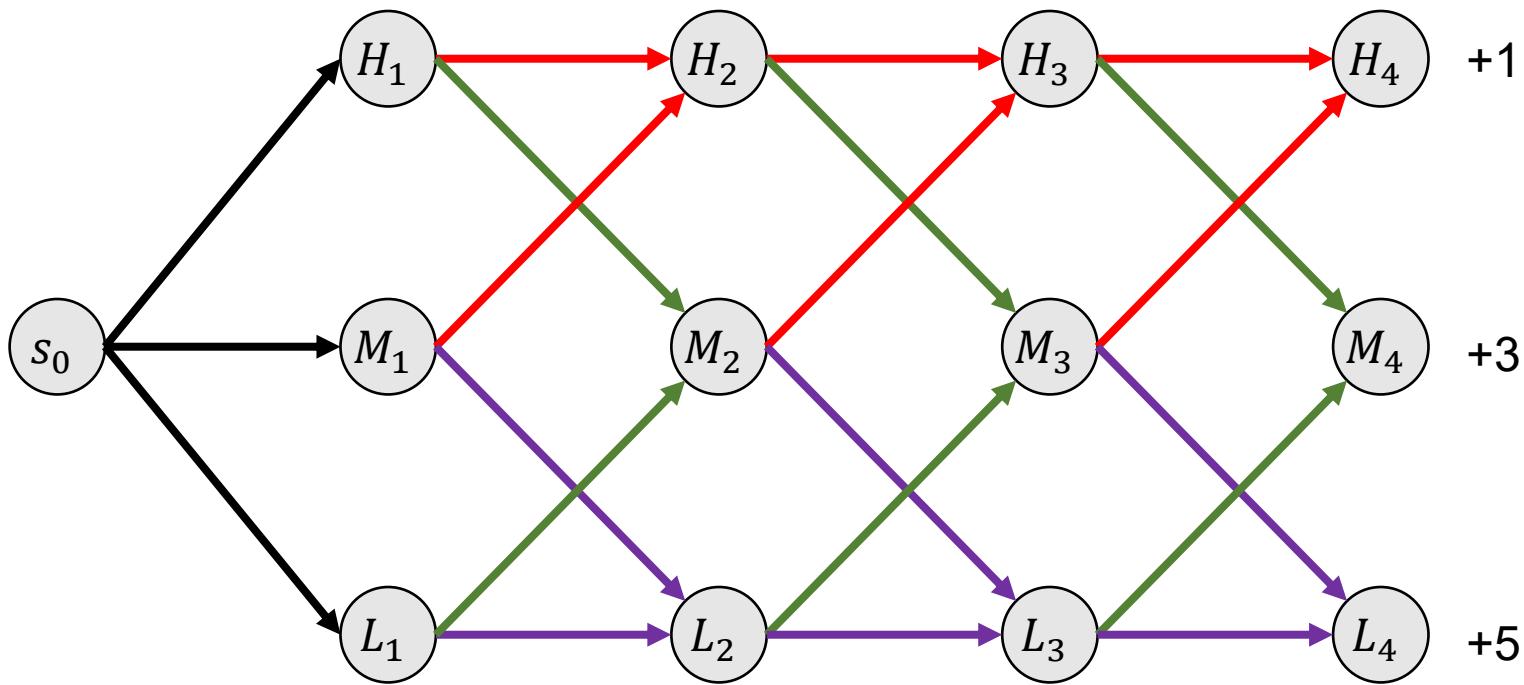
→ 0
 → 0
 → -0.5
 → -1.0

General rule:

$$Q^*(s, a) = R(s, a) + V^*(\text{next_state}(s, a))$$

$$V^*(s) = \max_a Q^*(s, a)$$

$$\pi^*(s) = \operatorname{argmax}_a Q^*(s, a)$$



General algorithm:

Repeat until Q, V no longer changes:

$$Q(s, a) \leftarrow R(s, a) + V(\text{next_state}(s, a)) \quad \text{for all } (s, a)$$

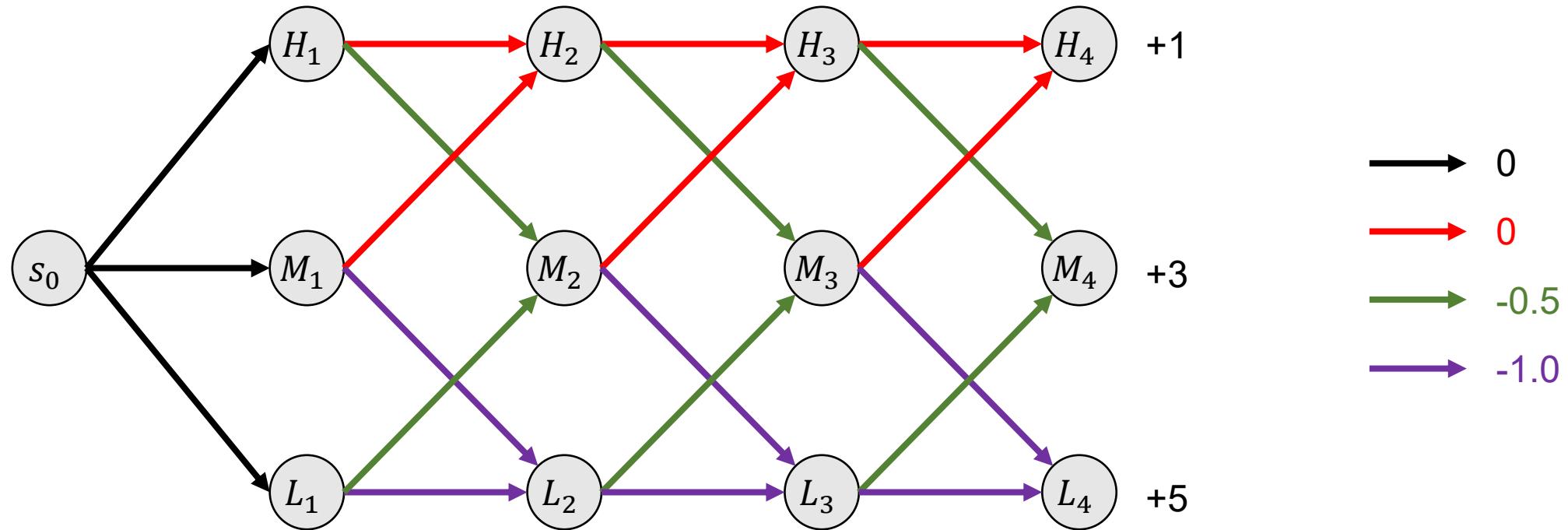
$$V(s) = \max_a Q(s, a) \quad \text{for all } s$$

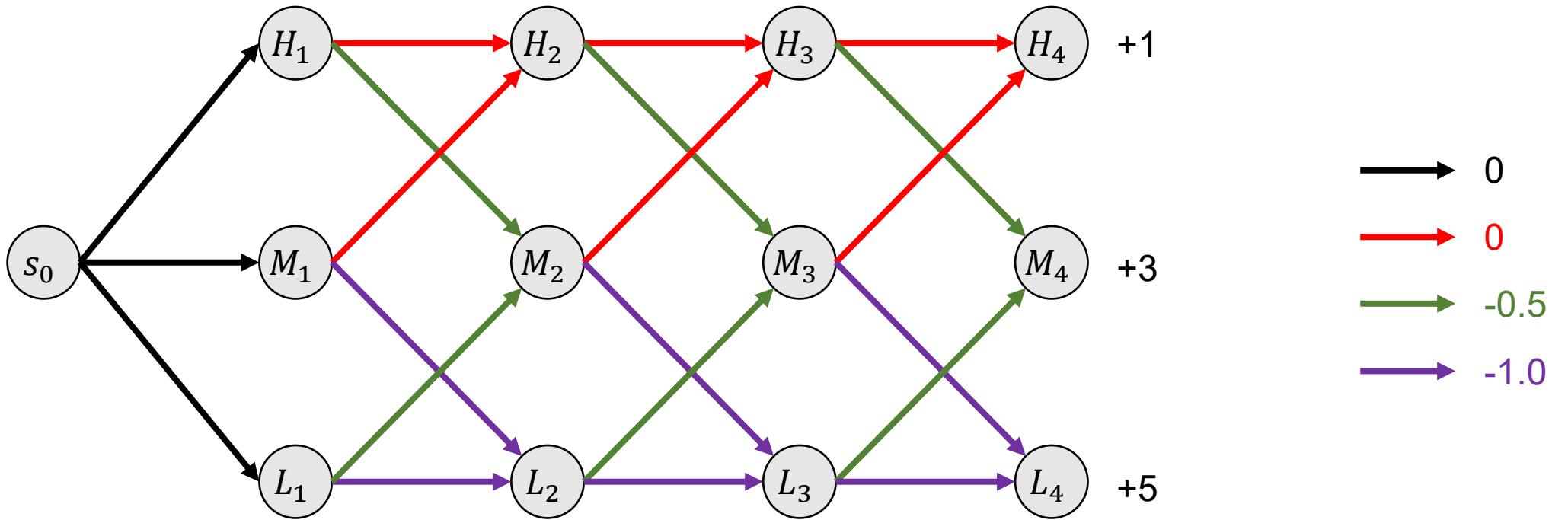
$$\pi^*(s) = \operatorname{argmax}_a Q(s, a)$$

Stochastic Worlds

Now, suppose taking an action does **not** lead to the desired state deterministically.

Instead, **with probability 0.8**, it goes to the state as specified in the figure;
with probability 0.1 each, it goes to the other two states.





$$V^*(H_4) =$$

$$Q^*(H_3, \textcolor{red}{R}) =$$

$$V^*(H_3) =$$

$$Q^*(H_2, \textcolor{red}{R}) =$$

$$V^*(M_4) =$$

$$Q^*(M_3, \textcolor{red}{R}) =$$

$$V^*(M_3) =$$

$$Q^*(M_2, \textcolor{red}{R}) =$$

$$V^*(L_4) =$$

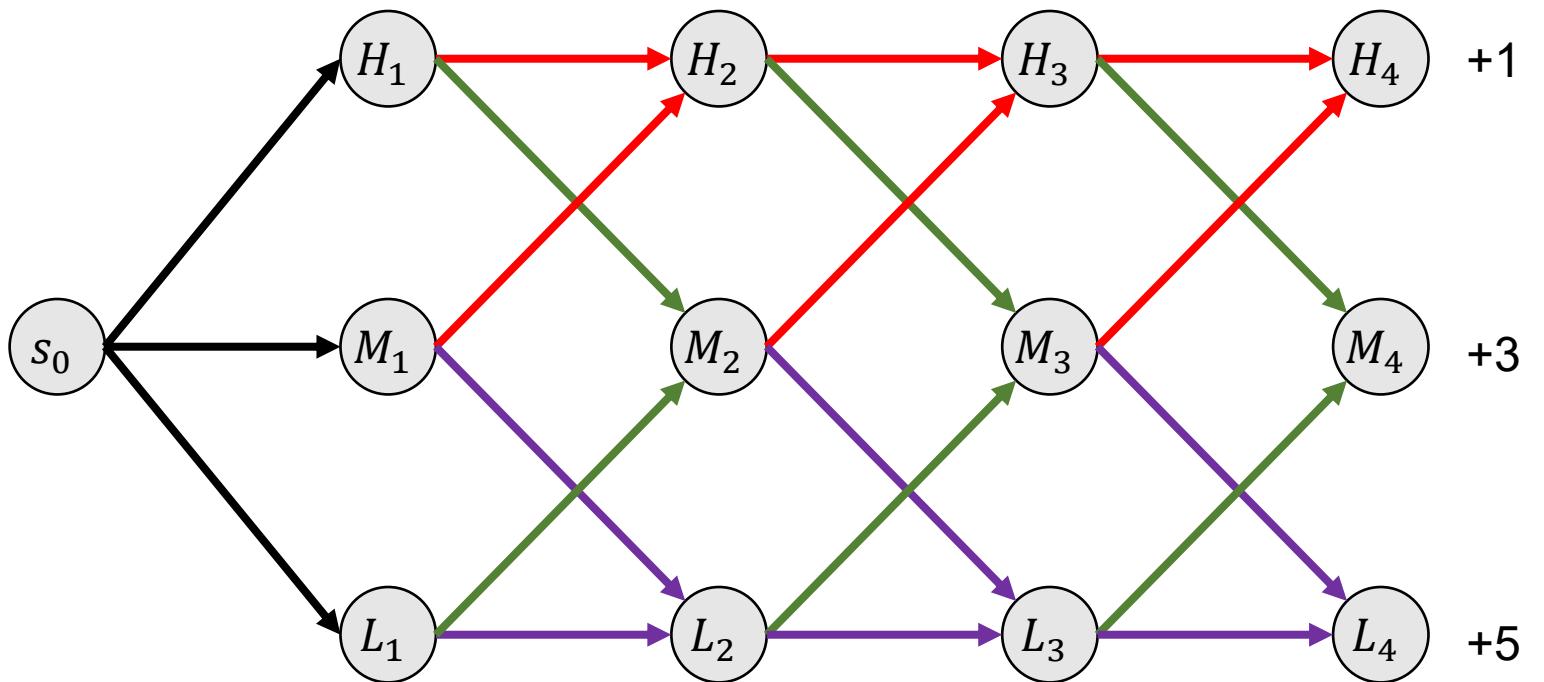
$$Q^*(L_3, \textcolor{green}{G}) =$$

$$V^*(L_3) =$$

$$Q^*(L_2, \textcolor{green}{G}) =$$

$$Q^*(L_3, \textcolor{violet}{P}) =$$

$$Q^*(L_2, \textcolor{violet}{P}) =$$

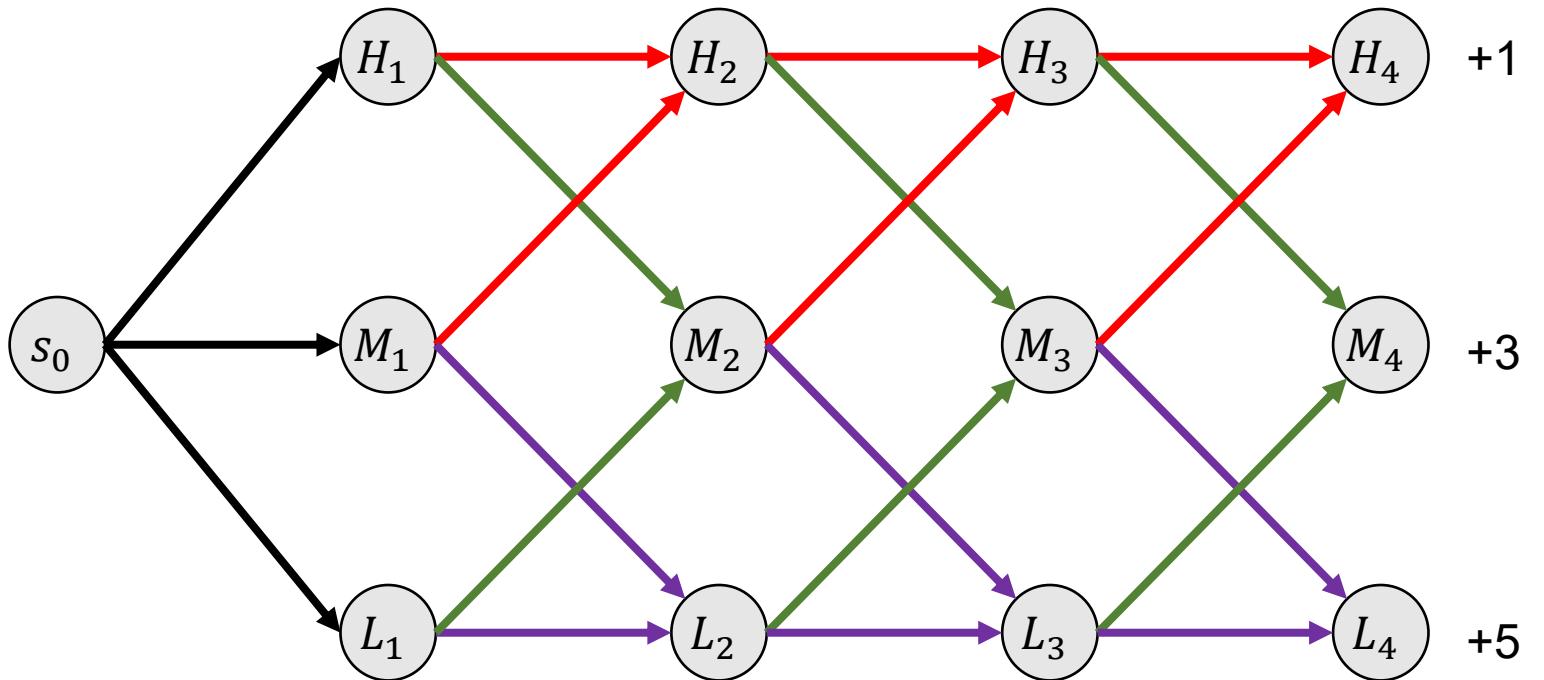


General rule:

$$Q^*(s, a) = R(s, a) + \sum_{s'} P(s'|s, a) V^*(s')$$

$$V^*(s) = \max_a Q^*(s, a)$$

$$\pi^*(s) = \operatorname{argmax}_a Q^*(s, a)$$



General algorithm (Value Iteration):

Repeat until Q, V no longer changes:

$$Q(s, a) \leftarrow R(s, a) + \sum_{s'} P(s'|s, a) V^*(s') \quad \text{for all } (s, a)$$

$$V(s) = \max_a Q(s, a) \quad \text{for all } s$$

$$\pi^*(s) = \operatorname{argmax}_a Q(s, a)$$

