Atari Breakout with $\text{LTL}_f/\text{LDL}_f$ Goals

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Introduction

The main goal of the project is to train an agent acting on a non-Markovian reward decision process (NMRDP) environment.

Rewards are define through LTL_f/LDL_f formulas, defining complex behaviour made up of multiple steps over time.

The learning is done using classical reinforcement learning algorithm working on MDP environments.

Q-Learning

Q-Learning is a temporal difference (TD) reinforcement learning algorithm.

The Q-function is approximated through a Q-table that stores the expected rewards for taking action A in state S.

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha\Big[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)\Big]$$

Off-policy algorithm: action at time $t+1$ independent from current policy.

Converges to optimal policy if all state-action pairs are continuously updated.

SARSA

SARSA is a TD reinforcement learning algorithm which uses a quintuple $\langle S_t, A_t, R_t, S_{t+1}, A_{t+1} \rangle$ from which takes name.

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \Big[R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t) \Big]$$

On-policy algorithm: action A_{t+1} chosen following current policy.

Converge to optimal policy if each state-action pair is visited infinitely often.

$\text{LTL}_f/\text{LDL}_f$ Non-Markovian Rewards

$\text{LTL}_f/\text{LDL}_f$ non-Markovian rewards + integration in our project.

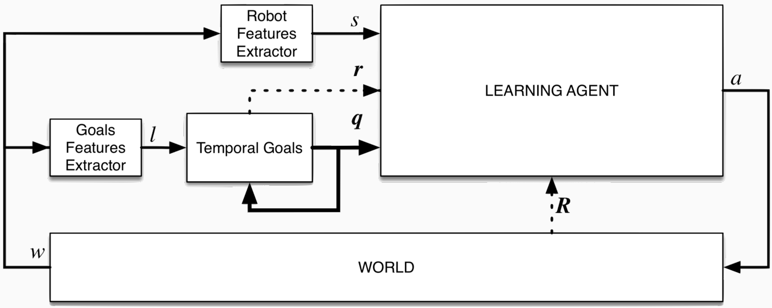


Figure 1: Pipeline describing how the agent is interacting with the world and how the robot features extractor and the goal features extractor are used in order to handle non-Markovian rewards.

$\text{LTL}_f/\text{LDL}_f$ Non-Markovian Rewards

Reward for destroying the block rows in order from top to bottom.

$$\langle(\neg\varphi_0 \wedge \neg\varphi_1 \wedge \neg\varphi_2)^*; (\varphi_0 \wedge \neg\varphi_1 \wedge \neg\varphi_2); (\varphi_0 \wedge \neg\varphi_1 \wedge \neg\varphi_2)^*;$$
$$(\varphi_0 \wedge \varphi_1 \wedge \neg\varphi_2); (\varphi_0 \wedge \varphi_1 \wedge \neg\varphi_2)*; (\varphi_0 \wedge \varphi_1 \wedge \varphi_2)\rangle tt$$

where φ_i indicates the i-th row.

$(\neg\varphi_0 \wedge \neg\varphi_1 \wedge \neg\varphi_2)^*$ all rows not destructed for an indefinite amount of time.

$(\varphi_0 \wedge \neg\varphi_1 \wedge \neg\varphi_2)$ first row destructed, other still there.

$\text{LTL}_f/\text{LDL}_f$ Non-Markovian Rewards

$\text{LTL}_f/\text{LDL}_f$ transformed to an equivalent automaton.

Automaton representation given in input to the learning agent.

Learning agent input: $\langle$environment state, automaton state$\rangle$

PyGame Breakout

Starting from the work presented in [4] the agents were trained on a modified PyGame Breakout with a 6×18 grid.

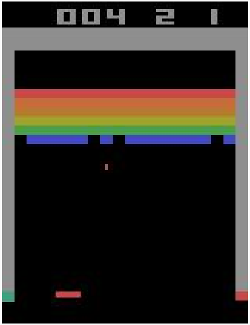
Game state already stored inside the class instance (ball position, paddle position, blocks status).

Atari Breakout

Breakout from OpenAI Gym: toolkit for comparing learning algorithm. Provides easy access to state and reward. No assumption on the agent.

Class stores pixels status. Need to extract information about the game state from it.

The environment is more stochastic.



Implementation

Robot Features Extraction

Algorithms.

Goal Features Extraction

Algorithms.

Temporal Goals

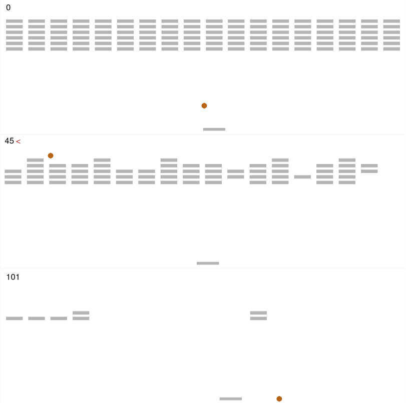
Algorithms.

Experiments

Experiments

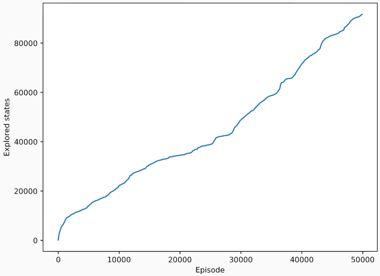
All the experiments.

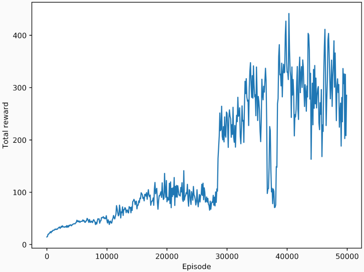
Experiments



Description.

Experiments



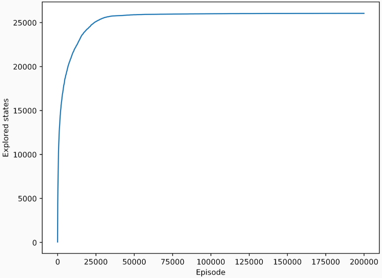


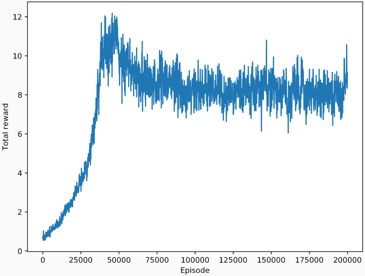
PyGame SARSA.

Experiments

Atari frames.

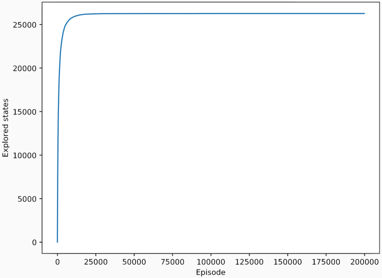
Experiments

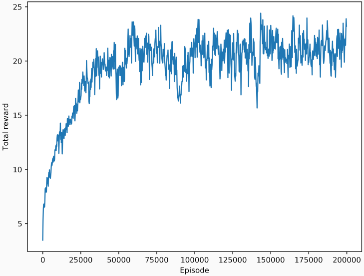




Atari Q-Learning.

Experiments





Atari SARSA.

Conclusion

Conclusion.

Q&A

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