EAI 2021

Reasoning Agents

Presentation

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Reinforcement Learning in Regular Decision Processes

Algorithm and experiments explanation

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Outline

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Team

Francesco Starna

Graziano Specchi

Lorenzo Guercio

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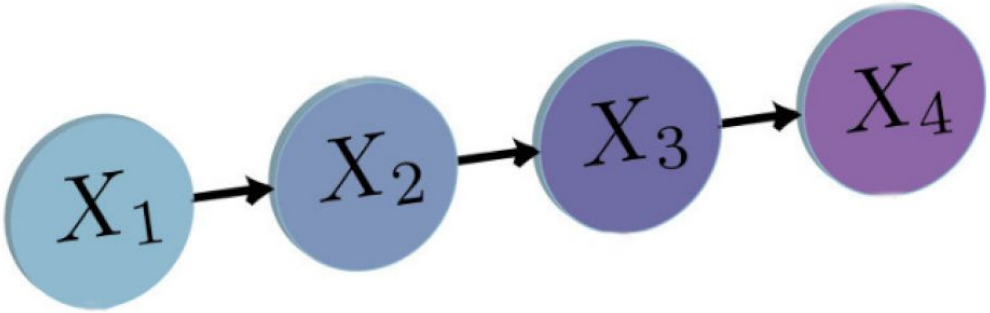
Motivations

Reinforcement Learning has been using the Markov Assumption



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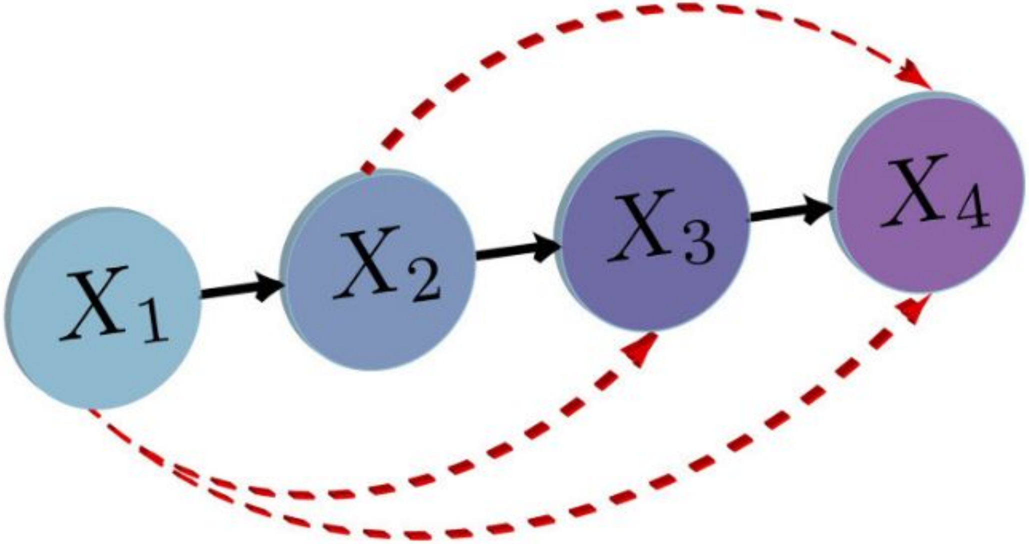
But there are some domains in which it is not possible to neglect the past



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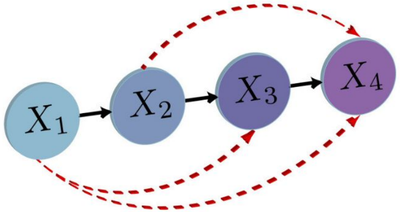

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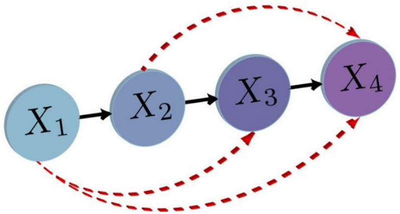

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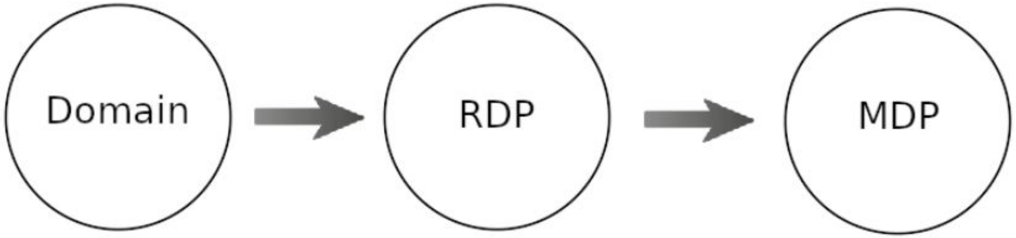
Regular Decision Processes have been proposed to overcome this issue

The knowledge of a RDP allows to compute an equivalent Markov Decision Process (MDP)



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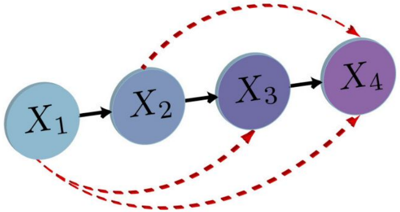

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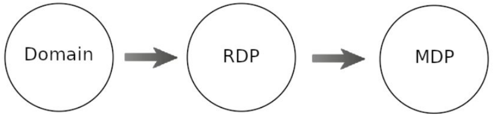
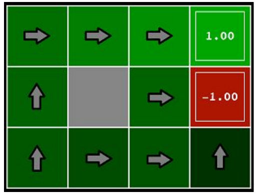


The resulting MDP can be solved by using already existing techniques

e.g. Value Iteration



Regular Decision Processes

Non-markovian Decision Process

Rewards depend on the sequence of past states rather than current state

Regular Expression Dependence

Transition and Reward functions are regular functions of history $(a_1 s_1 r_1, a_2 s_2 r_2 \ldots a_n s_n r_n)$

Several Formalisms

LDLf formulas, FST, regular expressions, probabilistic automata

[Regular Decision Processes: A Model for Non-Markovian Domains. 2019]

Reinforcement Learning Algorithm

Representing RDP as PDFA

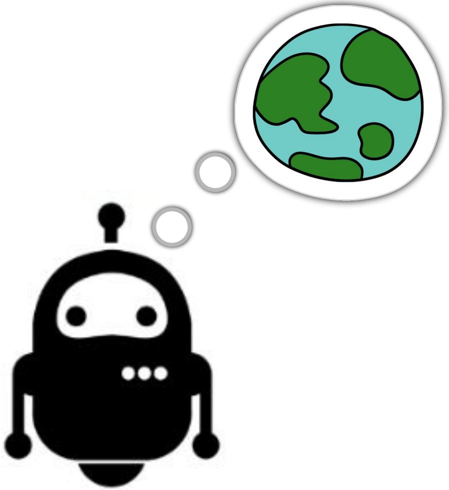
Transducer of dynamics of RDP to probabilistic automata

Learning PDFA

AdaCT learns the hypothesis graph

Solve MDP

Transition function of PDFA to build a MDP



[Efficient PAC Reinforcement Learning in Regular Decision Processes. 2021]

Sampling

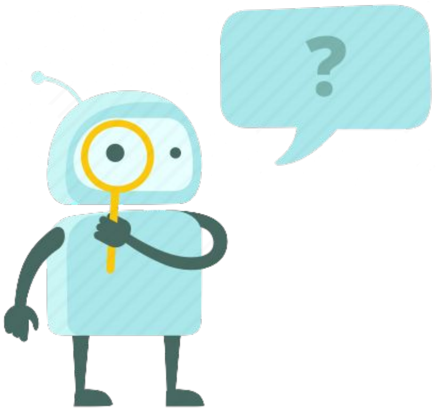
Sampling AdaCT MDP FST

Exploration Policy

Agent explores domain choosing an action uniformly at random

Stop Probability

Add stop action “$” with stop probability 1/(10*n^+1)



Learning Probabilistic Deterministic Finite-Automata

Sampling AdaCT MDP FST

PDFA <Q, Σ, τ, λ, ξ, q_0>

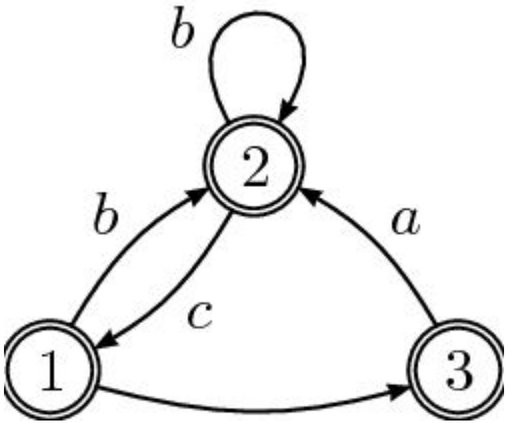
States, alphabet, transition, probability, eos, initial state

Hypothesis Graph

Nodes and edges are states and transition function

AdaCT Algorithm

[Learning probabilistic automata: A study in state distinguishability. 2013]



Learning Probabilistic Deterministic Finite-Automata

Sampling AdaCT MDP FST

Inputs: alphabet size $|\Sigma|$, upper bound n, confidence parameter δ, sample S with N examples

Output: hypothesis graph G

Max. n° steps: $n^*|\Sigma|$

The algorithm guarantees that at each step one transition is added to G

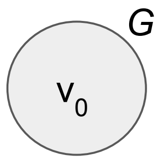
Learning Probabilistic Deterministic Finite-Automata

Sampling AdaCT MDP FST

Two periods:

- **‘Important period’:** the graph built in this period is theoretically guaranteed to be a good representation of the target *T*. Nodes added during this period are called ‘safe nodes’
- **Second period:** transitions added during this period could possibly be wrong

At the start, *G* consists of a single node whose attached multiset equals *S*



Learning Probabilistic Deterministic Finite-Automata

Sampling — AdaCT — MDP — FST

Routine:

- Creation of candidate nodes $u = v_u\, \sigma$ with multiset (initially empty) S_u
- For each string $x\xi = \sigma_0\, \sigma_1 ... \sigma_k$ in the training sample S, traverse the graph matching each observation σ_i :
  - All observations are matched to a state and the example is discarded
  - Observation σ_{i-1} lead to node w but there is no edge out of w labeled by σ_i . The suffix $\sigma_{i+1} \ldots \sigma_k$ is added to the multiset of the candidate
- Choose the candidate $u = v_u\, \sigma$ whose multiset has maximum cardinality
- Check if the candidate is a distinct state of the target calling 'TestDistinct'

Learning Probabilistic Deterministic Finite-Automata

Sampling | AdaCT | MDP | FST

TestDistinct:

- **'Not Clear'**: Choose the safe *v* that has not been distinguished from *u* and add an edge from v_u to *v* labeled by σ
- **All 'Distinct'**: Candidate node *u* is promoted to a safe node. *G* gets a new node labeled with *u* and an edge from v_u to *u* labeled by σ

Algorithm 4: Test Distinct

Input : a candidate node u and a safe node v
Output: $Distinct$ or $NotClear$
$m_u \longleftarrow |S_u|$; $s_u \longleftarrow |prefixes(S_u)|$
$m_v \longleftarrow |S_v|$; $s_v \longleftarrow |prefixes(S_u)|$
$t_{u,v} \longleftarrow \sqrt{\frac{2}{min(m_u,m_v)} \cdot ln\frac{8(s_u+s_v)}{\delta_0}}$
$d \longleftarrow max(L_\infty(\hat{S}_u,\hat{S}_v), prefL_\infty(\hat{S}_u,\hat{S}_v))$
if $d > t_{u,v}$ **then**
  return $Distinct$
else
  return $NotClear$

AdaCT pseudo-code

Sampling — AdaCT — MDP — FST

Algorithm 1: AdaCT

Inputs : alphabet size Σ, upper bound of the number of states of the target n, confidence parameter δ, sample S drawn from the target PDFA T

Output: Hypothesis graph H

```
H ⟵ init hypothesis graph with a node (initial state, multiset S);
M ⟵ n ∗ Σ, maximum steps;
SN ⟵ initialstate, safe nodes array;
for i ≤ M do
    CN ⟵ createCandidateNodesArray;
    if length(CN)=0 then
        return H
    end
    CN ⟵ populateMultisets(initial node);
    N ⟵ select the node with maximum cardinality;
    for j ≤ length(SN) do
        res ⟵ TestDistinct(N, SN_i, H, CN, δ, n, Σ);
        if res = 'Not Clear' then
            Add a transition from the parent of the candidate to the unclear node
        end
    end
    if res = 'Distinct' then
        Take the previous safe node;
        Add the link between the previous safe node and the new safe node;
        Add the new node to the graph;
    end
end
return H
```

Equivalent Markov Decision Process

Sampling — AdaCT — MDP — FST

MDP <Q, A, D^M, R, q_0, γ>

Compute equivalent MDP from PDFA

Theorem

If π_* is an optimal policy for the equivalent MDP, then $\pi_* \tau$ is optimal for the original RDP.

Dynamic Function

Probability function of Multisets

$$\mathbf{D}^{\hat{M}}(q_2, r | q_1, a) = (|A|/(1-p)) \sum_{s:\hat{\tau}'(q_1, asr)=q_2} \hat{\lambda}(q_1, asr).$$

Value Iteration

Solve MDP to find optimal policy π^*

repeat
  $i \leftarrow i+1$
  for each state s **do**
    for each action a **do**
      $V^i(s) = \sum_{s'} \mathrm{T(s'|s,a)}(R(s,a) + \gamma V^{i-1}(s'))$
    end for
  end for
  for each state s **do**
    $\pi^i(s) = \operatorname*{argmax}_a \sum_{s'} \mathrm{T(s'|s,a)}(R(s,a) + \gamma V^i(s')$

Transducer Composition

Sampling · AdaCT · MDP · FST

FST $\langle Q, q_0, S, \tau, A, \theta \rangle$

Transition and Reward functions of RDP
can be represented by Finite-state transducers

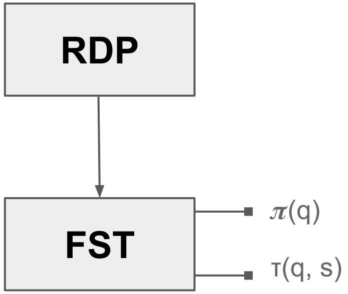
Composition

Find the mapping $\pi(\tau(\cdot))$ dropping actions and rewards

Resulting Transducer

Minimal representation of RDP, where

- $\theta(q) = \pi(q) \rightarrow a$
- $\tau(q, s) \rightarrow q$



Algorithm pseudo-code

Algorithm 5: Reinforcement Learning RL

Input : Actions A, discount factor γ, required precision ϵ, confidence parameter δ, upper bound $\hat{n}$ on transducer states

Output: transducer of policy π

$p \longleftarrow 1/(10 \cdot \hat{n} + 1)$ ⟵ maximum exploration

$X \longleftarrow$ generate episodes under exploration policy π_p

$\hat{\Sigma} \longleftarrow$ symbols in X

$\hat{R}_{max} \longleftarrow$ max reward in X

$\hat{\mathcal{A}} \longleftarrow$ learn PDFA by calling $AdaCT(\hat{n}, |\hat{\Sigma}|, \delta, X)$

$\hat{M} \longleftarrow$ compute MDP induced by $\hat{\mathcal{A}}$ and γ

$m \longleftarrow \lceil \frac{1}{1-\gamma} \cdot ln\left(\frac{2 \cdot \hat{R}_{max}}{\epsilon \cdot (1-\gamma)^2}\right) \rceil$ ⟵ iterations of Value Iteration algorithm

$\pi \longleftarrow$ solve $\hat{M}$ by calling $ValueIteration(\hat{M}, m)$

return transducer composition of π and transition function τ' of $\hat{\mathcal{A}}$

<u>Theorem</u>

Algorithm is PAC-RL w.r.t. the parameters

$$\mathbf{d}_{\mathcal{P}} = \left(|A|, \frac{1}{1-\gamma}, R_{\max}, n, \frac{1}{\rho}, \frac{1}{\mu}, \frac{1}{\eta}\right)$$

RL Algorithm Considerations

Fast Learning

How fast an agent learns a near-optimal policy

Probably Approximately Correct (PAC)

Look for ε-optimal policies with probability $1-\delta$

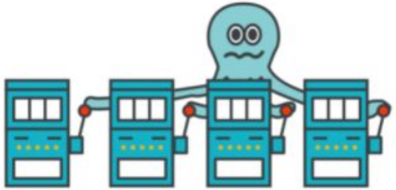
Exponentially-many Episodes Required

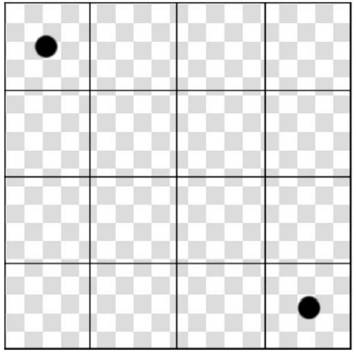
History length proportional to transducer states

Experiments

Rotating MAB

Multi-armed bandit with rotating probabilities



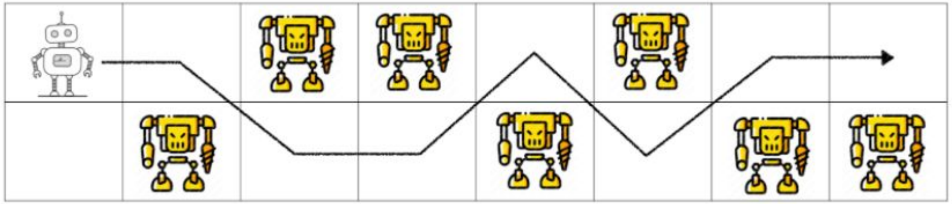


Rotating Maze

Maze domain with position and orientation variables

Enemy Corridor

2 x N corridor with enemies



Parameters

Parameters	γ	ϵ	δ	$\lvert X \rvert$	$\lvert \pi \rvert$	l
Description	discount factor	required accuracy	confidence of success	number of samples	number of learned policies	expected episode length
Values	0.1	0.01	0.1	50000-500000	5-10	10-15

List of parameters used in the RL algorithm

Number of samples: gets higher with the increasing complexity

Number of learned policies: algorithm repeated between 5 and 10 times to find the average reward

Episode length: indicates the stop probability value ***p = 1/(l+1)***

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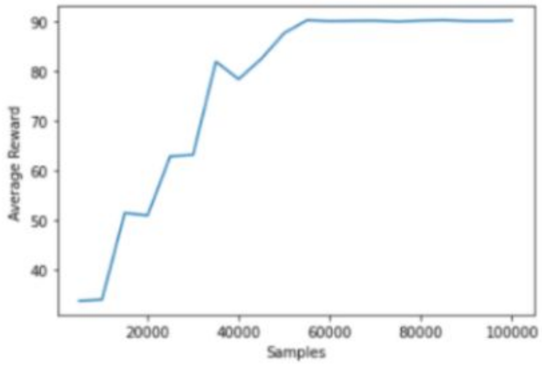
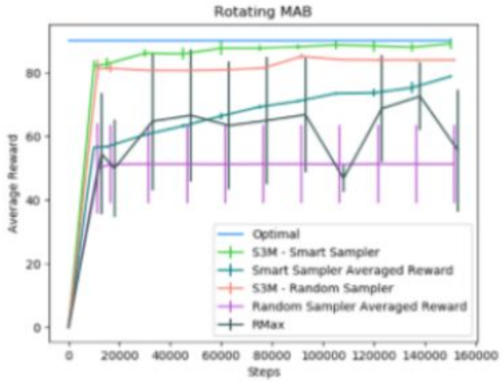
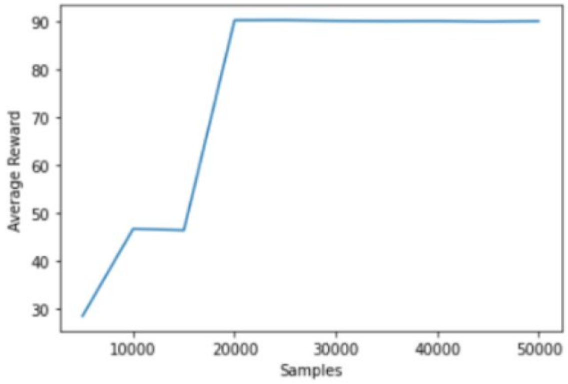
Results: Rotating MAB

MAX average reward: 90



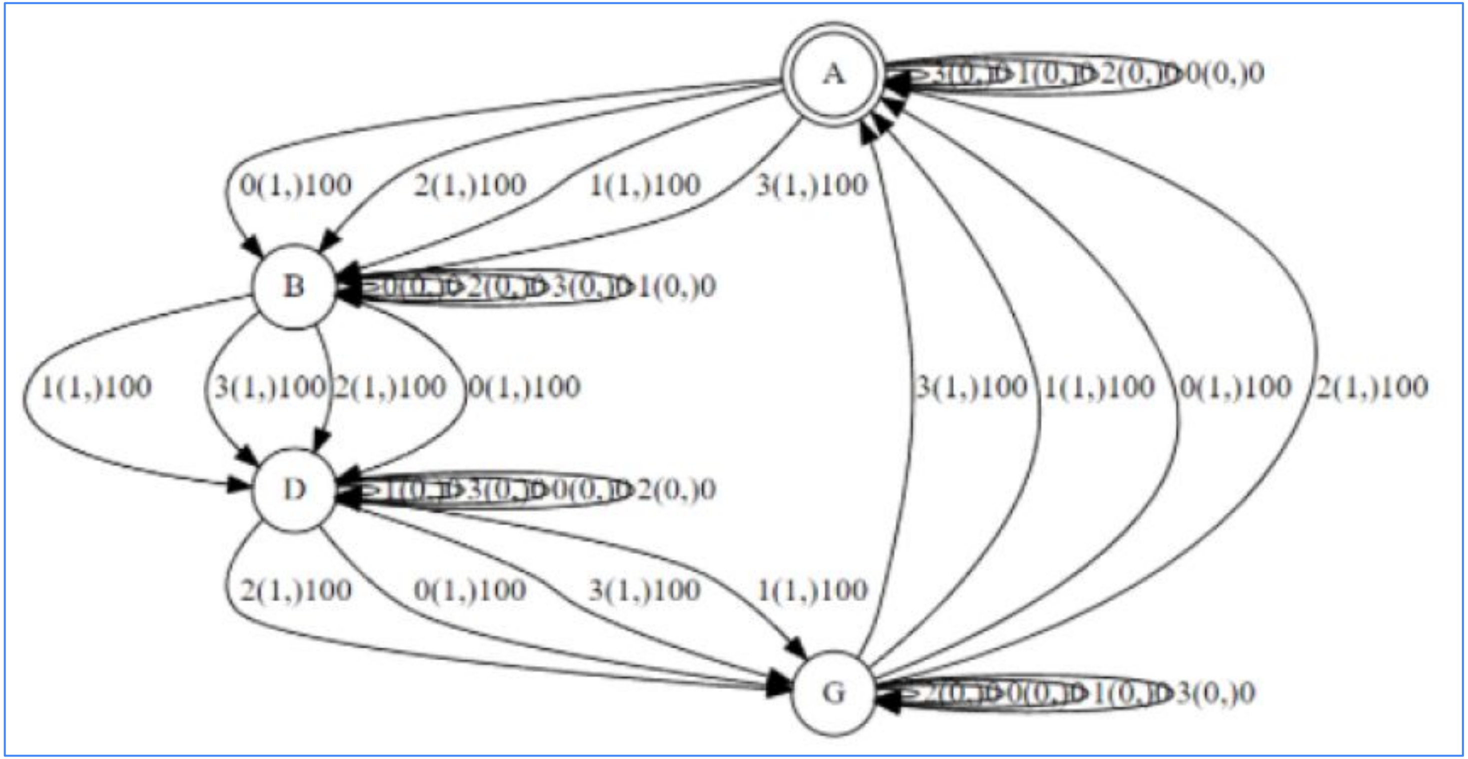


Comparison with the results obtained by Abadi and Brafman (*l = 10*)



Result obtained with expected episode length *l* = 40

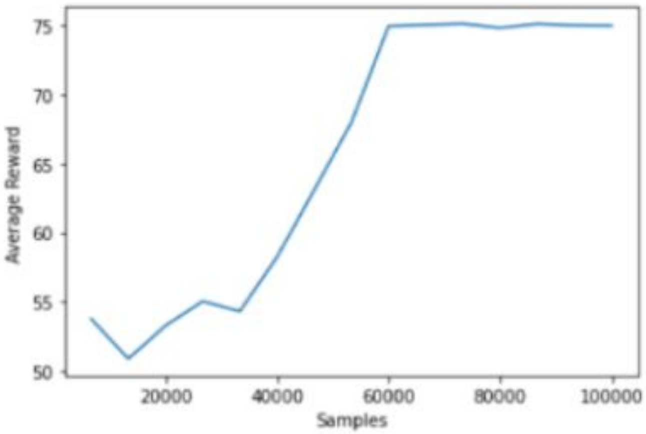
Results: Rotating MAB

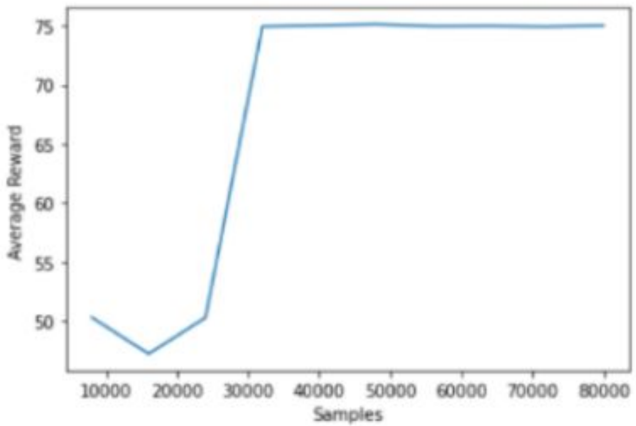


Graph of the Rotating MAB domain

Results: Enemy Corridor

MAX average reward: 75





Left image → episode length ***l* = 20**

Right image → episode length ***l* = 80**

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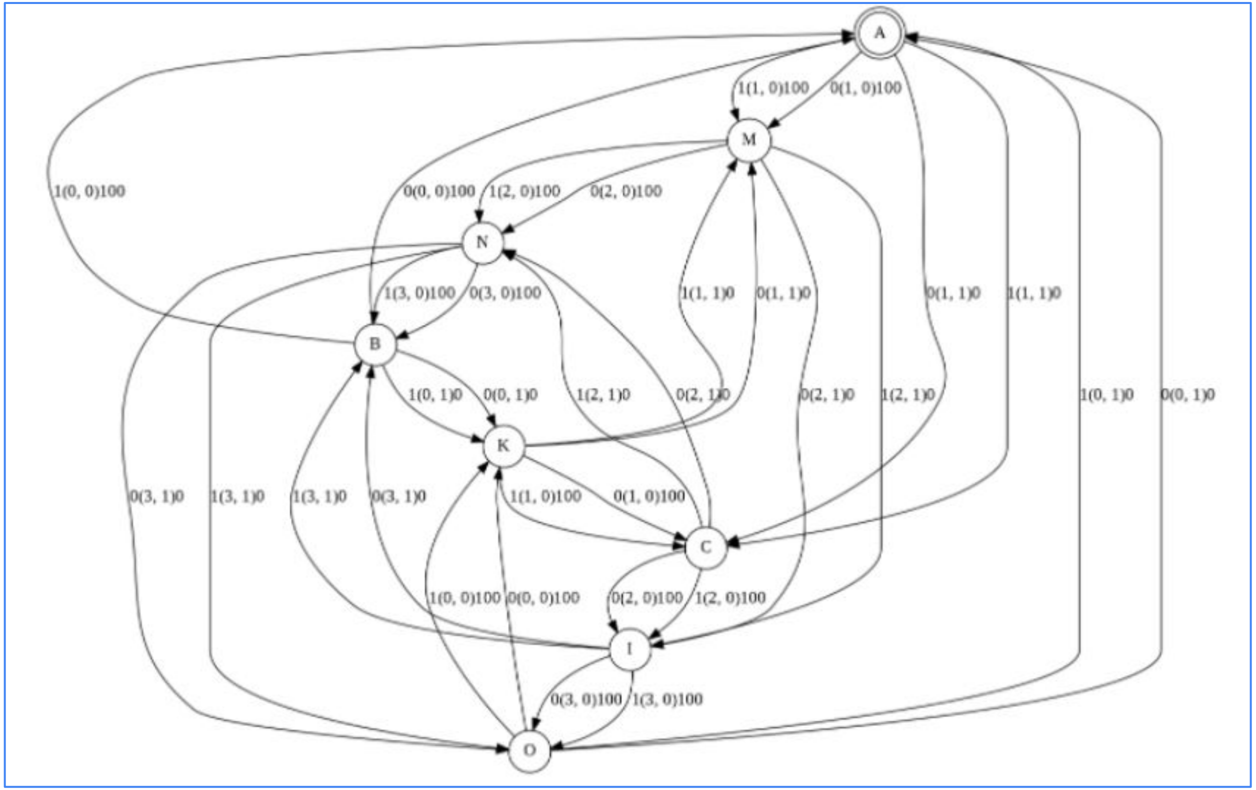
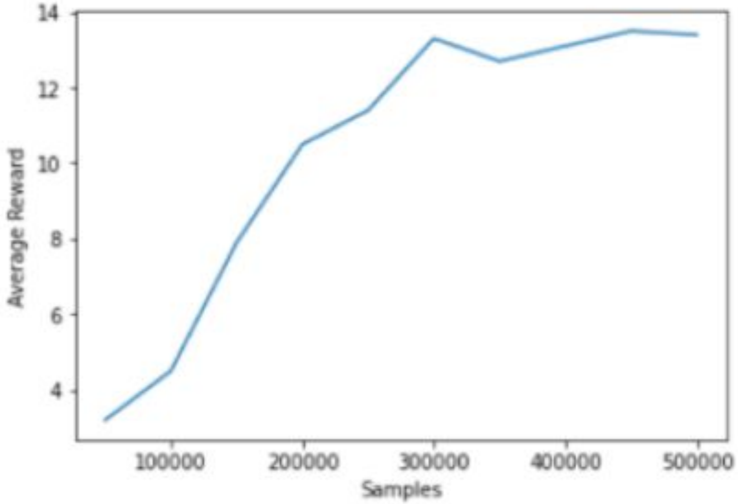
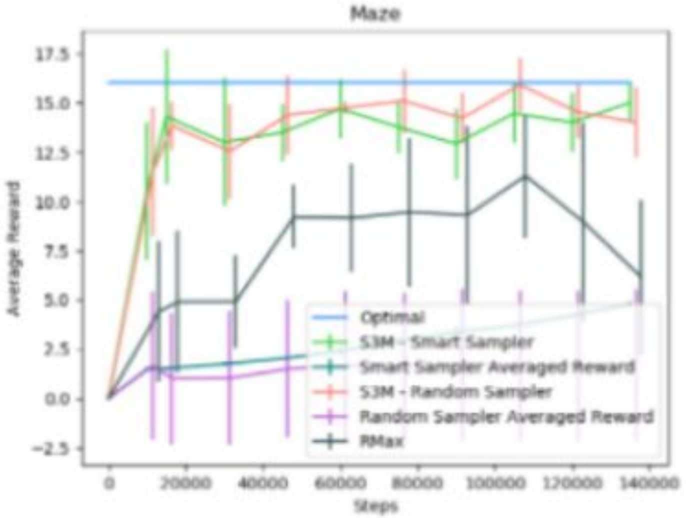
Results: Enemy Corridor



Graph of the Enemy Corridor domain

Results: Rotating Maze





Different environment: reward is only given at the target → lower average reward (MAX: 20)

Worse performances with respect to Abadi and Brafman

High number of samples needed → bad performances

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Conclusions

PROs

- 1) Optimal performances for Rotating MAB and Enemy Corridor
- 2) Perfect learning of small and medium domains with a sufficient number of samples
- 3) Linear method with respect to the number of samples used

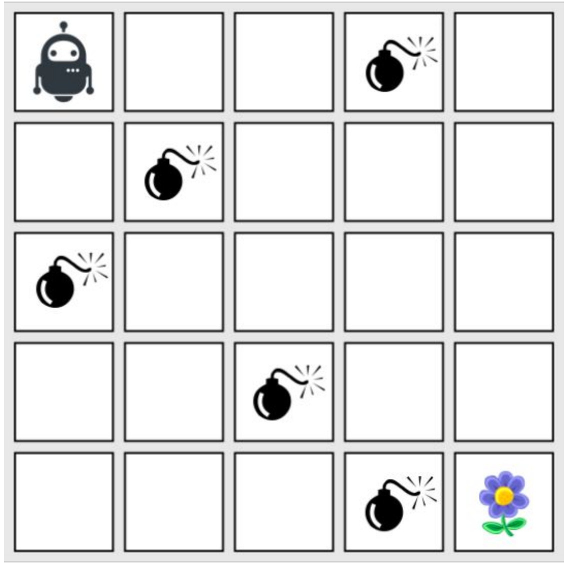
CONs

- 1) Mediocre performances for Rotating Maze
- 2) High computational cost for a big environment, too many samples needed
- 3) Less efficient for environments with many terminal states

Suitable Environment

Minefield

- N x M grid
- Actions → {*Right, Left, Down*}
- Rewards → {-20 bomb, 20*N flower}
- Observations → {*n*, *m*, bool: *bomb*}
- Initial state → (0, 0)
- Final state → (N, M)
- Probabilities → **1/m**, ∀ [1, n-1]; **1/m-1** with n = 0,N.
  When the agent hits the bomb they shift down.



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Thanks