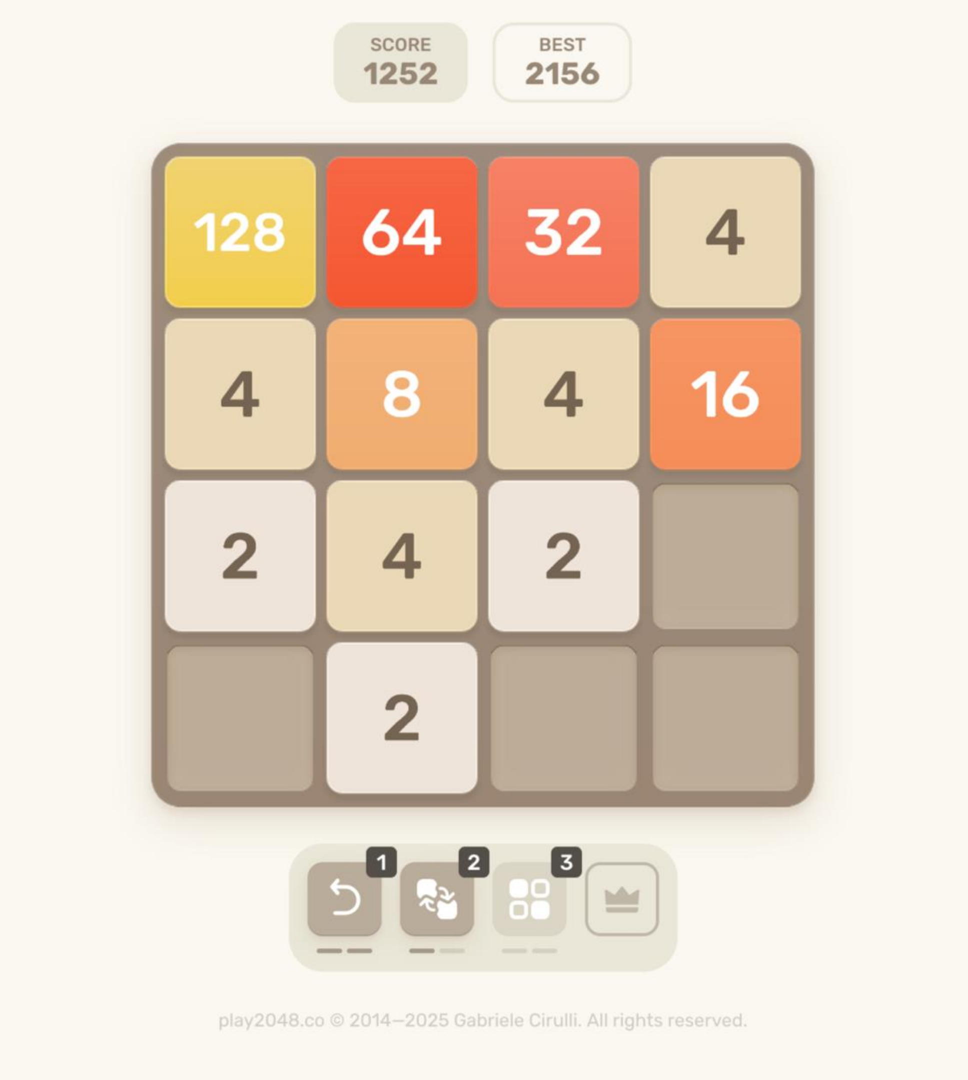
2048

Reinforcement Learning final project

01

THE GAME MECHANICS

A small intro to 2048



THE GRID

4 x 4 grid

Each tile can be either

- Empty (0)
- A power of 2

GAME MECHANICS

MOVE

Move the tiles up, down, left or right

MERGE

Merge two concurrent tiles of the same value

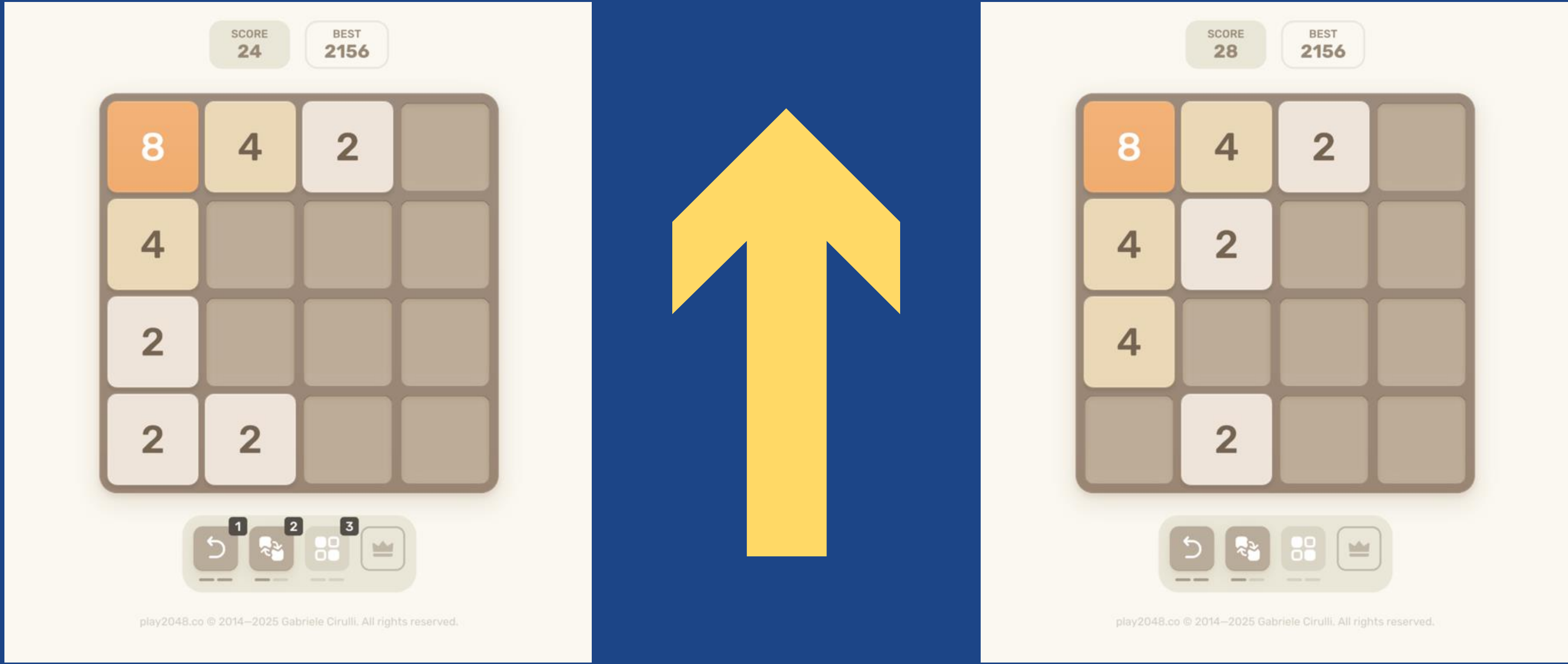
NEW TILE

Add a new tile in a random position after each move

REWARD

Get the sum of the merged tiles as reward

ACTIONS


SCORE
24
BEST
2156
8 4 2
4
2
2 2
1 2 3
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SCORE
28
BEST
2156
8 4 2
4 2
4
2
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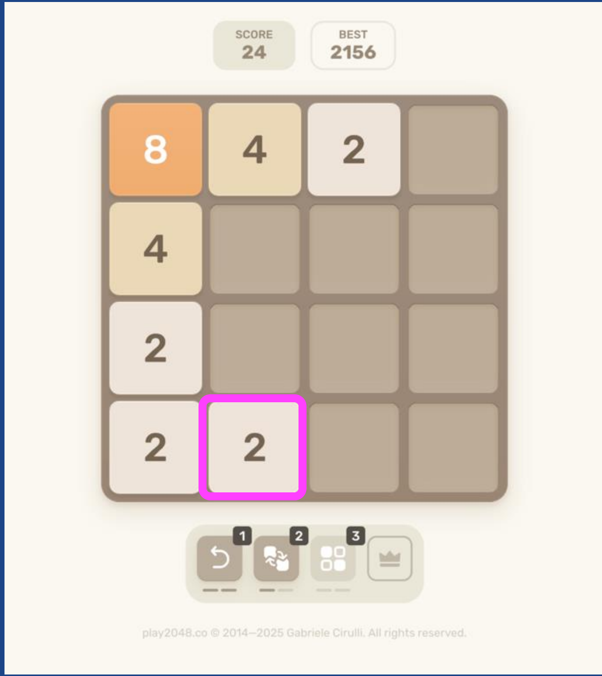
MOVE


SCORE
24
BEST
2156
8
4
2
4
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2
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1
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3
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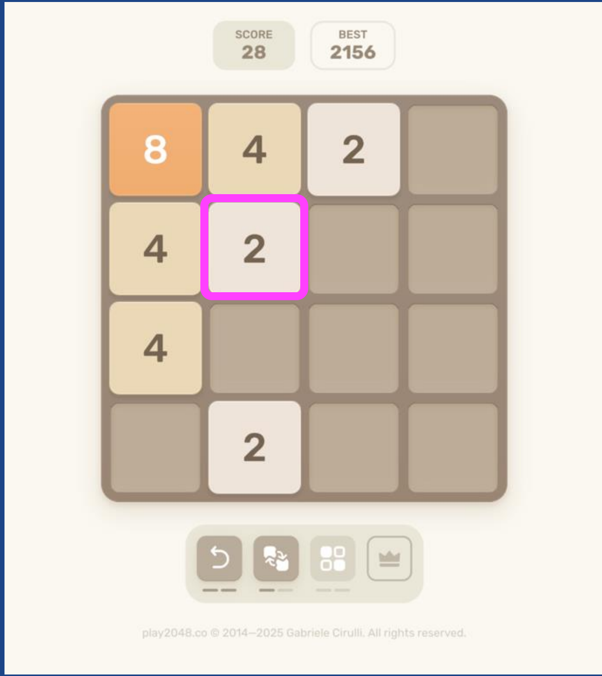
SCORE
28
BEST
2156
8
4
2
4
2
4
2
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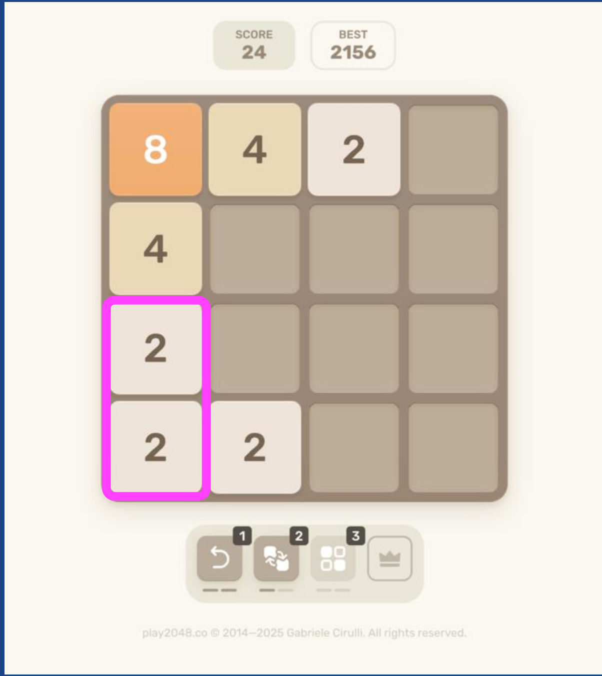
MERGE


SCORE
24
BEST
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8 4 2
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2 2
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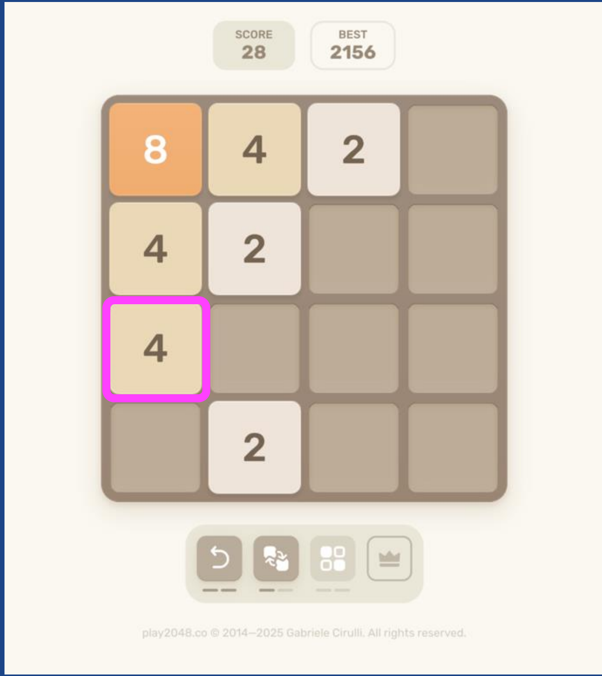
SCORE
28
BEST
2156
8 4 2
4 2
4
2
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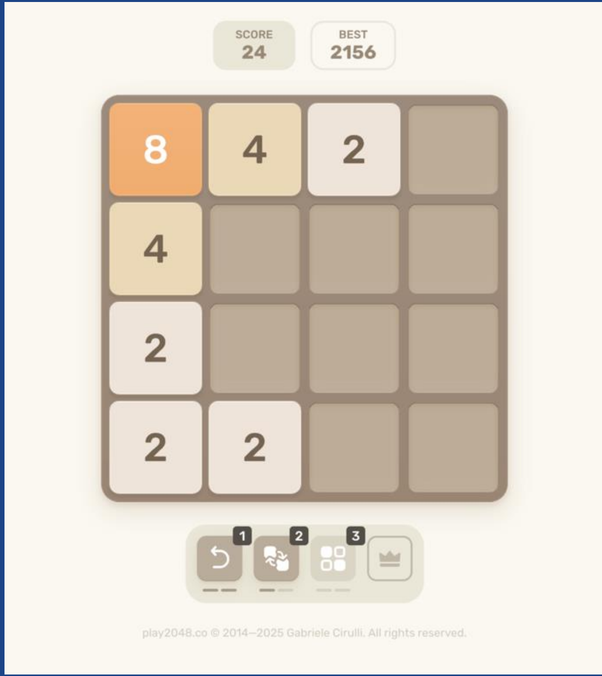
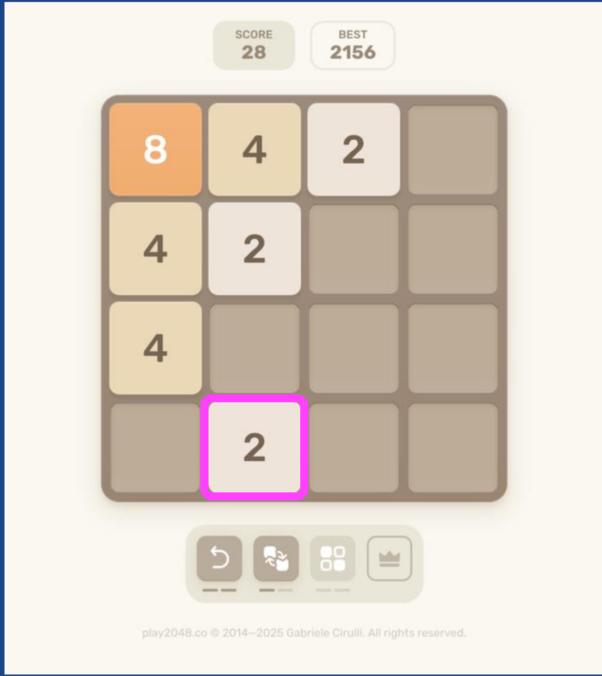
NEW TILE

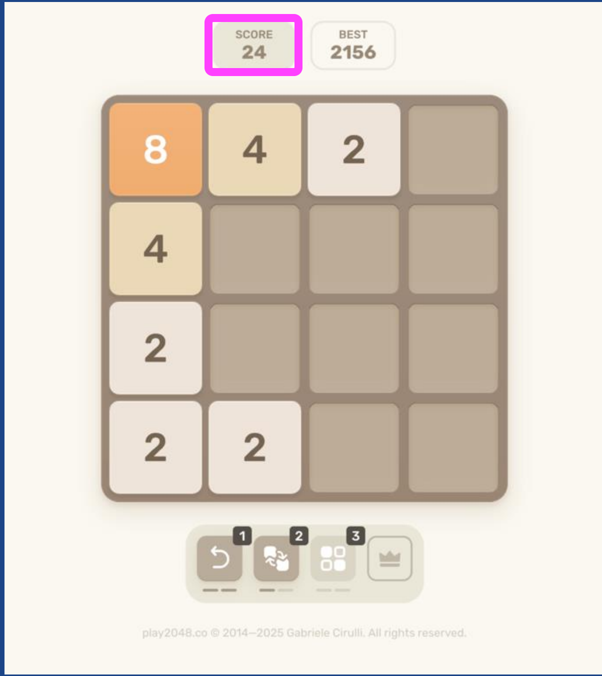


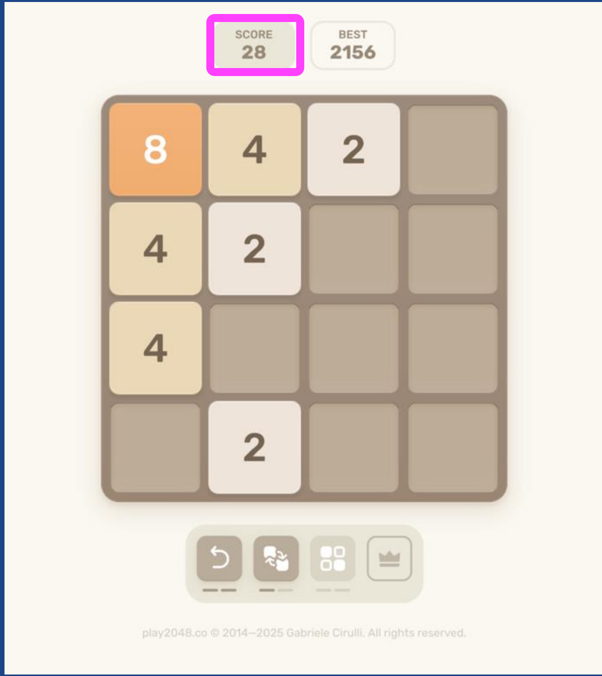
2 - 90%

4 - 10%



REWARD


SCORE
24
BEST
2156
8
4
2
4
2
2
2
1
2
3
play2048.co © 2014–2025 Gabriele Cirulli. All rights reserved.


SCORE
28
BEST
2156
8
4
2
4
2
4
2
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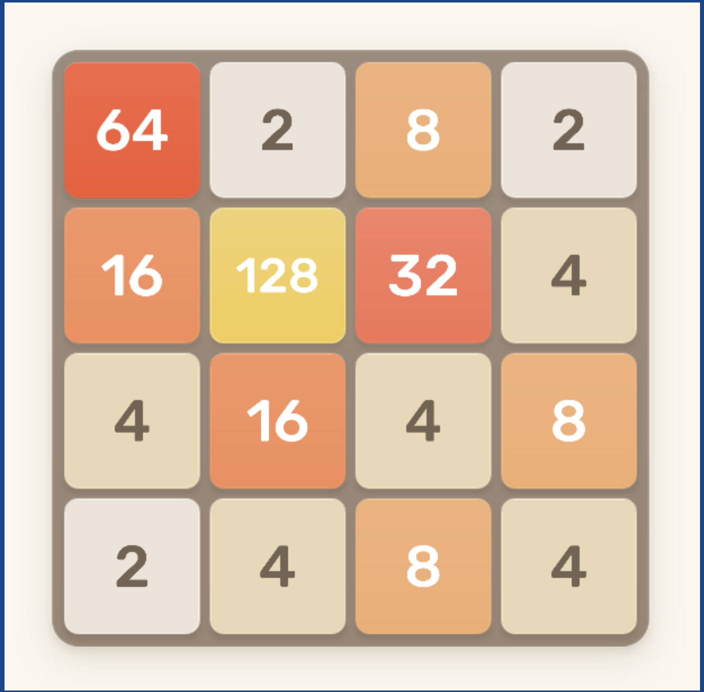
GAME OVER



02

SOLVING STRATEGIES

FINITE MARKOV DECISION PROCESS

STATE SPACE

16 cells that can assume 12 values each
(0, 2, …, 2048)

ACTION SPACE

4 actions: up, down, left and right

REWARD

Sum of the merged tiles, -10 each time the move does not change the grid

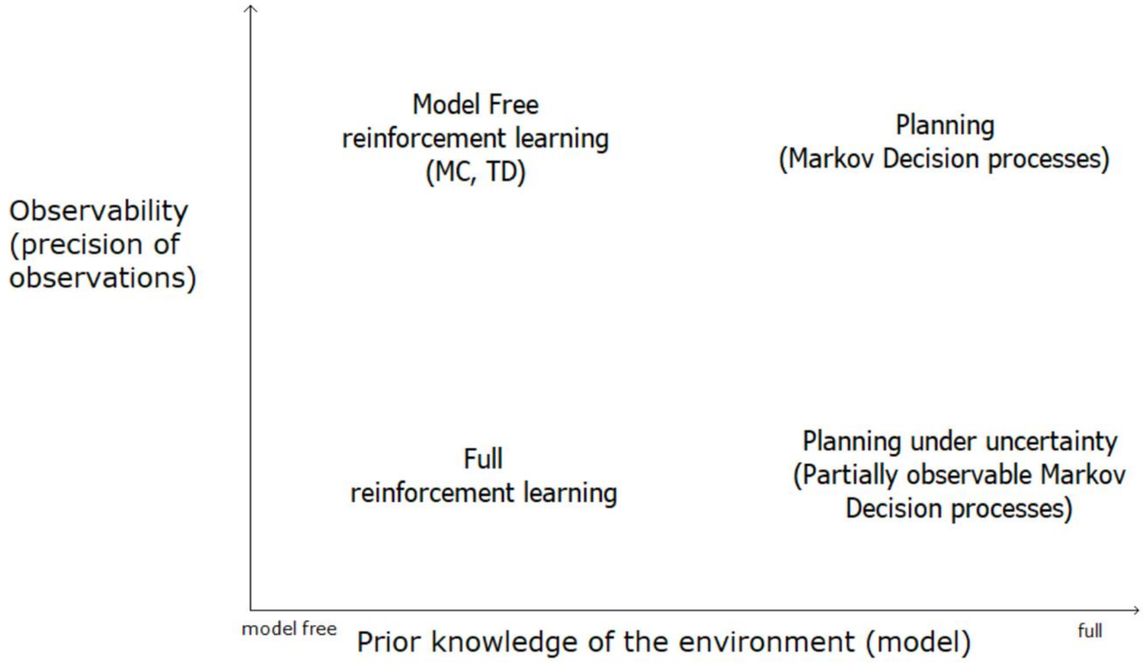
TRANSITIONS

Stochastic, due to adding the new tile in a random position

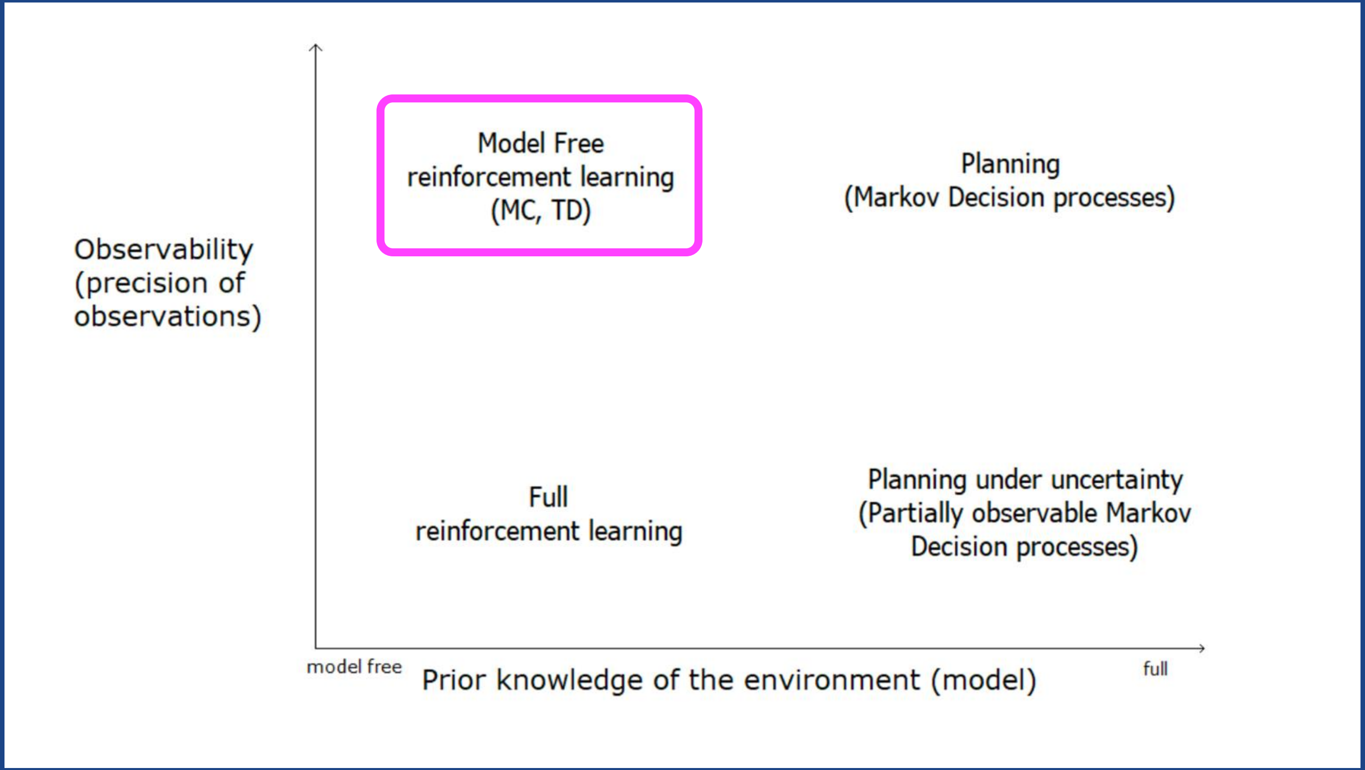
SOLVING STRATEGIES

1. Stochastic transitions
2. Fully observable states

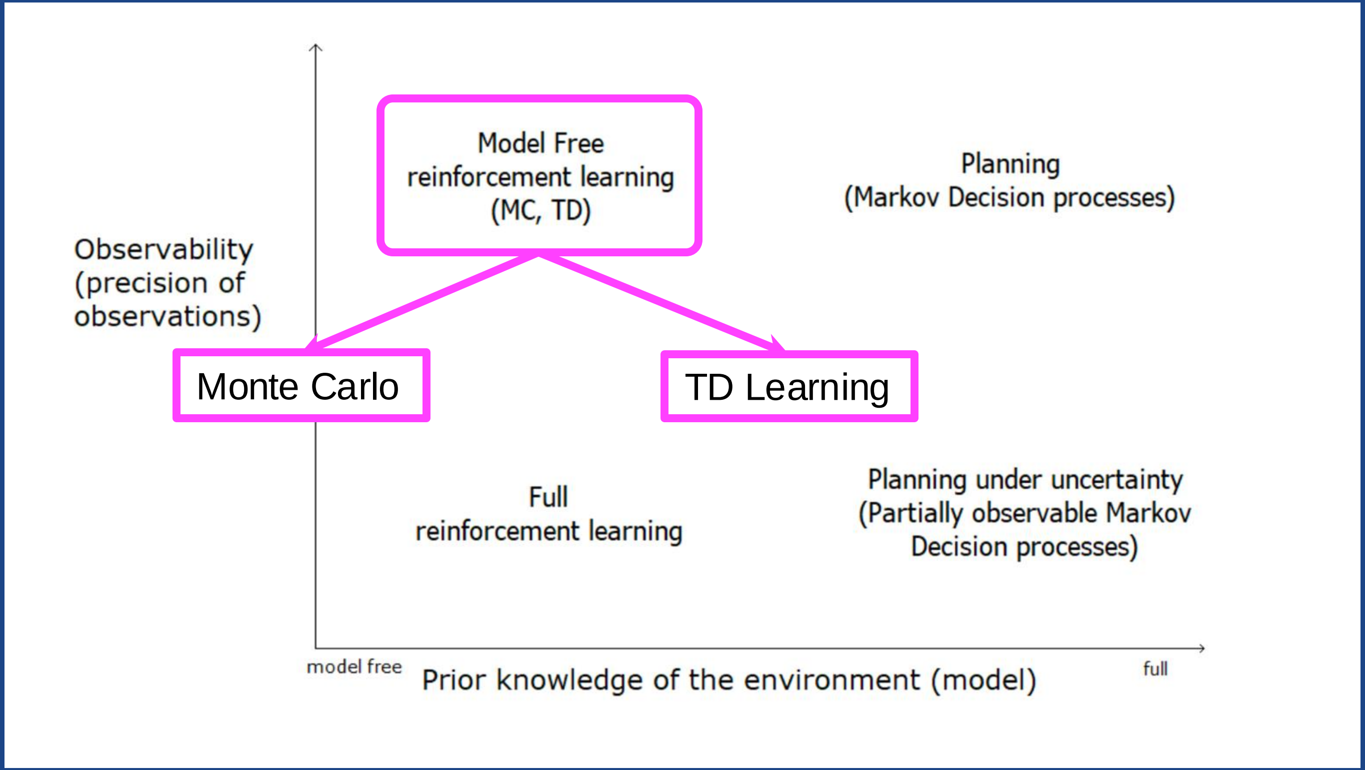
OBSERVABILITY AND KNOWLEDGE



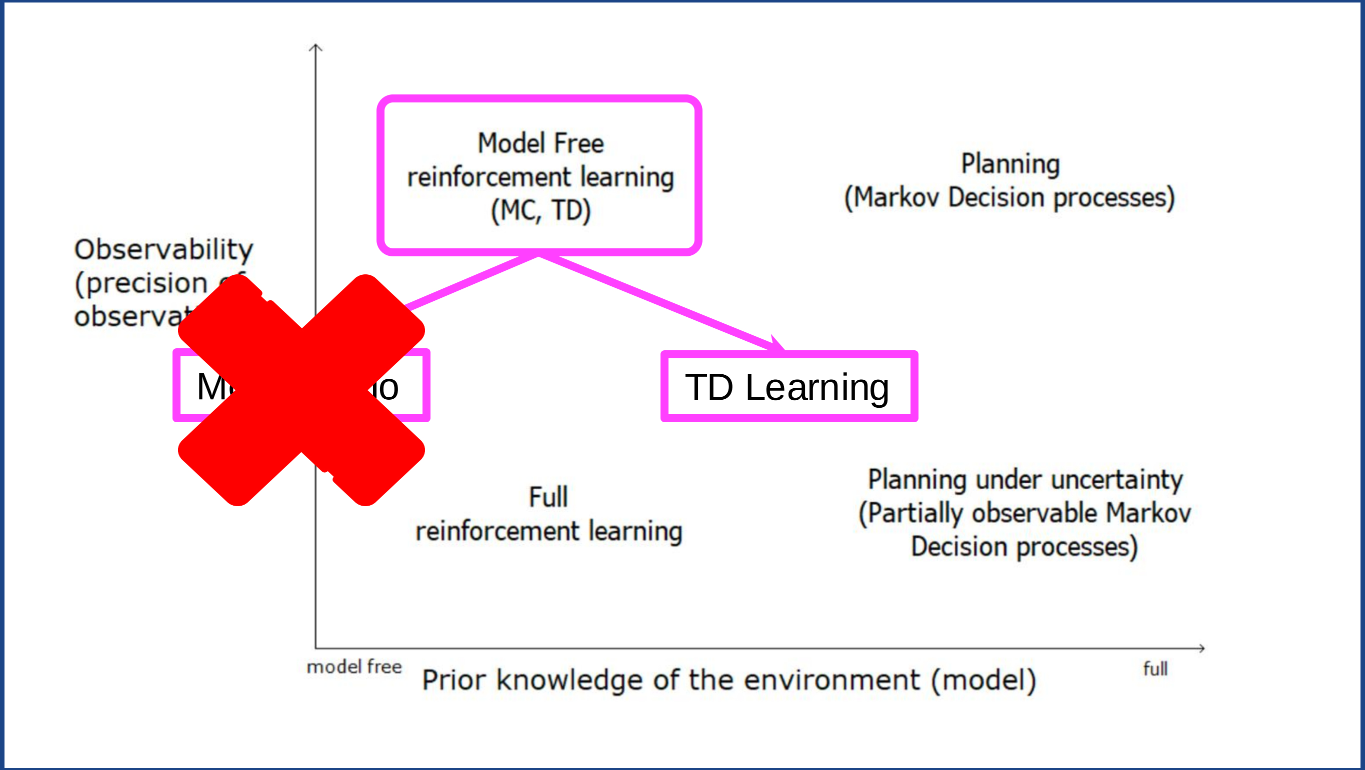
OBSERVABILITY AND KNOWLEDGE



OBSERVABILITY AND KNOWLEDGE



OBSERVABILITY AND KNOWLEDGE



03

Q-LEARNING

Q-LEARNING

Initialize $Q(s,a)$ arbitrarily

Repeat (for each episode):

  Initialize s

  Repeat (for each step of episode):

    Choose a from s using policy derived from Q

    Take action a, observe r, s'

    Update

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$$

    $s \leftarrow s'$;

  Until s is terminal

Q-LEARNING

Initialize $\boxed{Q(s,a)}$ arbitrarily

\# states x # actions

Repeat (for each episode):

Initialize s

Repeat (for each step of episode):

Choose a from s using policy derived from Q

Take action a, observe r, s'

Update

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$$

$s \leftarrow s'$;

Until s is terminal

STATE SPACE SIZE

12

STATES

$0, 2^1, 2^2, \ldots, 2^{11}$

16

CELLS

In the 4 x 4 grid

10^{17}

STATE SPACE SIZE

04

DEEP Q-LEARNING

KEY POINT

Q(s, a) and Q(s’, a’) are calculated using neural networks, called **policy network** and **target network** respectively

THE NEURAL NETWORKS

Target Network

$$Q(s,a) \leftarrow \boxed{Q(s,a)} + \alpha[r + \gamma \max_{a'} \boxed{Q(s',a')} - \boxed{Q(s,a)}]$$

Policy Network

THE NEURAL NETWORKS

The neural networks
are trained using a
batch of past games

THE NEURAL NETWORKS

ARCHITECHTURE

The two networks have the same architecture

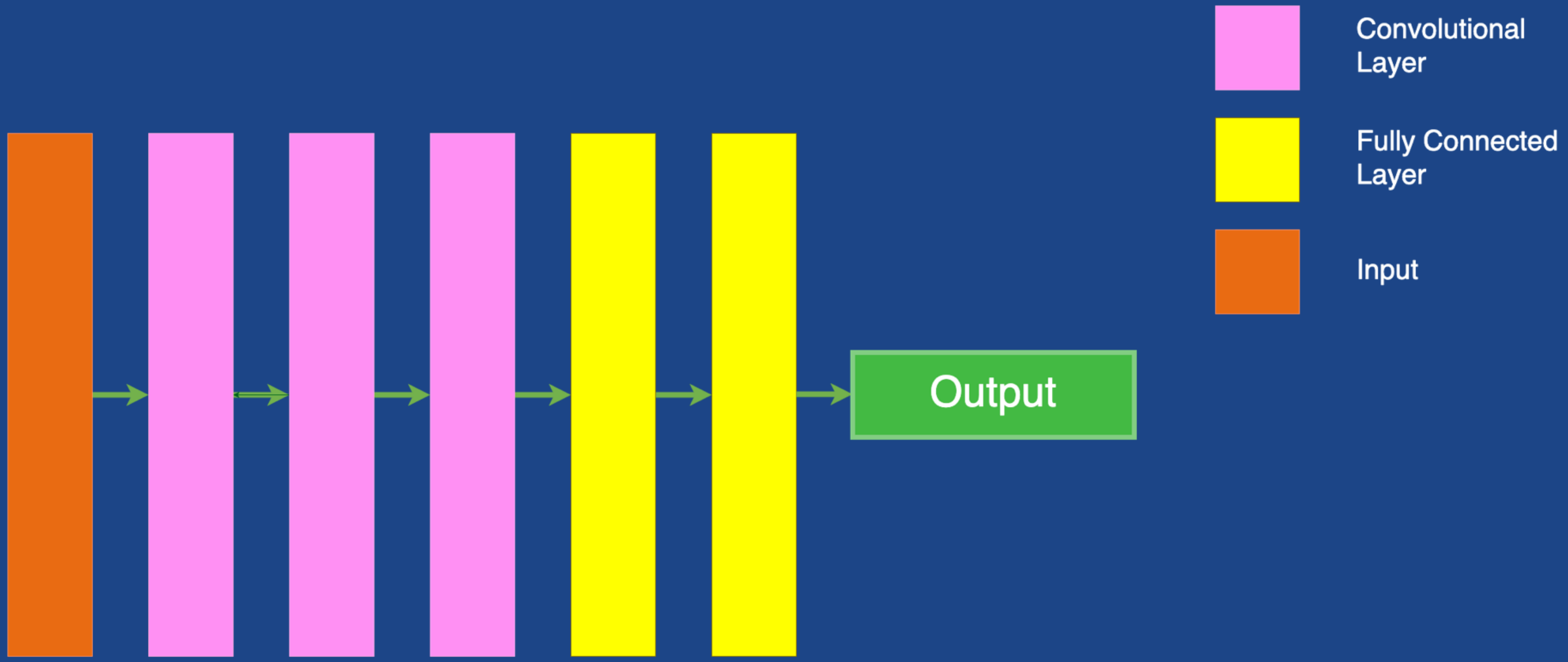
UPDATES

- The weights of the policy network are updated after each episode
- The weights of the target network are updated every **m** episodes

THE NEURAL NETWORKS

- 3 x convolutional layers with 128 channels
- Batch normalization layer after each convolutional layer
- 2 x fully connected layer with 128 channels
- ReLU activation function

THE NEURAL NETWORKS



POLICY

Epsilon-greedy policy
with decaying epsilon

POLICY

WITH PROBABILITY ε

Perform a random action

WITH PROBABILITY $1 - \varepsilon$

Choose the action that maximizes $Q(s', a')$

OPTIMIZATION

- 1000 episodes
- 100 epochs of optimization
- ADAM optimizer with 1e-5 learning rate
- Size of the replay buffer: 50000
- γ: 0.99
- ε: starting from 0.9, decays of a factor of 0.999, minimum value of 0.01
- Batch size: 64
- One-hot encoding for training

DEEP Q-LEARNING

Algorithm 1 Training Loop

Initialize policy and target networks with the same weights: $\theta \leftarrow \theta_{\text{target}}$
Initialize replay buffer $\mathcal{D}$ with capacity N
Set discount factor γ, learning rate, target update frequency C, exploration rate ϵ, minimum epsilon ϵ_{min} and decay rate ϵ_{decay}
for N episodes **do**
  Start the game with just one random tile on the board
  while game is not over **do**
    Choose action a using ϵ-greedy policy:
    if random number $< \epsilon$ **then**
      Choose a random action a
    else
      Choose $a = \arg\max_{a'} Q(s, a'; \theta)$
    end if
    Take action a and get reward r, next state s', and *game over* status
    if state = next state and the game is not over **then**
      reward $\leftarrow$ reward - penalty
    end if
    Store transition (s, a, r, s', *game over*) in replay buffer $\mathcal{D}$
    Update state $s \leftarrow s'$
  end while
  Train the policy network
  Decay exploration rate as $\epsilon \leftarrow \max(\epsilon_{min}, \epsilon \cdot \epsilon_{decay})$
end for

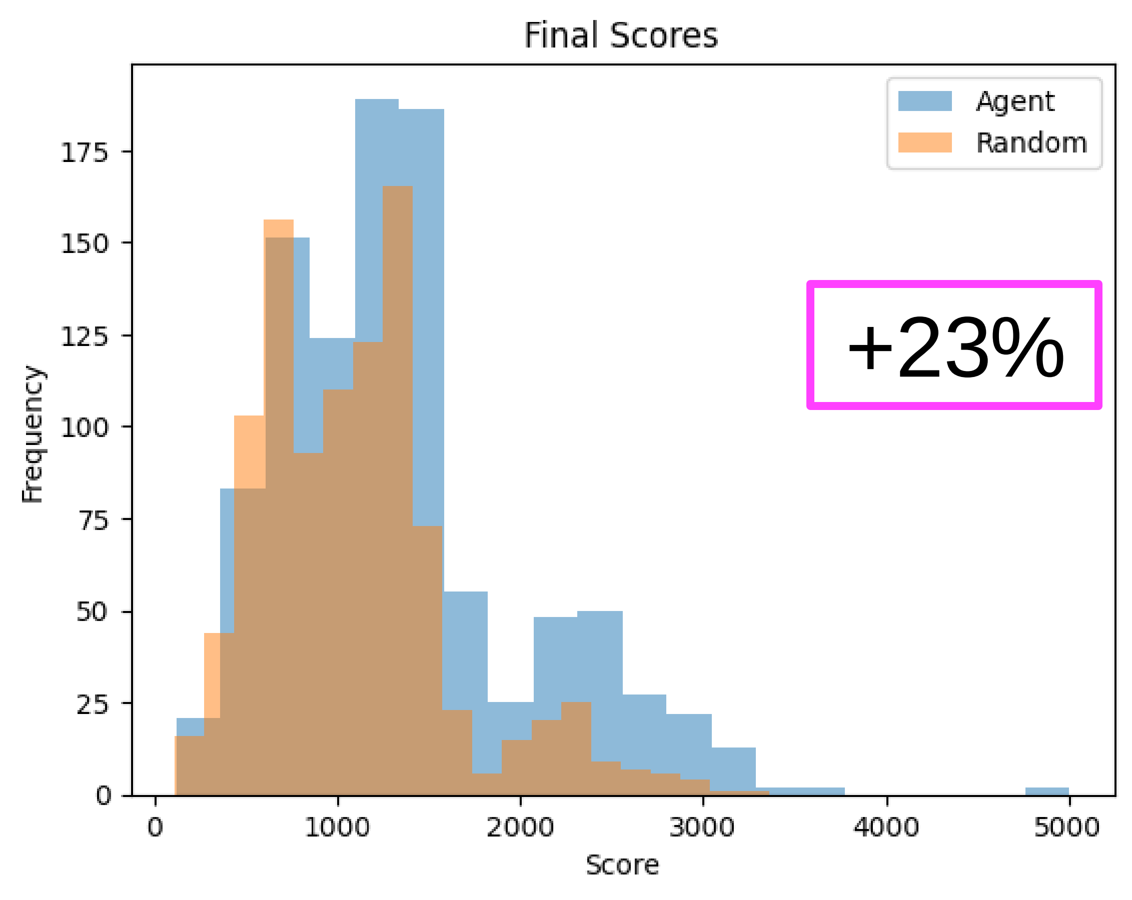
DEEP Q-LEARNING

Algorithm 2 Neural Network Training

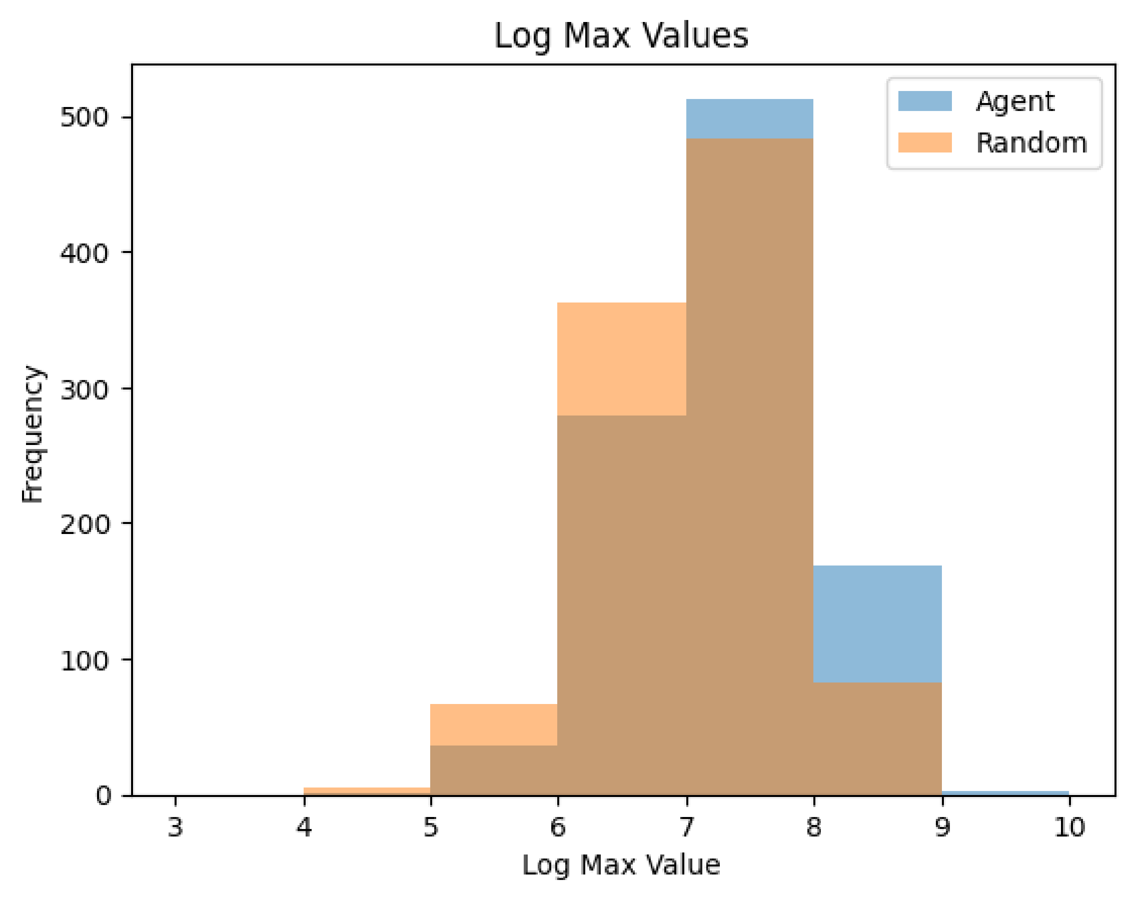
for M epochs **do**
    Sample a batch of B transitions $(s, a, r, s', \text{done})$ from replay buffer $\mathcal{D}$
    Compute current Q-values: $Q(s, a; \theta)$ using the policy network
    Compute target Q-values $Q(s', a'; \theta_{\text{target}})$ using the target network:
    if done is True **then**
        $y = r$
    else
        $y = r + \gamma \cdot \max_{a'} Q(s', a'; \theta_{\text{target}})$
    end if
    Compute loss between $Q(s, a; \theta)$ and y
    Perform backward pass and update Q-network weights θ
    if episode % C == 0 **then**
        Update target network weights: $\theta_{\text{target}} \leftarrow \theta$
    end if
end for

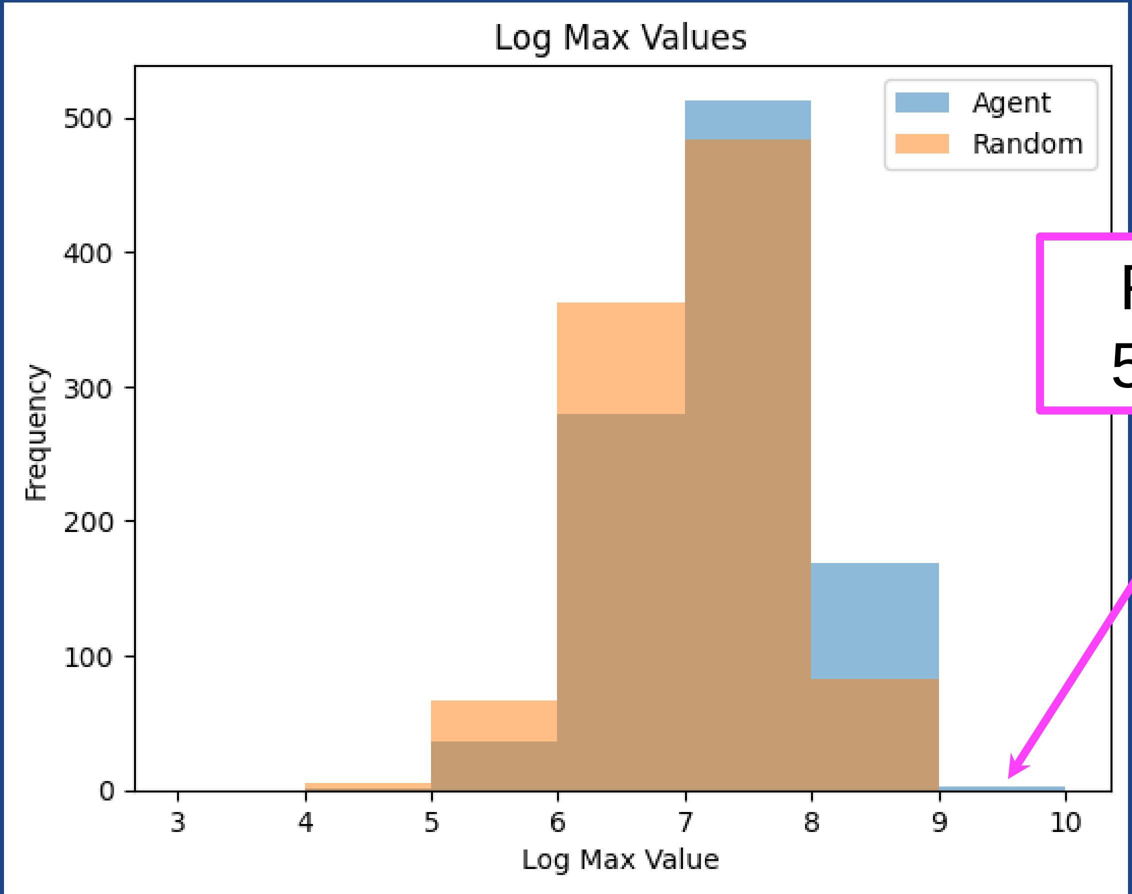
05

RESULTS

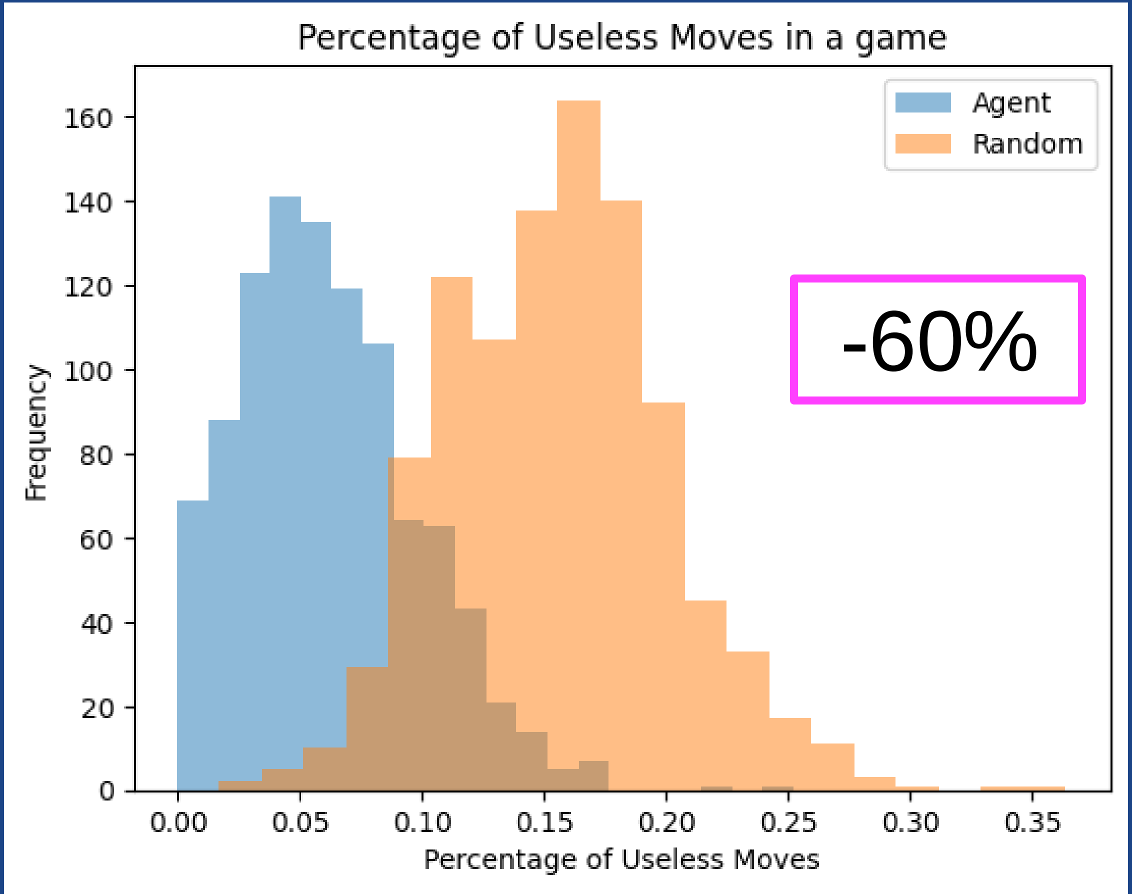


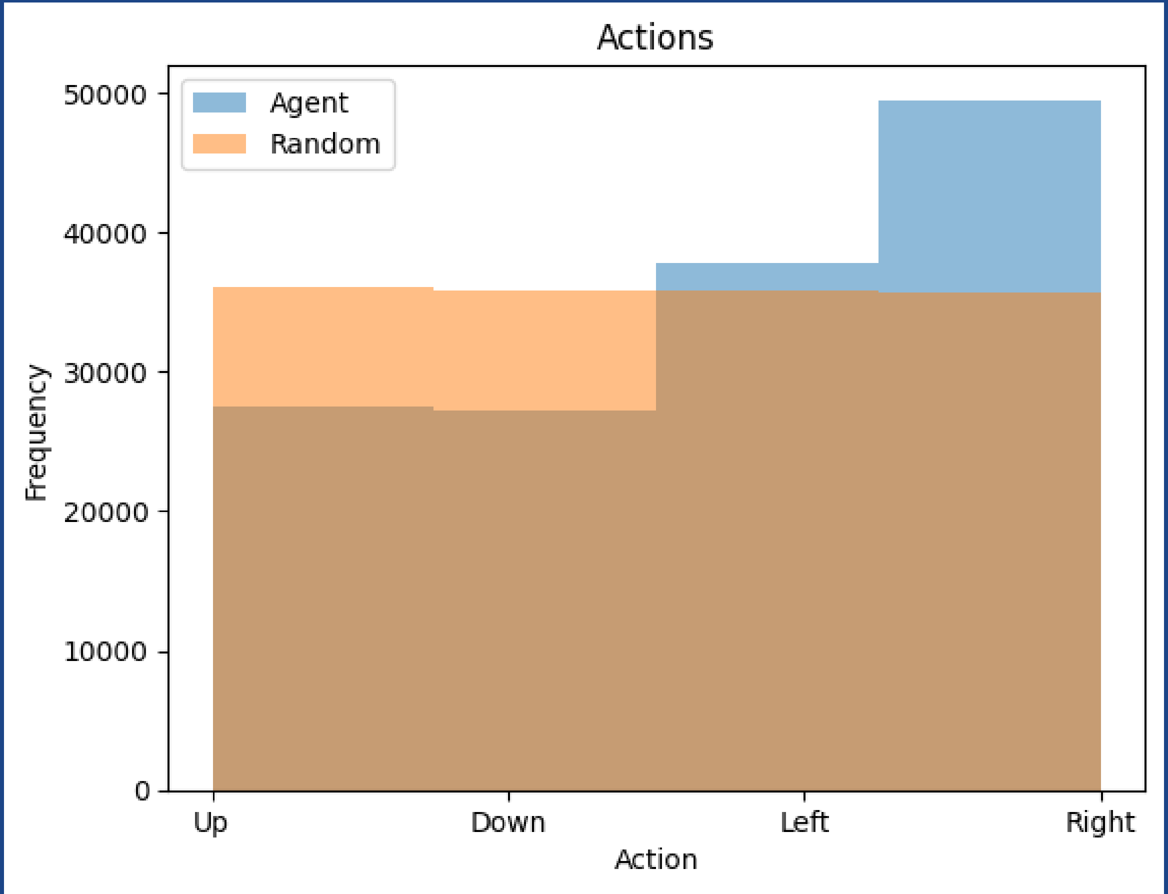
Final Scores
Agent
Random
+23%
Frequency
0
25
50
75
100
125
150
175
0
1000
2000
3000
4000
5000
Score


Log Max Values
Agent
Random
Frequency
0
100
200
300
400
500
3
4
5
6
7
8
9
10
Log Max Value



Reaches 512 twice


Percentage of Useless Moves in a game
Agent
Random
-60%
Frequency
0
20
40
60
80
100
120
140
160
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
Percentage of Useless Moves

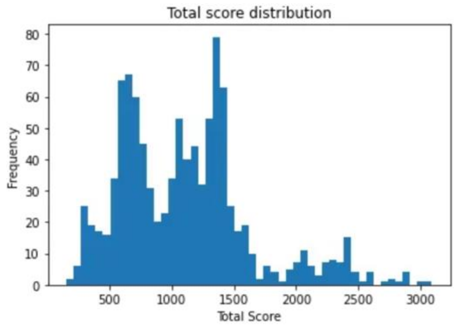


Actions
Agent
Random
50000
40000
30000
20000
10000
0
Frequency
Up
Down
Left
Right
Action

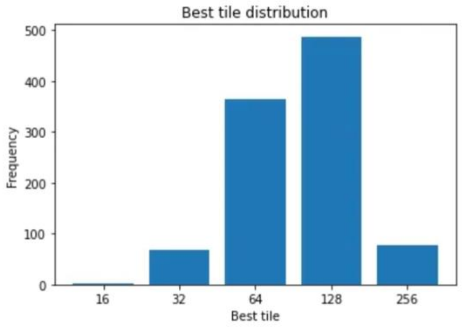
06

SIMILAR WORKS

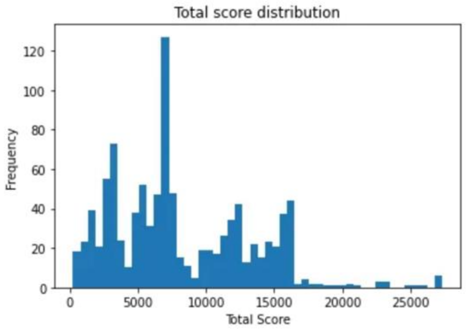
Playing 2048 with Deep Q-Learning by Lok Hin Chan



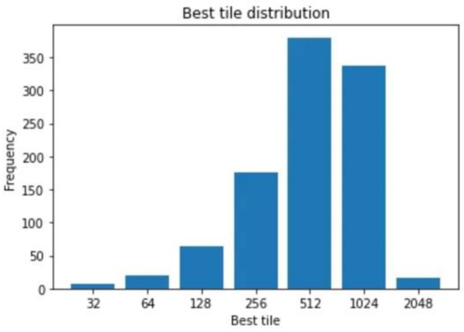
Source by the Author



Source by the Author



Source by the Author



Source by the Author

Playing 2048 with Deep Q-Learning by Lok Hin Chan

```
class ConvBlock(nn.Module):
    def __init__(self, input_dim, output_dim):
        super(ConvBlock, self).__init__()
        d = output_dim // 4
        self.conv1 = nn.Conv2d(input_dim, d, 1, padding='same')
        self.conv2 = nn.Conv2d(input_dim, d, 2, padding='same')
        self.conv3 = nn.Conv2d(input_dim, d, 3, padding='same')
        self.conv4 = nn.Conv2d(input_dim, d, 4, padding='same')

    def forward(self, x):
        x = x.to(device)
        output1 = self.conv1(x)
        output2 = self.conv2(x)
        output3 = self.conv3(x)
        output4 = self.conv4(x)
        return torch.cat((output1, output2, output3, output4), dim=1)

class DQN(nn.Module):

    def __init__(self):
        super(DQN, self).__init__()
        self.conv1 = ConvBlock(16, 2048)
        self.conv2 = ConvBlock(2048, 2048)
        self.conv3 = ConvBlock(2048, 2048)
        self.dense1 = nn.Linear(2048 * 16, 1024)
        self.dense2 = nn.Linear(1024, 4)

    def forward(self, x):
        x = x.to(device)
        x = F.relu(self.conv1(x))
        x = F.relu(self.conv2(x))
        x = F.relu(self.conv3(x))
        x = nn.Flatten()(x)
        x = F.dropout(self.dense1(x))
        return self.dense2(x)
```

Playing 2048 with Deep Q-Learning by Lok Hin Chan

The following parameters are used to train the model to play 2048:

- Size of memory buffer: 50000
- Optimizer: Adam
- Learning Rate: 5e-5
- γ: 0.99
- ε: Starting from 0.9 and decays by a factor of 0.9999 for each episode until it reaches 0.01
- Batch size: 64

Playing 2048 with Deep Q-Learning by Lok Hin Chan

Finally after training the model for 20000 episodes, some of the episodes does manage to reach tile 2048, for example the one below:

06

FUTURE IMPROVEMENTS

POSSIBLE IMPROVEMENTS

- Penalize distance between high-value tiles
- Trying Double Q-Learning, where we separate action selection and evaluation
- Prioritized Experience Replay
- n-step TD learning instead of 1-step: target q-value calculated over n-steps
- Hyperparameter tuning

THANKS!

Credits:

Playing 2048 with Deep Q-Learning by Lok Hin Chan