



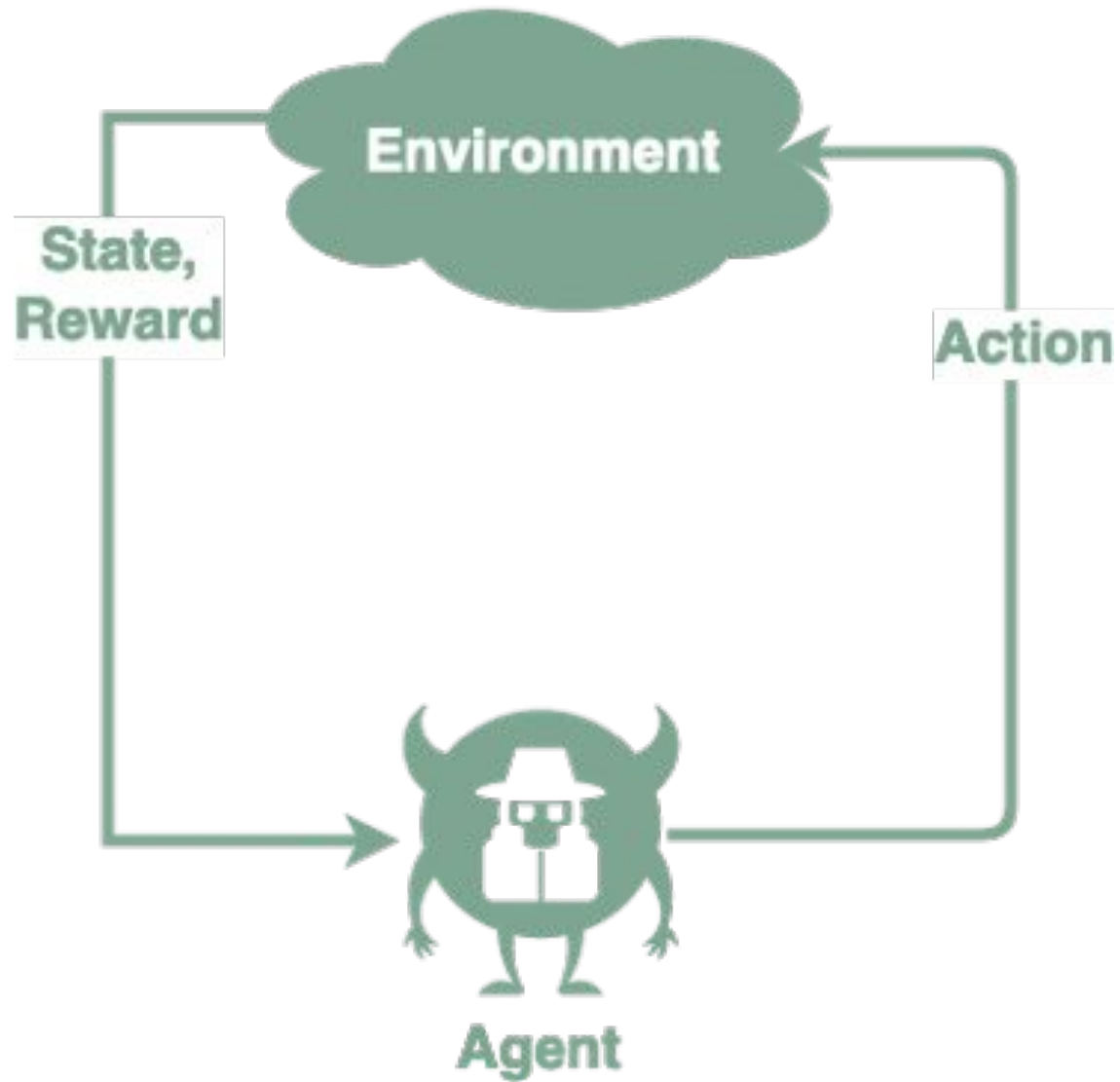
# Reinforcement Learning

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[www.signavio.com](http://www.signavio.com)

What is RL?



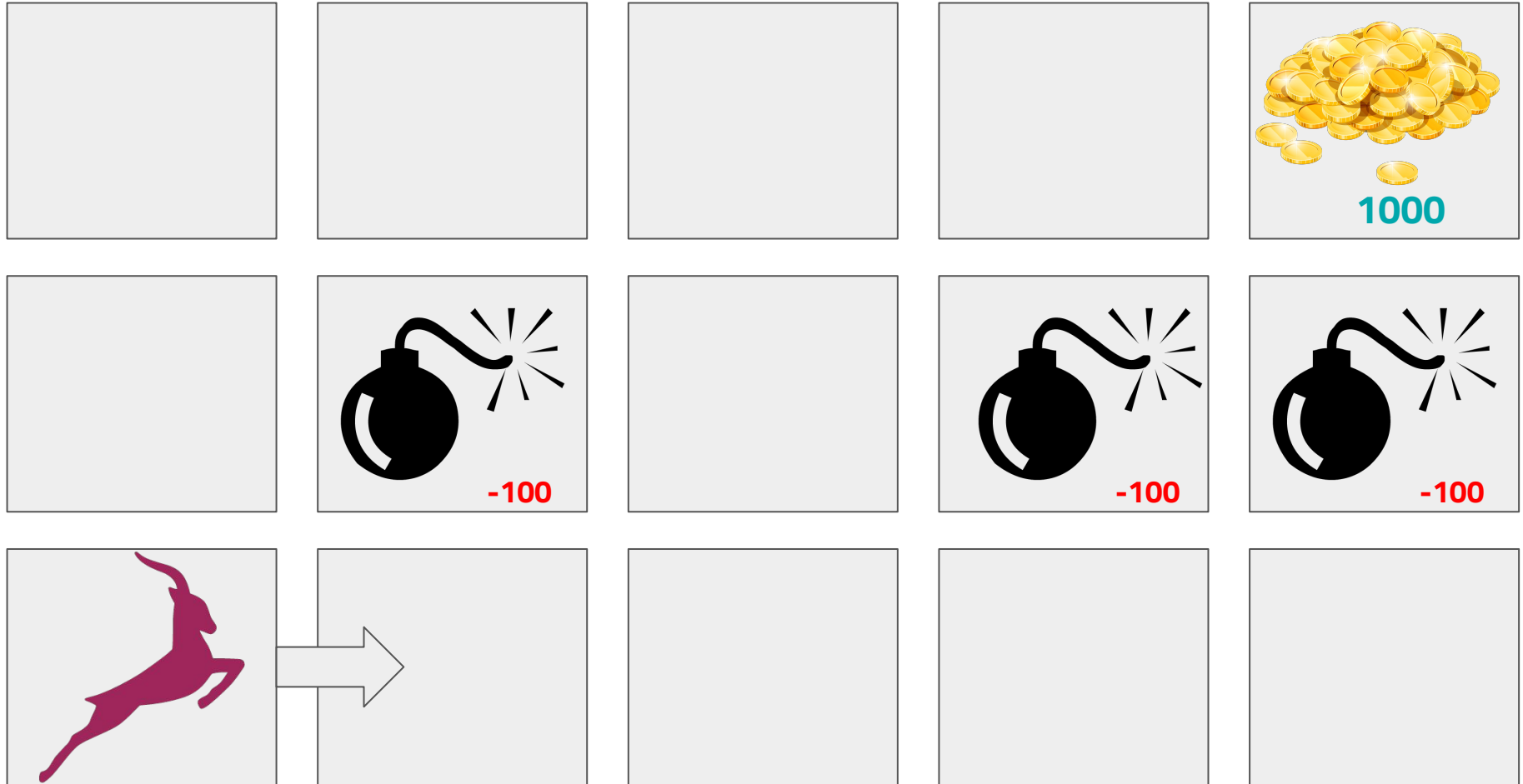
# What is RL?

- An agent learns through iterative interactions with an environment
- “Trial and error” approach (very roughly)
- RL log entry: tuple (State, Action, Time, Reward)
- How to select actions that maximize long-term rewards?
- How to design rewards?

# Exploration vs. Exploitation

- **Explore:**  
try to find better actions
- **Exploit:**  
execute action with highest expected utility, given the knowledge we have
- Explore too much  
⇒ regret caused by lack of commitment
- Exploit too much  
⇒ regret caused by lack of knowledge  
⇒ get stuck in local maximum

# Grid World / Markov Decision Processes



# Bellman equation & Markov Decision Processes

Bellman equation:

$$U(s) = \max_{a \in A(s)} (R(s, a) + \gamma U(s'))$$

- $s$ : Current state
- $A(s)$ : all possible actions at state  $s$
- $s'$ : Future state
- $R(s, a)$ : Immediate reward of  $S$  after action  $a$
- $\gamma$ : Discount factor

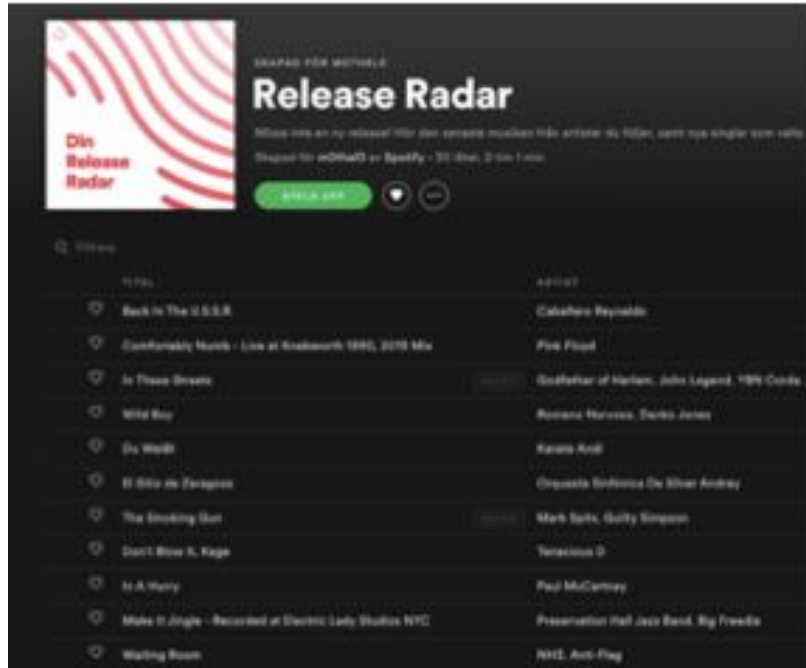
⇒ Take the action that maximizes the immediate reward plus all time-discounted future rewards



# Applications - The Obvious Ones



# Applications - The Useful Ones



McInerney, James, et al. "Explore, exploit, and explain: personalizing explainable recommendations with bandits." *Proceedings of the 12th ACM Conference on Recommender Systems*. ACM, 2018.



Hwangbo, Jemin, et al. "Learning agile and dynamic motor skills for legged robots." *arXiv preprint arXiv:1901.08652* (2019).

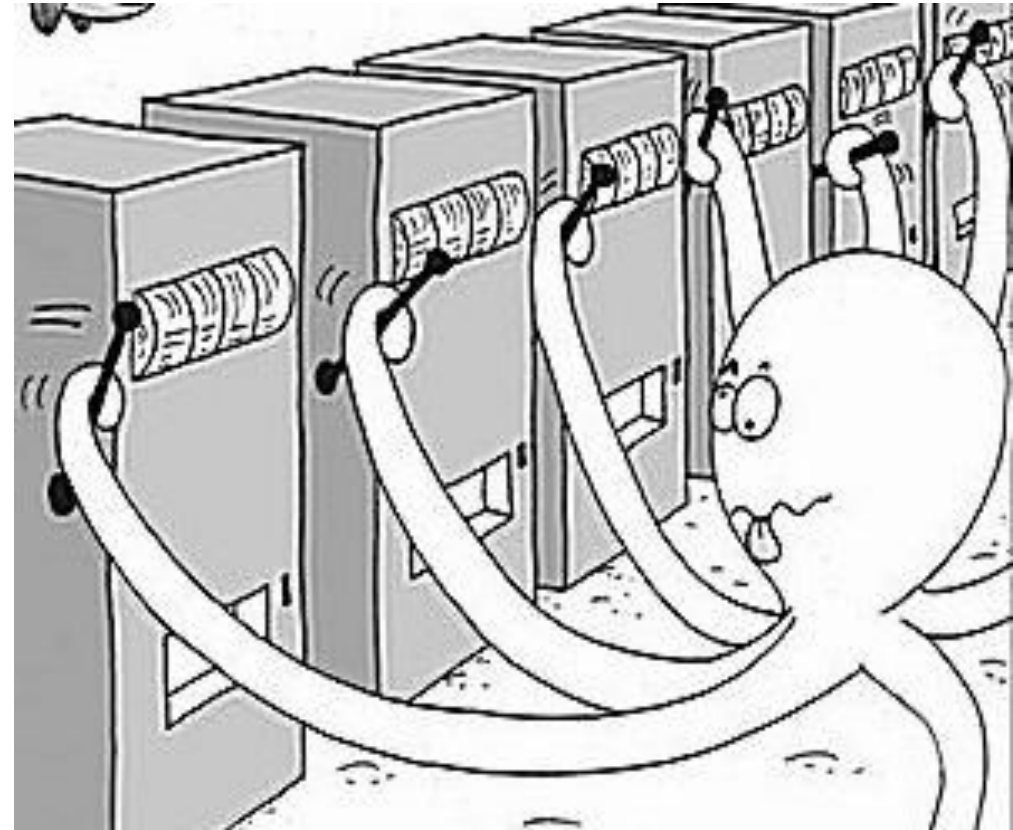


# Algorithm I: (Deep) Q-Learning

- Learn action-utility (Q)
- Does not require underlying formal model (only state and actions)
- Example: The expected reward of my actions [a, b, c] in state S is [3, 4, 5].
  - ⇒ If the agent **exploits**, it takes action c,  
If it explores, it takes a random action
- Problem: infinite state spaces:
  - ⇒ Approximate, discretize
- Often: neural network "under the hood"

# Algorithm II: Multi-Armed Bandits I

- $N$  possible actions
- Each action has unknown expected reward (random variable)
- Goal: find best (or at least “good” action)



<http://www.primarydigit.com/blog/multi-arm-bandits-explorationexploitation-trade-off>

## Algorithm II: Multi-Armed Bandits II

- $N$  arms,  $0 < \epsilon < 1$
- At iteration  $i$ ,  $0 < i < N$ :
  - Pull arm  $i$ .
  - Log reward returned by arm  $i$ .
- At iteration  $i$ ,  $i > N$ :
  - If  $\epsilon > \text{random}(0,1)$ : Pull random arm
  - Else: Pull arm with highest expected reward
  - Update expected reward of pulled arm

Thanks!



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