Lecture 9: Model-free learning

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References

These slides are almost the exact copy of Practical RL course week 3 slides.
Special thanks to YSDA team for making them publicly available.

Original slides link: week03_model_free

Outline

- Value iteration brief overview
- Learning from trajectories
  - MC approach
  - Temporal difference
- Q-learning
- Exploration-exploitation tradeoff
- SARSA
- Experience replay
- Practice

Explaining goals to agent through reward

Reward hypothesis (R.Sutton)

Goals and purposes can be thought of as the maximization of the expected value of the cumulative sum of a received scalar signal

Explaining goals to agent through reward

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Cumulative reward is called a return:

$$G_t \triangleq R_t + R_{t+1} + R_{t+2} + \ldots + R_T$$

E.g.: reward in **chess** – value of taken opponent's piece

Explaining goals to agent through reward

Reward hypothesis (R.Sutton)

> Goals and purposes can be thought of as the maximization of the expected value of the cumulative sum of a received scalar signal

Cumulative reward is called a return:

end of an episode

$$\boxed{G_t} \triangleq \boxed{R_t} + R_{t+1} + R_{t+2} + \ldots + R_{\boxed{T}}$$

immediate reward

E.g.: reward in **chess** – value of taken opponent's piece

E.g.: data center non-stop cooling system

- **S**tates – temperature measurements
- **A**ctions – different fans speed
- **R = 0** for exceeding temperature thresholds
- **R = +1** for each second system is cool

What could go wrong with such a design?

E.g.: data center non-stop cooling system

- **S**tates – temperature measurements
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What could go wrong with such a design?

Infinite return for non optimal behaviour!

$$G_t = 1 + 1 + 0 + 1 + 1 + 0 + ... = \sum_{t=1}^{\infty} R_t = \infty$$

E.g.: cleaning robot

- **S**tates – dust sensors, air
- **A**ctions – cleaning / rest / conditioning on or off
- **R = 100** for long tedious floor cleaning task done
- **R = 1** for turning air conditioning on-off
- Episode ends each day

What could go wrong with such a design?

E.g.: cleaning robot

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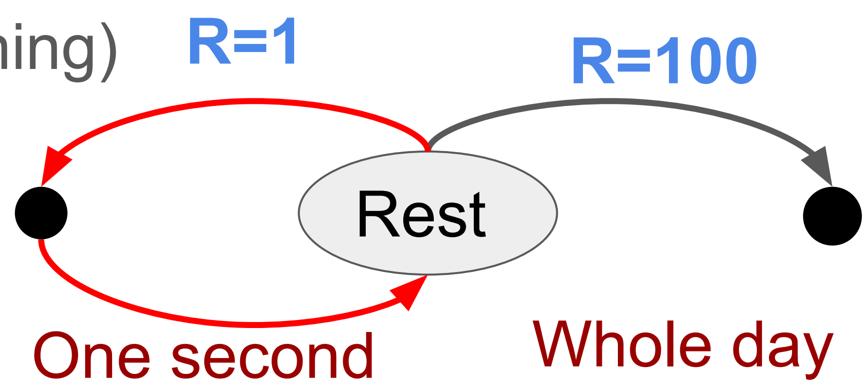
What could go wrong with such a design?

Reward(air) < Reward(cleaning)
Time(air) << Time(cleaning)

Positive feedback loop!



OpenAI blog post about faulty rewards: https://openai.com/blog/faulty-reward-functions/

Reward discounting

Reward discounting

Get rid of infinite sum by discounting $0 \leq \gamma < 1$

$$G_t \triangleq R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \dots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

discount factor

The same cake compared to today's one worth

- γ times less tomorrow
- γ^2 times less the day after tomorrow

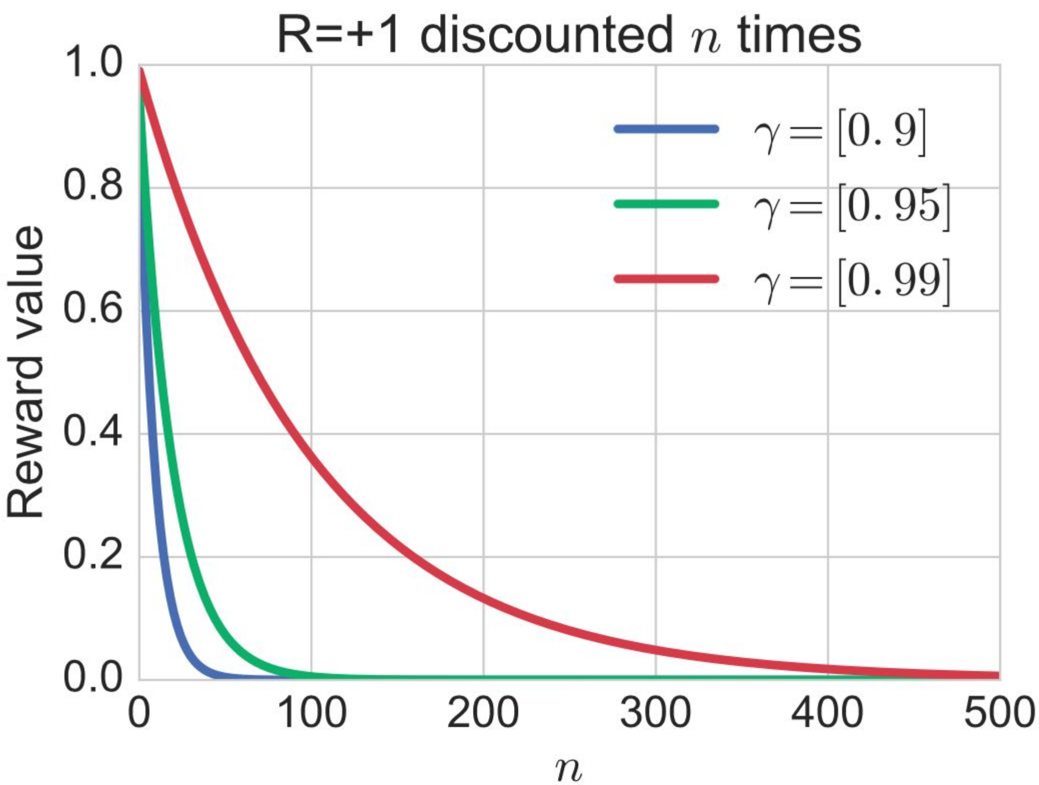
γ will eat it day by day

Discounting makes sums finite

Maximal return for **R = +1**

$$G_0 = \sum_{k=0}^{\infty} \gamma^k = \frac{1}{1-\gamma}$$

γ	0.9	0.95	0.99
$\frac{1}{1-\gamma}$	10	20	100



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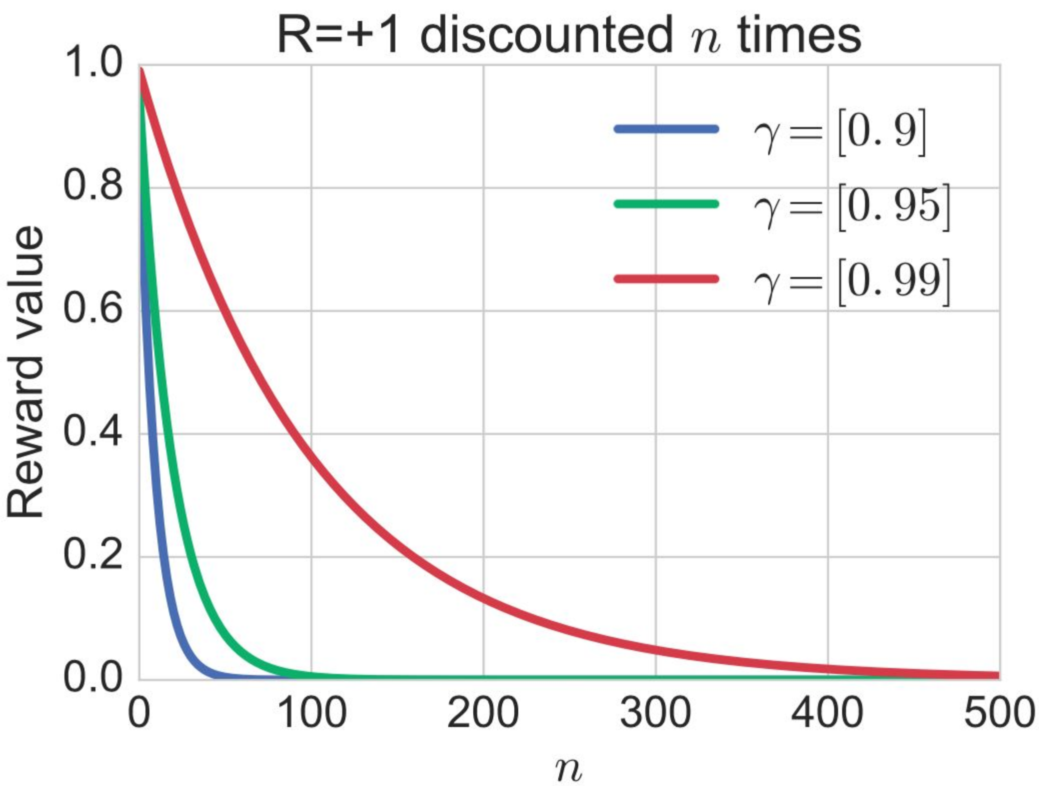
Any discounting changes optimisation task and its solution!



Discounting is inherent to humans

- Quasi-hyperbolic $f(t) = \beta\gamma^t$
- Hyperbolic discounting $f(t) = \dfrac{1}{1 + \beta t}$

Laibson, D. (1997). Golden eggs and hyperbolic discounting. The Quarterly Journal of Economics, 112(2), 443-478.

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Mathematical convenience

$$\begin{aligned} G_t &= R_t + \gamma(R_{t+1} + \gamma R_{t+2} + \ldots) \\ &= \boxed{R_t + \gamma\, G_{t+1}} \end{aligned}$$

Remember this one!
We will need it later

Laibson, D. (1997). Golden eggs and hyperbolic discounting. The Quarterly Journal of Economics, 112(2), 443-478.

Discounting is a stationary end-of-effect model

Any action affects (1) immediate reward (2) next state

Discounting is a stationary end-of-effect model

Any action affects (1) immediate reward (2) $\boxed{\text{next state}}$

Action indirectly affects future rewards

But how long does this effect lasts?

$$
\begin{aligned}
G_0 &= R_0 + \gamma R_1 + \gamma^2 R_2 + \ldots + \gamma^T R_T \\
&= (1-\gamma) R_0 \\
&\quad + (1-\gamma)\gamma (R_0 + R_1) \\
&\quad + (1-\gamma)\gamma^2 (R_0 + R_1 + R_2) \\
&\quad \cdots \\
&\quad + \gamma^T \cdot \sum_{t=0}^{T} R_t
\end{aligned}
$$

G is expected return under stationary end-of-effect model

Discounting is a stationary end-of-effect model

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&\quad + \boxed{(1-\gamma)} \boxed{\gamma} (R_0 + R_1) \\
&\quad + \boxed{(1-\gamma)} \gamma^2 (R_0 + R_1 + R_2) \\
&\quad \cdots \\
&\quad + \gamma^T \cdot \sum_{t=0}^{T} R_t
\end{aligned}
$$

"End of effect" probability

"Effect continuation" probability

G is expected return under stationary end-of-effect model

Reward design – don’t shift, reward for WHAT

- E.g.: chess – value of taken opponent's piece
  - Problem: agent will not have a desire to win!
- E.g.: cleaning robot, **+100** (cleaning), **+0.1** (on-off)
  - Problem: agent will not bother cleaning the floor!

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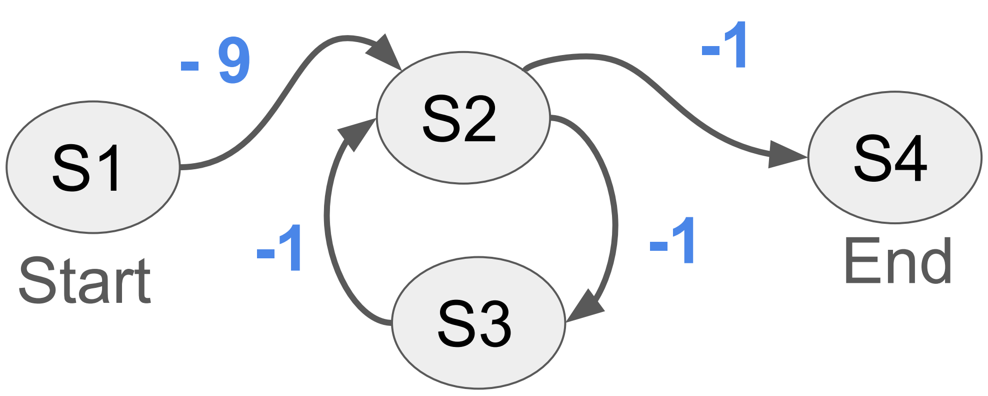
Take away: reward only for WHAT, but never for HOW



Reward design – don’t shift, reward for WHAT

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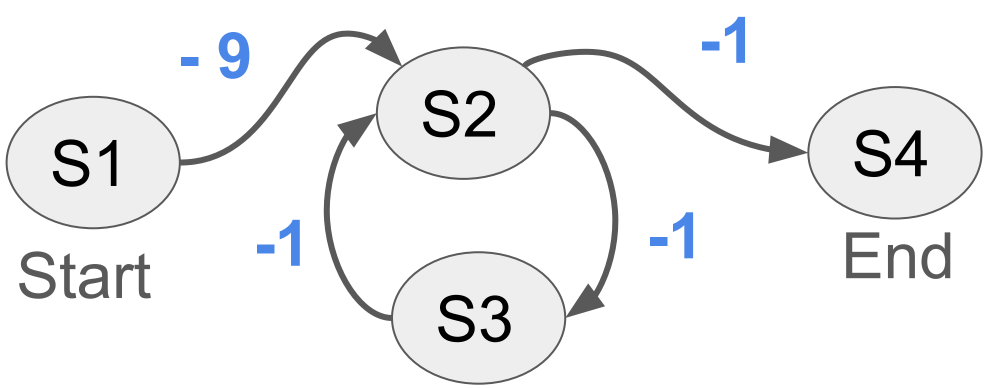


Take away: do not subtract mean from rewards

Reward design – scaling, shaping

What transformations do not change optimal policy?

- Reward **scaling** – division by positive constant
  - May be useful in practise for approximate methods

Ng, A. Y., Harada, D., & Russell, S. (1999, June). Policy invariance under reward transformations: Theory and application to reward shaping. In ICML (Vol. 99, pp. 278-287).

Reward design – scaling, shaping

What transformations do not change optimal policy?

- Reward **scaling** – division by positive constant
  - May be useful in practise for approximate methods
- Reward **shaping** – we could add to all rewards in MDP values of potential-based shaping function F(s, a, s') without changing an optimal policy:

$$F(s, a, s') = \gamma\Phi(s') - \Phi(s)$$

Intuition: when no discounting F adds as much as it subtracts from the total return

Ng, A. Y., Harada, D., & Russell, S. (1999, June). Policy invariance under reward transformations: Theory and application to reward shaping. In ICML (Vol. 99, pp. 278-287).

Previously...

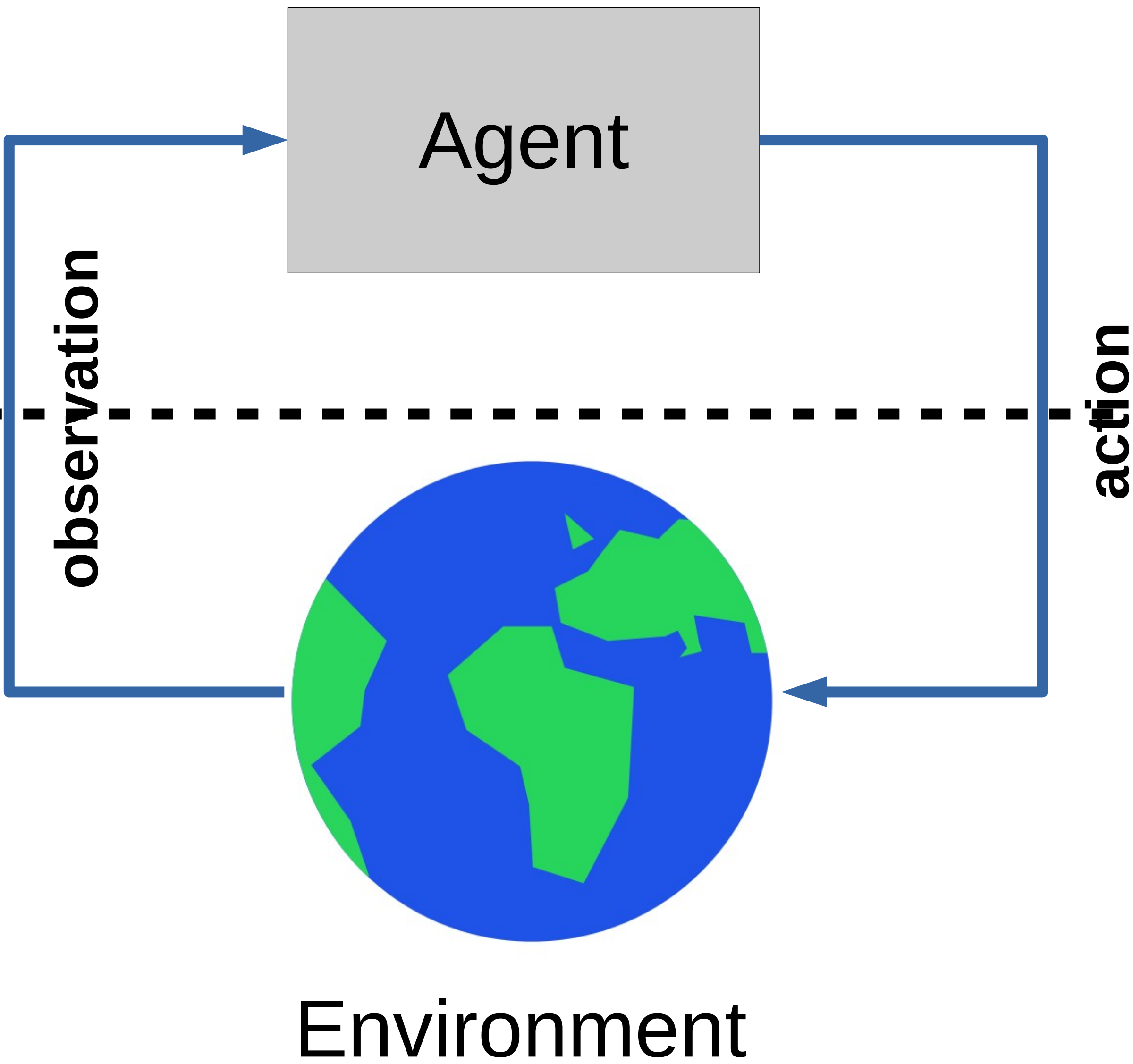
- **V(s)** and **V*(s,a)**
- know V* and P(s'|s,a) → know optimal policy
- We can learn V* with dynamic programming

$$V_{i+1}(s) := max_a [r(s,a) + \gamma \cdot E_{s' \sim P(s'|s,a)} V_i(s')]$$

Decision process in the wild

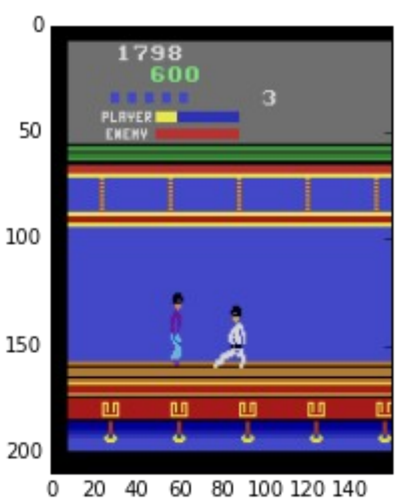
Can do anything

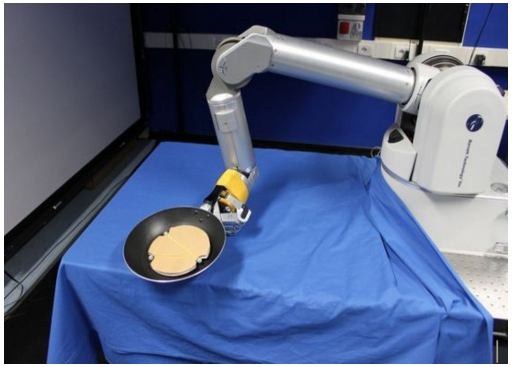
Can't even see
(worst case)



Decision process in the wild

Can do anything





Model-free setting:

We don't know actual

$P(s',r|s,a)$

Whachagonnado?

Model-free setting:

We don't know actual

P(s',r|s,a)

Learn it?

Get rid of it?

More new letters

- **V_π(s)** – expected G from state **s** if you follow **π**
- **V*(s)** – expected G from state s if you follow **π***

More new letters

- $\mathbf{V_\pi(s)}$ – expected G from state **s** if you follow **π**
- $\mathbf{V^*(s)}$ – expected G from state s if you follow **π***

- $\mathbf{Q_\pi(s,a)}$ – expected G from state **s**
  - if you start by taking action **a**
  - and follow **π** from next state on

- $\mathbf{Q^*(s,a)}$ – guess what it is :)

More new letters

- $\mathbf{V_{\pi}(s)}$ – expected G from state **s** if you follow $\boldsymbol{\pi}$
- $\mathbf{V^{*}(s)}$ – expected G from state s if you follow $\boldsymbol{\pi^{*}}$

- $\mathbf{Q_{\pi}(s,a)}$ – expected G from state **s**
  – if you start by taking action **a**
  – and follow $\boldsymbol{\pi}$ from next state on

- $\mathbf{Q^{*}(s,a)}$ – same as $\mathbf{Q_{\pi}(s,a)}$ where $\boldsymbol{\pi = \pi^{*}}$

Trivia

- Assuming you know **Q*(s,a)**,
  - how do you compute **π***
  - how do you compute **V*(s)**?
- Assuming you know V(s)
  - how do you compute **Q(s,a)?**

To sum up

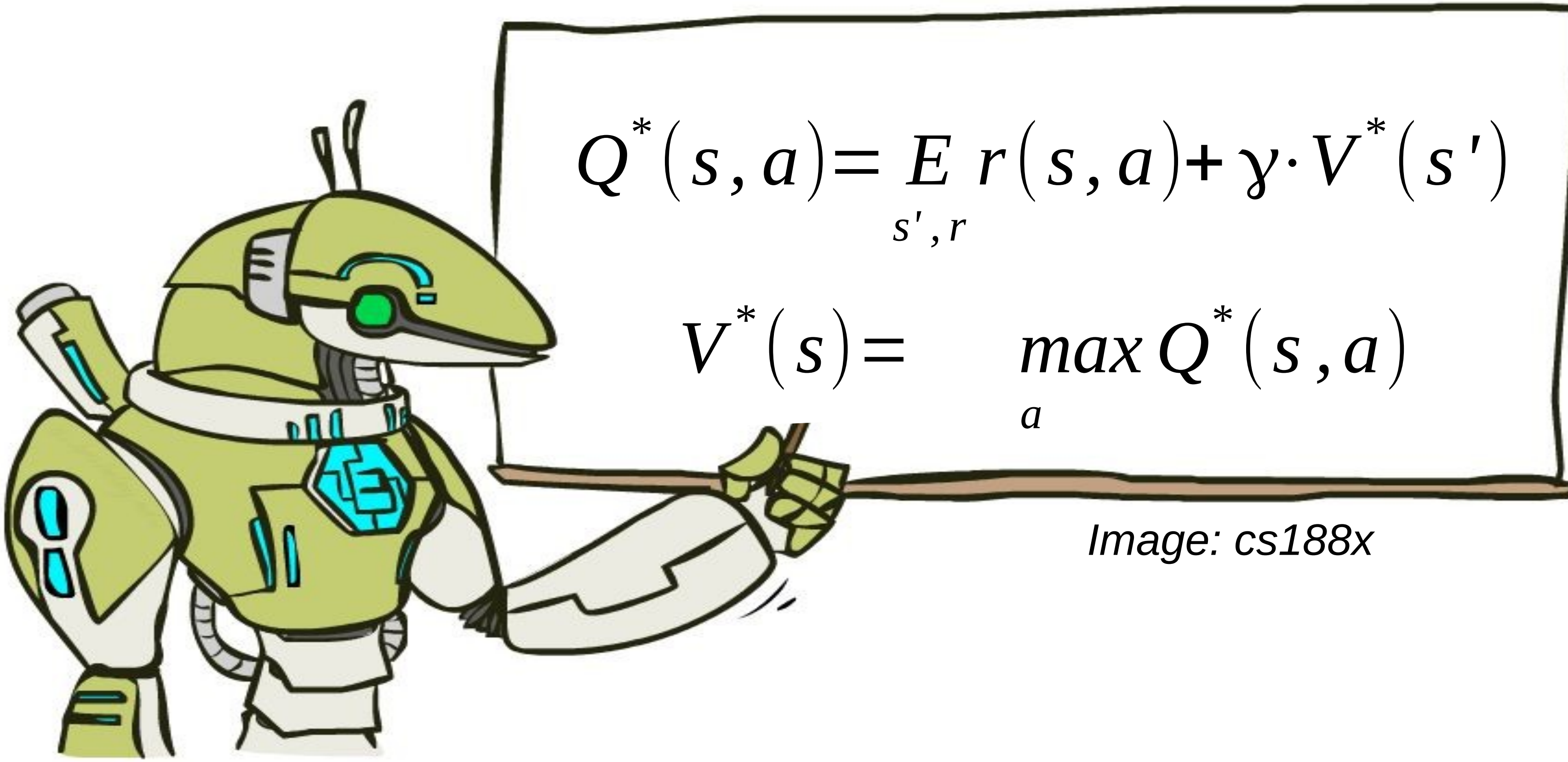
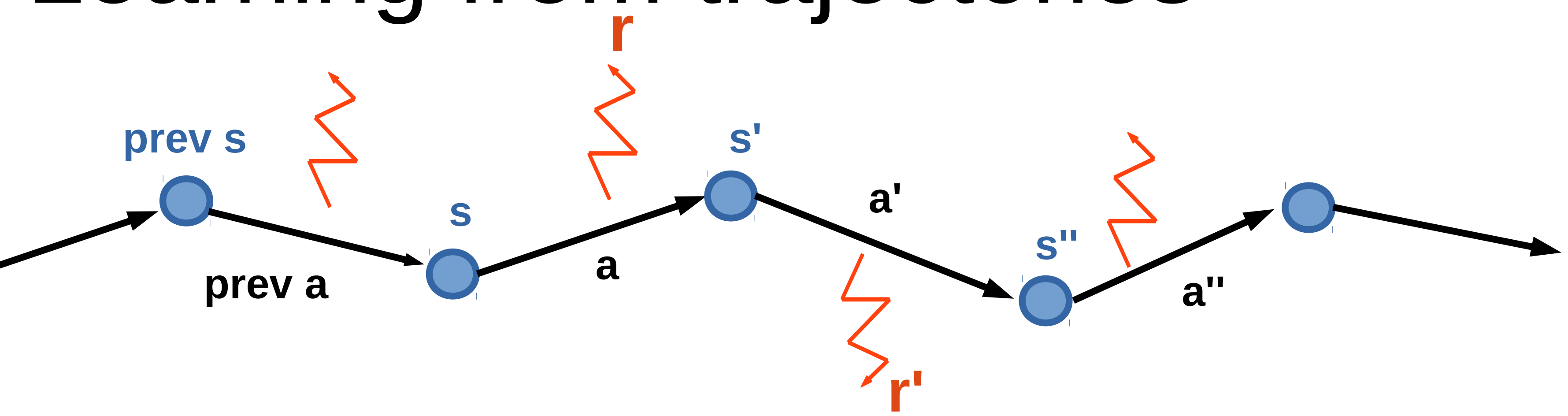


Image: cs188x

Action value Q_π(s,a) is the expected total reward **G** agent gets from state **s** by taking action **a** and following policy **π** from next state.

$$\pi(s) : argmax_a Q(s,a)$$

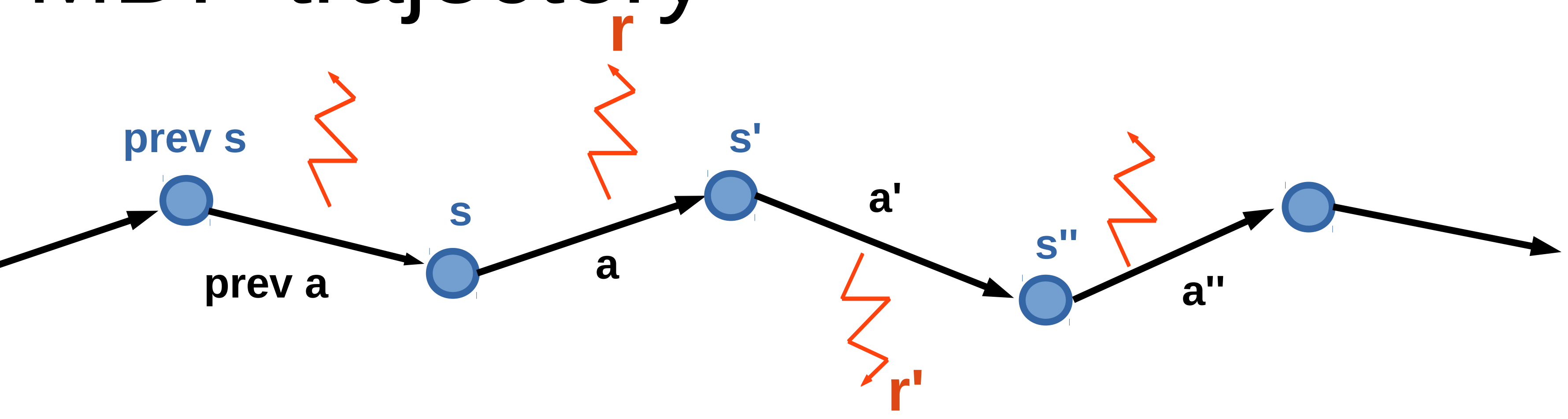
Learning from trajectories



Model-based: you know P(s'|s,a)
- can apply dynamic programming
- can plan ahead

Model-free: you can sample trajectories
- can try stuff out
- insurance not included

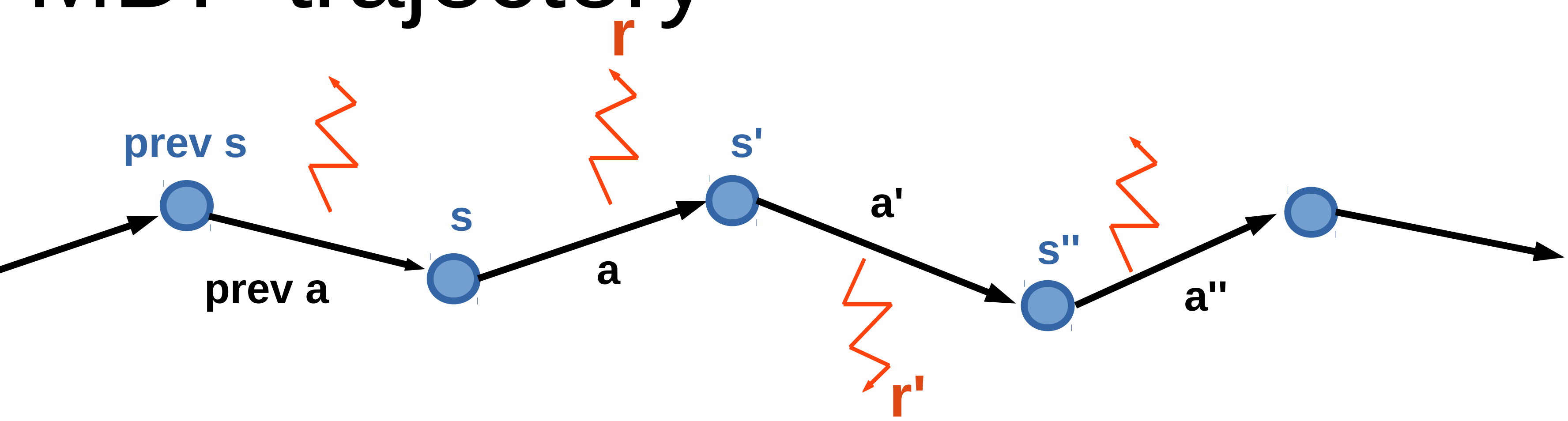
MDP trajectory



- Trajectory is a sequence of
  - states (s)
  - actions (a)
  - rewards (r)

- We can only sample trajectories

MDP trajectory



- Trajectory is a sequence of
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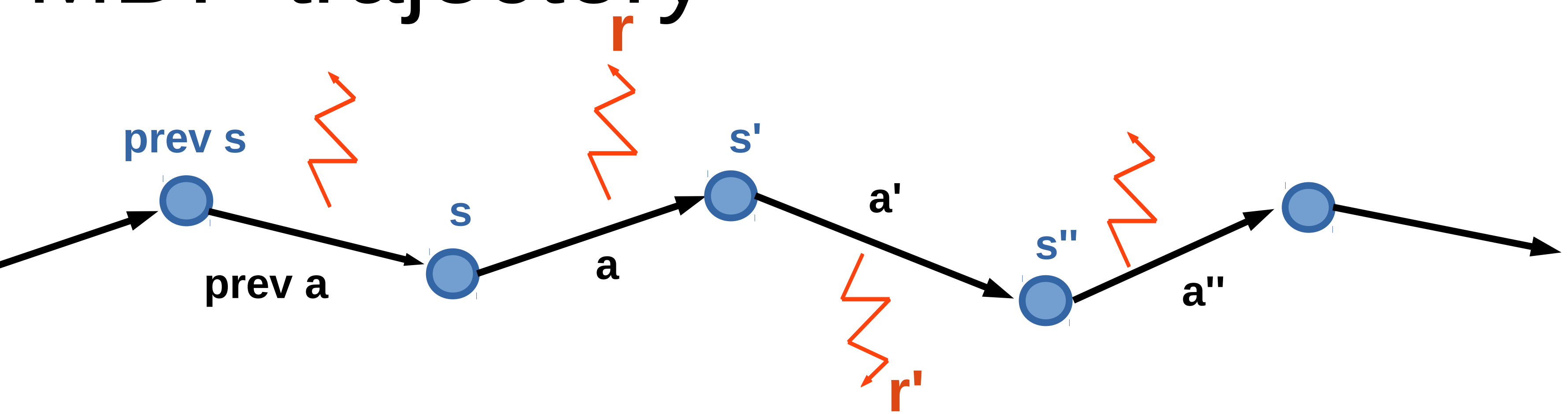
Q: What to learn?
V(s) or Q(s,a)

- We can only sample trajectories

MDP trajectory



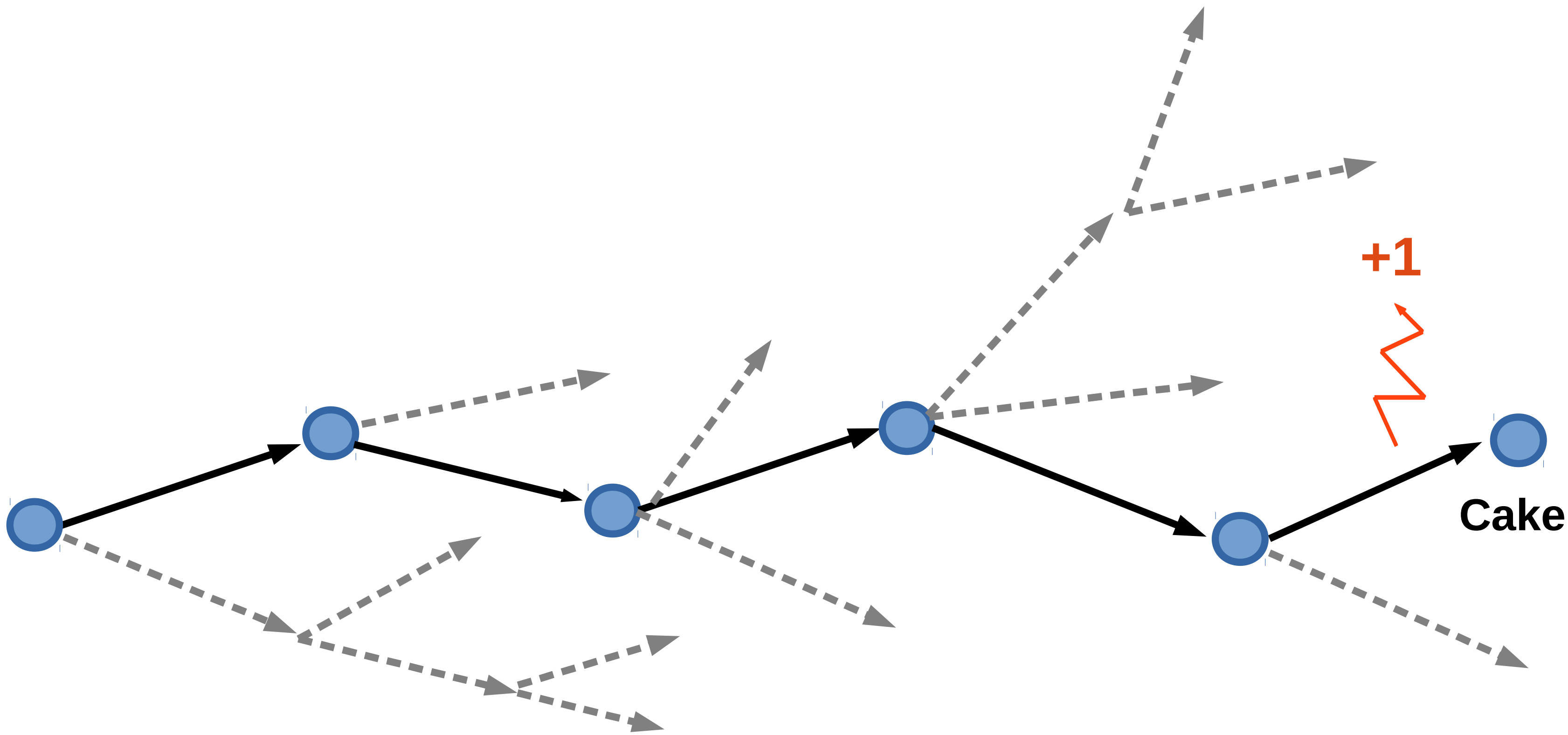
- Trajectory is a sequence of
  - states (s)
  - actions (a)
  - rewards (r)
- We can only sample trajectories

Q: What to learn?
V(s) or <u>Q(s,a)</u>

V(s) is useless
without P(s'|s,a)

Idea 1: monte-carlo

- Get all trajectories containing particular (s,a)
- Estimate G(s,a) for each trajectory
- Average them to get expectation



Idea 1: monte-carlo

- Get all trajectories containing particular (s,a)
- Estimate G(s,a) for each trajectory
- Average them to get expectation

takes a lot of sessions

Image: super meat boy

Idea 2: temporal difference

- Remember we can improve Q(s,a) iteratively!

$$Q(s_t, a_t) \leftarrow \underset{r_t, s_{t+1}}{E} r_t + \gamma \cdot max_{a'} Q(s_{t+1}, a')$$

Idea 2: temporal difference

- Remember we can improve Q(s,a) iteratively!

$$Q(s_t, a_t) \leftarrow \underset{r_t, s_{t+1}}{E} r_t + \gamma \cdot max_{a'} Q(s_{t+1}, a')$$

That's Q*(s,a)

That's value for π*
aka optimal policy

Idea 2: temporal difference

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$$Q(s_t, a_t) \leftarrow \underset{r_t, s_{t+1}}{E} \; r_t + \gamma \cdot max_{a'} Q(s_{t+1}, a')$$

That's Q*(s,a)

That's something we don't have

What do we do?

That's value for π*
aka optimal policy

Idea 2: temporal difference

Idea 2: temporal difference

- Replace expectation with sampling

$$\underset{r_t, s_{t+1}}{E} r_t + \gamma \cdot max_{a'} Q(s_{t+1}, a') \approx \frac{1}{N} \sum_i r_i + \gamma \cdot max_{a'} Q(s_i^{next}, a')$$

Idea 2: temporal difference

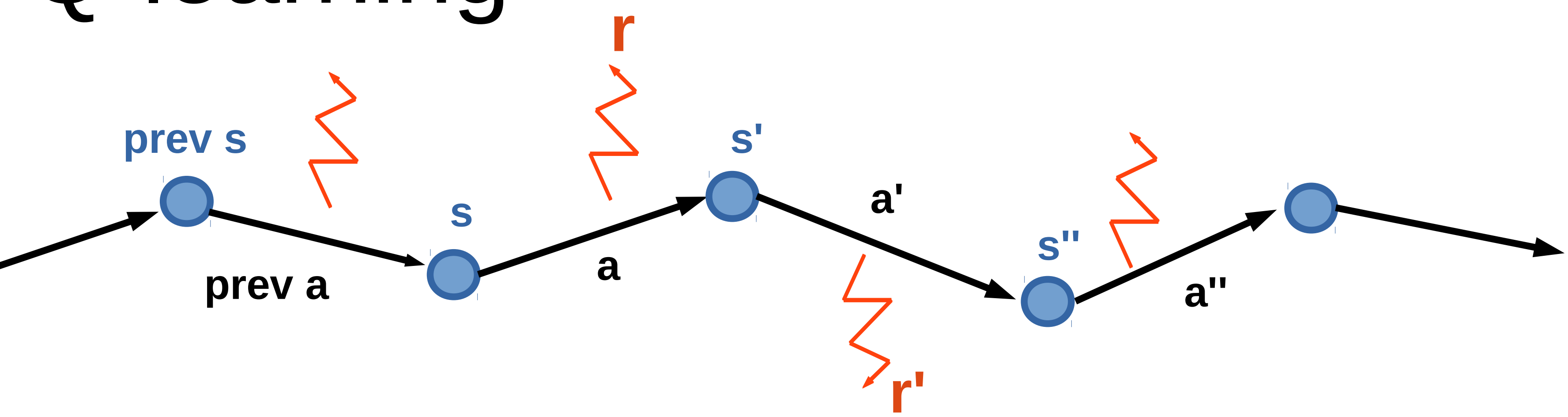
- Replace expectation with sampling

$$\underset{r_t, s_{t+1}}{E} r_t + \gamma \cdot max_{a'} Q(s_{t+1}, a') \approx \frac{1}{N} \sum_i r_i + \gamma \cdot max_{a'} Q(s_i^{next}, a')$$

- Use moving average with just one sample!

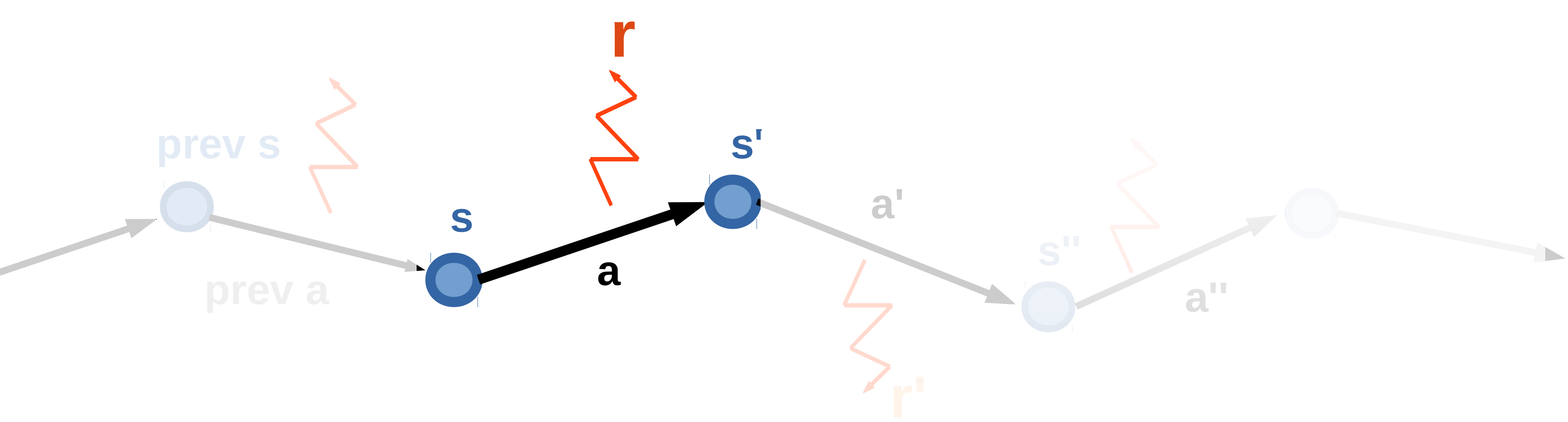
$$Q(s_t, a_t) \leftarrow \alpha \cdot (r_t + \gamma \cdot max_{a'} Q(s_{t+1}, a')) + (1 - \alpha) Q(s_t, a_t)$$

Q-learning



- Works on a sequence of
  - states (s)
  - actions (a)
  - rewards (r)

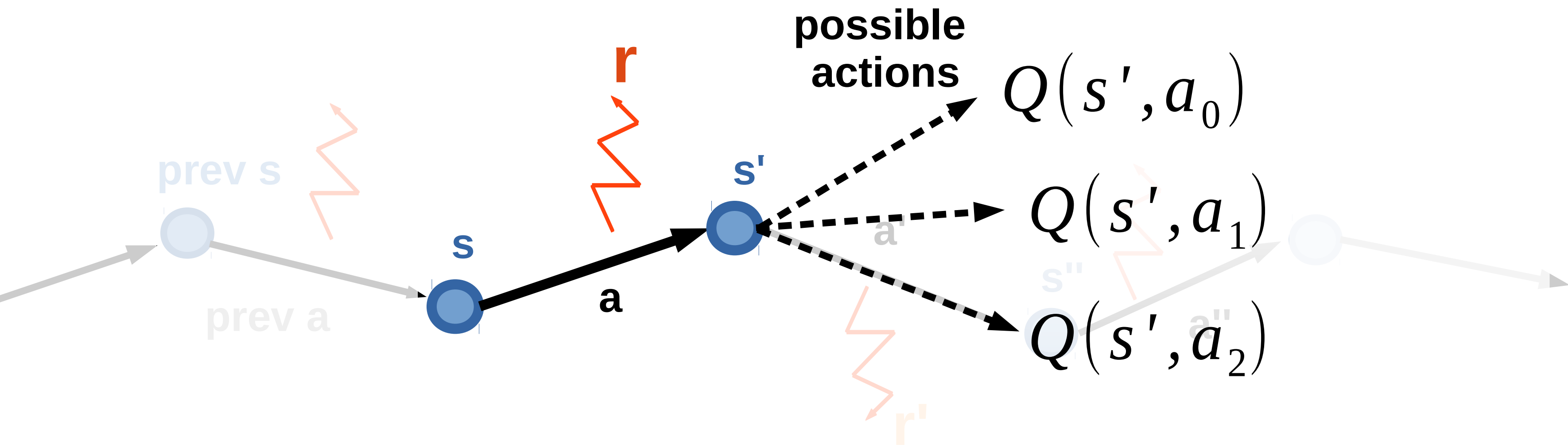
Q-learning



Initialize Q(s,a) with zeros

- Loop:
  - Sample <**s**,**a**,**r**,**s'**> from env

Q-learning



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- Loop:
  - Sample <**s**,**a**,**r**,**s'**> from env
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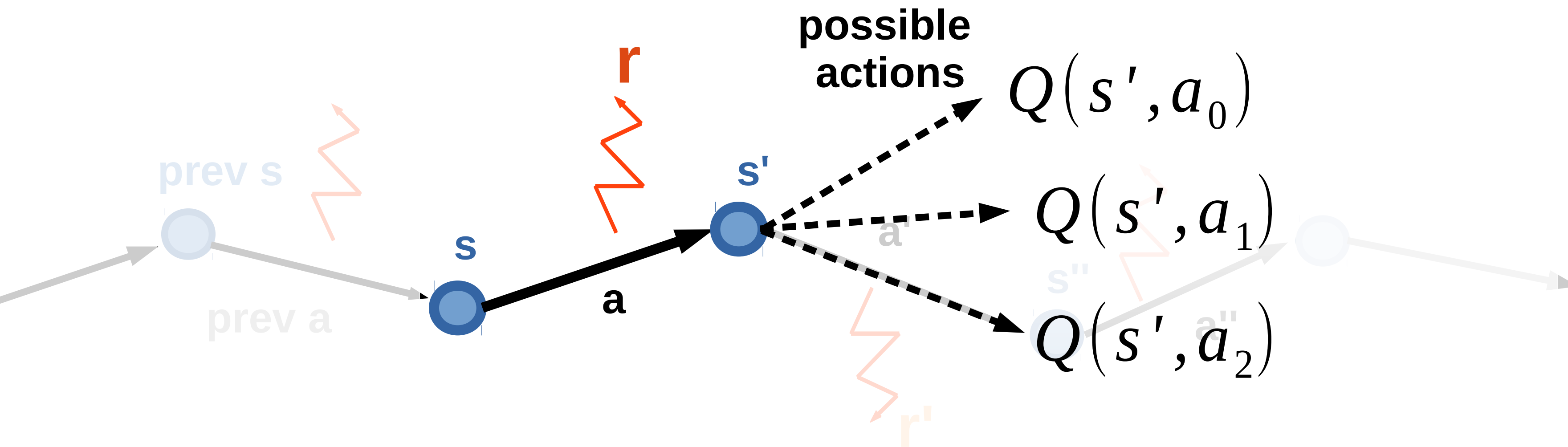
Q-learning



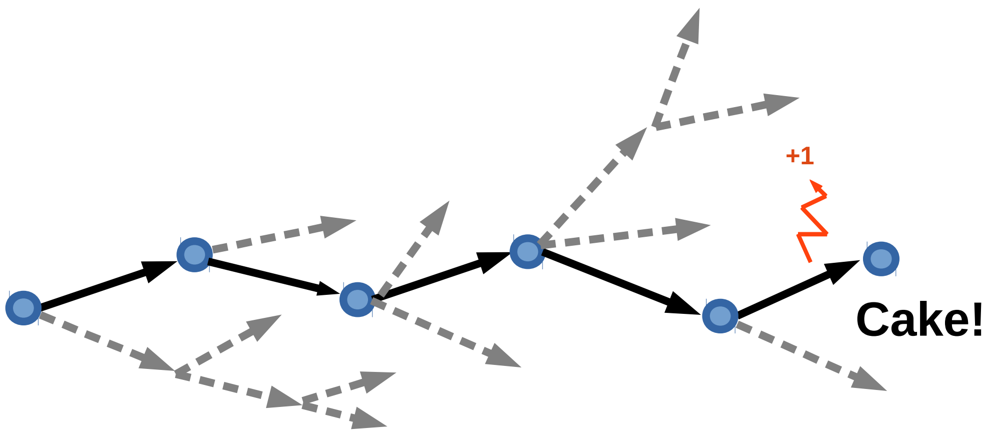
Initialize Q(s,a) with zeros

- Loop:
  - Sample <**s**,**a**,**r**,**s'**> from env
  - Compute $\hat{Q}(s,a) = r(s,a) + \gamma \max_{a_i} Q(s', a_i)$
  - Update $Q(s,a) \leftarrow \alpha \cdot \hat{Q}(s,a) + (1-\alpha) Q(s,a)$

Recap

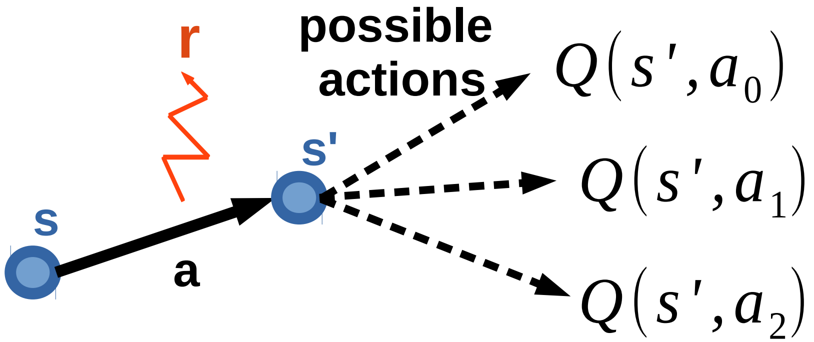
Monte-carlo

- Averages Q over sampled paths



Temporal Difference

- Uses recurrent formula for Q

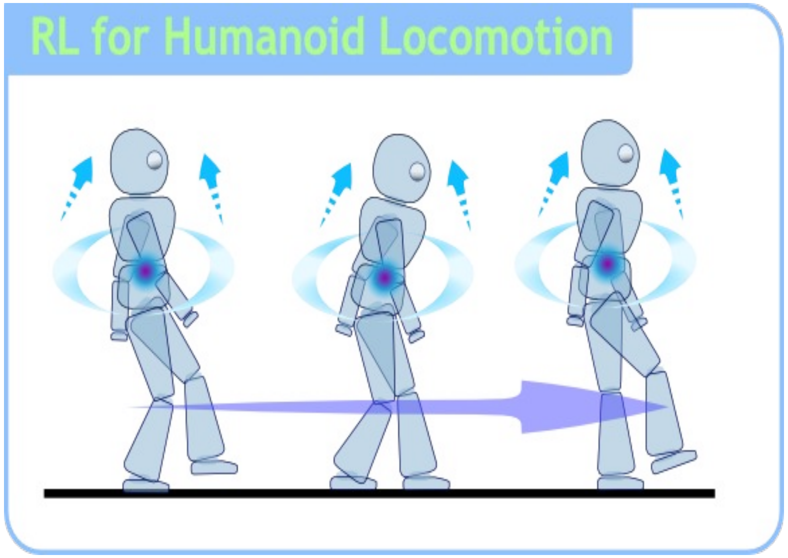


Nuts and bolts: MC vs TD

Monte-carlo	**Temporal Difference**
• Averages Q over sampled paths	• Uses recurrent formula for Q
• Needs full trajectory to learn	• Learns from partial trajectory Works with infinite MDP
• Less reliant on markov property	• Needs less experience to learn

What could possibly go wrong?

Our mobile robot learns to walk.

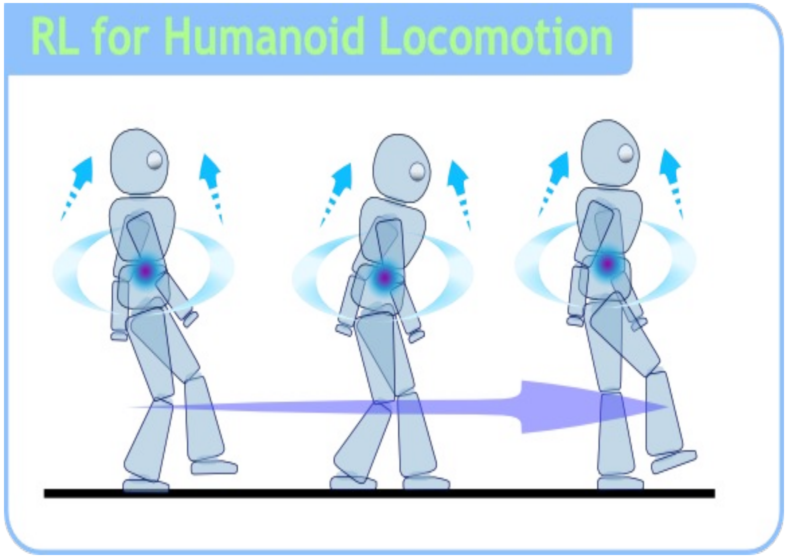


Initial Q(s,a) are zeros
robot uses argmax Q(s,a)

He has just learned to crawl with positive reward!

What could possibly go wrong?

Our mobile robot learns to walk.



Initial Q(s,a) are zeros
robot uses argmax Q(s,a)

Too bad, now he will never learn to walk upright =(

What could possibly go wrong?

New problem:

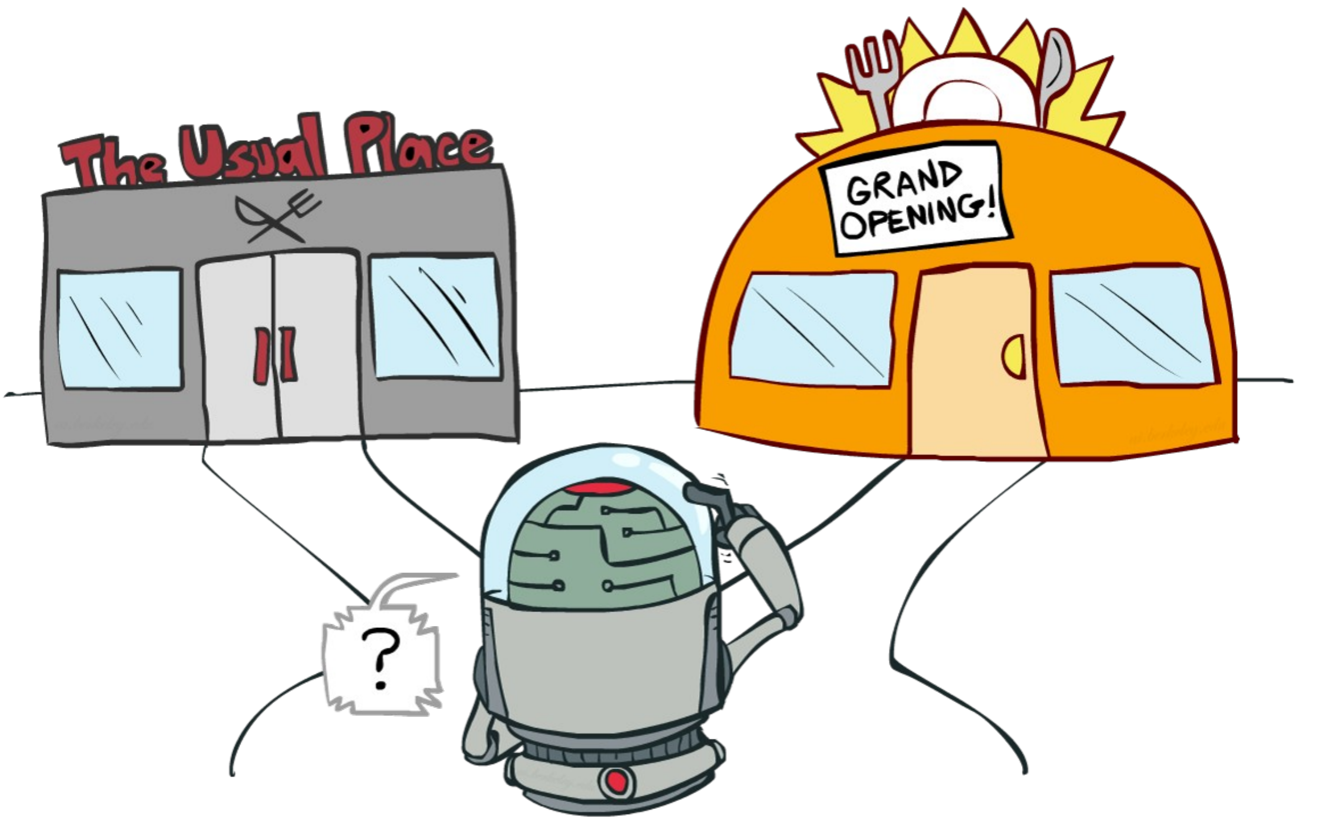
If our agent always takes “best” actions from his current point of view,

How will he ever learn that other actions may be better than his current best one?

Ideas?

Exploration Vs Exploitation

Balance between using what you learned and trying to find something even better



Exploration Vs Exploitation

Strategies:

- ε-greedy
  - With probability ε take random action; otherwise take optimal action.

Exploration Vs Exploitation

Strategies:

- ε-greedy
  - With probability ε take random action; otherwise take optimal action.
- Softmax

  Pick action proportional to softmax of shifted normalized Q-values.

$$\pi(a|s) = softmax\left(\frac{Q(s,a)}{\tau}\right)$$

- More cool stuff coming later

Exploration over time

Idea:

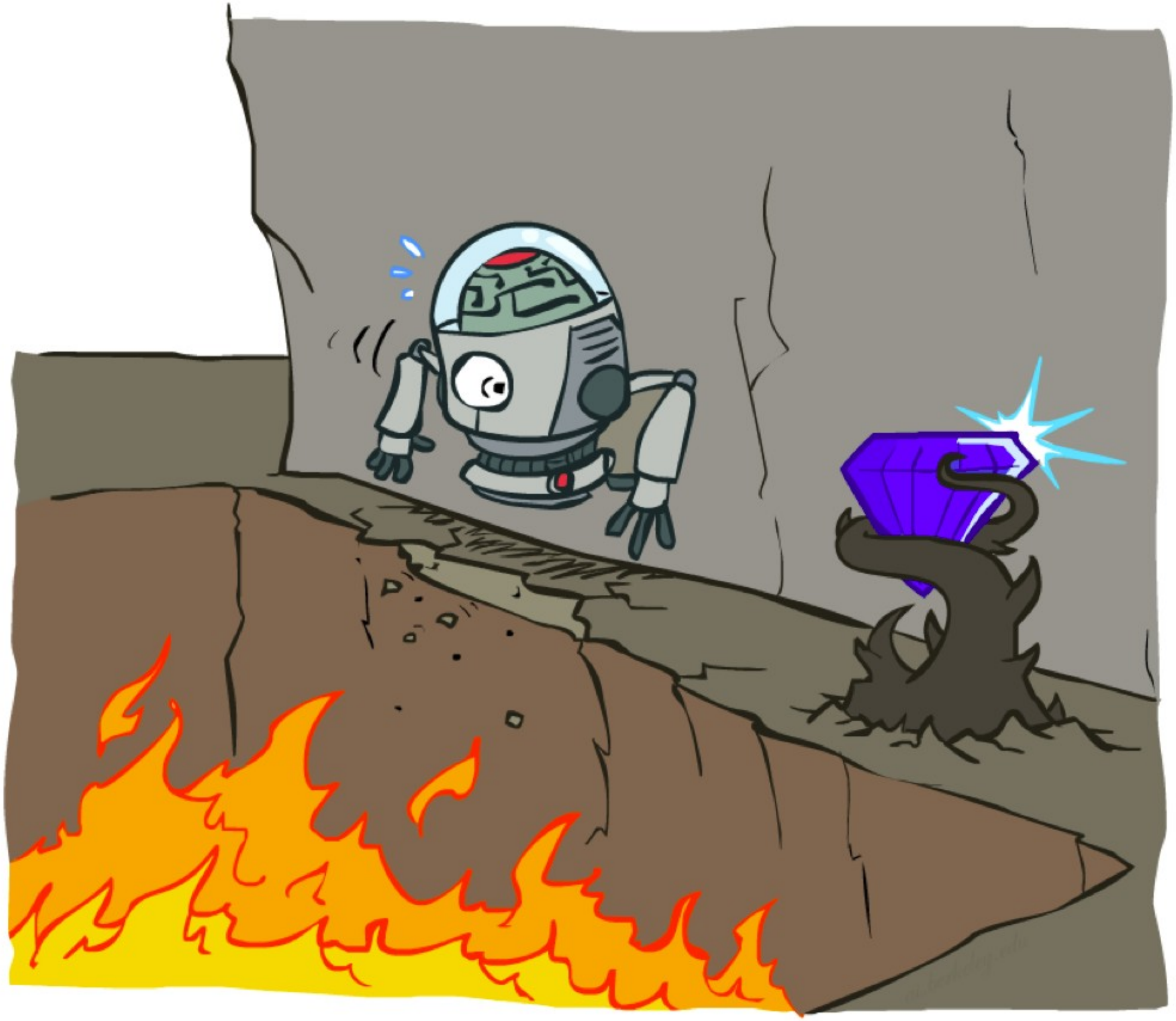
If you want to converge to optimal policy,
you need to gradually reduce exploration

Example:

Initialize ε-greedy $\varepsilon = 0.5$, then gradually reduce it

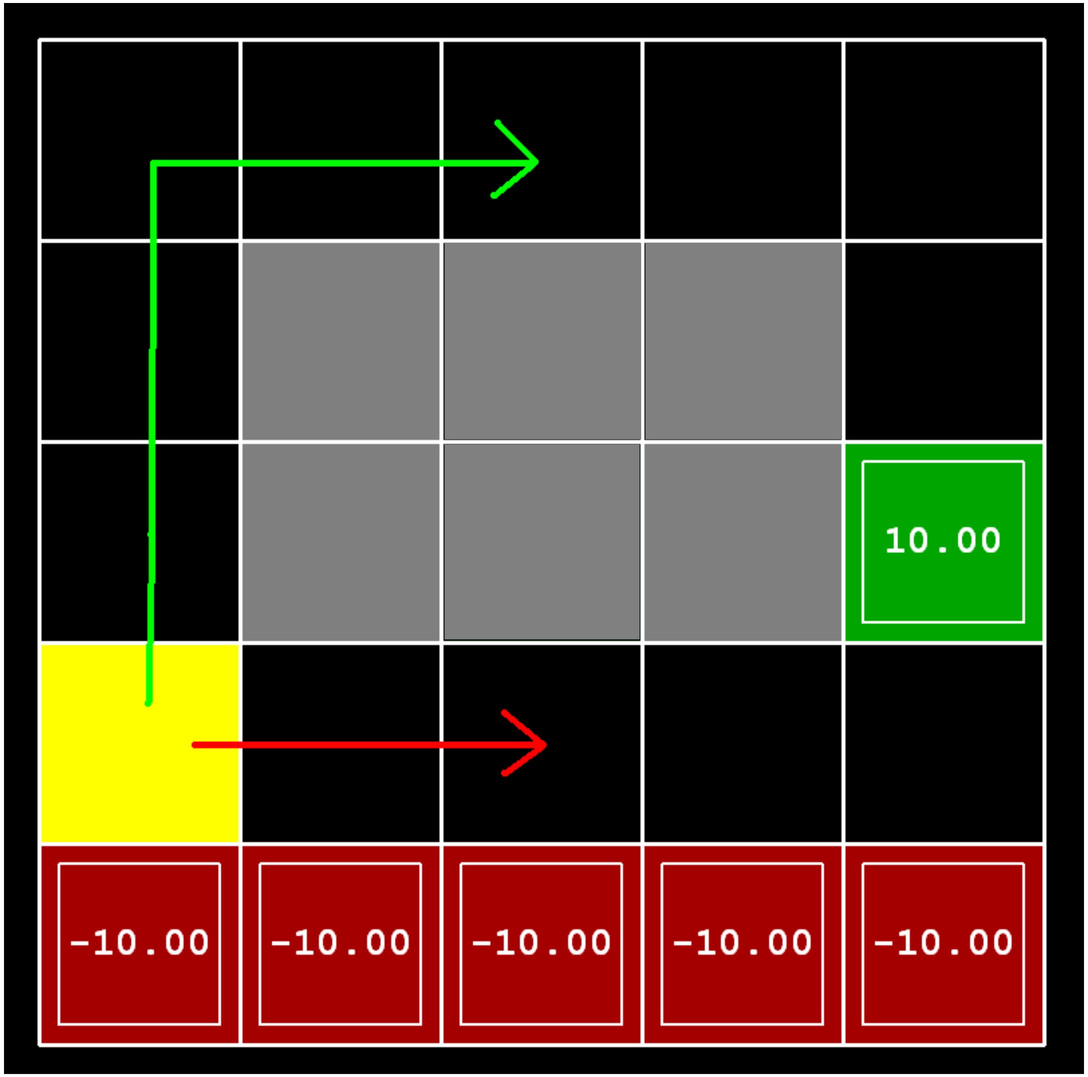
- If $\varepsilon \to 0$, it's **greedy in the limit**
- Be careful with non-stationary environments

Cliff world



Picture from Berkeley CS188x

Cliff world



Conditions

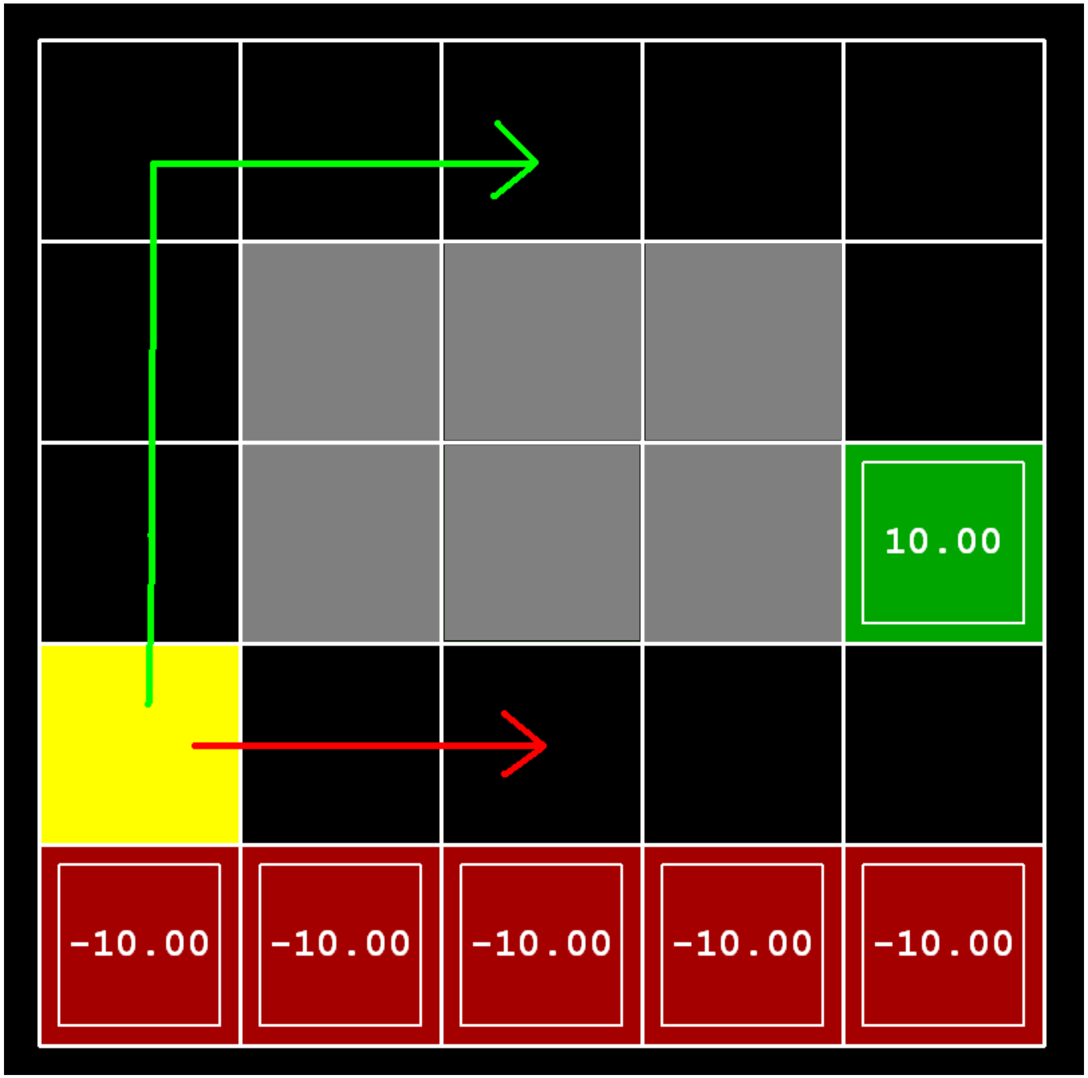
- Q-learning

$$\gamma = 0.99 \quad \epsilon = 0.1$$

- no slipping

Trivia:
What will q-learning learn?

Cliff world



Conditions

- Q-learning

$\gamma = 0.99 \quad \epsilon = 0.1$

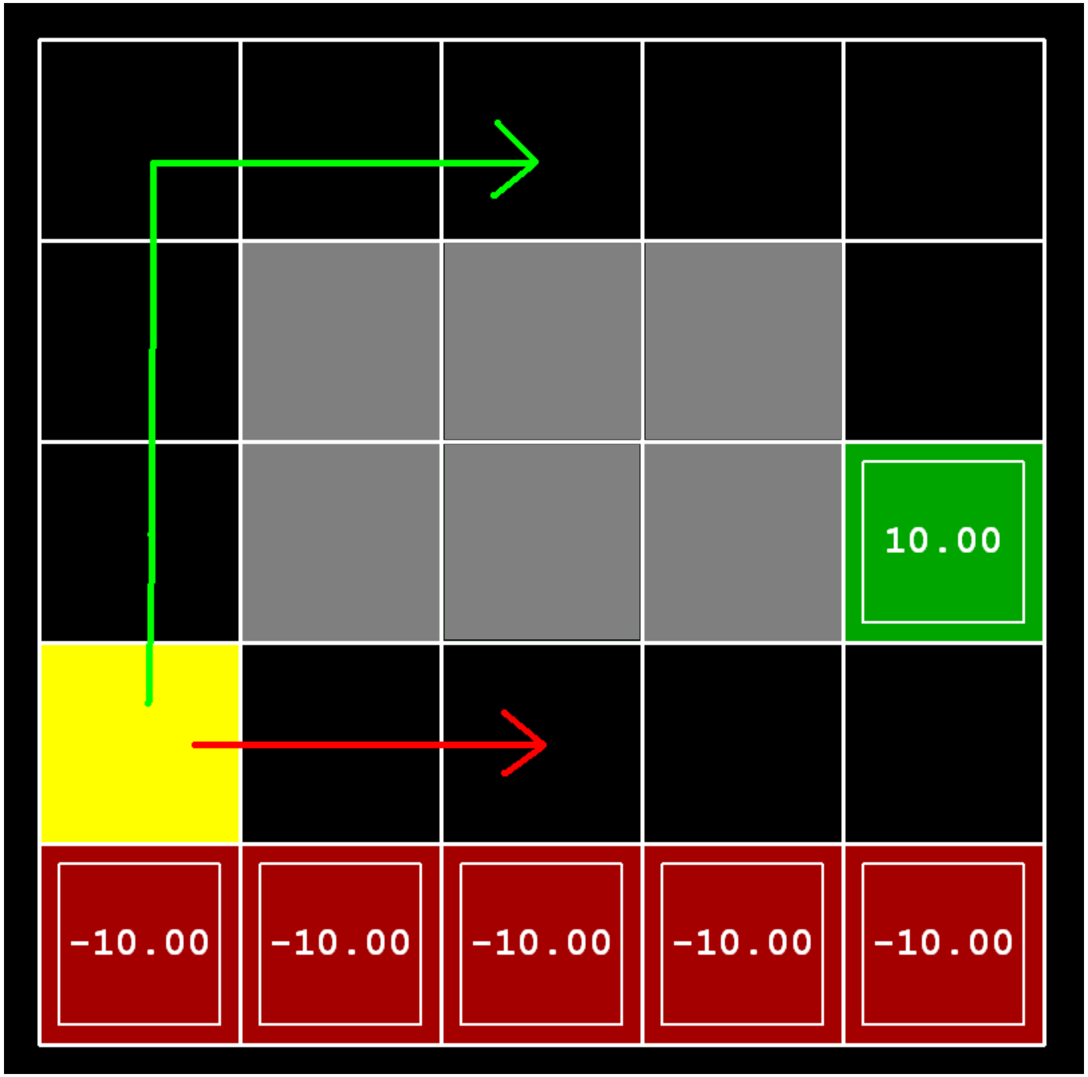
- no slipping

Trivia:
What will q-learning learn?

follow the short path

Will it maximize reward?

Cliff world



Conditions

- Q-learning

$$\gamma = 0.99 \quad \epsilon = 0.1$$

- no slipping

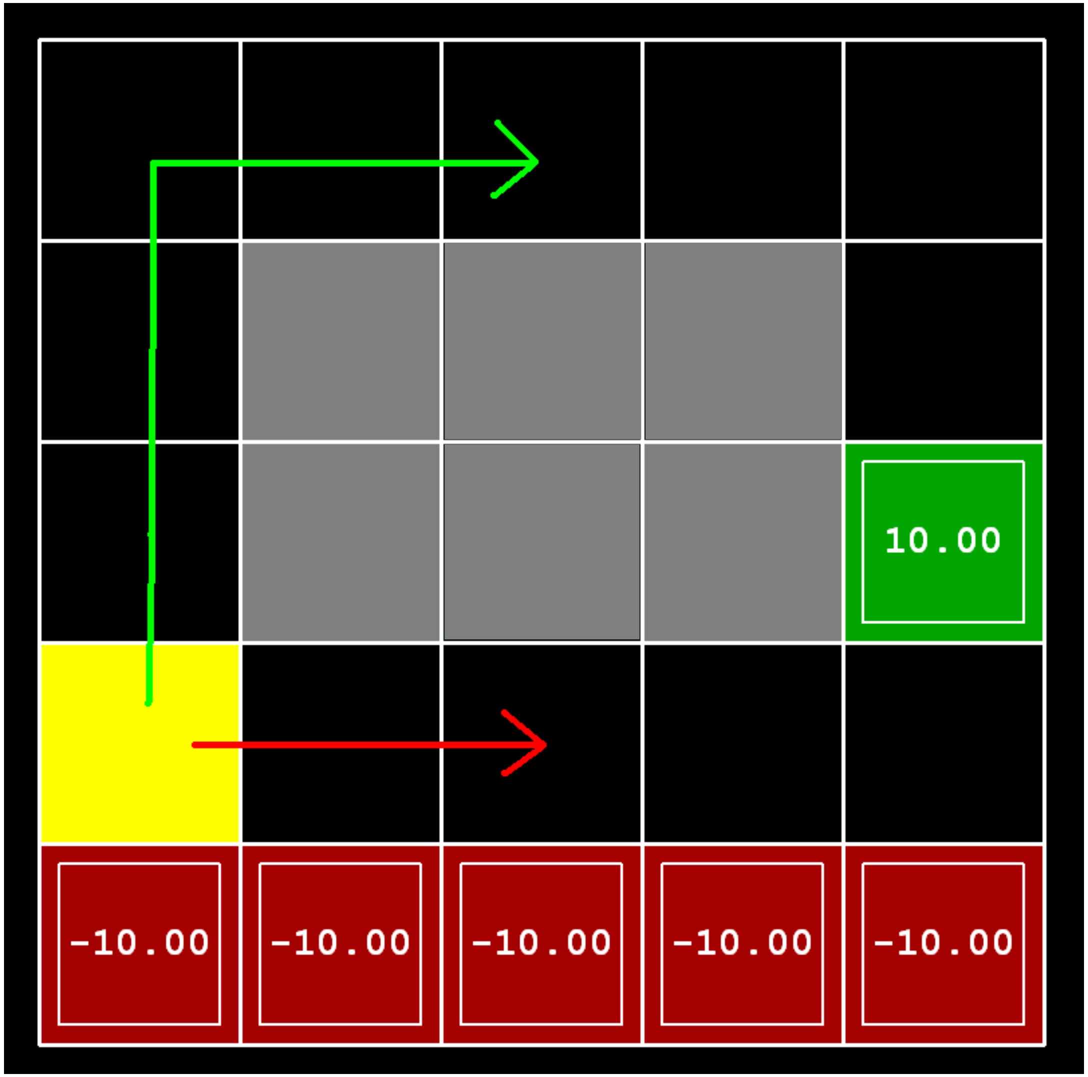
Trivia:
What will q-learning learn?

follow the short path

Will it maximize reward?

no, robot will fall due to epsilon-greedy "exploration"

Cliff world



Conditions

- Q-learning

$\gamma = 0.99 \quad \epsilon = 0.1$

- no slipping

Decisions must account for actual policy!
e.g. ε-greedy policy

Generalized update rule

Update rule (from Bellman eq.)

$$Q(s_t, a_t) \leftarrow \alpha \cdot \hat{Q}(s_t, a_t) + (1-\alpha) Q(s_t, a_t)$$

"better Q(s,a)"

Q-learning VS SARSA

Update rule (from Bellman eq.)

$$Q(s_t, a_t) \leftarrow \alpha \cdot \hat{Q}(s_t, a_t) + (1-\alpha) Q(s_t, a_t)$$

"better Q(s,a)"

Q-learning

$$\hat{Q}(s,a) = r(s,a) + \gamma \cdot \max_{a'} Q(s', a')$$

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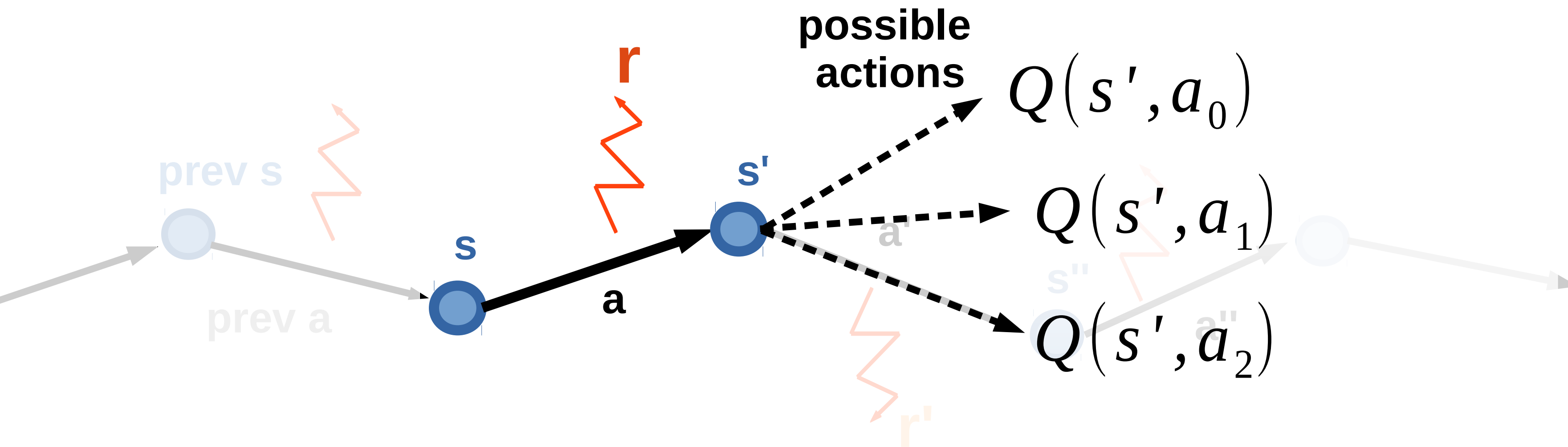
EV- SARSA

$$\hat{Q}(s,a) = r(s,a) + \gamma \cdot \underset{a' \sim \pi(a'|s')}{E} Q(s',a')$$

Recap: Q-learning

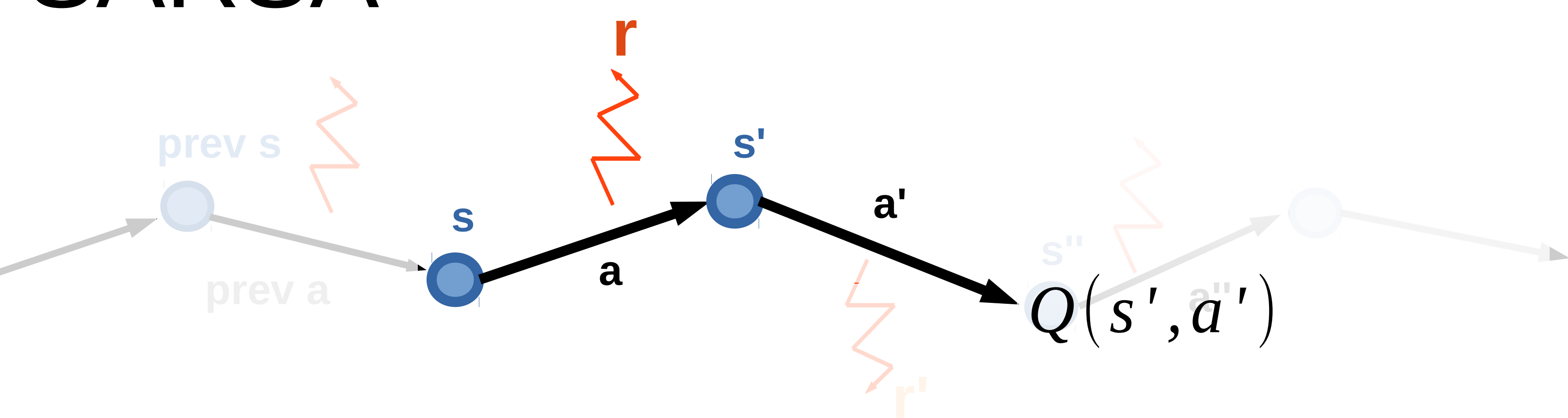


$$\forall s \in S, \forall a \in A, Q(s,a) \leftarrow 0$$

Loop:

- Sample <**s**,**a**,**r**,**s'**> from env
- Compute $\hat{Q}(s,a) = r(s,a) + \gamma \max_{a_i} Q(s',a_i)$
- Update $Q(s,a) \leftarrow \alpha \cdot \hat{Q}(s,a) + (1-\alpha) Q(s,a)$

SARSA



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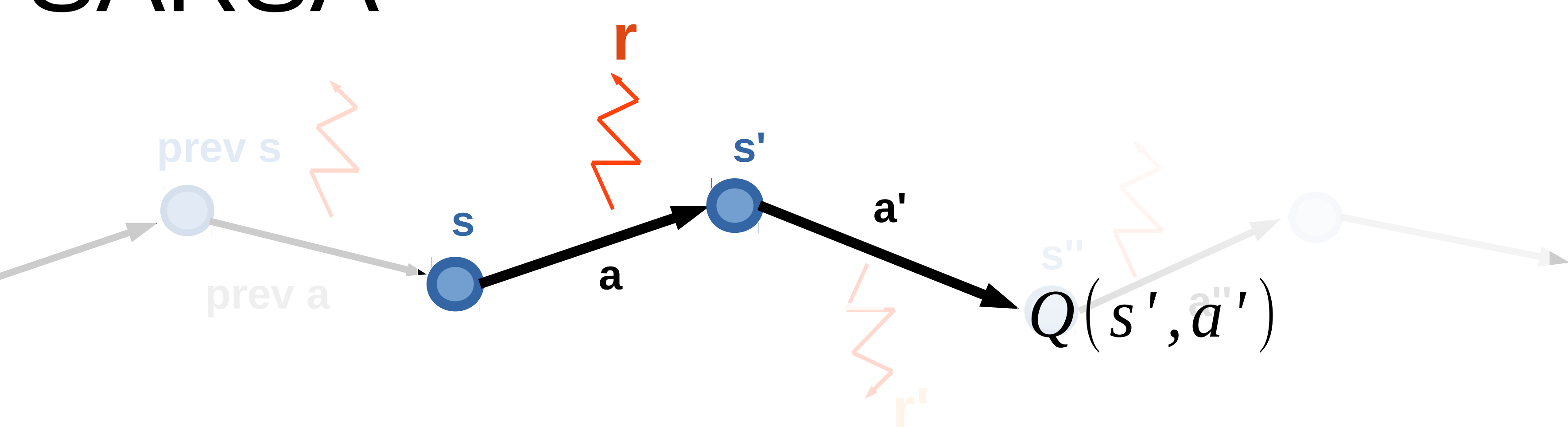
SARSA



$$\forall s \in S, \forall a \in A, Q(s,a) \leftarrow 0$$

Loop:

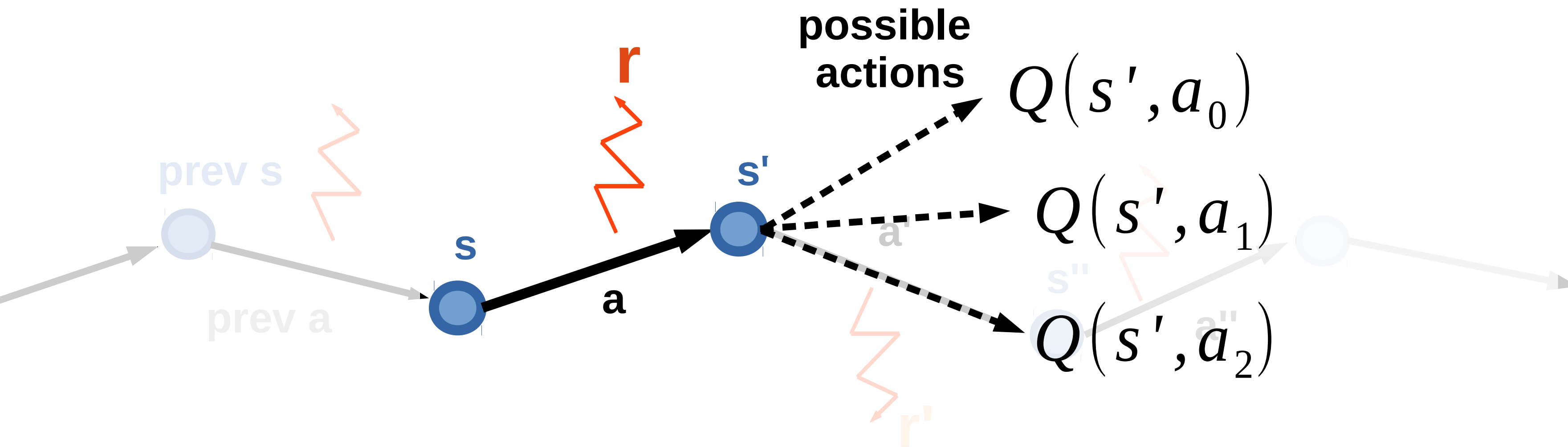
hence "SARSA"

- Sample <**s**,**a**,**r**,**s'**,**a'**> from env
- Compute $\hat{Q}(s,a) = r(s,a) + \gamma Q(s',\underline{a'})$

  next action (not max)

- Update $Q(s,a) \leftarrow \alpha \cdot \hat{Q}(s,a) + (1-\alpha) Q(s,a)$

Expected value SARSA



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Loop:

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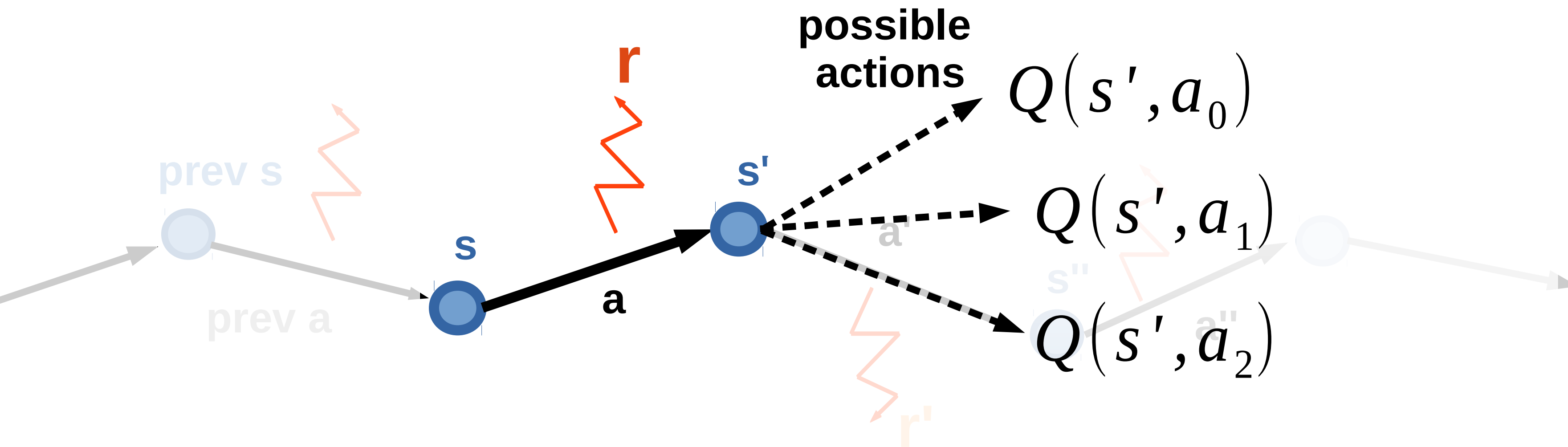
Expected value SARSA



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Loop:

- Sample <**s**,**a**,**r**,**s'**> from env

Expected value

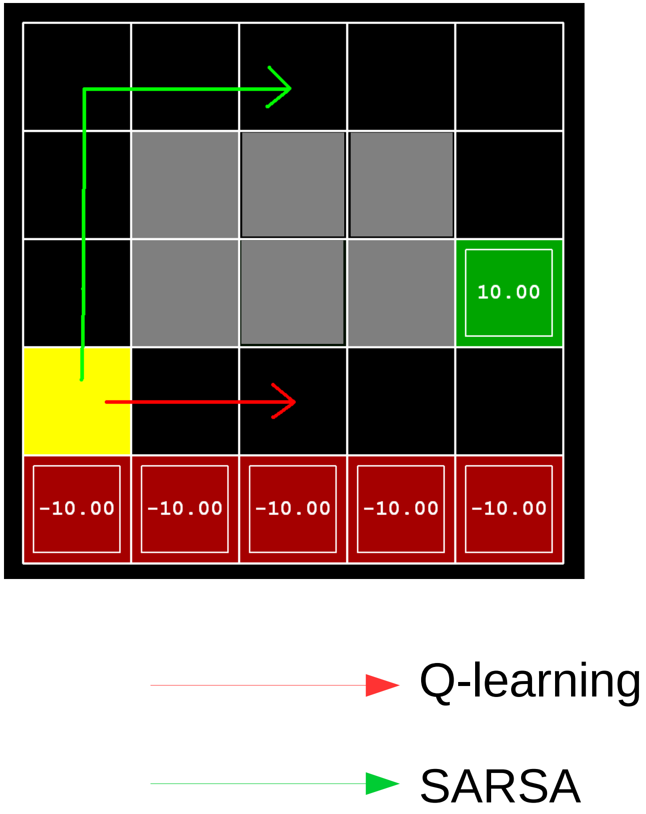
- Compute $\hat{Q}(s,a) = r(s,a) + \gamma \underset{a_i \sim \pi(a|s')}{E} Q(s',a_i)$

- Update $Q(s,a) \leftarrow \alpha \cdot \hat{Q}(s,a) + (1-\alpha) Q(s,a)$

Difference

- SARSA gets optimal rewards under current policy

- Q-learning policy **would be** optimal under



On-policy vs Off-policy

Two problem setups

on-policy

Agent **can** pick actions

- Most obvious setup :)
- Agent always follows his **own** policy

off-policy

Agent **can't** pick actions

- Learning with exploration, playing without exploration
- Learning from expert (expert is imperfect)
- Learning from sessions (recorded data)

On-policy vs Off-policy

Two problem setups

on-policy

Agent **can** pick actions

- On-policy algorithms **can't** learn off-policy

off-policy

Agent **can't** pick actions

- Off-policy algorithms **can** learn on-policy

  learn optimal policy even if agent takes random actions

Q: which of Q-learning, SARSA and exp. val. SARSA will **only** work on-policy?

On-policy vs Off-policy

Two problem setups

on-policy	**off-policy**
Agent **can** pick actions	Agent **can't** pick actions
– On-policy algorithms **can't** learn off-policy	– Off-policy algorithms **can** learn on-policy
– SARSA	– Q-learning
– more later	– Expected Value SARSA

On-policy vs Off-policy

Two problem setups

on-policy	**off-policy**
Agent **can** pick actions	Agent **can't** pick actions
– On-policy algorithms **can't** learn off-policy	– Off-policy algorithms **can** learn on-policy
– SARSA	– Q-learning
– more coming soon	– Expected Value SARSA

On-policy vs Off-policy

Two problem setups

on-policy

Agent **can** pick actions

- On-policy algorithms **can't** learn off-policy
- SARSA
- more coming soon

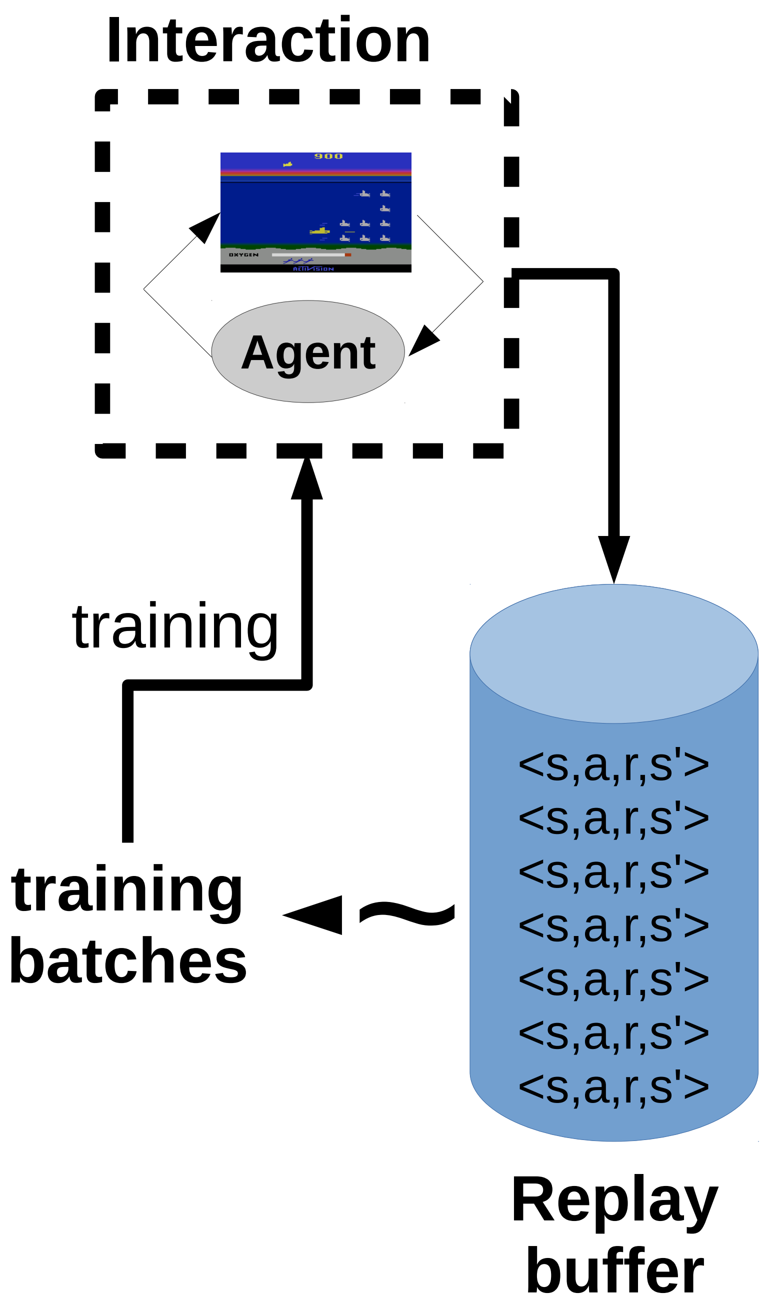
off-policy

Agent **can't** pick actions

- Off-policy algorithms **can** learn on-policy
- Q-learning
- Expected Value SARSA

Experience replay

Idea: store several past interactions
<s,a,r,s'>
Train on random subsamples



Experience replay

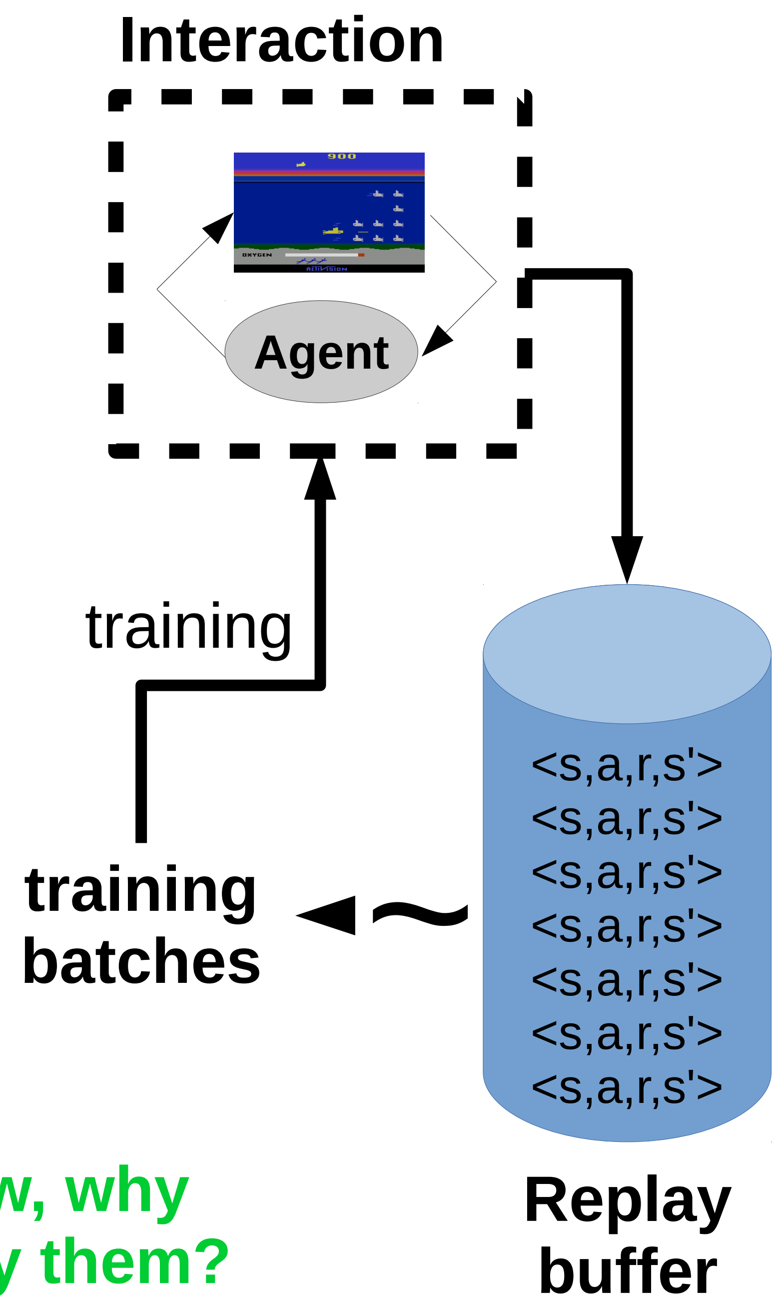
Idea: store several past interactions
<s,a,r,s'>
Train on random subsamples

Training curriculum:
- play 1 step and record it
- pick N random transitions to train

Profit: you don't need to re-visit same (s,a) many times to learn it.

Only works with off-policy algorithms!

Btw, why only them?



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Experience replay

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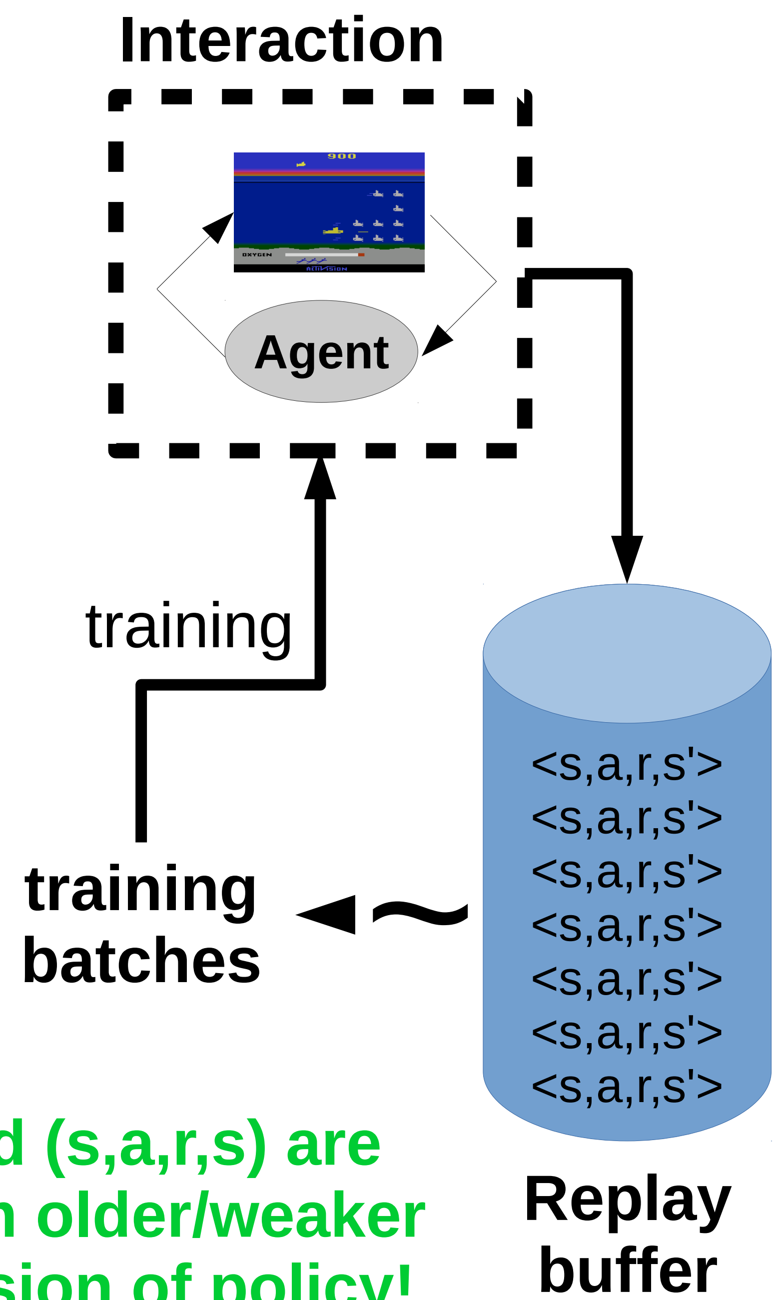


Old (s,a,r,s) are from older/weaker version of policy!

New stuff we learned

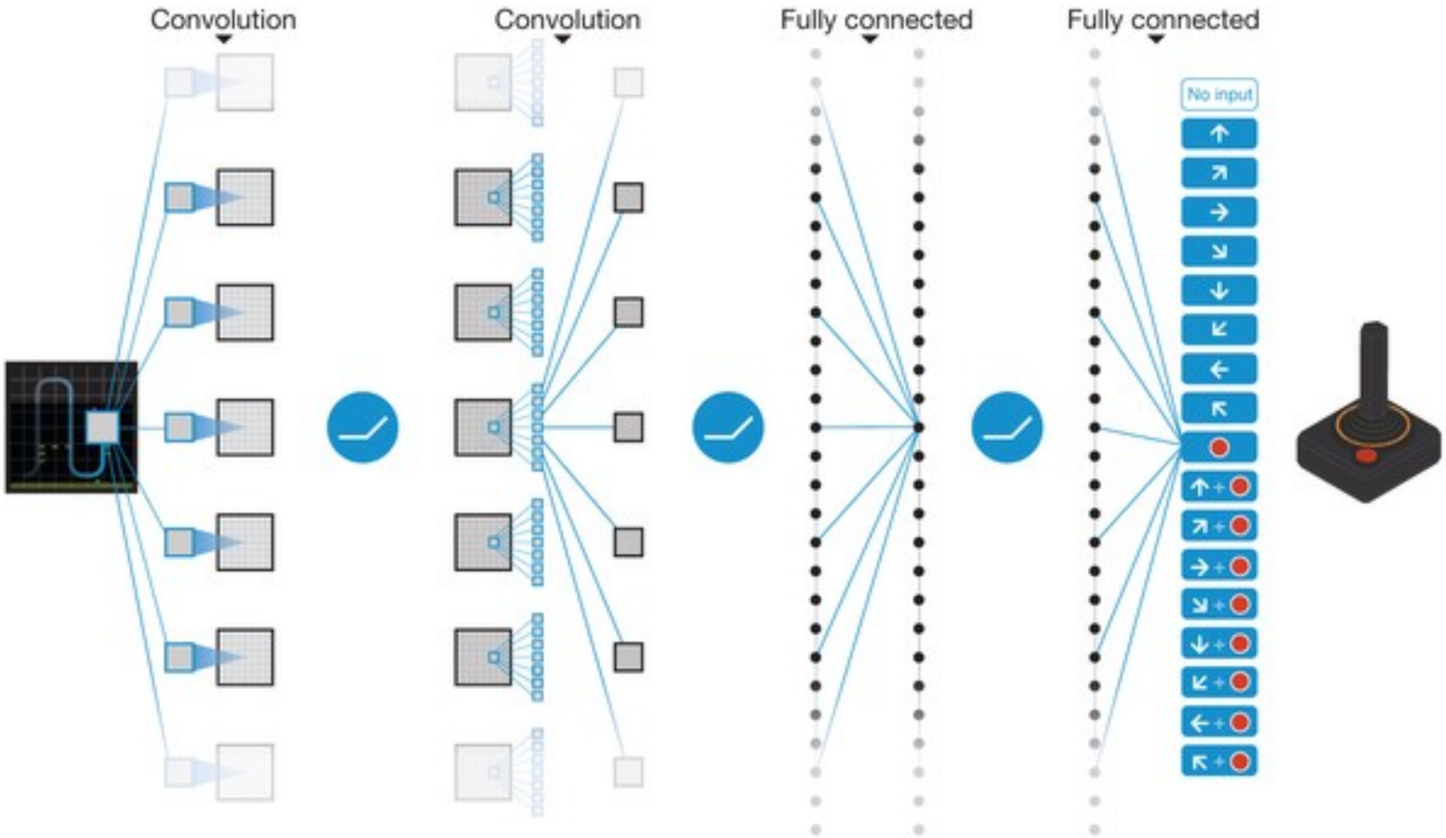
- Anything?

New stuff we learned

- Q(s,a),Q*(s,a)
- Q-learning, SARSA
  - We can learn from trajectories (model-free)
- Exploration vs exploitation (basics)
- Learning On-policy vs Off-policy
  - Using experience replay

Coming next...

- What if state space is large/continuous
  - Deep reinforcement learning



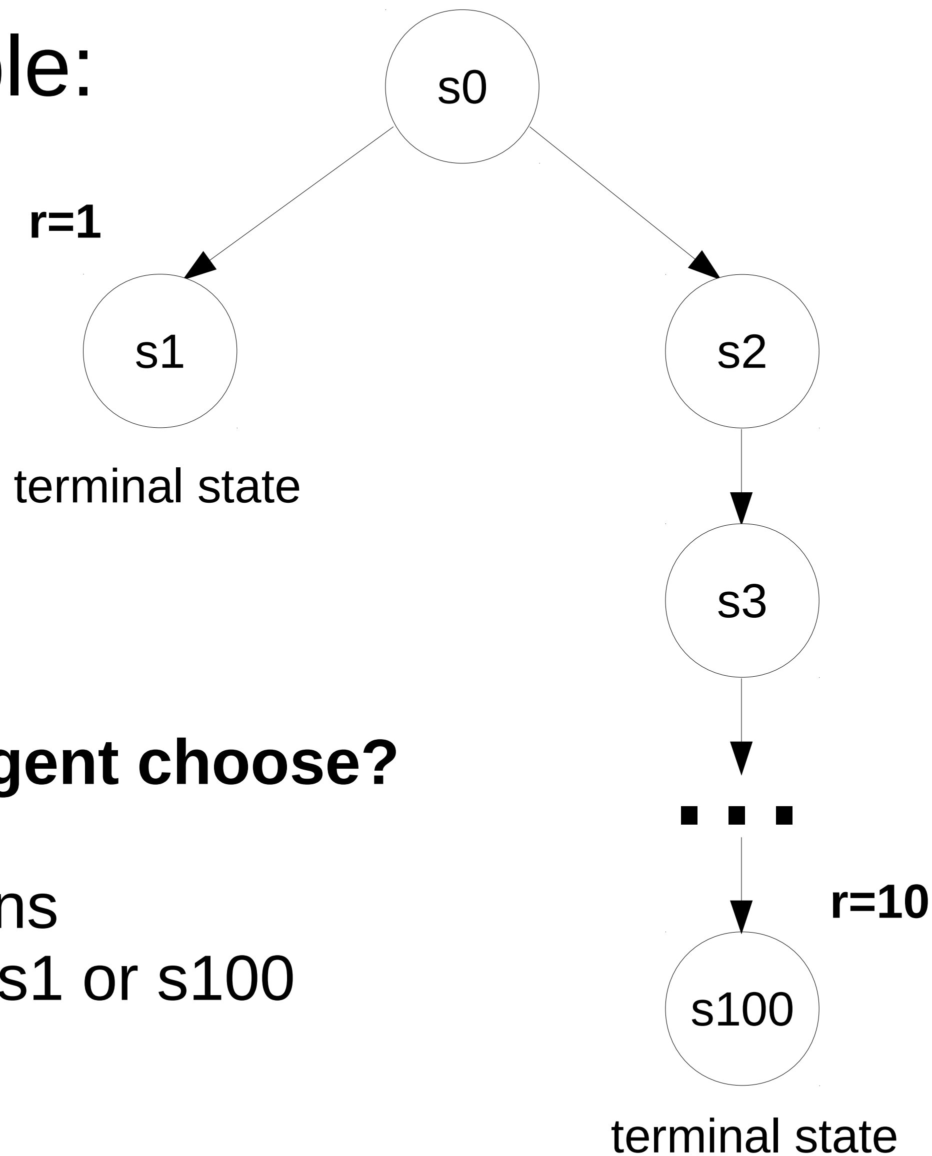
Outro and Q & A

- Remember what Q(s, a) and V(s) functions do
- Remember both about exploration and exploitation
  - At least using greedy policy or softmax smoothing
- Remember the difference between on-policy and off-policy algorithms!
  - On-policy algorithms **can't** learn off-policy (e.g. SARSA)
  - Off-policy algorithms **can** learn on-policy (e.g. Q-learning)
- Experience replay: no need to re-visit same (s,a) many times to learn it.
  - Works only with off-policy algorithms

Remember discounted rewards?

Discounted reward fails #1

Trivial example:

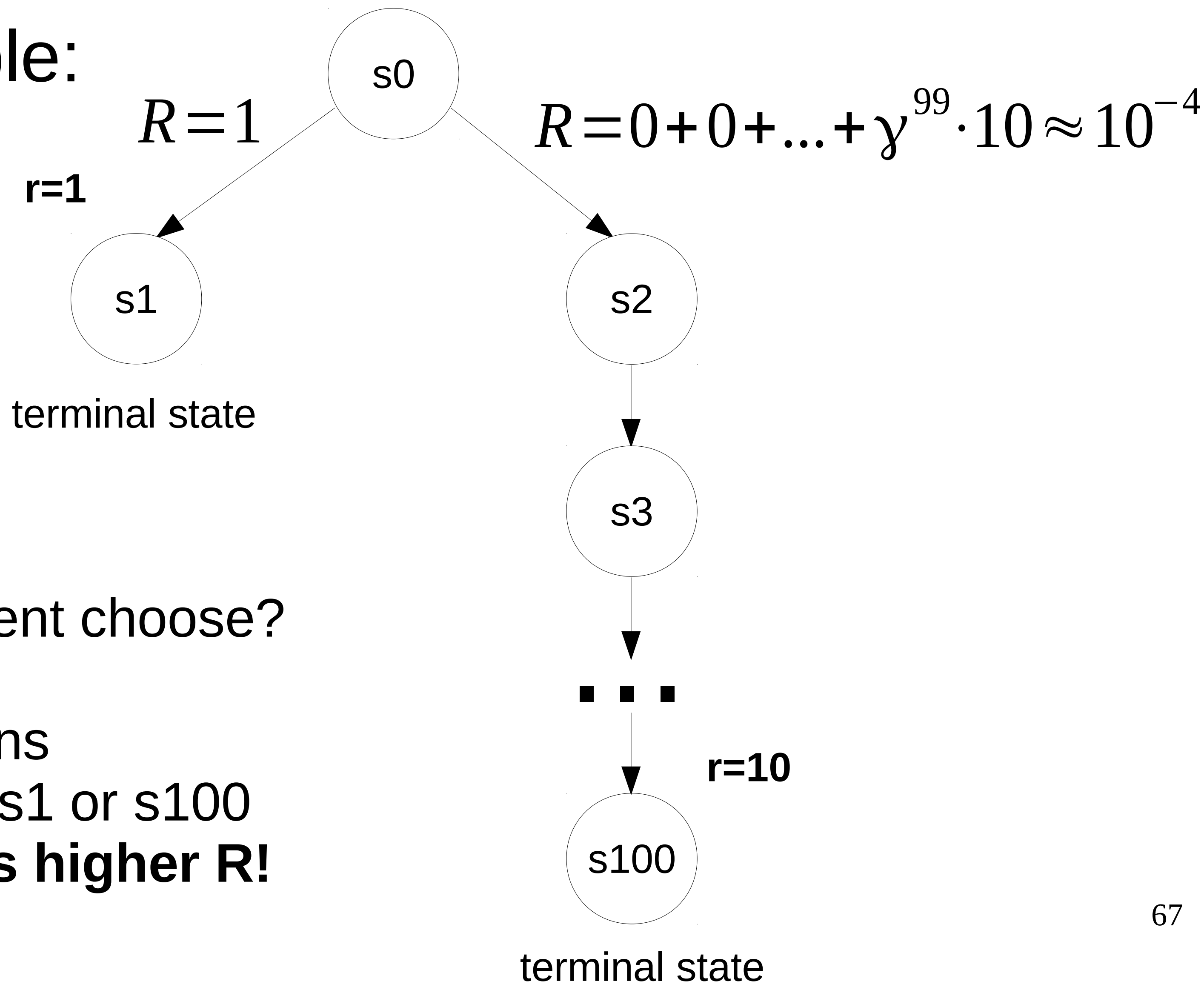


What path will agent choose?

- γ=0.9
- arrows = actions
- game ends at s1 or s100

Discounted reward fails #1

Trivial example:



What path will agent choose?

- γ=0.9
- arrows = actions
- game ends at s1 or s100
- **left action has higher R!**

Discounted reward fails #2

Deephack'17 qualification round, Atari Skiing

- You steer the red guy
- Session lasts ~5k steps
- You get -3~-7 reward each tick
  (faster game = better score)
- At the end of session, you get up to r=-30k
  (based on passing gates, etc.)
- Q-learning with gamma=0.99 fails
  it doesn't learn to pass gates

What's the problem?

http://rl.deephack.me/

Discounted reward fails #2

Deephack'17 qualification round, Atari Skiing

- You steer the red guy
- Session lasts ~5k steps

- You get -3~-7 reward each tick
  (faster game = better score)

- At the end of session, you get up to r=-30k
  (based on passing gates, etc.)

  - Q-learning with gamma=0.99 fails

http://rl.deephack.me/

Discounted reward fails #3

CoastRunner7 experiment (openAI)

- You control the boat
- Rewards for getting to checkpoints
- Rewards for collecting bonuses
- What could possibly go wrong?
- “Optimal” policy video:
  https://www.youtube.com/watch?v=tlOIHko8ySg

https://openai.com/blog/faulty-reward-functions/

Nuts and bolts: MC vs TD

Monte-carlo

- Ignores intermediate rewards
  doesn't need **γ** (discount)
- Needs full episode to learn
  Infinite MDP are a problem
- Doesn't use Markov property
  Works with non-markov envs

Temporal Difference

- Uses intermediate rewards
  trains faster under right **γ**
- Learns from incomplete episode
  Works with infinite MDP
- Requires markov property
  Non-markov env is a problem

Nuts and bolts: discount

- Effective horizon $$1+\gamma+\gamma^2+\ldots=\frac{1}{(1-\gamma)}$$

  Heuristic: your agent stops giving a damn in *this many* turns.

  Typical values:
  - γ=0.9, 10 turns
  - γ=0.95, 20 turns
  - γ=0.99, 100 turns
  - γ=1, infinitely long

  Higher γ = less stable algorithm.
  γ=1 only works for episodic MDP (finite amount of turns).

Nuts and bolts: discount

- Effective horizon $$1+\gamma+\gamma^2+\ldots=\frac{1}{(1-\gamma)}$$

  Heuristic: your agent stops giving a damn in *this many* turns.

- Atari Skiing, reward was delayed by in 5k steps
- γ=0.99 is not enough
- γ=1 and a few hacks works better
- Or use a better reward function