# Atari Breakout with LTL<sub>f</sub>/LDL<sub>f</sub> Goals

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# Introduction

Intro.

## **Q-Learning**

Q-Learning brief description.

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

#### SARSA

SARSA brief description.

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

# LTL<sub>f</sub>/LDL<sub>f</sub> Non-Markovian Rewards

 $LTL_f/LDL_f$  non-Markovian rewards + integration in our project.

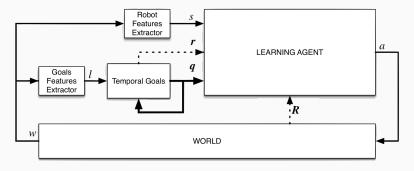


Figure 1: Pipeline describing how the agent is interacting with the world and how the robot features extractor and the goal features extractor are used in order to handle non-Markovian rewards.

# PyGame Breakout

Results of the paper and our starting point.

# PyGame Breakout $(6 \times 18)$

Our results on 6×18 non-Atari Breakout + video.

### Atari Breakout

Introduction to Gym + ALE
Differences with non-Atari Breakout (initial hypotheses)



Implementation

### **Atari Wrappers**

#### Atari wrappers from OpenAI baselines:

- EpisodicLifeEnv: make an "end of life" be the end of the episode resetting the environment only on the true game over, this helps in value estimation
- FireResetEnv: use "Fire" as starting action in order to launch the ball
- MaxAndSkipEnv: returns only the skip-th frame, this reduces the amount of frame the agent has to deal with (set to 4 in the main experiments)

- · extracting paddle position
- extracting ball position
- features can be increased with ball direction
- previous positions could help the training too
- · more features increase the state space
- OpenCV

Extracting **paddle position** from the observation: tensor of dimension (210,160,3) where each value represents a color of the pixel.

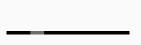


Considering only the **lower part** of the observation which contains the paddle.



Converting the image to **gray-scale** in order to reduce the number of channels.

This makes it easier to apply a threshold function.



#### Determine the position of the paddle:

- apply a threshold function to obtain a black and white image
- · find contours
- · extract centroid of the paddle
- paddle<sub>x</sub> = 35

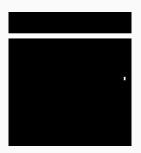
Similarly, extract **ball position** from initial observation.



Considering only the **upper part** of the observation which contains the ball.



- inRange function to consider only pixels with the same color of the ball, obtain a black and white image
- remove the remaining bricks by checking sorrounding pixels, width of the ball is much smaller



#### Determine the position of the ball:

- find contours
- extract centroid of the ball
- $ball_x = 135, ball_y = 77$



Return the difference between the position of the paddle and the ball on the x axis and the position of the ball on the y axis:

$$(ball_x - paddle_x + 143, ball_y) = (243, 77)$$

#### **Goal Features Extraction**

Extract a binary representation of the bricks from the observation:

It will be used to evaluate fluents in temporal goals.



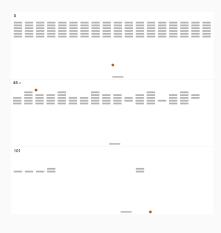
### Temporal Goals

string formula to break rows from top to bottom:

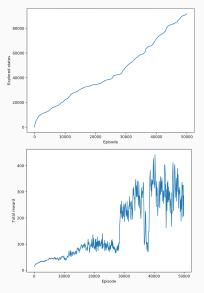
```
<(!l0 & !l1 & ... & !l5)*;
( l0 & !l1 & ... & !l5);
...
( l0 & l1 & ... & !l5)*;
( l0 & l1 & ... & l5)>tt
```

- parsed with LDLfParser (FLLOAT)
- LDLfFormula passed to abstract class TemporalEvaluator
- automaton is being created (RLTG, DFA built upon Pythomata) in order to create the extended MDP

All the experiments.



Description.



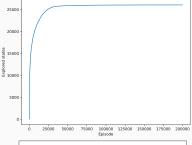
PyGame SARSA.

#### Atari frames.

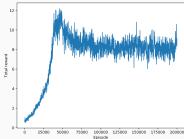


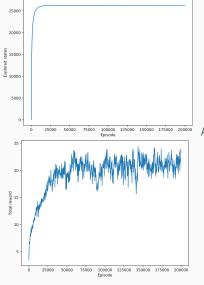






Atari Q-Learning.





Atari SARSA.

# Conclusion

Conclusion.



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