FROM MAB TO RL … … AND BEYOND

Francesco Trovò and Alberto Maria Metelli

Machine Learning Modena Meetup

27th January 2021

SHORT BIOS

POLITECNICO
MILANO 1863

DIPARTIMENTO DI ELETTRONICA
INFORMAZIONE E BIOINGEGNERIA

AIRLAB
ARTIFICIAL INTELLIGENCE AND ROBOTICS LAB

Assistant professor
Research interest in online learning
Course in AI @uniBG

Research assistant
Research interest in reinforcement learning
Oral @NeurIPS 2018

MACHINE LEARNING AND ALGORITHMIC GAME THEORY GROUP

Expertise in:

- Reinforcement learning
- Algorithmic game theory
- Online learning

341 +
Articoli scientifici pubblicati

5,307 +
Citazioni scientifiche

30 +
Progetti industriali

ML cube

www.mlcube.com

- Innovative startup (founded in 2020)
- Bridging the expertise of academics to the industrial world
- Developing AI projects for the industrial and web world
- Developing ML platform

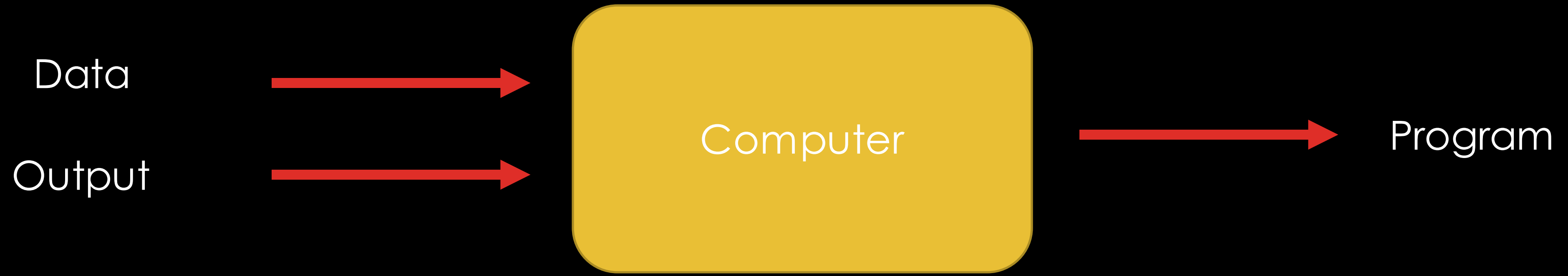
spin off®
POLITECNICO DI MILANO

PART I
MULTI-ARMED BANDITS

Francesco Trovò

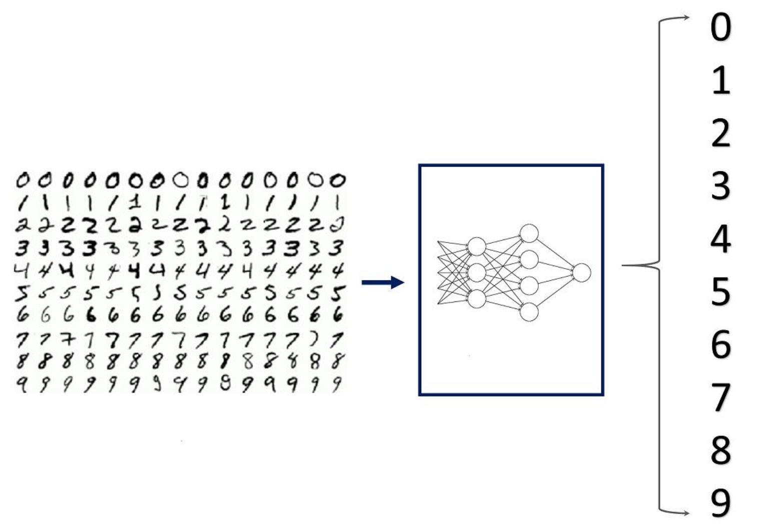
CLASSICAL ML

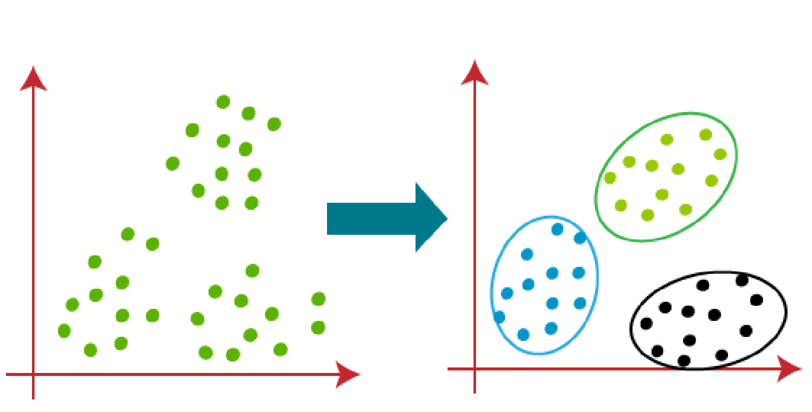
- *"A computer program is said to learn from **experience E** with respect to some **class of tasks T** and **performance measure P** if its performance at tasks in T, as measured by P, improves with experience E"*



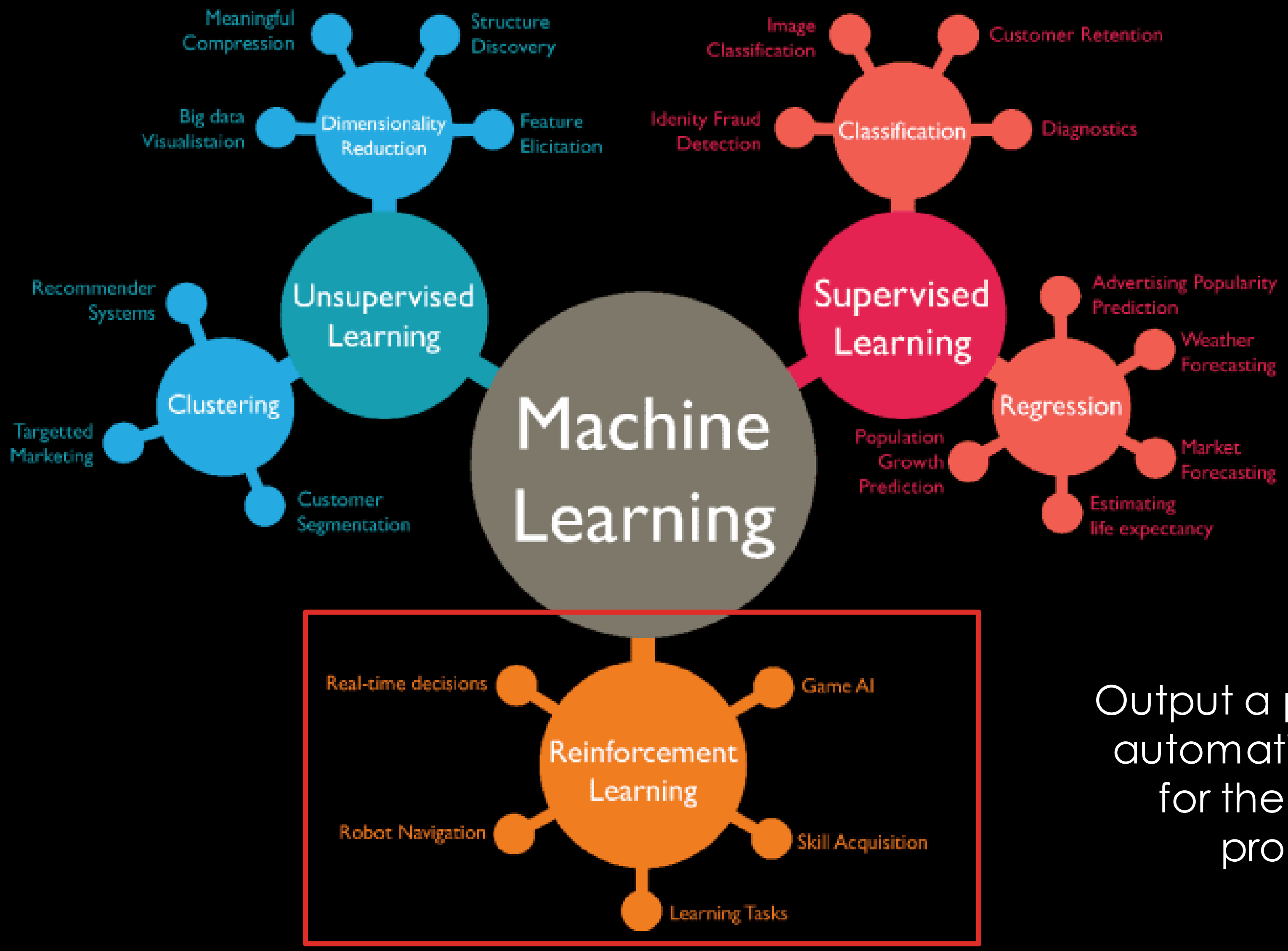
OUTPUT

Prediction or Structure in the data





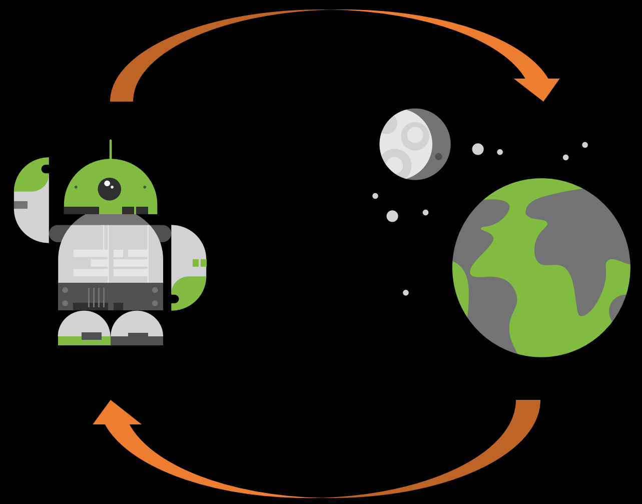
Supervised vs Unsupervised



Output a policy or an automatic decision for the specific problem

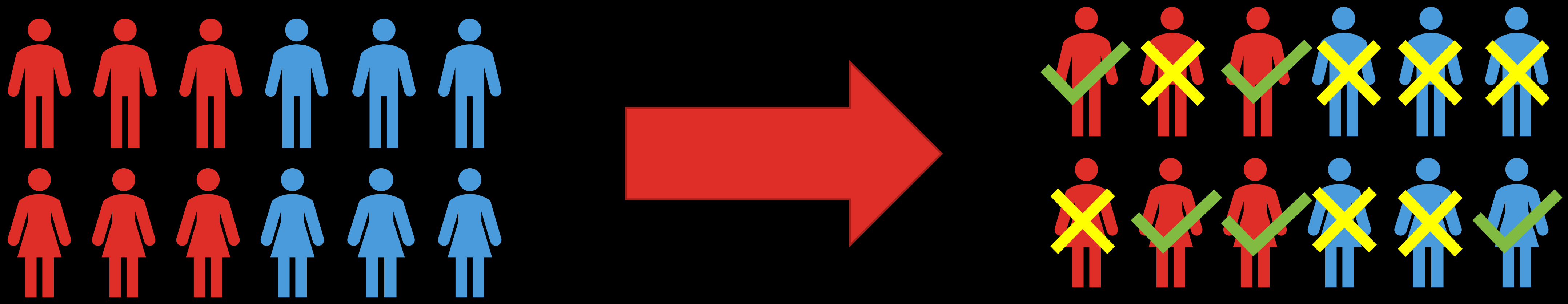
SEQUENTIAL DECISION PROBLEM

- In some setting we are required to take a **decision**
- Therefore, the task is to learn a policy or strategy
- As a new data is coming we want to update our knowledge and act accordingly



HOW MAB ARE BORN

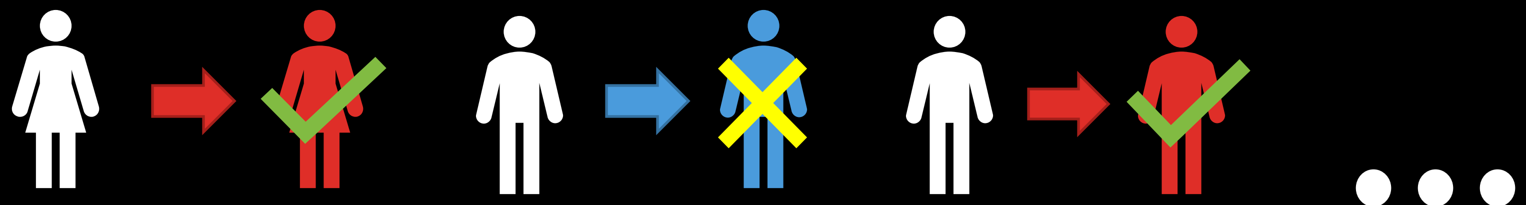
Classical Clinical Trial: red and blue pills



Use statistics to infer which treatment is the most promising one

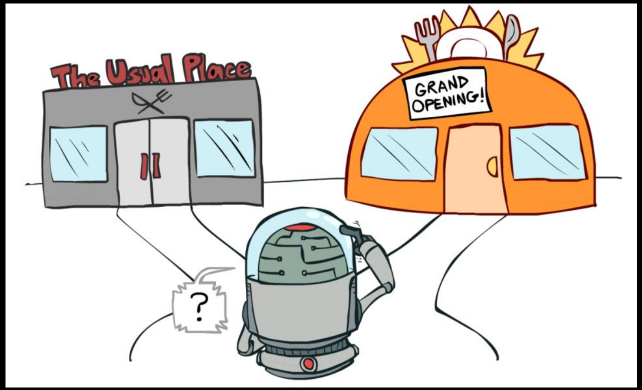
SEQUENTIAL PROCESS

- Design a clinical trial to minimize the number of suboptimal treatments provided to patients



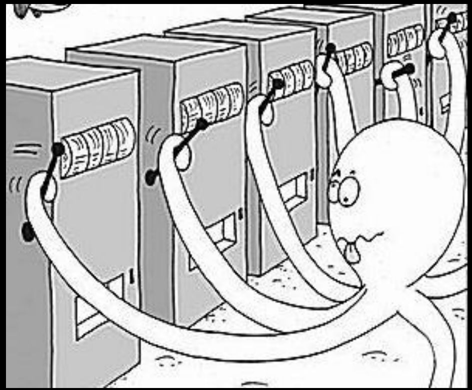
- We call the loss incurred due to lack of information **regret**

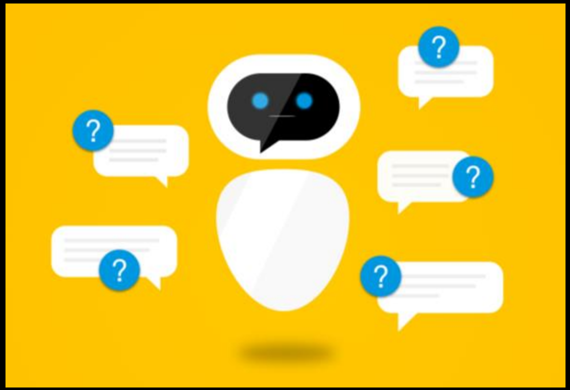
MULTI-ARMED BANDIT: A COMMON SETTING TO MANY PROBLEMS



Restaurant selection problem

Slot selection problem

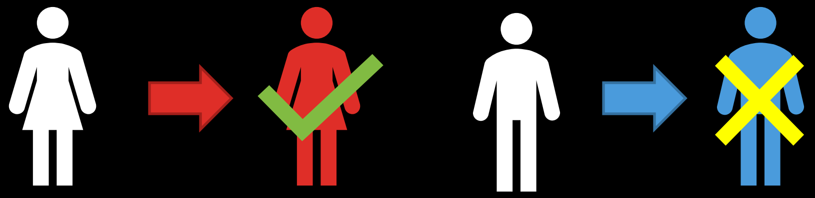




Dialogue model selection

MEAN IS NOT ENOUGH

- Assume value 1 for success and 0 for failure
- The empirical mean of the blue treatment is zero



- On the following patients we would only select the red treatment

WANDERING AROUND IS NOT HEALTHY

- Using this approach, we would have the same results in terms of regret as the classical clinical trial

- We need to solve the so called:

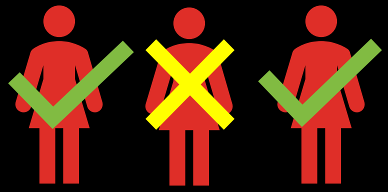
exploration vs. exploitation (dilemma)

Evaluate and refine the currently unexplored options

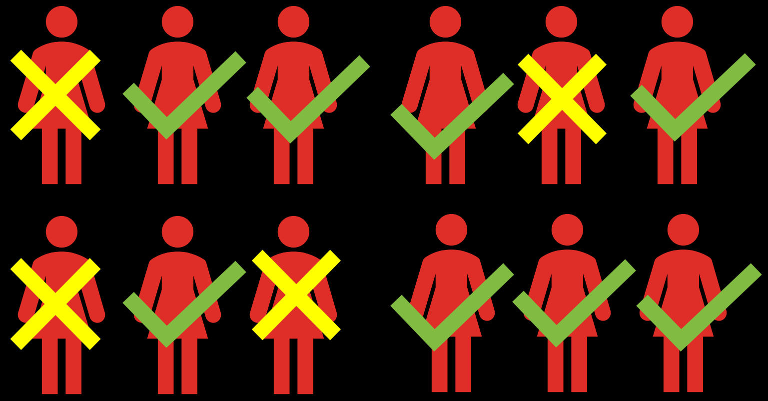
Using the currently available information to gain a profit

OPTIMISM IN THE FACE OF UNCERTAINTY

Setting 1



Setting 2



- We need to take into account also the uncertainty of the estimates
- "L'ottimismo è il profumo della vita!" (Tonino Guerra)

UCB1 ALGORITHM

Given a set of arms (options) $\mathrm{A} = \{a_1, \dots, a_K\}$

Compute the empiric mean

$$\hat{R}_t(a_i) = \frac{\sum_{i=1}^{t} r_{i,t} \, \mathbb{1}\{a_i = a_{i_t}\}}{N_t(a_i)} \quad \forall a_i$$

Compute the uncertainty bound

$$B_t(a_i) = \sqrt{\frac{2 \log t}{N_t(a_i)}} \quad \forall a_i$$

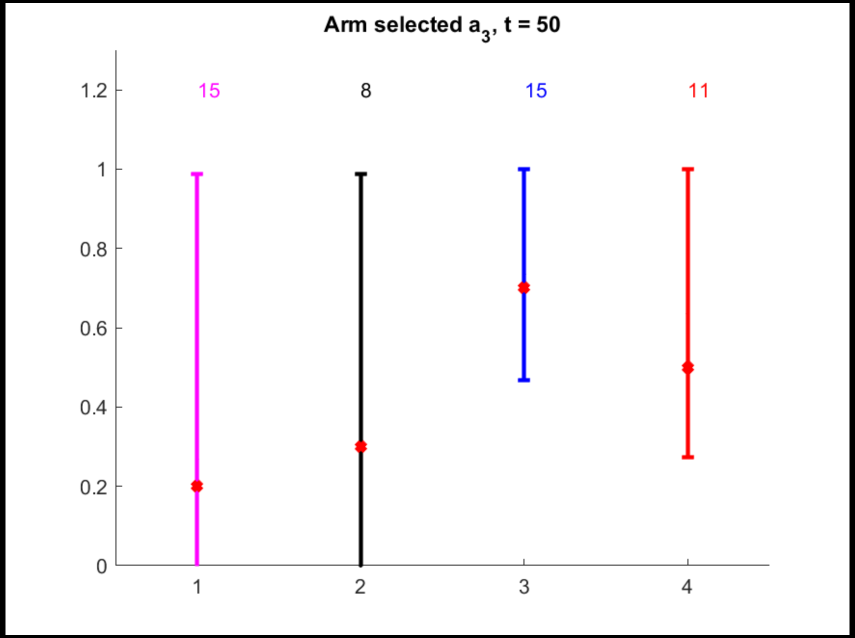
Select the arm with the largest UCB

$$a_{i_t} = \arg\max_{a_i \in \mathcal{A}} \left(\hat{R}_t(a_i) + B_t(a_i) \right)$$

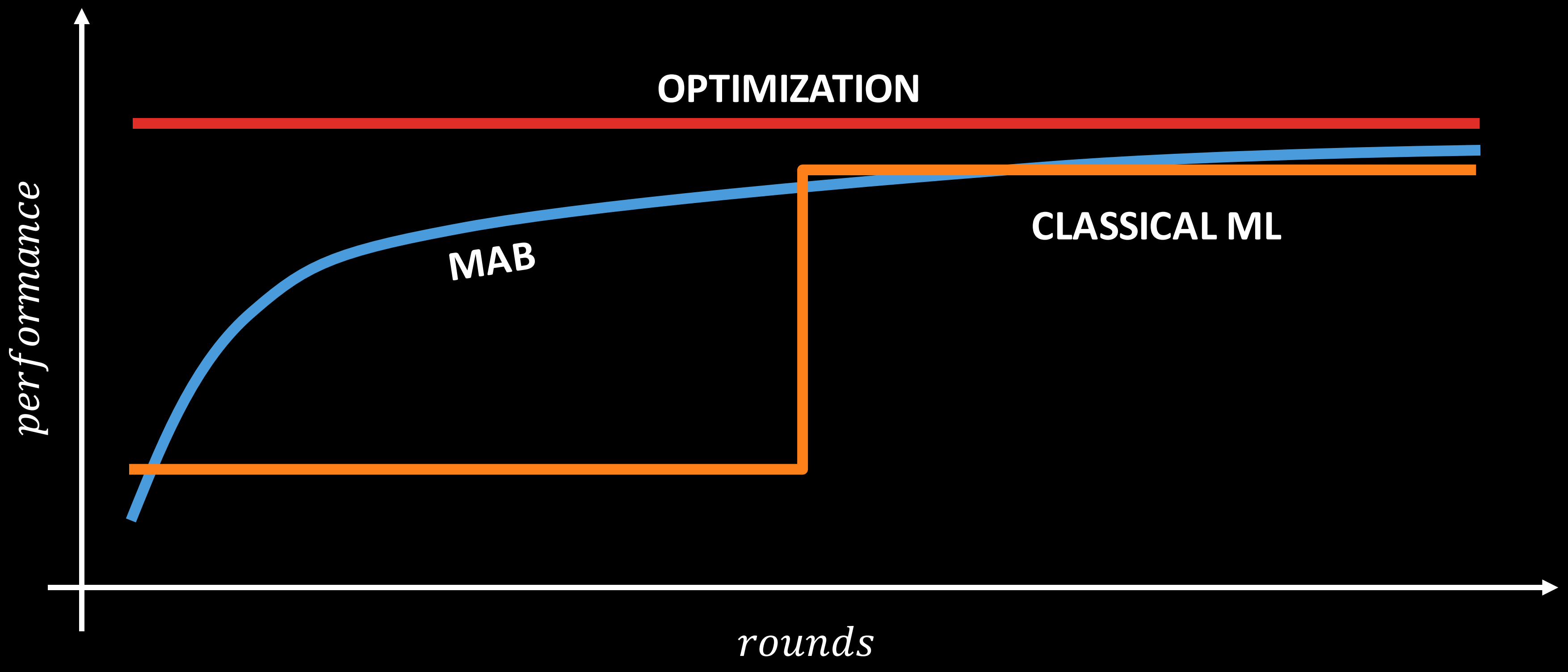
Auer, P., Cesa-Bianchi, N., & Fischer, P. (2002). Finite-time analysis of the multiarmed bandit problem. *Machine learning*, *47*(2), 235-256.

EXECUTION EXAMPLE

- $A = \{a_1, a_2, a_3, a_4\}$



SEQUENTIAL APPROACH ADVANTAGES



THEORETICAL GUARANTEE

- Lower Bound

$$\lim_{T\to\infty} L_T \geq \boxed{\log T} \sum_{a_i|\Delta_i>0} \frac{\Delta_i}{KL(\mathcal{R}(a_i), \mathcal{R}(a^*))}$$

- Upper bound UCB1

$$L_T \leq 8\boxed{\log T} \sum_{i|\Delta_i>0} \frac{1}{\Delta_i} + \left(1 + \frac{\pi^2}{3}\right)$$

PRACTICAL ISSUES

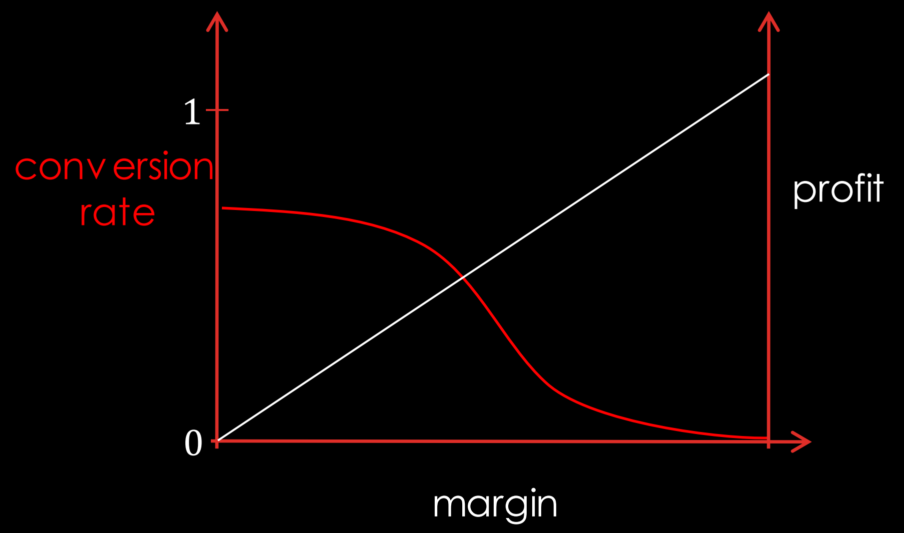
- It is a good alternative to A/B testing in general
  - Allows multiple options
  - Minimize the loss
  - Does not exclude completely the use of any option

- Even if this framework si formal and elegant, it hardly generalizes to real problems (too simple)

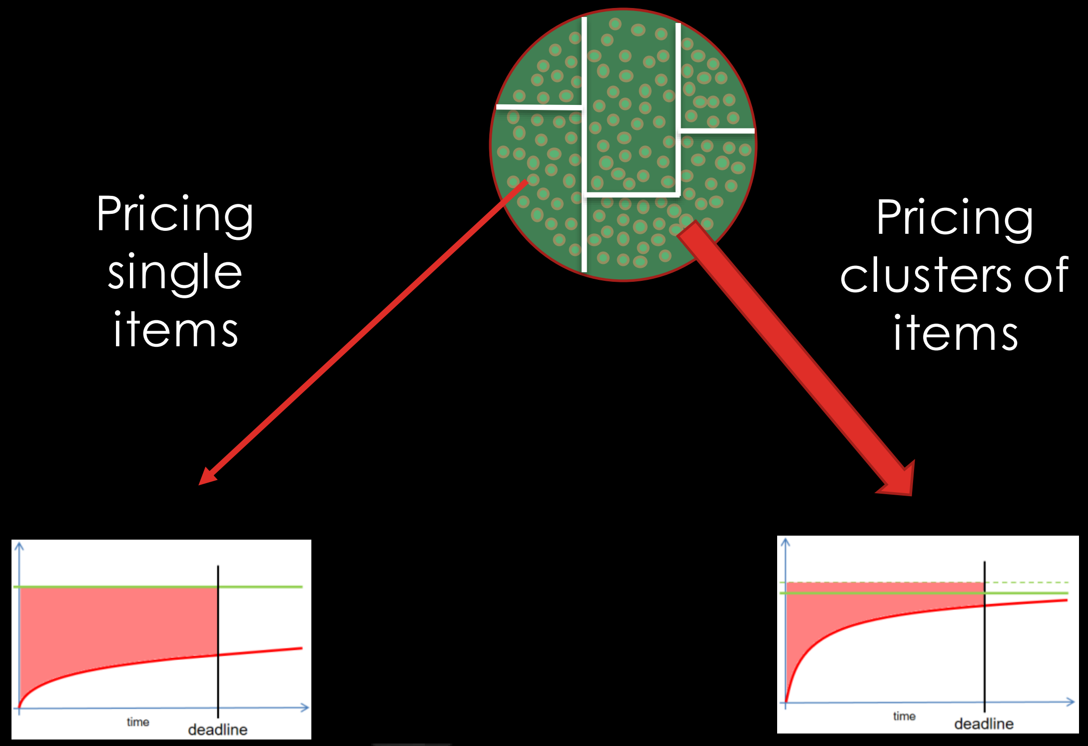
PRICING PROBLEM

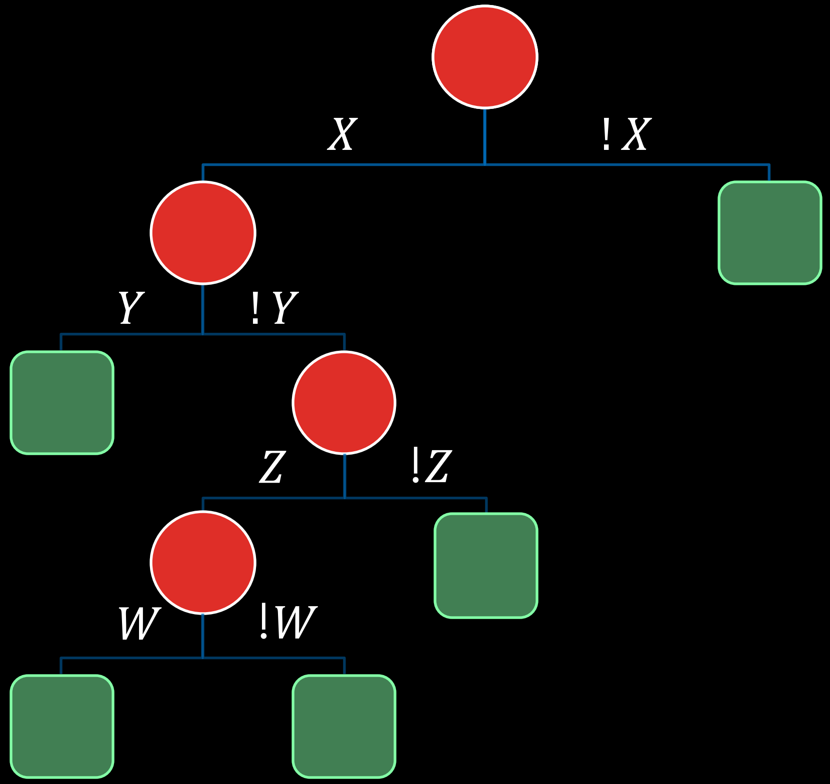
- Problem formulation:
  - Given an inventory of products
  - Select the most profitable price for each product

- Characteristics:
  1. Large inventory
  2. Continuous choice
  3. Non-stationarity



1. LARGE INVENTORY

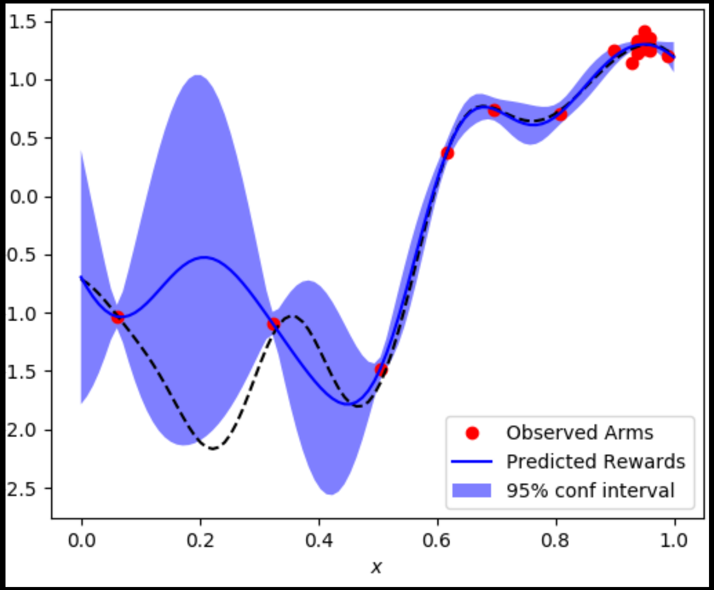




Trovò, F., Paladino, S., Simone, P., Restelli, M., & Gatti, N. (2017, May). Risk-averse trees for learning from logged bandit feedback. In *2017 International Joint Conference on Neural Networks (IJCNN)* (pp. 976-983). IEEE.

2. CONTINUOUS CHOICE

- Gaussian Process
- Selection of the next arm to play according to UCB provided by GPs



Srinivas, N., Krause, A., Kakade, S., & Seeger, M. (2010). Gaussian Process Optimization in the Bandit Setting: No Regret and Experimental Design. In *Proceedings of the 27th International Conference on Machine Learning*.

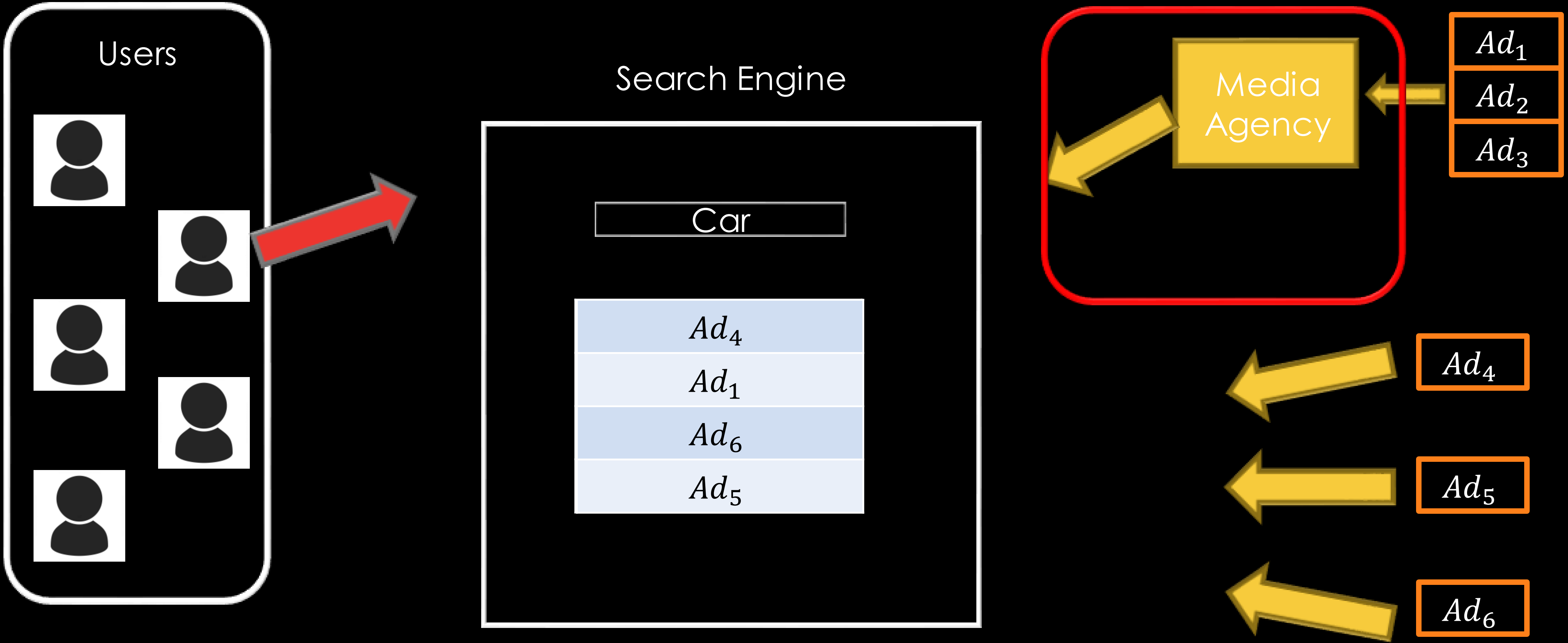
3. NON-STATIONARITY

- Apply a sliding window to the system

- Passive approach
- Active approaches aim at identifying a change in the distribution of the rewards

Trovo, F., Paladino, S., Restelli, M., & Gatti, N. (2020). Sliding-window thompson sampling for non-stationary settings. *Journal of Artificial Intelligence Research*, *68*, 311-364.

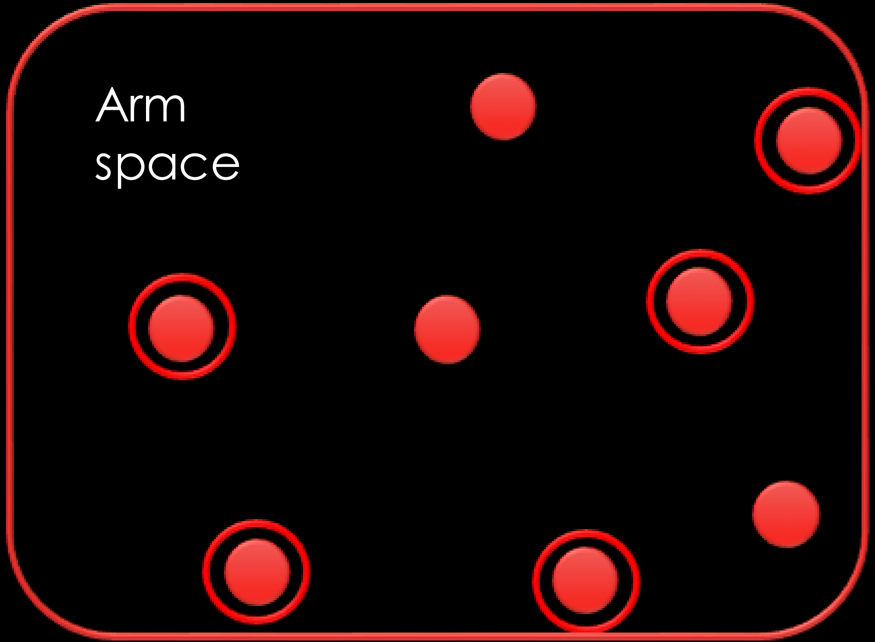
ADVERTISING PROBLEM



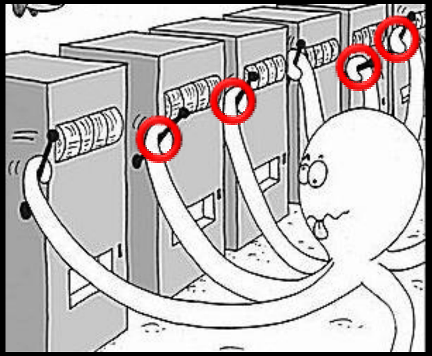
ADVERTISING MODEL

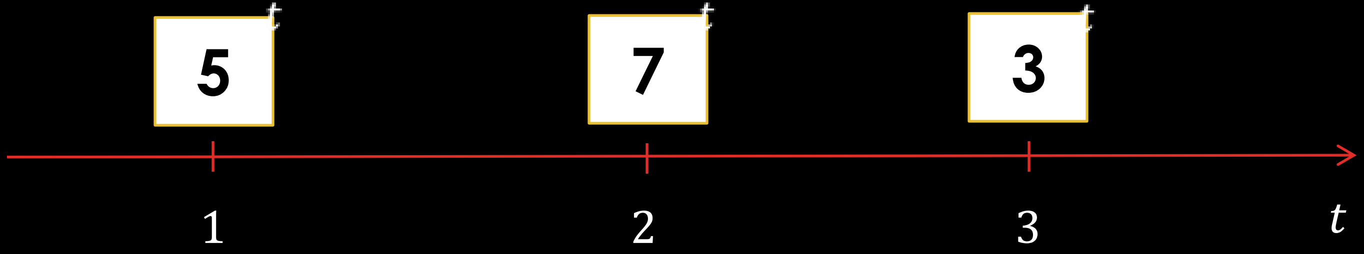
- Problem formulation:
  - Given a set of ads, select bid and budget
  - Assuring that the overall budget is no more than a given daily one

COMBINATORIAL BANDITS



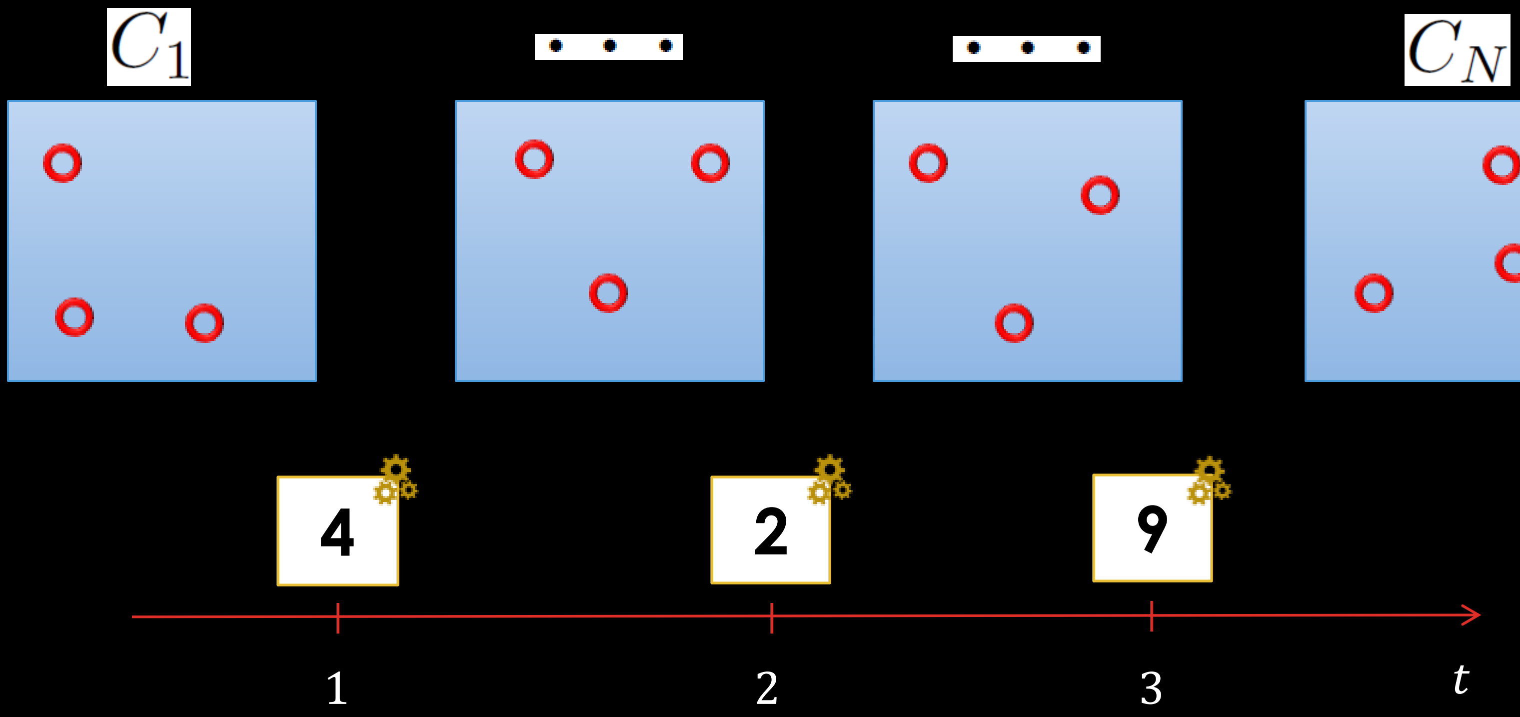
Optimization Oracle





CMAB FOR ADVERTISING

- Choose using Upper Confidence Bounds



Nuara, A., Trovo, F., Gatti, N., & Restelli, M. (2018). Online Joint Bid/Budget Optimization of Pay-per-click Advertising Campaigns. In *16th European Conference on Multi-Agent Systems* (pp. 1-15).

CONCLUSION

- MAB algorithms are only nice and elegant tools to study theoretically
- Its extensions are used in many applicative fields

Future directions:

- Fairness in MAB
- Dynamics in MAB
- Domain specific MAB

PART II
REINFORCEMENT LEARNING

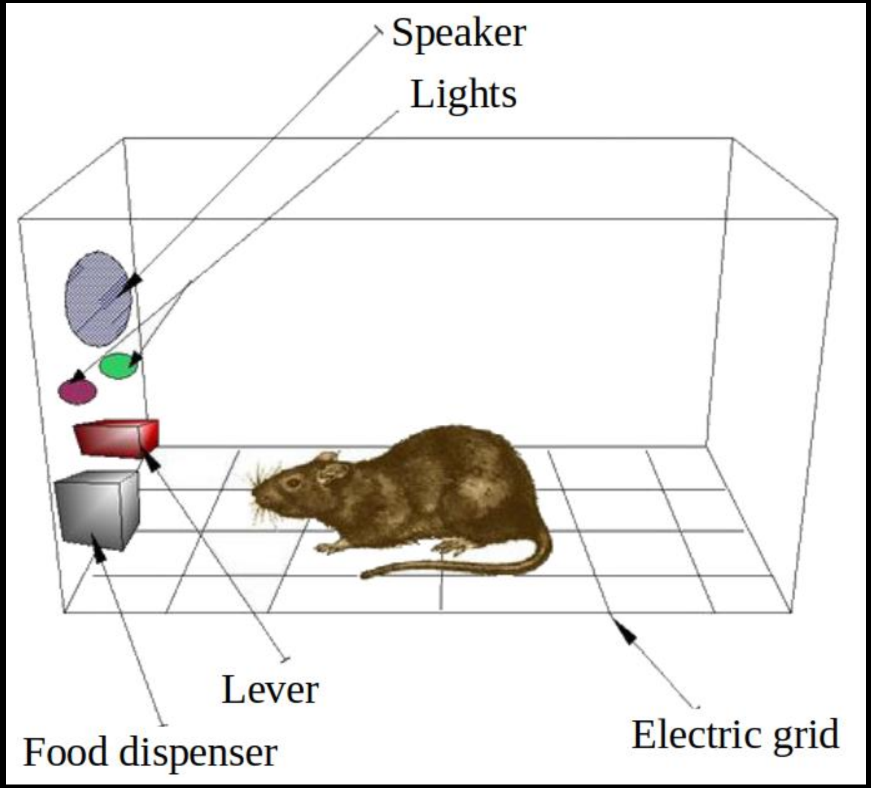
Alberto Maria Metelli

ORIGINS OF REINFORCEMENT LEARNING

- RL originates in **behavioral psychology**

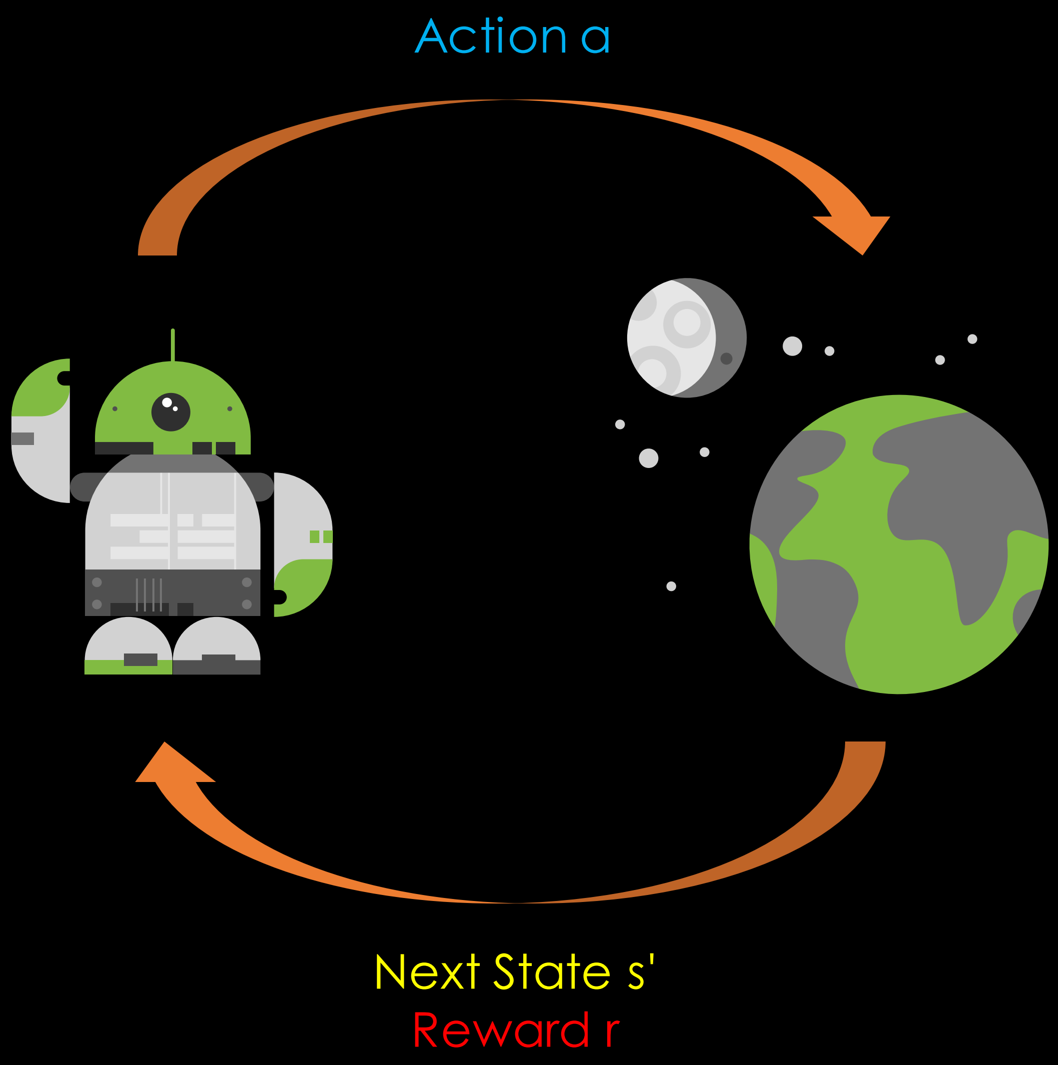
«a consequence applied that will strengthen an organism's future behavior whenever that behavior is preceded by a specific antecedent stimulus»

- Skinner box → Operant conditioning



Burrhus F Skinner. The behavior of organisms: an experimental analysis. 1938.

AGENT AND ENVIRONMENT



At each step:

- The agent observes the **state** s
- The agent plays **action** $a \sim \pi(\bullet \mid s)$
- The environment transitions to the **next state** $s' \sim P(\bullet \mid s,a)$
- The environment emits a scalar **reward** $r = R(s,a)$

Martin L Puterman. Markov decision processes: discrete stochastic dynamic programming. John Wiley & Sons, 2014.

Richard S Sutton and Andrew G Barto. Reinforcement learning: An introduction. MIT press, 2018.

HOW DOES RL DIFFERS FROM MAB?

- **Same goal:** select actions to maximize cumulative rewards but …
- … actions may have **long–term** consequences
- … reward may be **delayed**
- … it may be better to **sacrifice** immediate reward to gain more long–term reward

WHEN TO USE RL INSTEAD OF AUTOMATIC CONTROL?

- When the environment dynamics is **unknown**
- When the environment dynamics is known but **too complex** to be effectively used

OPTIMALITY CRITERIA

Goal of an RL agent: maximize the (expected discounted) cumulative reward

$$\sum_{t \geq 0} \gamma^t \, r_t$$

$\gamma \approx 0$

«meglio un uovo oggi che una gallina domani?»

$\gamma \approx 1$

OPTIMAL VALUE FUNCTION AND OPTIMAL POLICY

- Maximum cumulative reward from (s,a)
- **Bellman** equation

$$Q^*(s,a) = r(s,a) + \gamma \sum_{s' \in S} P(s'|s,a) \max_{a' \in A} Q^*(s',a')$$

instantaneous reward

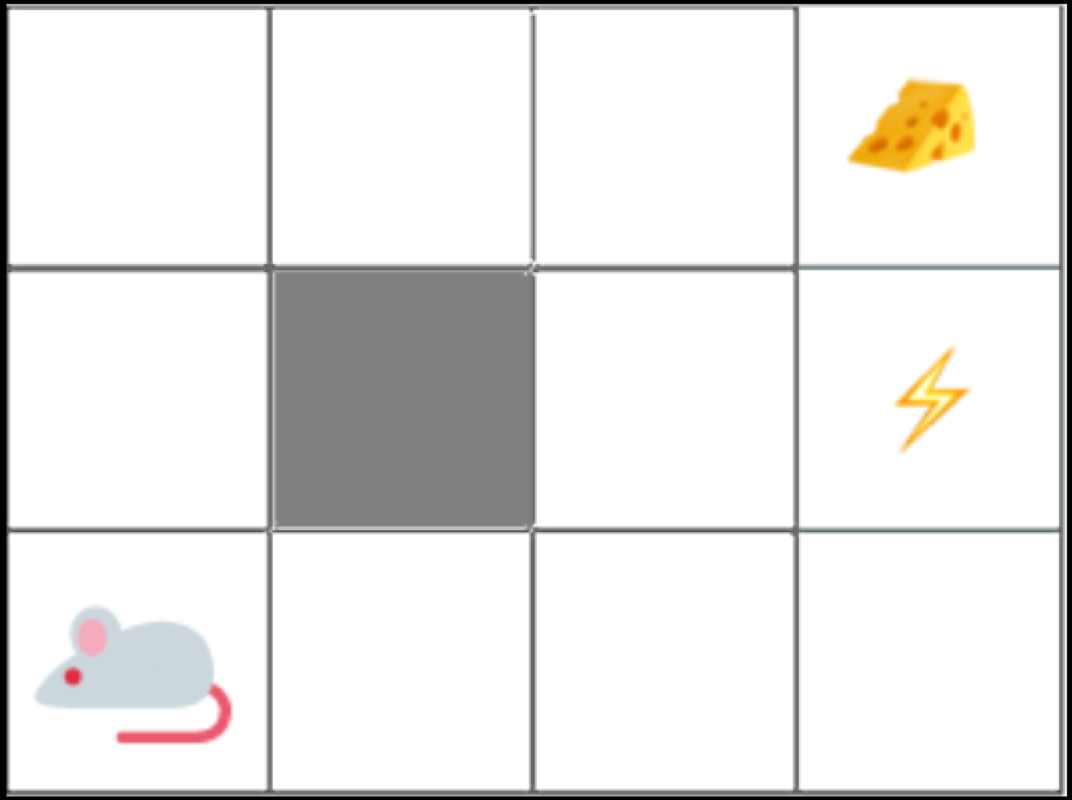
transition model

cumulative reward form next state on

- **Optimal** policy

$$\pi^*(s) = \text{argmax}_{a \in A} Q^*(s,a)$$

EXAMPLE



EXAMPLE

Reward

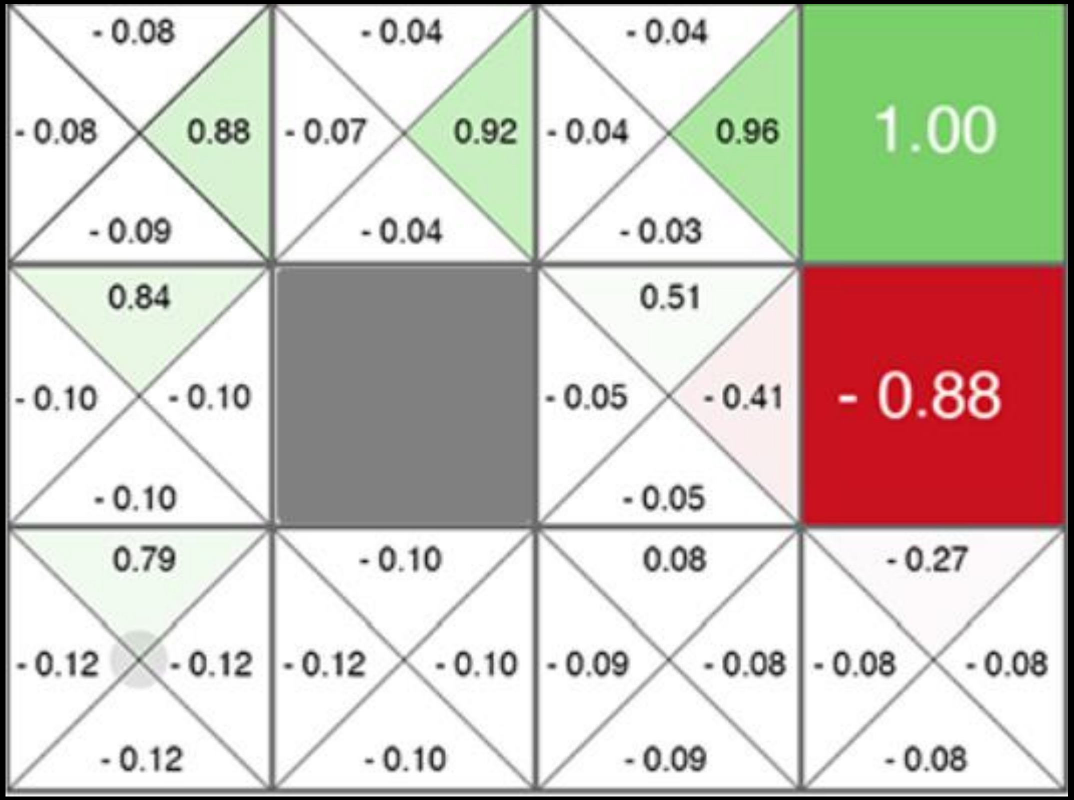
0	0	0	1.00
0		0	- 0.88
0	0	0	0

EXAMPLE

Reward

0	0	0	1.00
0		0	- 0.88
0	0	0	0

Q-function



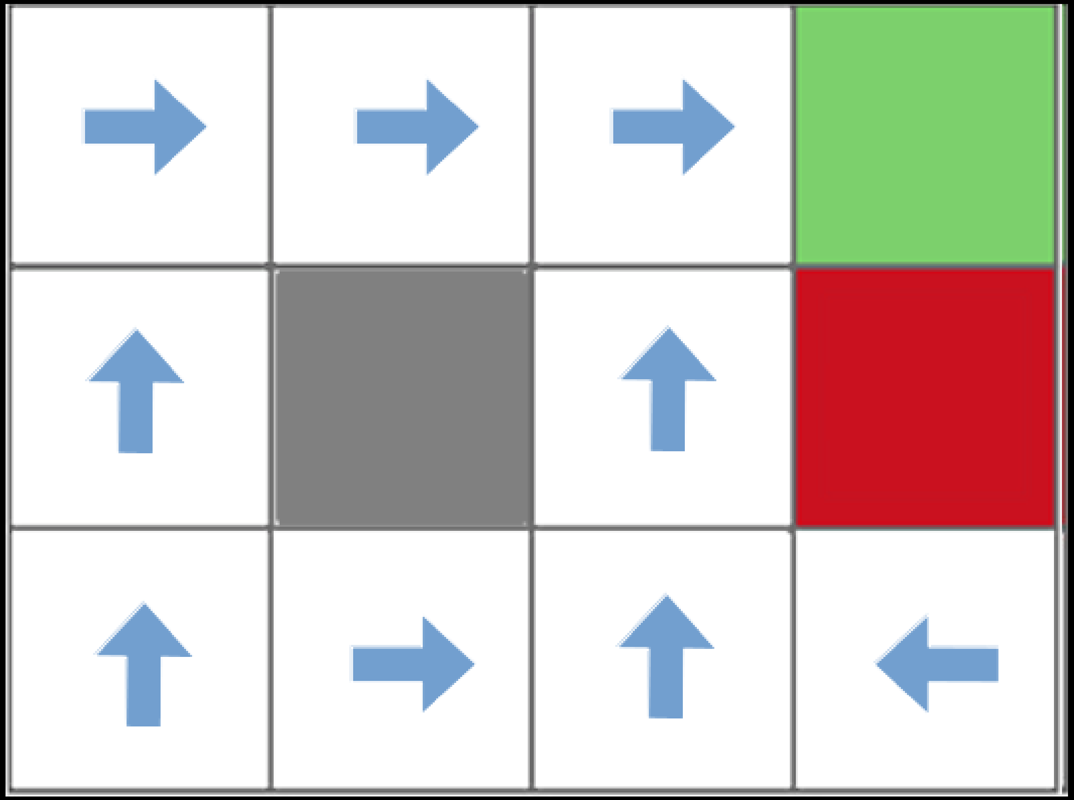
EXAMPLE

Reward

0	0	0	1.00
0		0	- 0.88
0	0	0	0

Policy

Q-function



LEARNING IN TABULAR PROBLEMS: Q-LEARNING

- **Problem:** learn the optimal value function from samples

Initialize Q

Observe the initial state s_0

For each step t=0, 1, …

  Select action a_t with an exploration policy

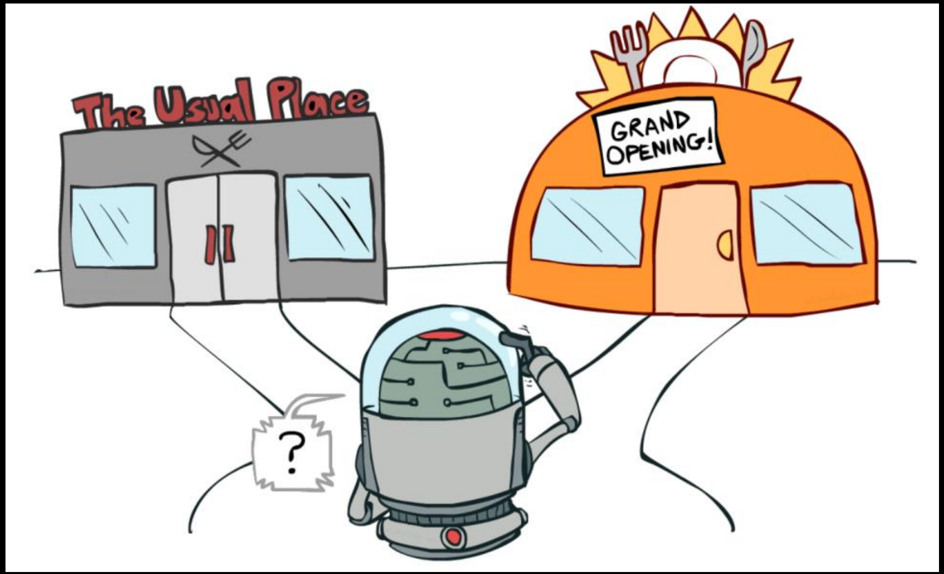
  Take action a_t and observe reward r_t and next state s_{t+1}

  Update $Q(s_t,a_t) \leftarrow (1-\beta)\ Q(s_t,a_t) + \beta[r_t + \gamma \max_a Q(s_{t+1},a)]$

- How to select the exploration policy?

EXPLORATION VS EXPLOITATION

- All actions should be tried sufficiently often!
- **exploration-exploitation** dilemma
- Cost of exploration (simulation vs real system)
- **Examples**: epsilon greedy, Boltzmann, UCB



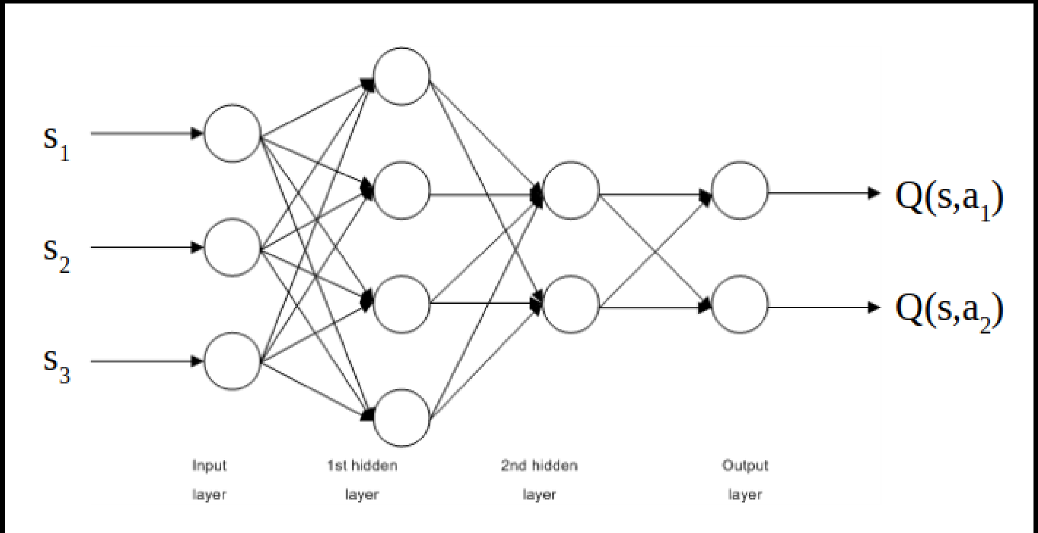
LEARNING WITH CONTINUOUS STATES

- What if the state space is infinite?
- **Function approximation**

$$Q(s_t, a_t; \theta)$$

- Minimize the loss via gradient descent over **θ** (not working well...)

$$\min_{\theta}\left(Q(s_t, a_t; \theta) - \left(r_t + \gamma \max_{a \in A} Q(s_{t+1}, a; \theta)\right)\right)^2$$



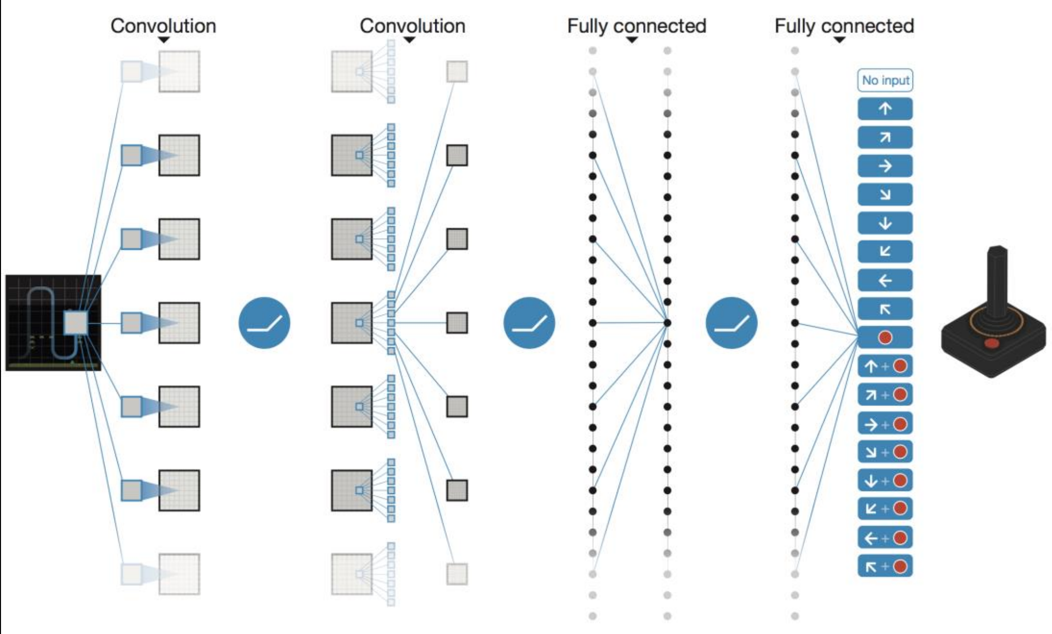
STEPS TOWARDS DEEP RL

$$\min_{\theta}\left(Q(s_t, a_t; \theta) - \left(r_t + \gamma \max_{a\in A} Q(s_{t+1}, a; \theta)\right)\right)^2$$

Not exactly **supervised learning**…

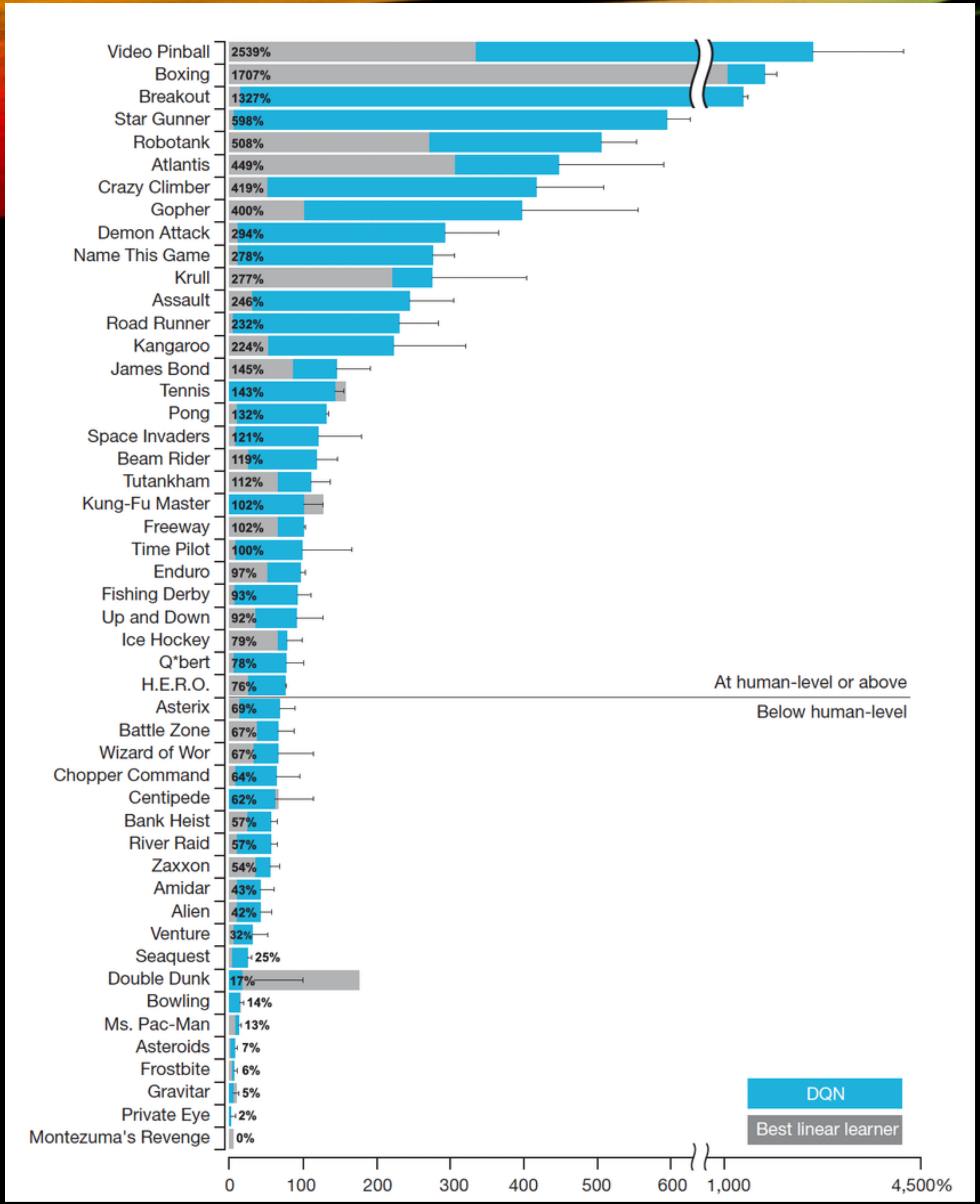
- Samples are dependent
- Learning stability

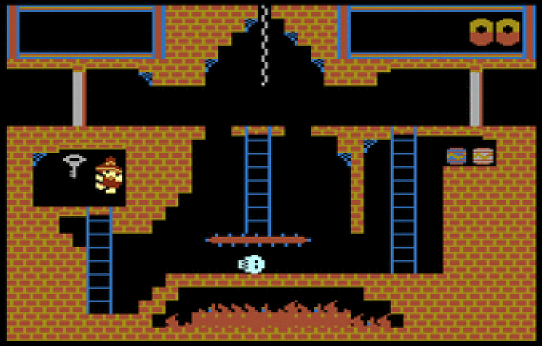
And some other triks… → DQN (Deep Q-Networks)



Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., … & Hassabis, D. (2015). Human-level control through deep reinforcement learning. nature, 518(7540), 529-533.

DQN ON ATARI

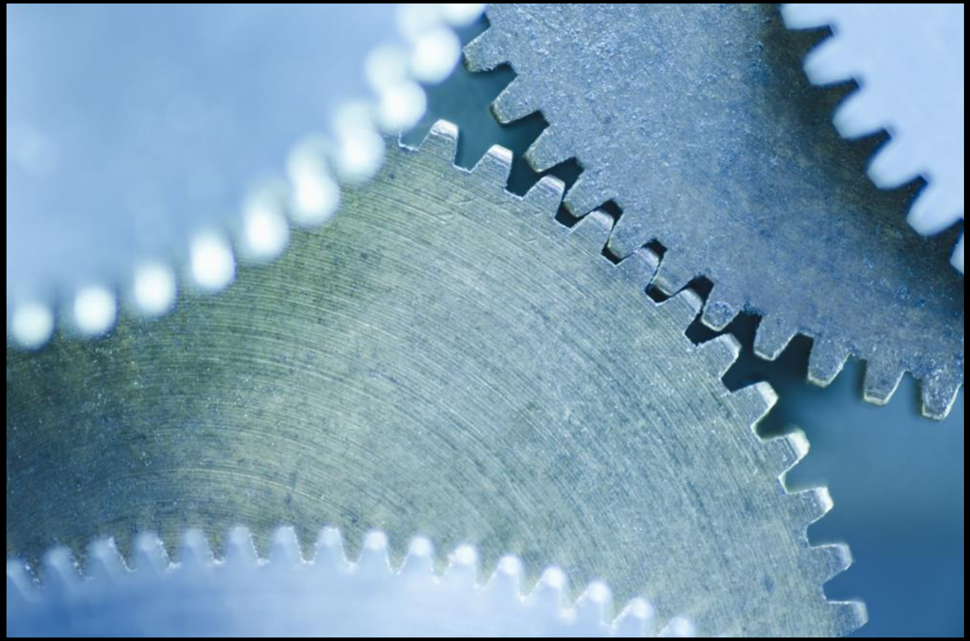




Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., ... & Hassabis, D. (2015). Human-level control through deep reinforcement learning. nature, 518(7540), 529-533.

TOWARDS REAL-WORLD APPLICATIONS

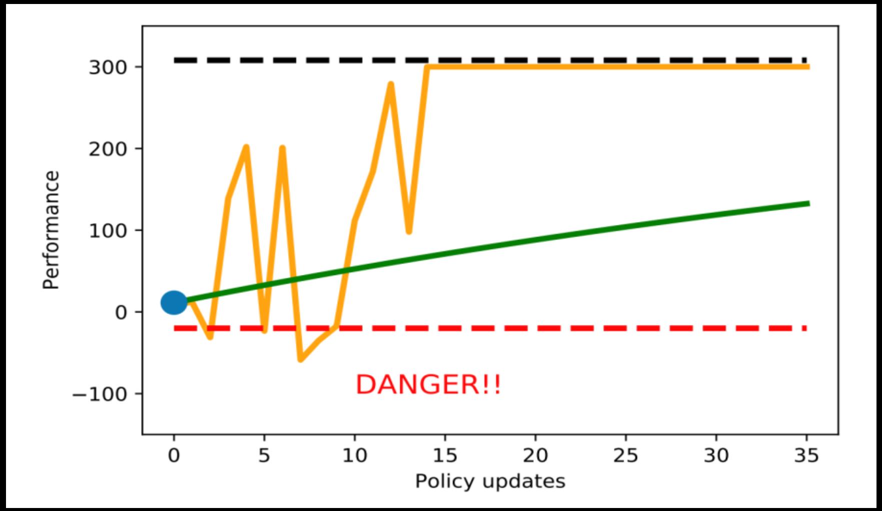
- Safe Behavior and Safe Learning
- Multi-objective tasks
- Interpretability
- Learn by imitation



SAFE REINFORCEMENT LEARNING

Learn a "safe" behavior

Learn/explore "safely"

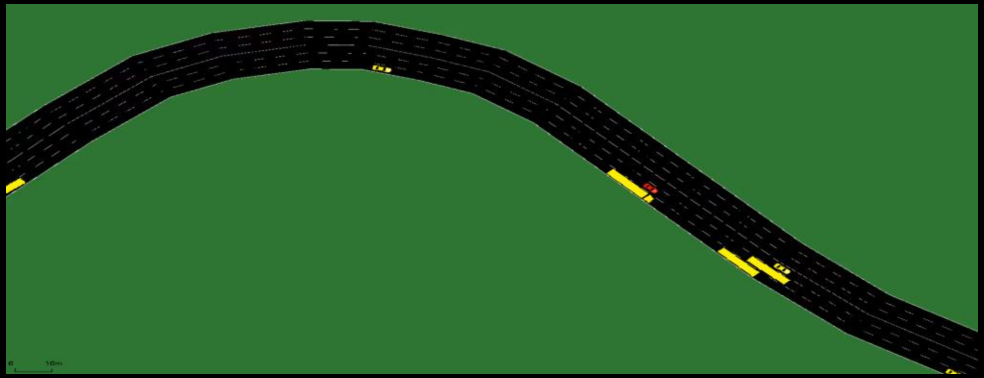


Garcıa, J., & Fernández, F. (2015). A comprehensive survey on safe reinforcement learning. Journal of Machine Learning Research, 16(1), 1437-1480.

Papini, Matteo, Andrea Battistello, and Marcello Restelli. "Balancing learning speed and stability in policy gradient via adaptive exploration." AISTATS 2020.

RL FOR AUTONOMOUS DRIVING

- **Goal**: display human-like behavior
- Two driving scenarios
  - Highway driving → **multiobjective**
  - Urban (intersection, roundabaout)
- Sensor inputs, discrete actions
- **Interpretability** → parametric rule-based policy



Likmeta, A., Metelli, A. M., Tirinzoni, A., Giol, R., Restelli, M., & Romano, D. (2020). Combining reinforcement learning with rule-based controllers for transparent and general decision-making in autonomous driving. *Robotics and Autonomous Systems*, *131*, 2020.

RL FOR DRIVING ON A TRACK

- **Goal**: minimize the lap time
- Human expert demonstration collected on a simulator
- **Objectives**
  - mimic the expert → **imitation learning**
  - improve the expert's policy → planning

… AND BEYOND

- Lifelong/Continual RL
- Meta RL
- Multi-Agent RL

POLITECNICO
MILANO 1863
DIPARTIMENTO DI ELETTRONICA
INFORMAZIONE E BIOINGEGNERIA

AIRLAB
ARTIFICIAL INTELLIGENCE AND ROBOTICS LAB

ML cube

THANK YOU!

Francesco Trovò
francesco1.trovo@polimi.it

Alberto Maria Metelli
albertomaria.metelli@polimi.it

ADDITIONAL REFERENCES

MAB

- Bubeck, S., & Cesa-Bianchi, N. (2012). Regret Analysis of Stochastic and Nonstochastic Multi-armed Bandit Problems. *Foundations and Trends® in Machine Learning*, *5*(1), 1-122.
- Lattimore, T., & Szepesvári, C. (2020). *Bandit algorithms*. Cambridge University Press.

RL

- Sutton, R. S., & Barto, A. G. (1998). *Introduction to reinforcement learning* (Vol. 135). Cambridge: MIT press.