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Pattern Analysis & Machine Intelligence Praktikum: MLPR-WS19

Week 12: Introduction into Reinforcement Learning

Reinforcement Learning: Applications

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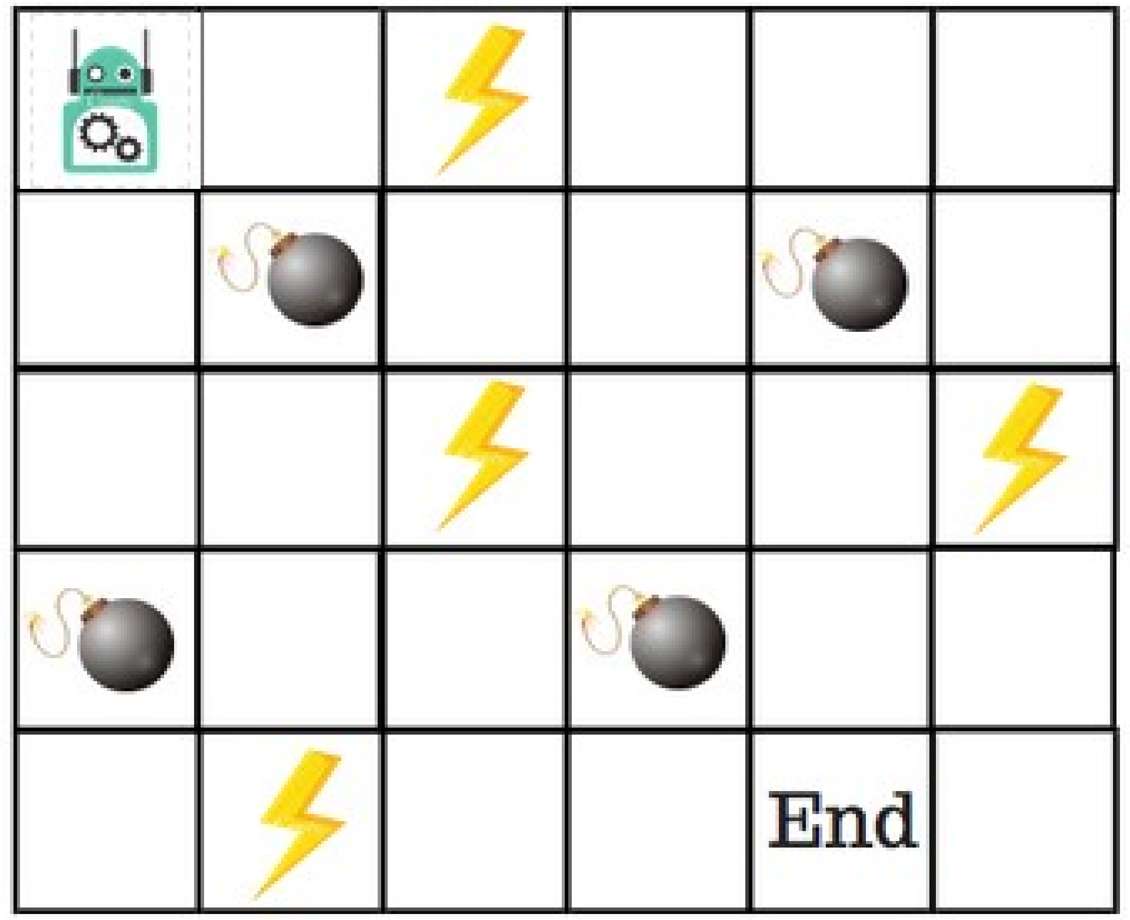
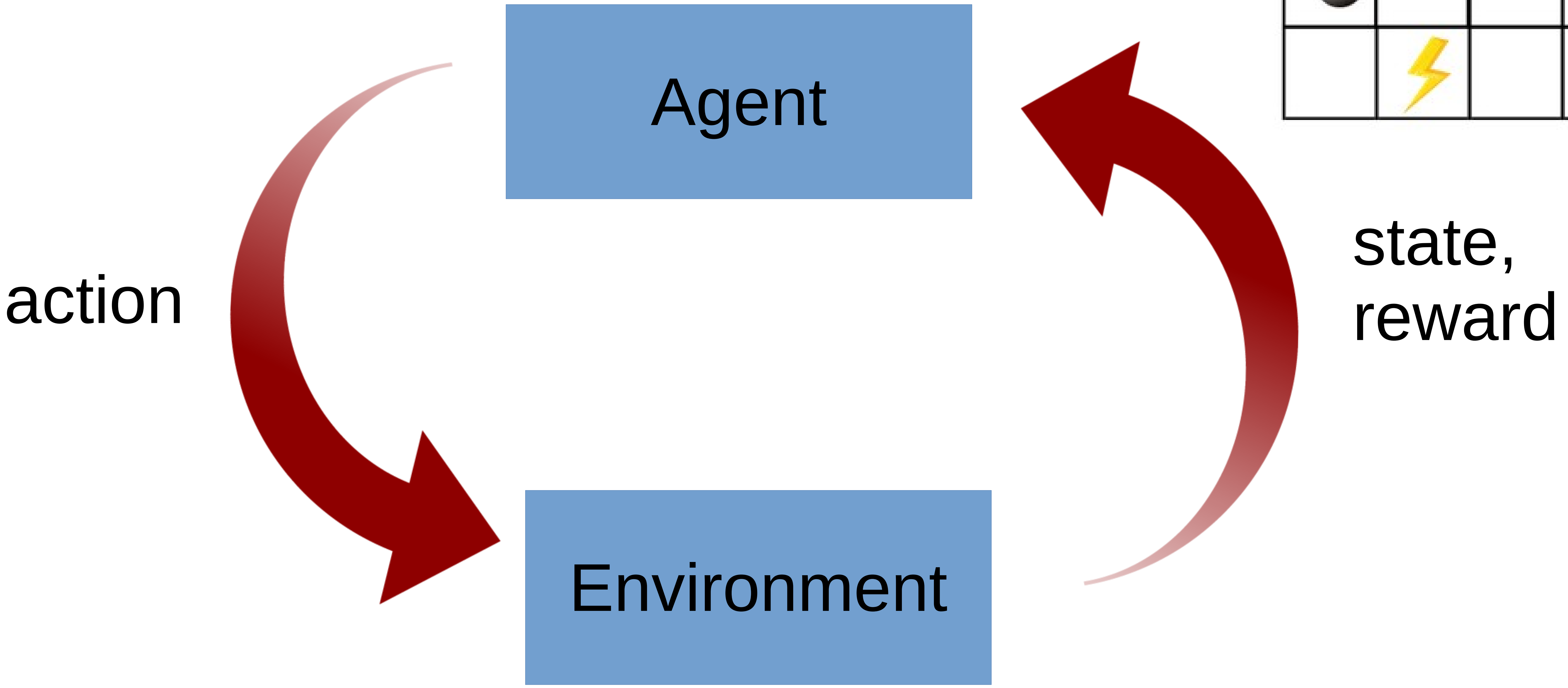
- Learning how to play games
- Robotics
- Finance
- Healthcare
- Meta-Learning

https://ai.googleblog.com/2018/06/scalable-deep-reinforcement-learning.html

Reinforcement Learning: Details

- Learning to maximize **rewards** by performing **actions** in an **environment**.

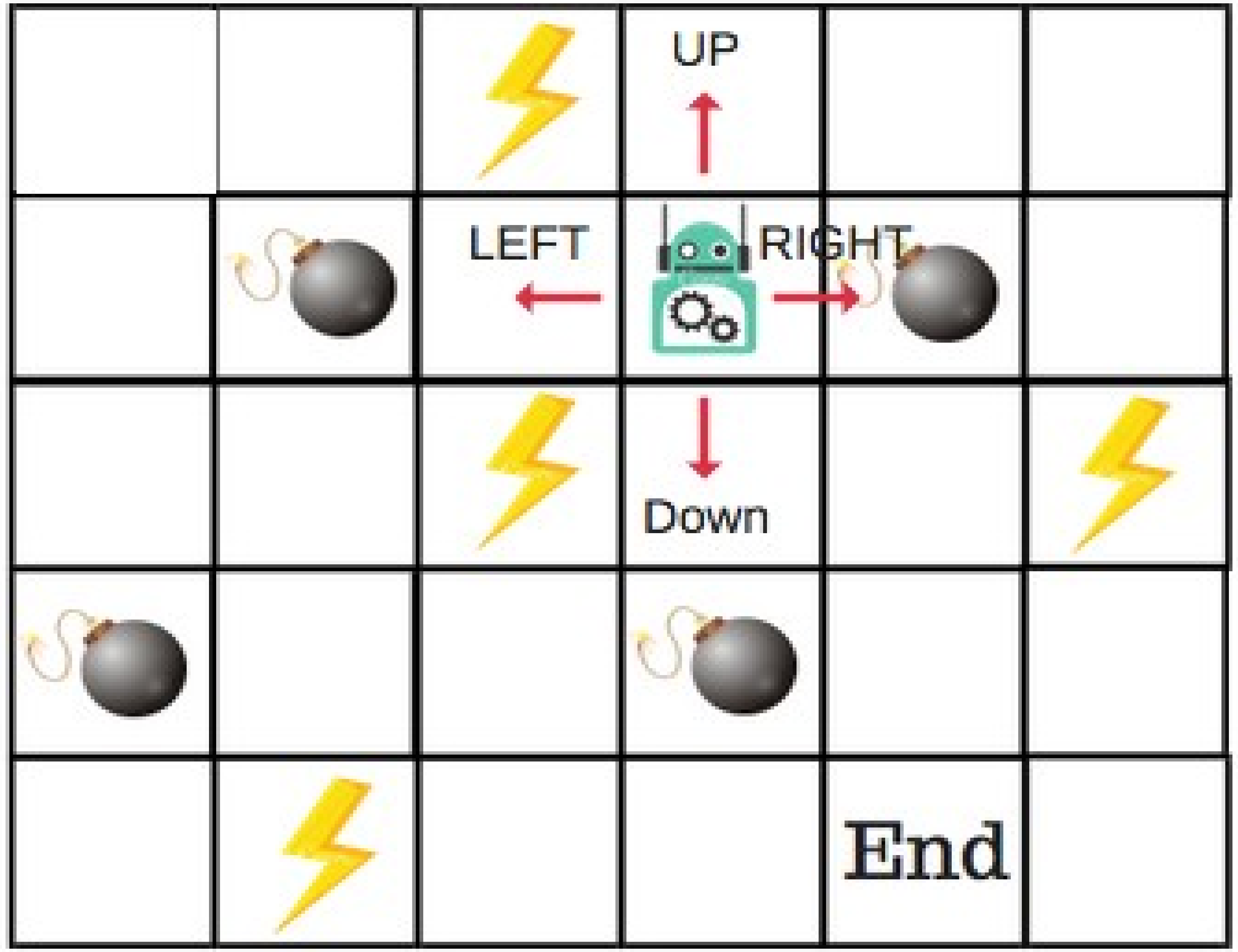




https://www.freecodecamp.org/news/an-introduction-to-q-learning-reinforcement-learning-14ac0b4493cc/

Reinforcement Learning: Details

- **Environment**: maze
- **Actions**: left/right/up/down
- **Rewards**:
  - -1 on each step,
  - -100 to step on mine
  - 1 for lightning charge
  - 100 for end
- **Policy**: mapping from states to actions, e.g.
  - always go left until wall, then right
  - after stepping on mine, always go right+down



https://www.freecodecamp.org/news/an-introduction-to-q-learning-reinforcement-learning-14ac0b4493cc/

Reinforcement Learning: Details

- **Q-Table**:

  a table storing the expected rewards for every (state, action)-pair

Actions :	↑	→	↓	←
Start				
Nothing / Blank				
Power				
Mines				
END				

https://www.freecodecamp.org/news/an-introduction-to-q-learning-reinforcement-learning-14ac0b4493cc/

Reinforcement Learning: Details

Scenario:

- a learning **agent**
- **S**: a set of possible states
- **A**: a set of possible actions
- a ***state transition*** function

$$\delta : S \, x \, A \rightarrow S$$

- a ***reward*** function

$$r : S \, x \, A \rightarrow \mathbb{R}$$

Feedback loop:

- the agent repeatedly chooses an action according to some ***policy***

$$\pi : S \rightarrow A$$

- the environment changes to a new state according to δ
- some states provide the agent with feedback (***reinforcement***)

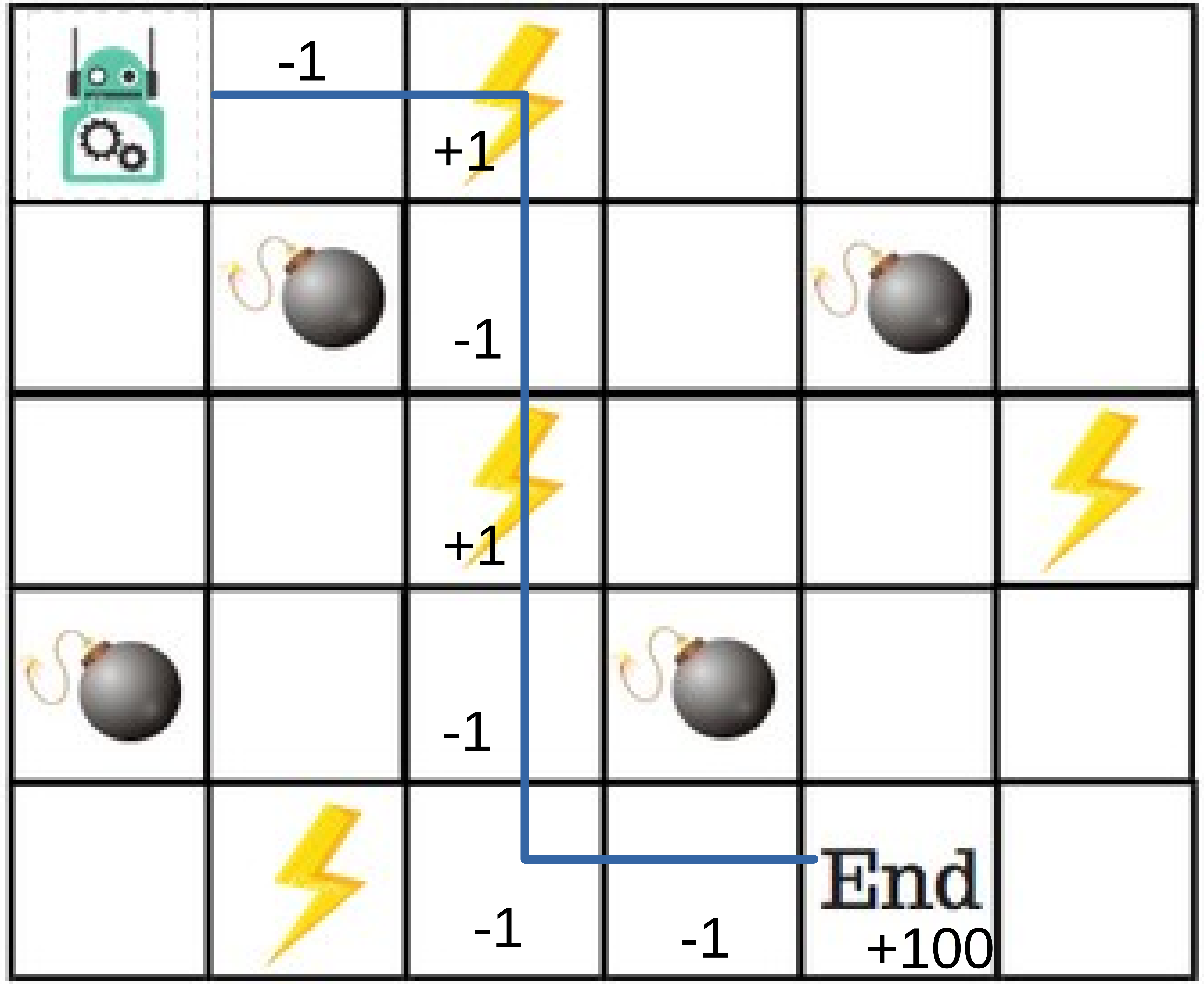
https://www.ke.tu-darmstadt.de/lehre/archiv/ss09/ki/reinforcement-learning.pdf

Reinforcement Learning: Reward

- Cumulative expected reward:

$$G_t = \sum_{i=0}^{\infty} \gamma^i * r_{t+i}$$

(γ makes the G_t finite)



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Reinforcement Learning: Optimal Policy

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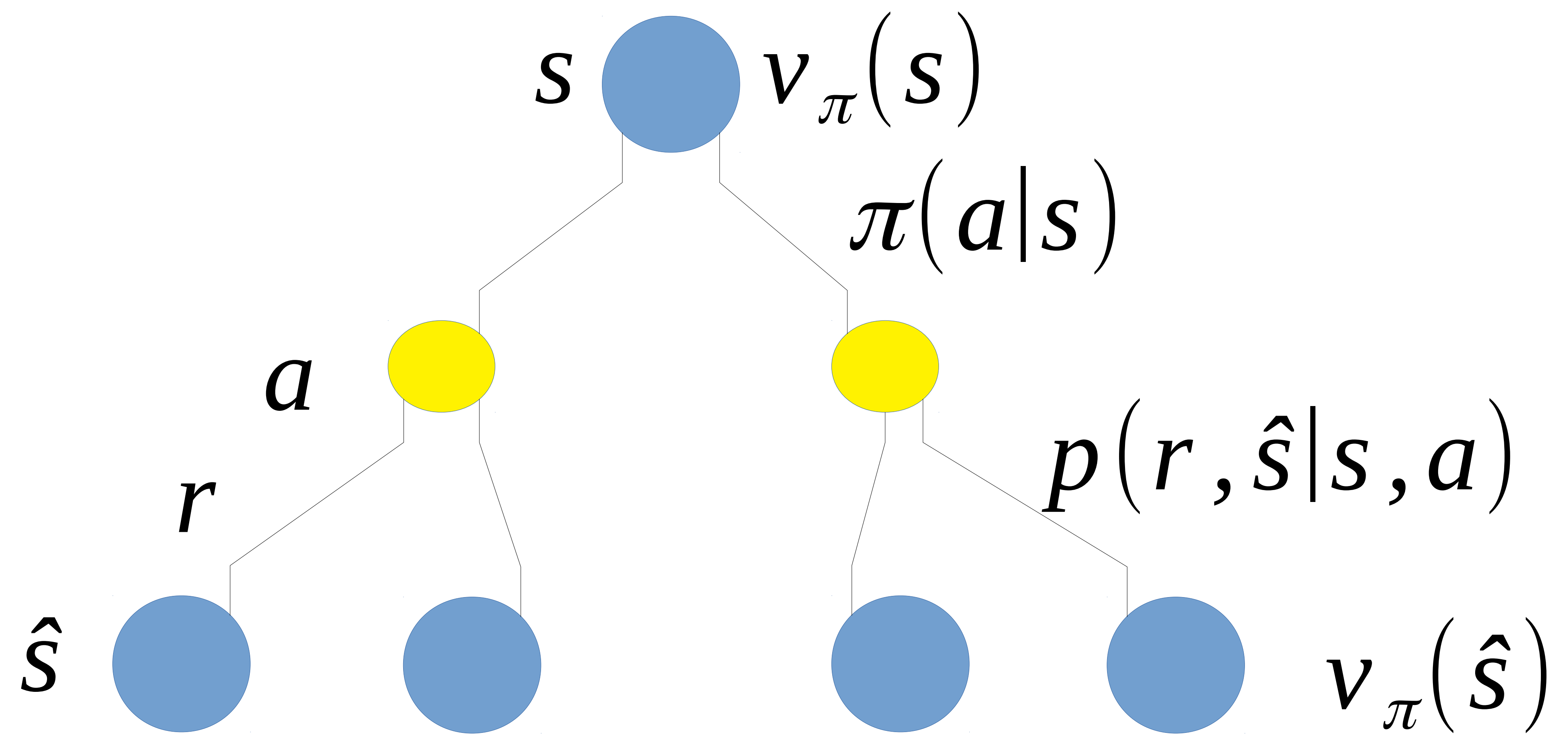


- Cumulative expected reward:

$$G_t = \sum_{i=0}^{\infty} \gamma^i * r_{t+i}$$

(γ makes the G_t finite)

- Bellman **expectation** for the state-value function:

$$v_\pi(s) = E[G_t | S_t = s] = E_\pi[R_t + \gamma * G_{t+1} | S_t = s]$$

$$= \underbrace{\sum_a \pi(a|s)}_{policy\ stochasticity} \underbrace{\sum_{r,\hat{s}} p(r,\hat{s}|s,a)}_{environment\ stochasticity} * [r + \gamma * \underbrace{E_\pi[G_{t+1}|S_{t+1} = \hat{s}]}_{v_\pi(\hat{s})}]$$

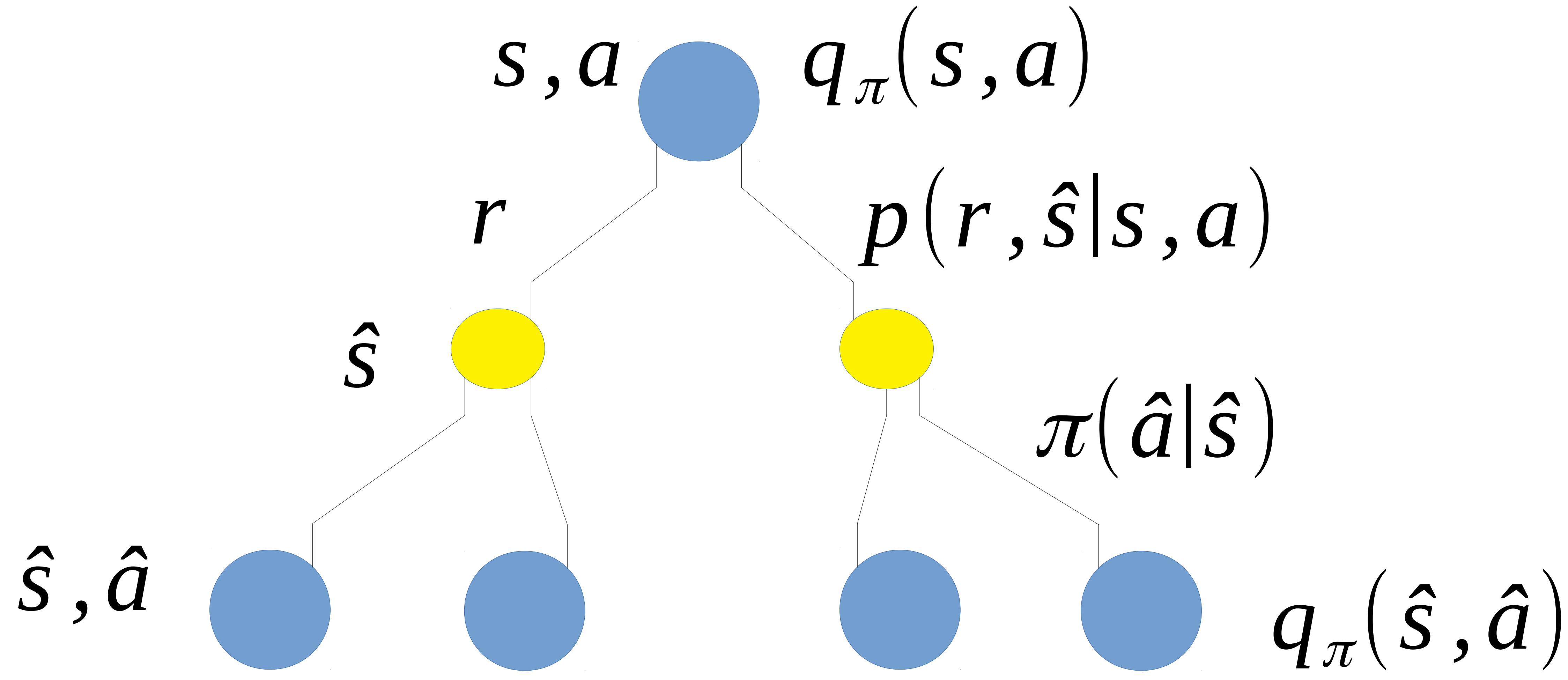
https://www.coursera.org/learn/practical-rl/home/welcome

https://www.ke.tu-darmstadt.de/lehre/archiv/ss09/ki/reinforcement-learning.pdf

Reinforcement Learning: Optimal Policy

- State-value to action-value function

$$v_\pi(s) = \sum_a \pi(a|s)\, q_\pi(s,a)$$



- Bellman **expectation** for the action-value function:

$$q_\pi(s,a) = E[G_t|S_t = s, A_t = a] = E_\pi[R_t + \gamma * G_{t+1}|S_t = s, A_t = a]$$
$$= \underbrace{\sum_{r,\hat{s}} p(r,\hat{s}|s,a)}_{environment\ stochasticity} * [r + \gamma * \underbrace{E_\pi[G_{t+1}|S_{t+1} = \hat{s}]}_{v_\pi(\hat{s})}]$$

https://www.coursera.org/learn/practical-rl/home/welcome

Reinforcement Learning: Optimal Policy

$$v_{opt}(s) = max_{\pi} v_{\pi}(s)$$
$$\pi_{opt} = arg\,max_{\pi} v_{\pi}(s)$$

$$q_{opt}(s,a) = max_{\pi} q_{\pi}(s,a)$$
$$\pi_{opt}(s) = arg\,max_{a} q_{\pi}(s,a)$$

Bellman **optimality** equations:

$$v_{opt}(s) = max_a \underbrace{\sum_{r,\hat{s}} p(r,\hat{s}|s,a)}_{environment\ stochasticity} * [r + \gamma * v_{opt}(\hat{s})]$$

$$q_{opt}(s,a) = \underbrace{\sum_{r,\hat{s}} p(r,\hat{s}|s,a)}_{environment\ stochasticity} * [r + \gamma * max_{\hat{a}} q_{opt}(\hat{s},\hat{a})]$$

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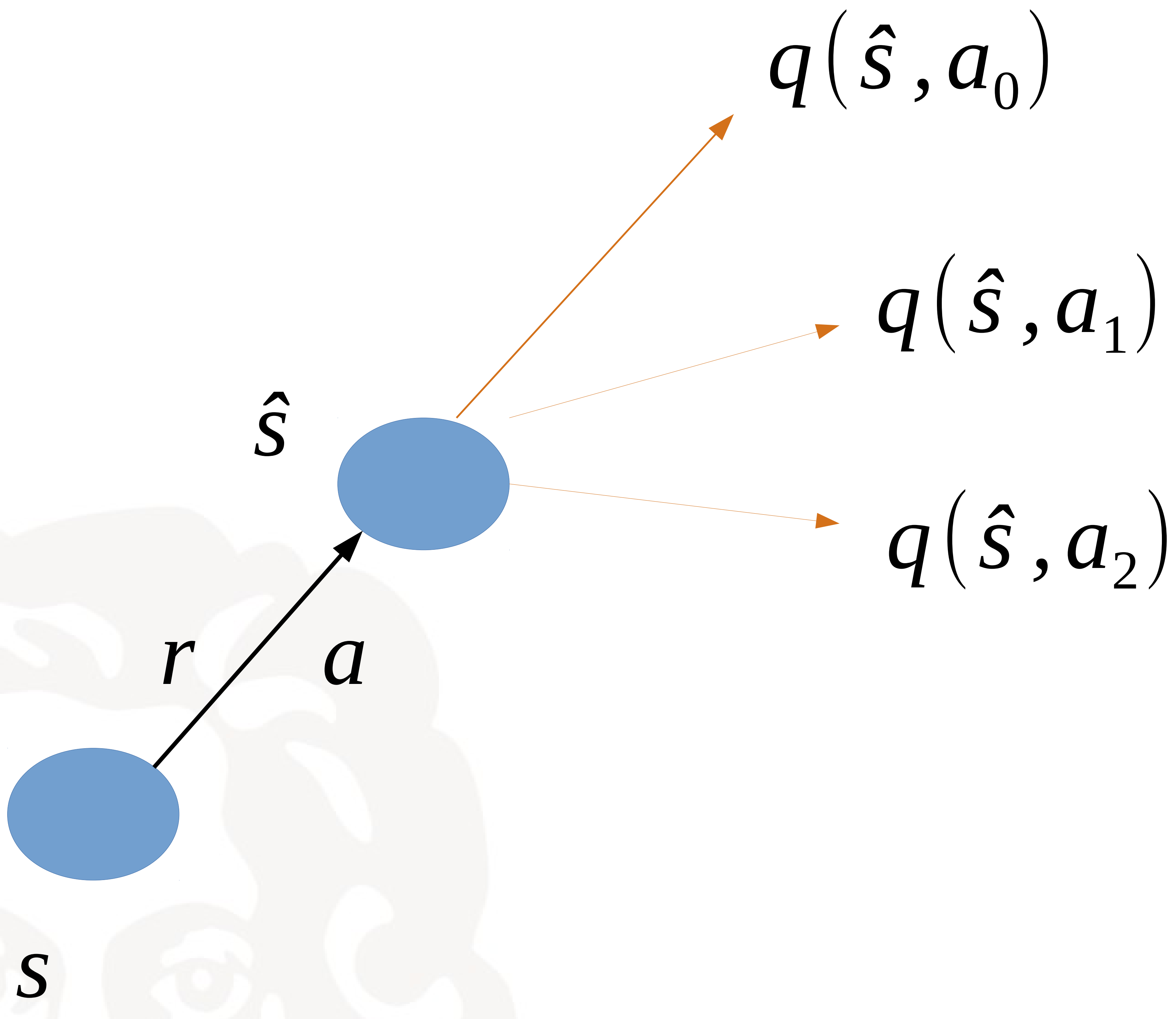
Reinforcement Learning: Q-Learning



Model-free (train on trajectories),
Off-policy (not train on own policy)

$$\forall s \in S, \forall a \in A, q(s,a) = 0$$

$$Loop:$$

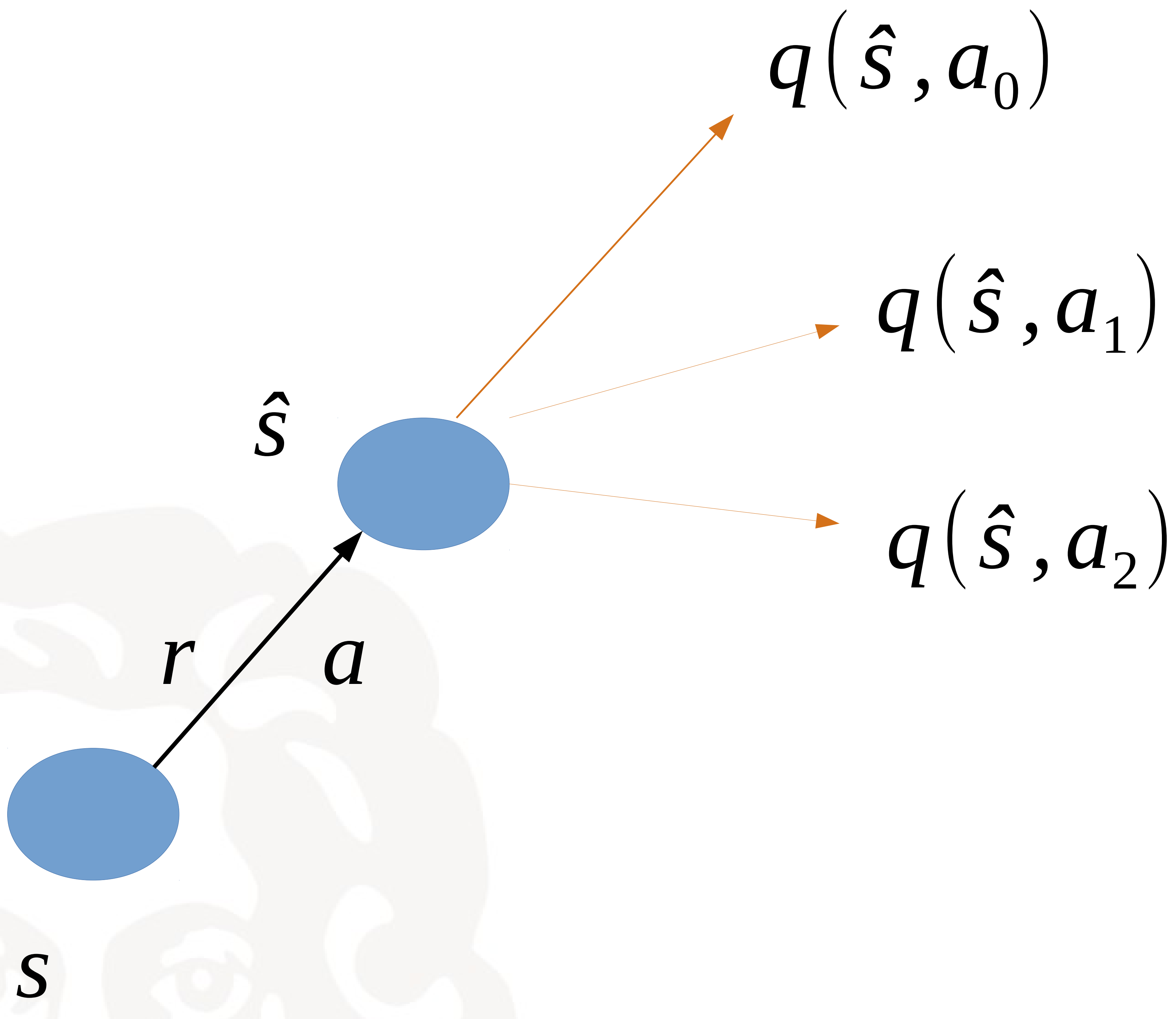
$$Sample <s, a, r, \hat{s}>$$

$$Compute\ \tilde{q}(s,a) = r(s,a) + \gamma * max_{a_i} q(\hat{s}, a_i)$$

$$Update\ q(s,a) = \alpha * \tilde{q}(s,a) + (1-\alpha) * q(s,a)$$

http://icaps18.icaps-conference.org/fileadmin/alg/conferences/icaps18/summerschool/lectures/Lecture5-rl-intro.pdf
https://www.coursera.org/learn/practical-rl/home/welcome

Reinforcement Learning: Q-Learning



How to sample ŝ?

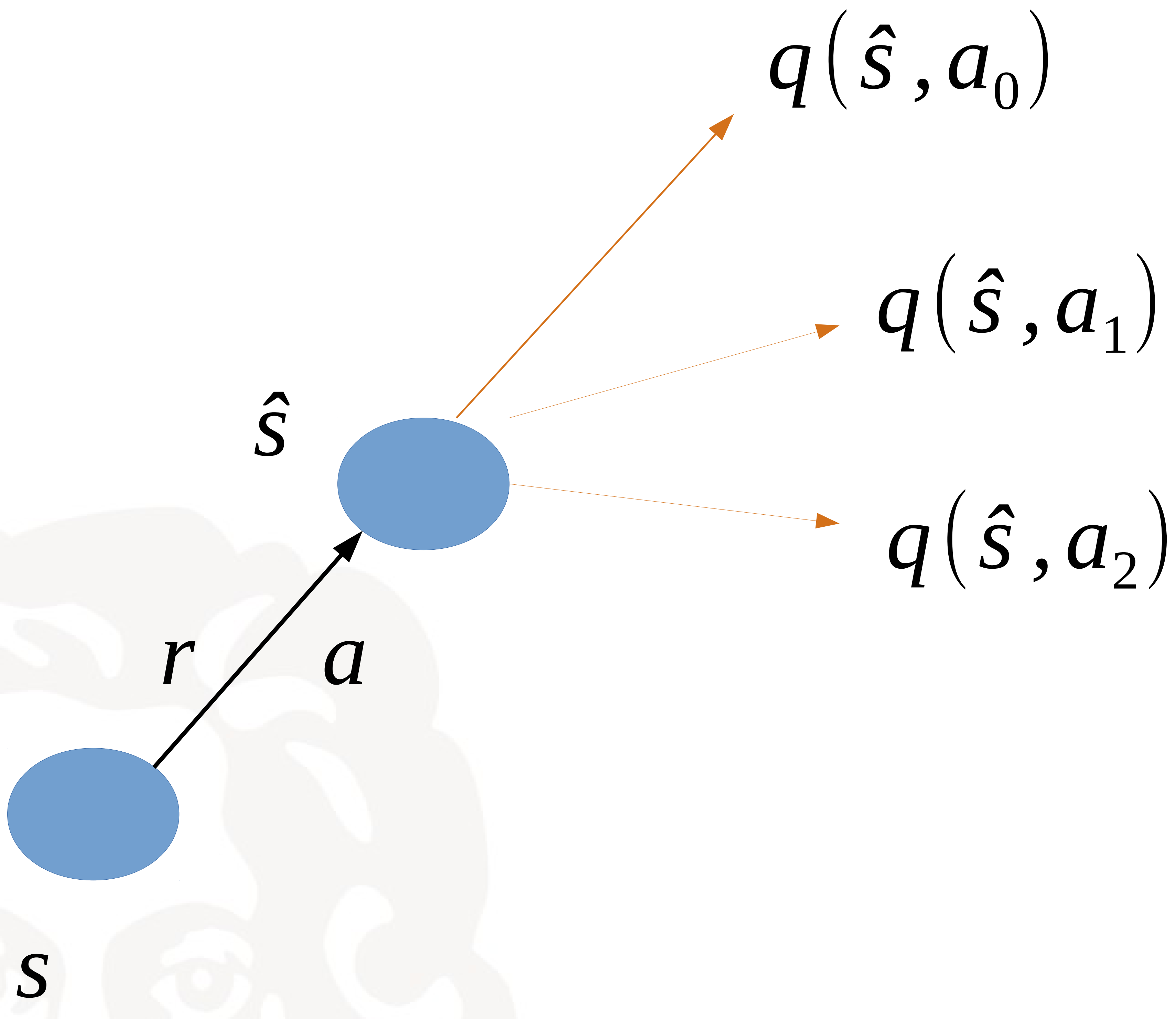
$$\epsilon - greedy\ policy$$

***Exploration-exploitation trade-off*:**

With probability ϵ choose a **random** action, else the **best** one.

https://www.coursera.org/learn/practical-rl/home/welcome

Reinforcement Learning: Openai Gym



https://gym.openai.com/envs/Taxi-v2/

https://www.coursera.org/learn/practical-rl/home/welcome