SEMESTER PROJECT : SPRING 2020
EURECOM

REINFORCEMENT LEARNING FOR CACHE-FRIENDLY RECOMMENDATIONS

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RECOMMENDATION APPLICATIONS

Use state-of-the art recommendation algorithms but ...

don't take into account network latency !

Cache-friendly recommender

Our goal

Recommendation algorithm

Users' preferences

Network latency

Cached-friendly recommender

Algorithm that recommends contents that can be cached and related

Reinforcement learning

Algorithm that learns by experience

REINFORCEMENT LEARNING

ONE OF THE THREE PARADIGMS OF MACHINE LEARNING

Like supervised and unsupervised learning, reinforcement learning is one of the three main parts of machine learning area

LEARN FROM EXPERIENCE

Algorithm that will interact with the user to learn his preferences and even more ...

Covered Today

Notations

Reinforcement learning concepts

Q-learning

Deep Q-learning

Double Q-learning

Limits & Conclusions

Notations

WHAT IS CACHED, RELATED ?

CATALOGUE

Videos, musics, movies are all coded in the same way as a file/content in the Catalogue

```
array([0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.91747976, 0.95267253, 0.        ,
       0.90697197, 0.        , 0.        , 0.        , 0.        ,
       0.97826924, 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.91222267, 0.        , 0.        , 0.85051224, 0.        ,
       0.84753072, 0.        , 0.        , 0.        , 0.        ,
       0.97477846, 0.        , 0.        , 0.88544912, 0.        ,
       0.91145699, 0.        , 0.        , 0.        , 0.        ])
```

U VALUES FOR CONTENT 0, CATALOGUE SIZE OF 50

Related

U MATRIX THAT GIVES A SCORE OF SIMILARITY

```
array([1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 1])
```

COST FOR THE CONTENTS

Cached

LIST THAT GIVES THE COST FOR CONSUMING A CONTENT

MARKOVIAN USER

- Leave the simulation with probability alpha
- Listen the suggestion with probability a (otherwise pick randomly a content among the catalogue)

Reinforcement learning concepts

AGENT, STATES,ACTIONS, REWARDS, ...

MARKOVIAN DECISION PROCESSES

AGENT

Recommendation algorithm

ENVIRONMENT

The user (like markovian user)

STATES/ACTIONS

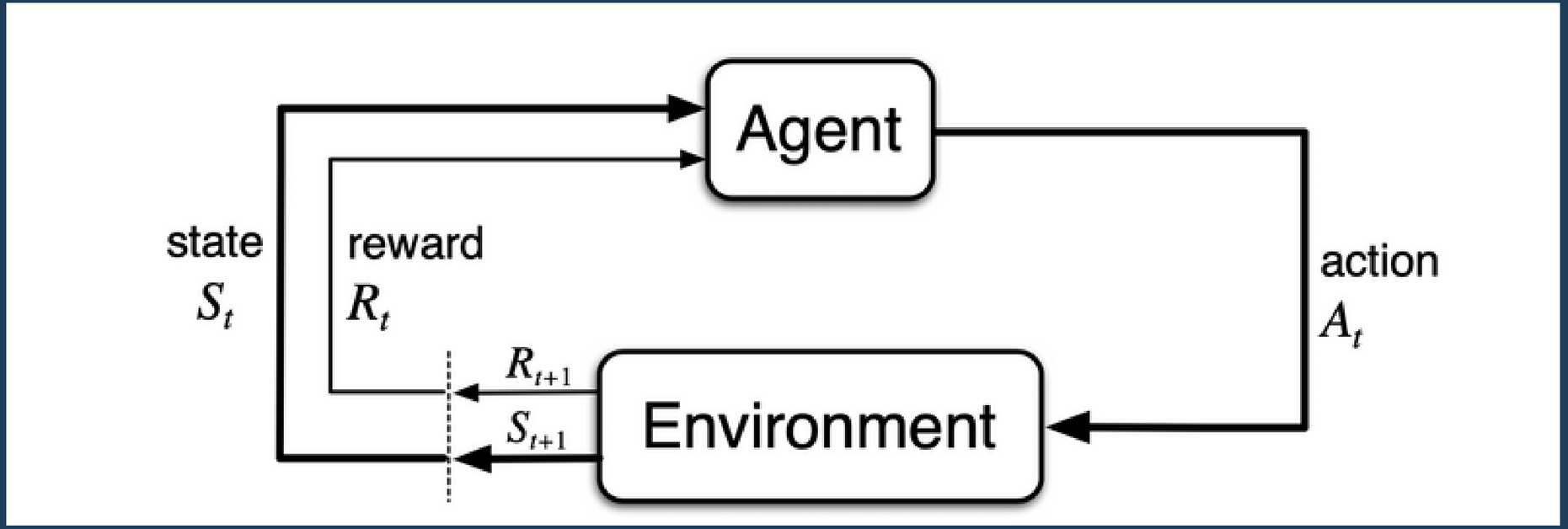
State : content that is consumed by the user
Action : content that is suggested by the agent

REWARD

Feedback

POLICY

Mapping from states to probabilities of selecting an action



Reinforcement learning timeline

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + ... + \gamma^{T-1} R_T = \sum_{k=0}^{T} \gamma^k R_{t+k+1}$$

EXPECTED RETURN

Expected reward from a given state

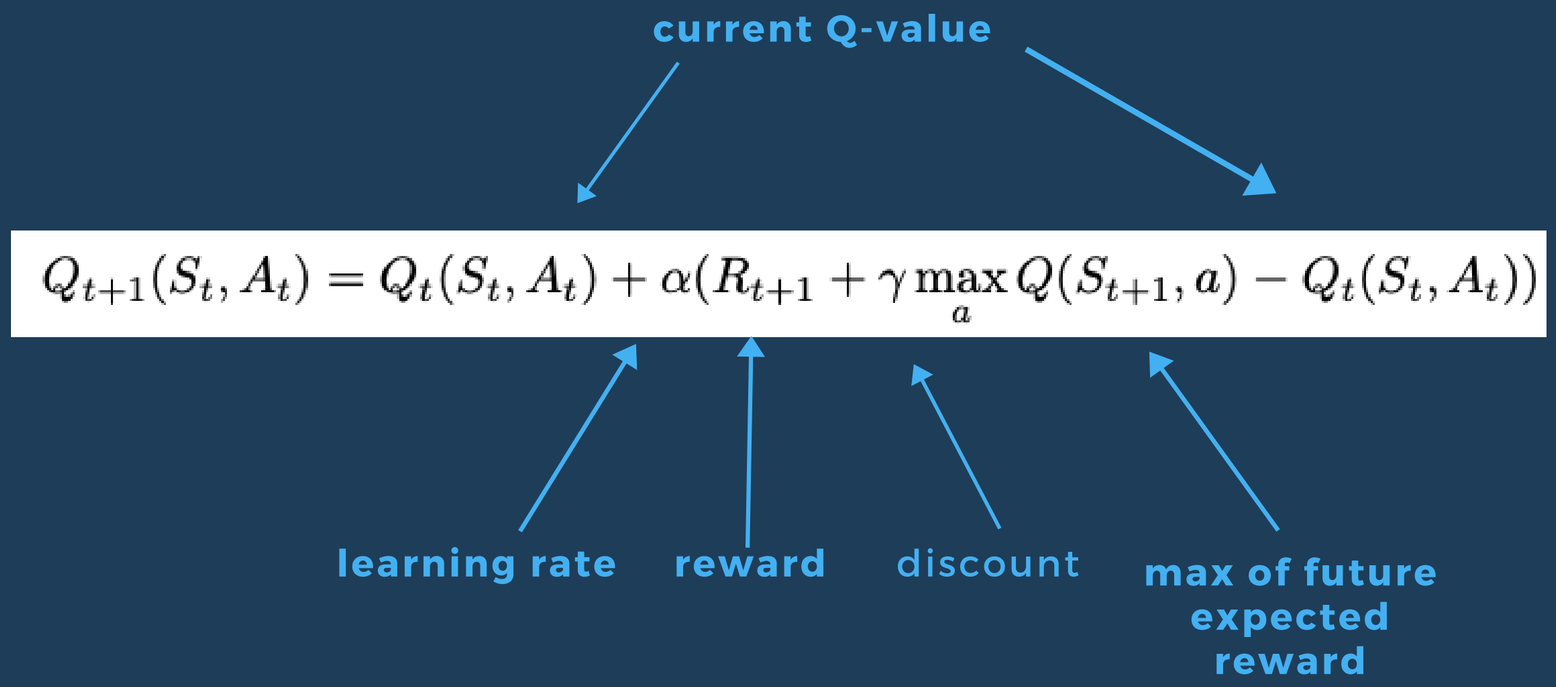
$$q_\pi(s, a) = E_\pi(G_t | S_t = s, A_t = a)$$

Q-TABLE

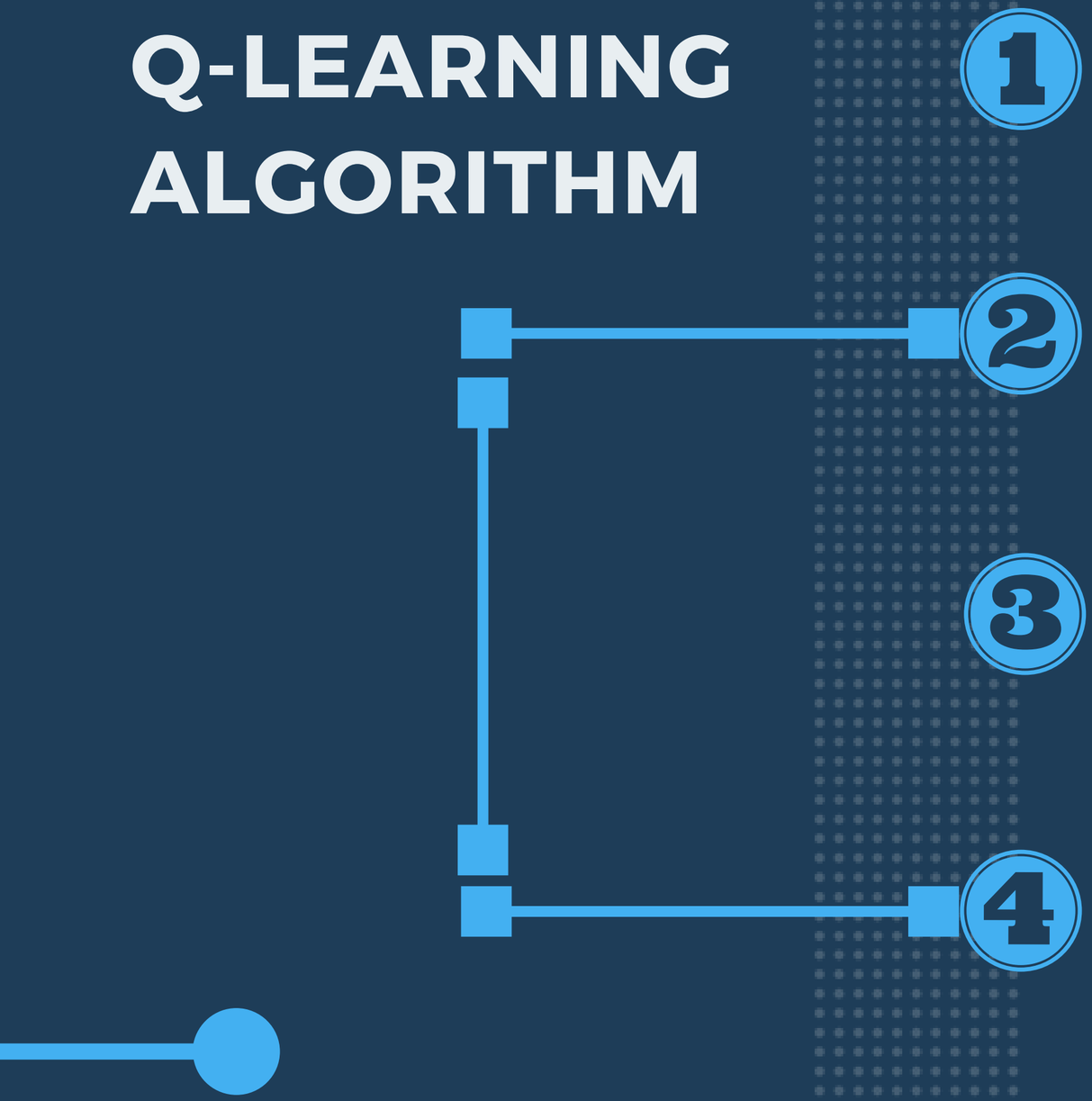
Action-value function that gives the expected return for each couple (state, action)

Q-learning

Q-LEARNING UPDATE RULE



Q-LEARNING ALGORITHM



1 Initialise the Q-table

Make zeros everywhere

2 Choose action from Q (epsilon-greedy)

Choose a content to recommend either by exploration or by exploitation

3 Perform action and get rewards

Interaction with the user and get the reward for the content that has been recommended

4 Update the Q table

Update the Q-table with the formula and start again from 2) with the new state

CHOOSE AN ACTION : EPSILON-GREEDY

EXPLORATION

- Search among all the catalogue to not miss good contents

EXPLOITATION

Exploit the learning process by taking the action that maximises the Q-table

Hyperparameters

LEARNING RATE

DISCOUNTED GAMMA

How far does the agent take into account the actions

RELATED CONTENTS

Number of related contents for each item

CACHED CONTENT

Number of cached content in the catalogue

ENVIRONMENT HYPERPARAMETERS

Results

- CATALOGUE OF SIZE 50
-10 RELATED CONTENTS BY STATE
-5 CACHED CONTENTS
-LEARNING RATE : 0.2

REWARDS

NEITHER CACHED NOR RELATED

0

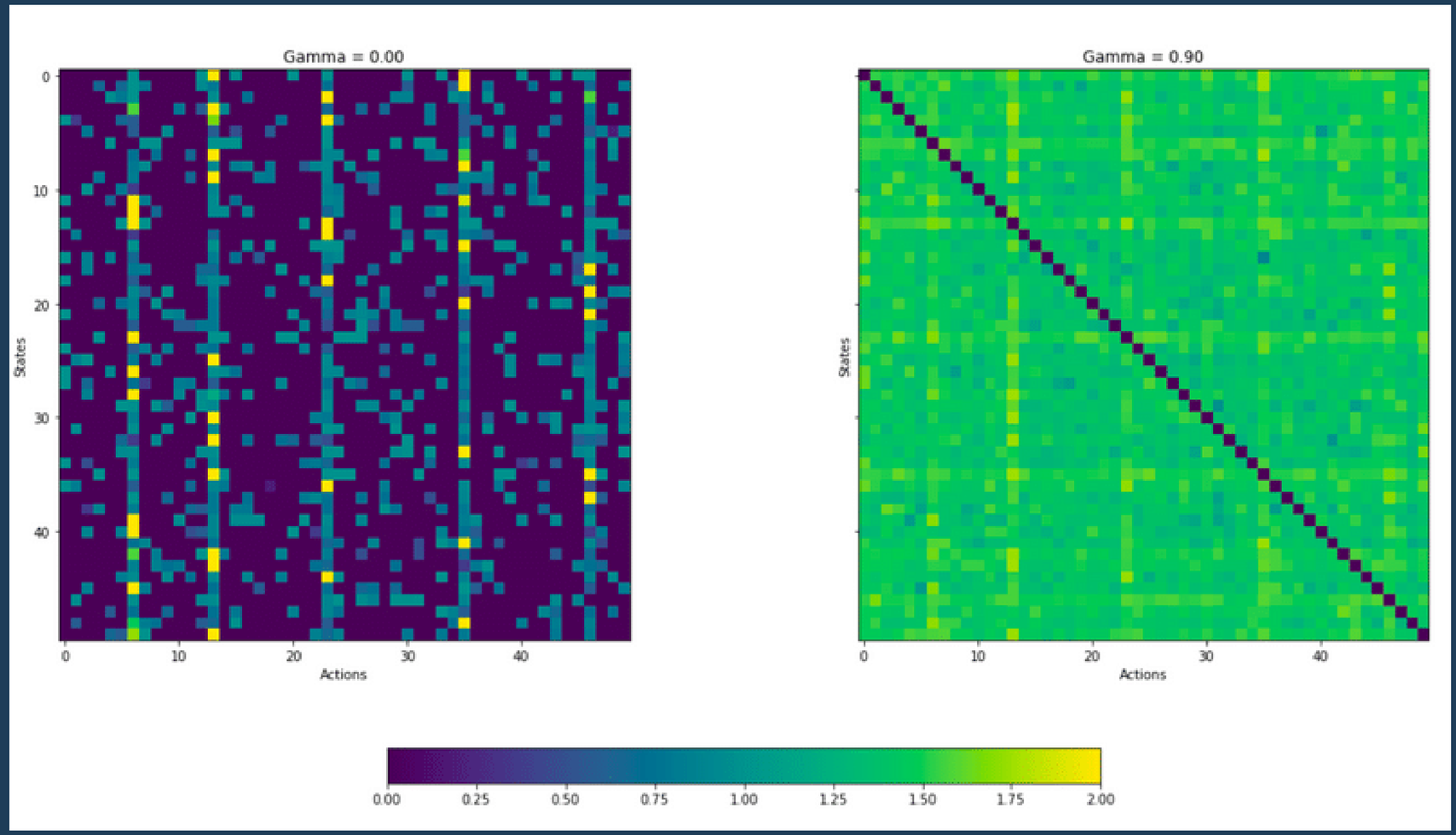
CACHED OR RELATED

+1

CACHED AND RELATED

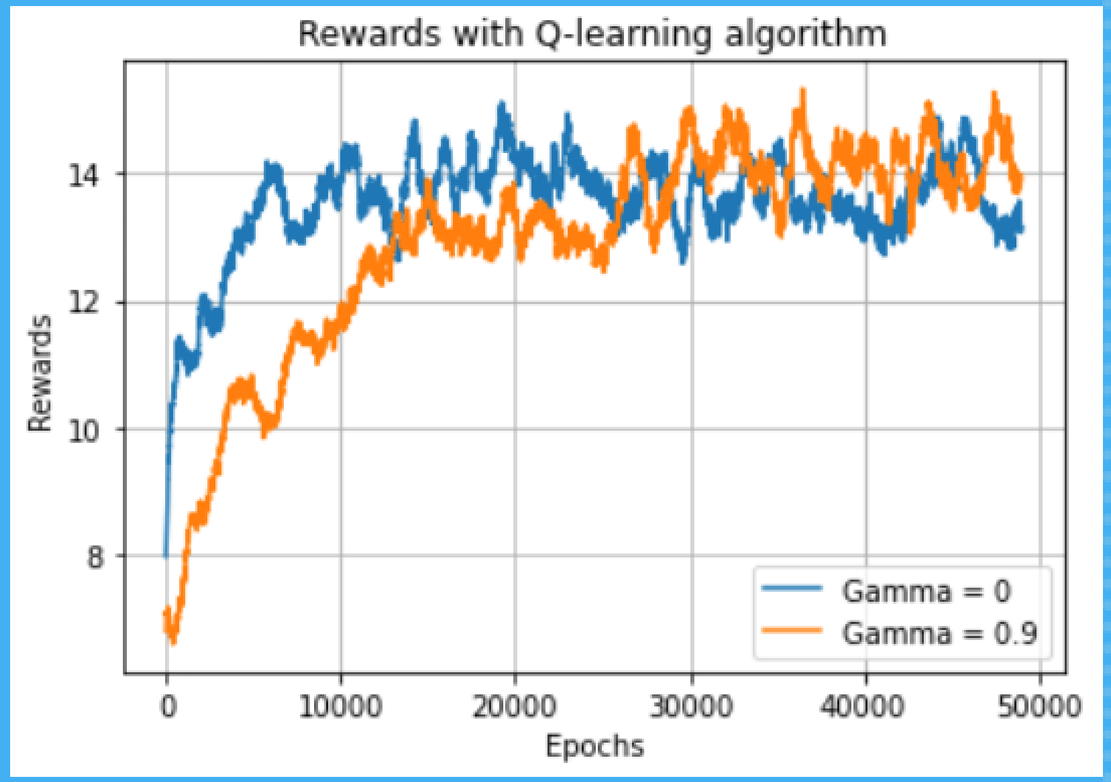
+2

Q-table

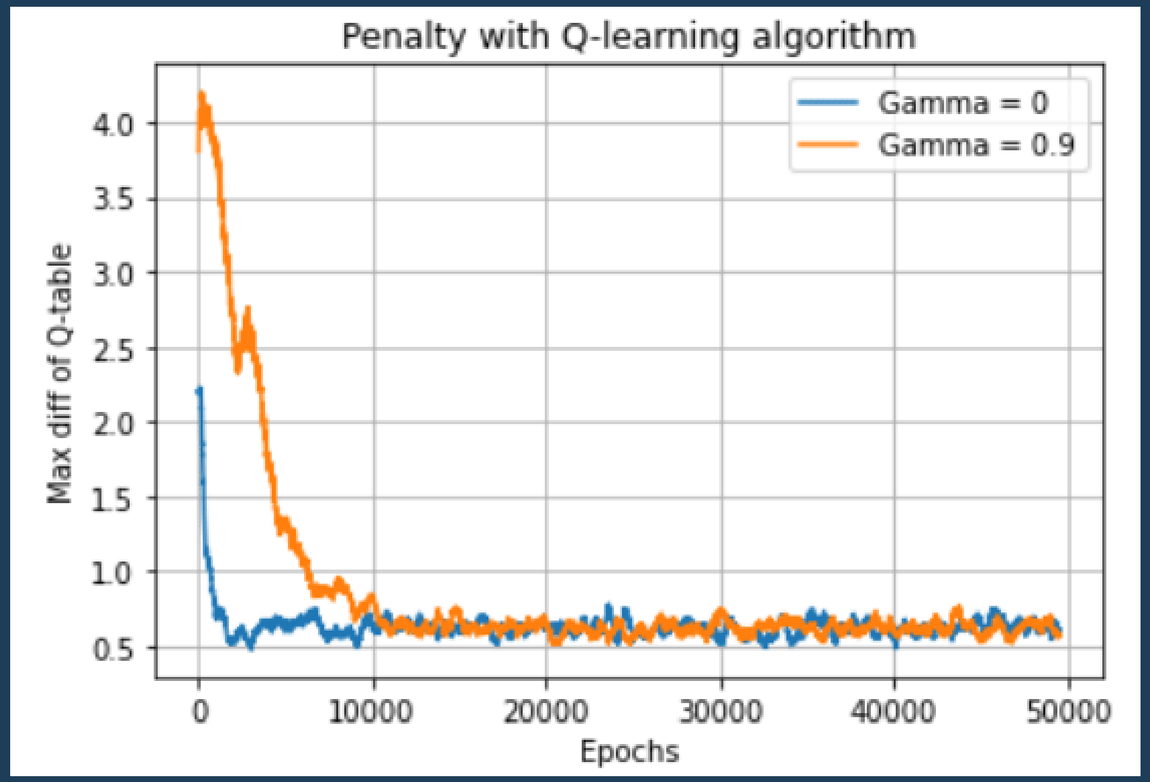


Gamma = 0 (left) and Gamma = 0.9 (right)

Rewards per epoch

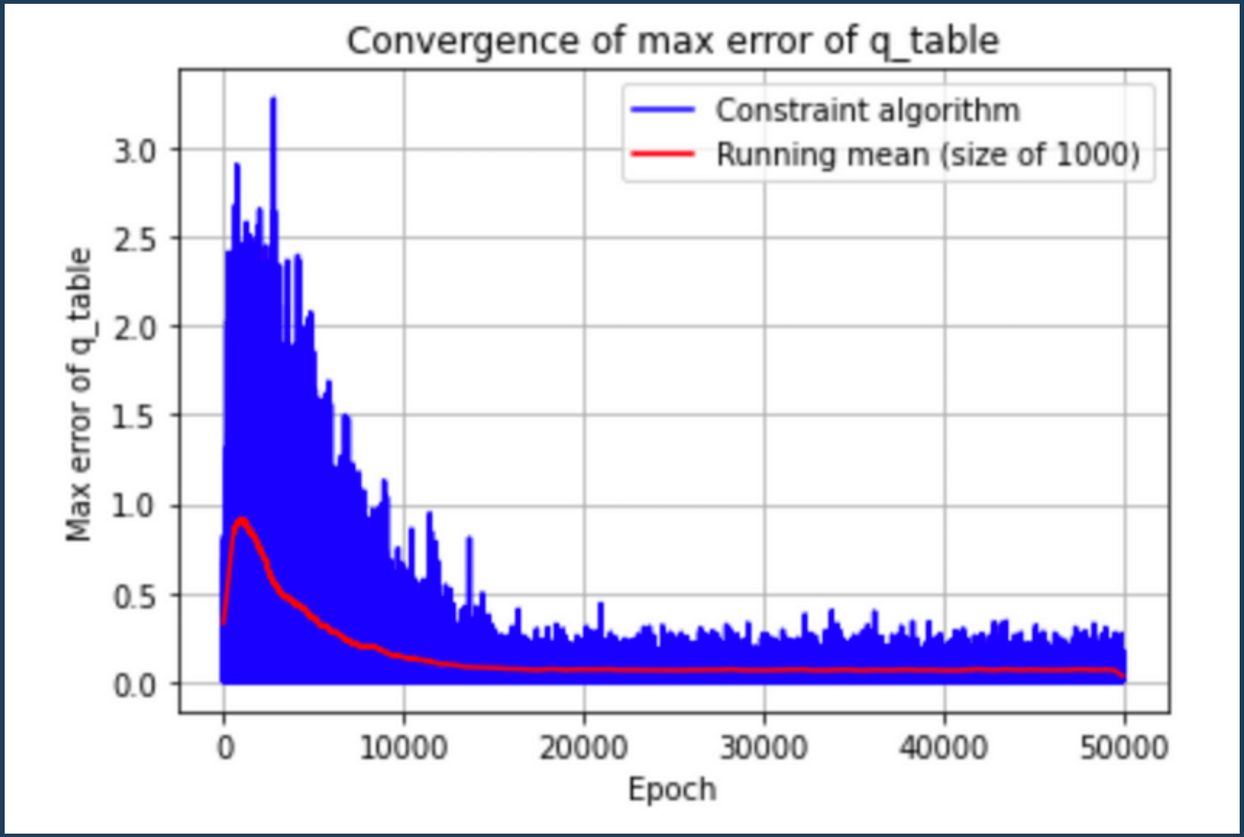


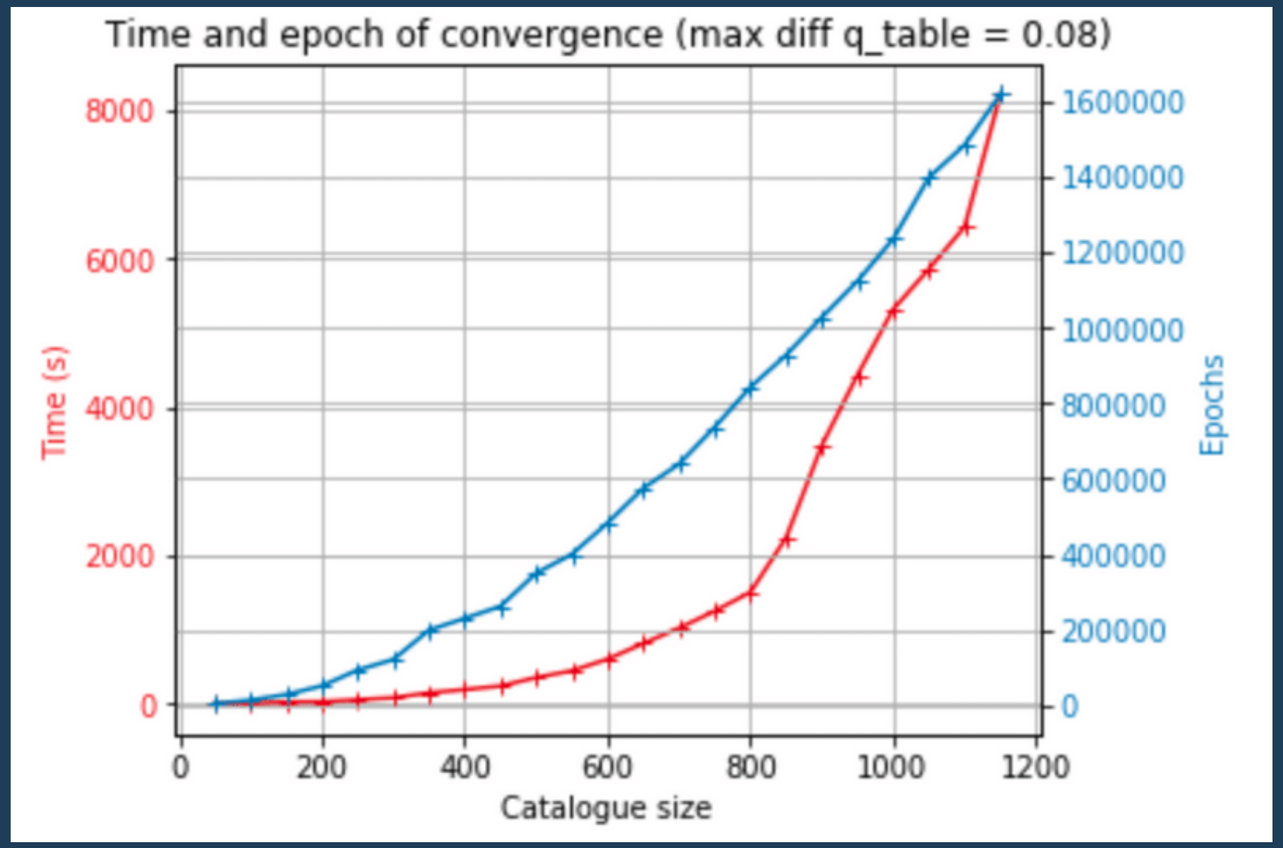
Penalty per epoch



Convergence criteria

Maximum difference of Q-table for one epoch





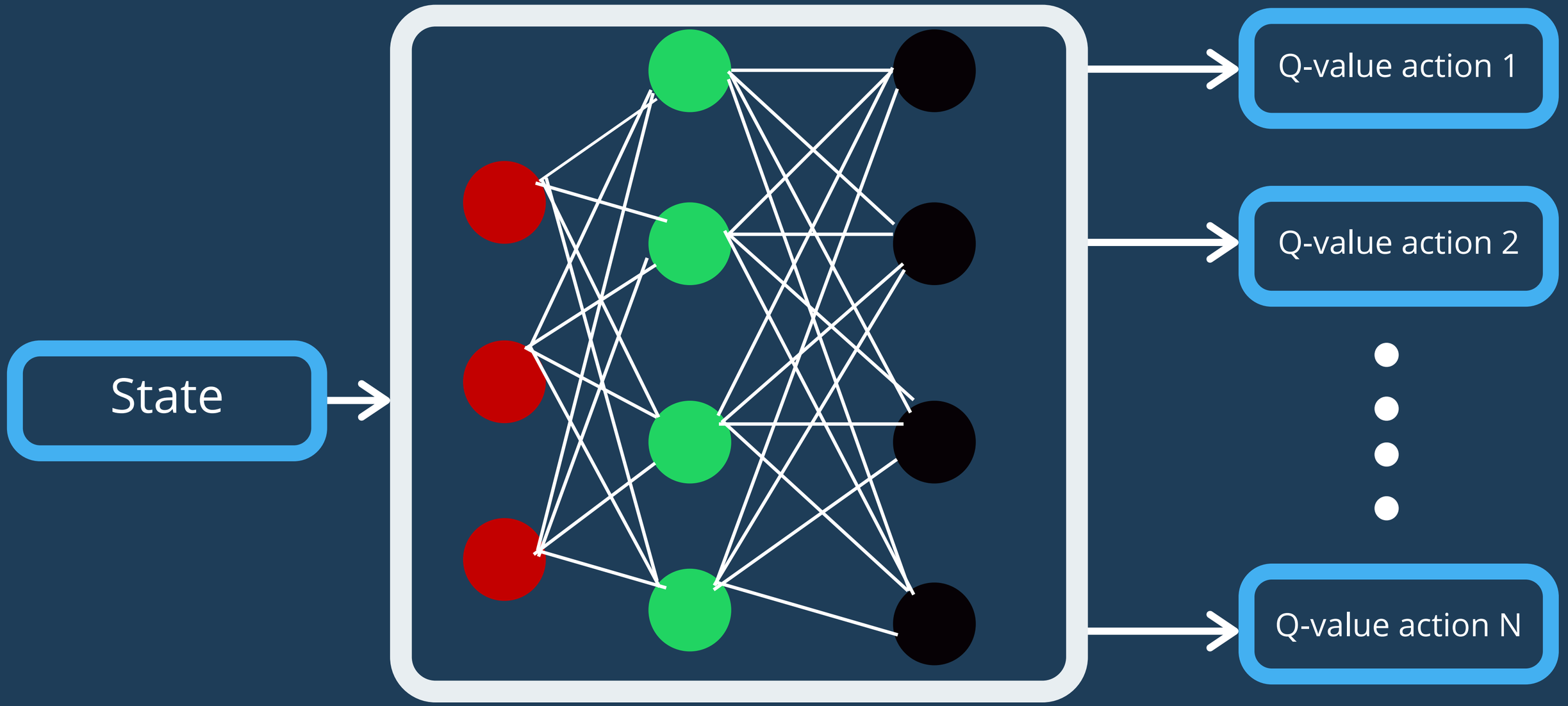
Time of convergence

Loop over the catalogue size

2 hours for catalogue size of 1200

Deep Q-learning

FUNCTION APPROXIMATION



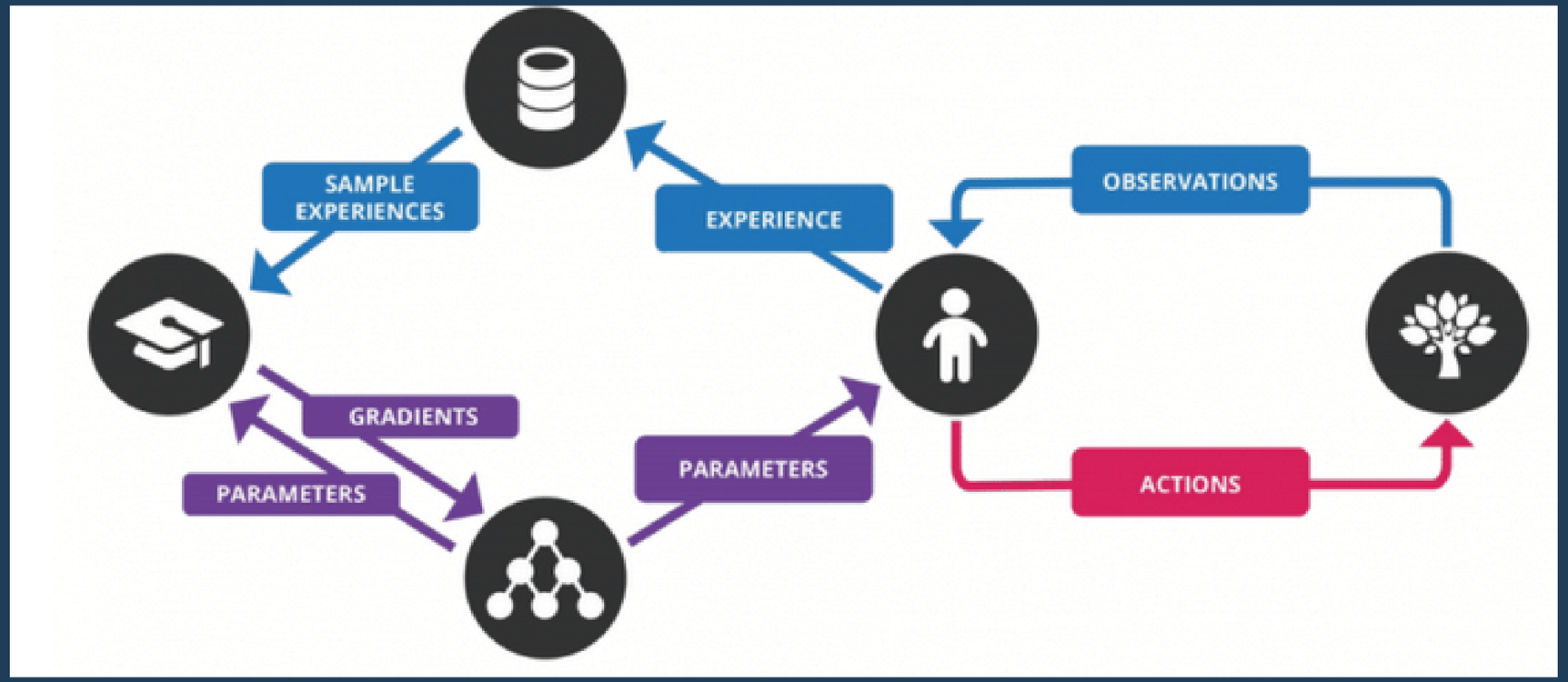
Deep Q-learning

Target

$$R(S_t, A_t) + \gamma \max_a Q(S_{t+1}, a, w)$$

Loss

$$loss = (R(S_t, A_t) + \gamma \max_a Q(S_{t+1}, a, w) - Q(S_t, A_t, w))^2$$



DEEP Q-LEARNING

MEMORY REPLAY

Store the experiences to make the training process more stable

STATE REPRESENTATION

HOT ENCODING

1 for the given state, 0 otherwise

U HOT ENCODED

Replace the state by the 1 for every related contents

REWARDS

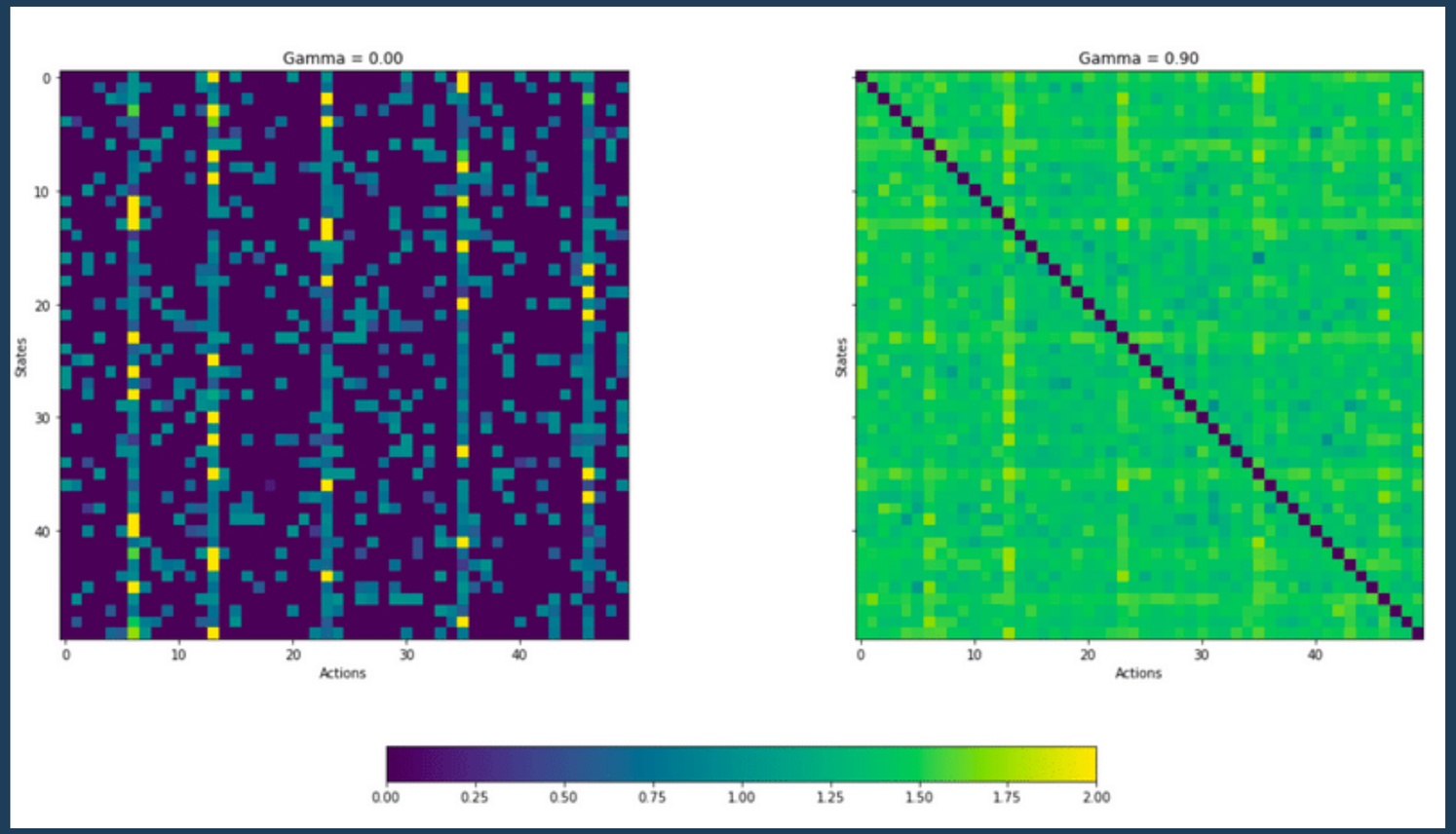
Replace the state by :
+2 if the content is related and cached
+1 if the content is either related or cached
0 otherwise

VALUABLE

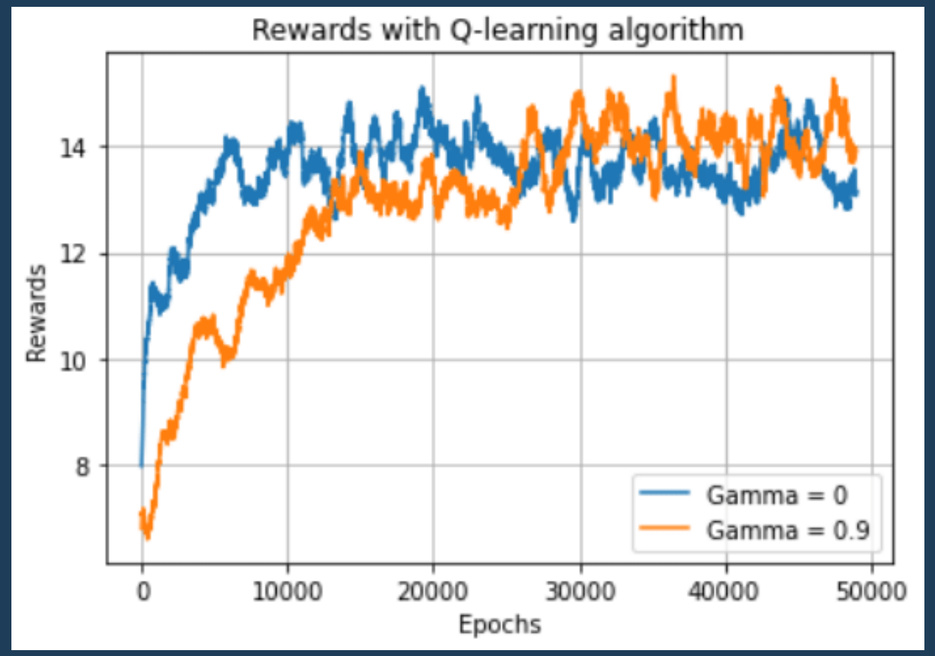
Rewards representation with :
+1 if the next state has contents related that are cached

Q-learning results

To compare to



Q-tables



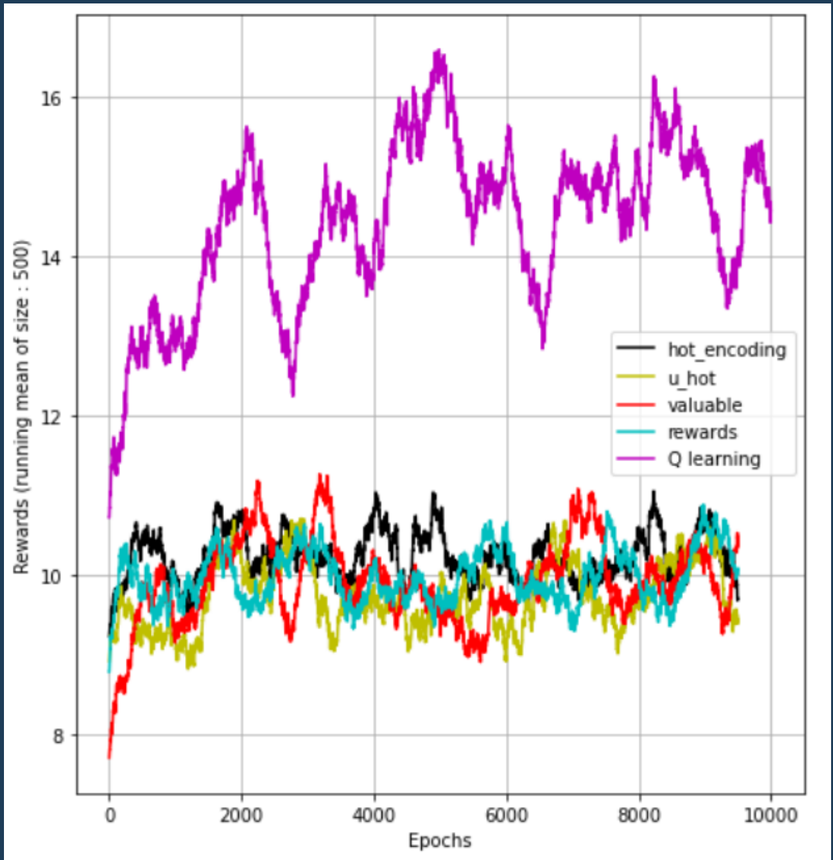
Rewards

Results

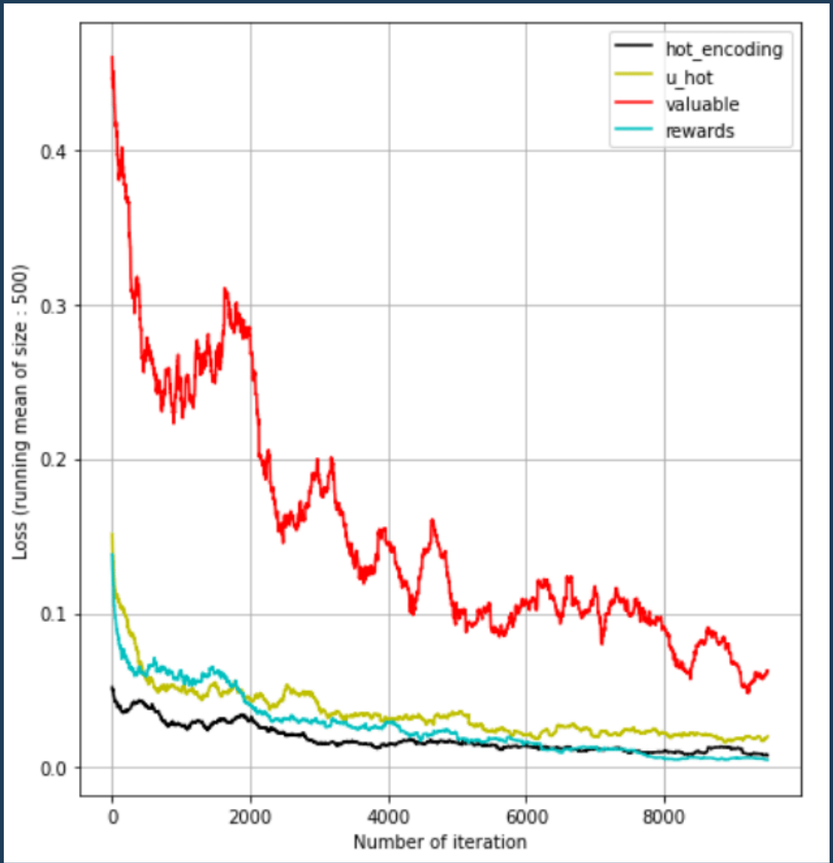
- CATALOGUE OF SIZE 50
-10 RELATED CONTENTS BY STATE
-5 CACHED CONTENTS
-LEARNING RATE : 1E-4
-MEMORY SIZE : 50
-BATCH-SIZE : 10
- NUMBER OF EPOCHS : 10 000

Rewards and loss for linear model

Gamma = 0



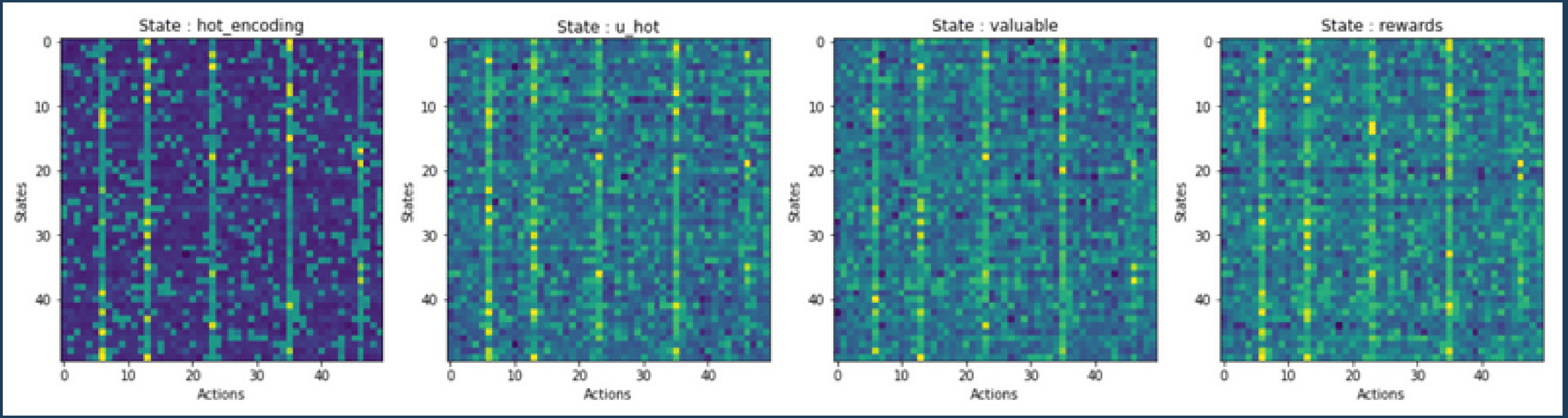
Rewards



Loss

Q-tables for linear model

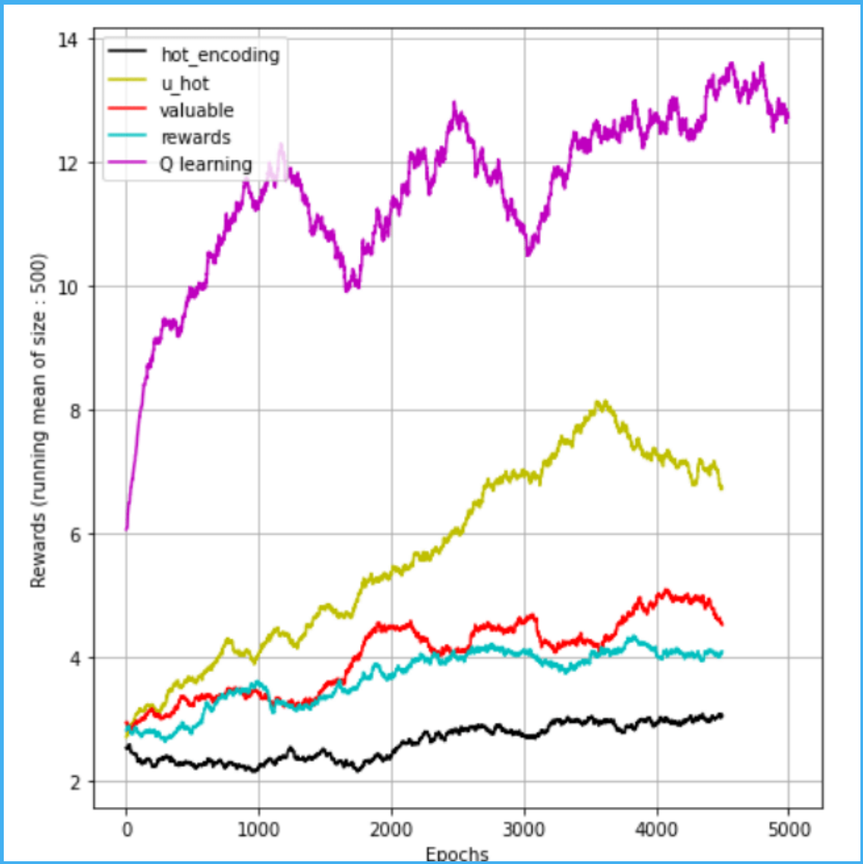
Gamma = 0



Hot encoding U hot encoding Valuable Rewards

Linear model

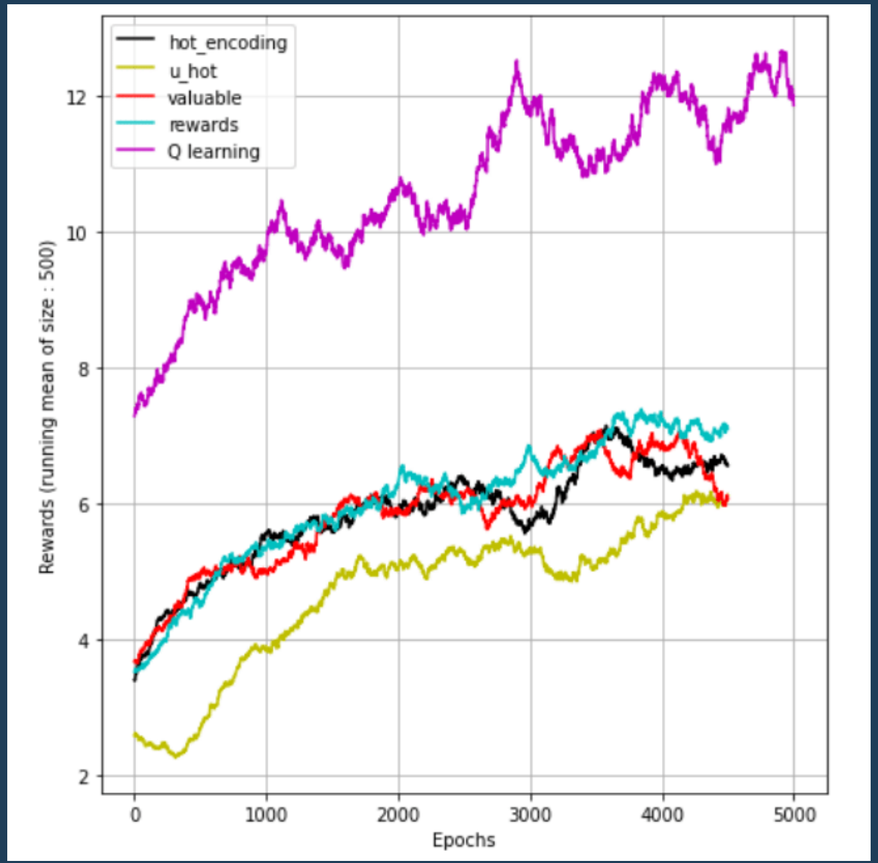
REWARDS



Gamma = 0.9

Fully connected model

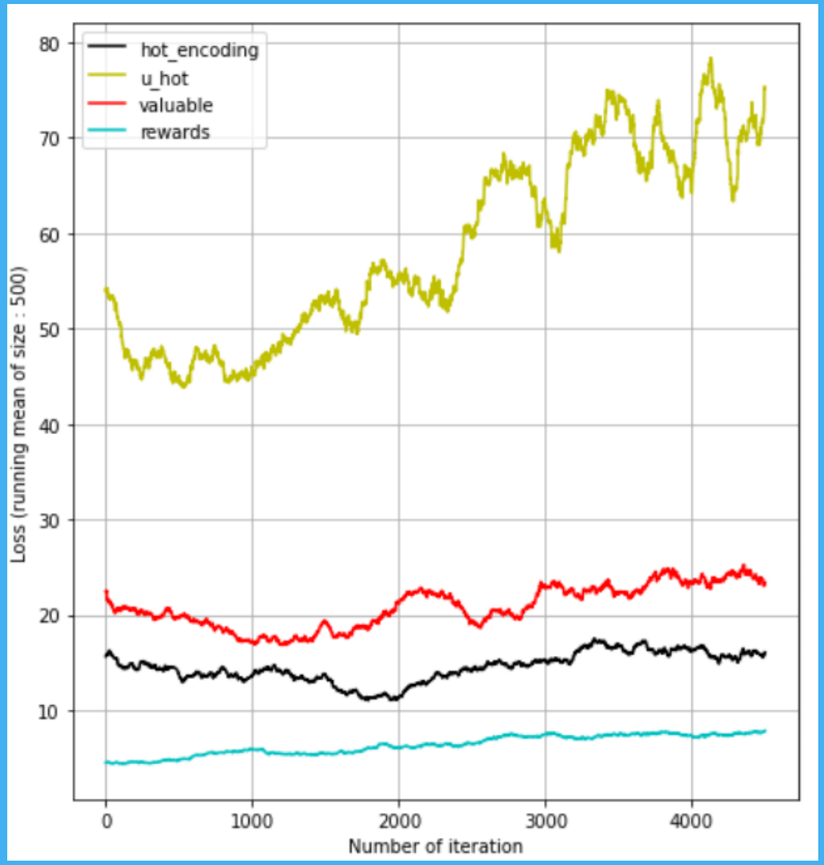
REWARDS



Gamma = 0.9

Linear model

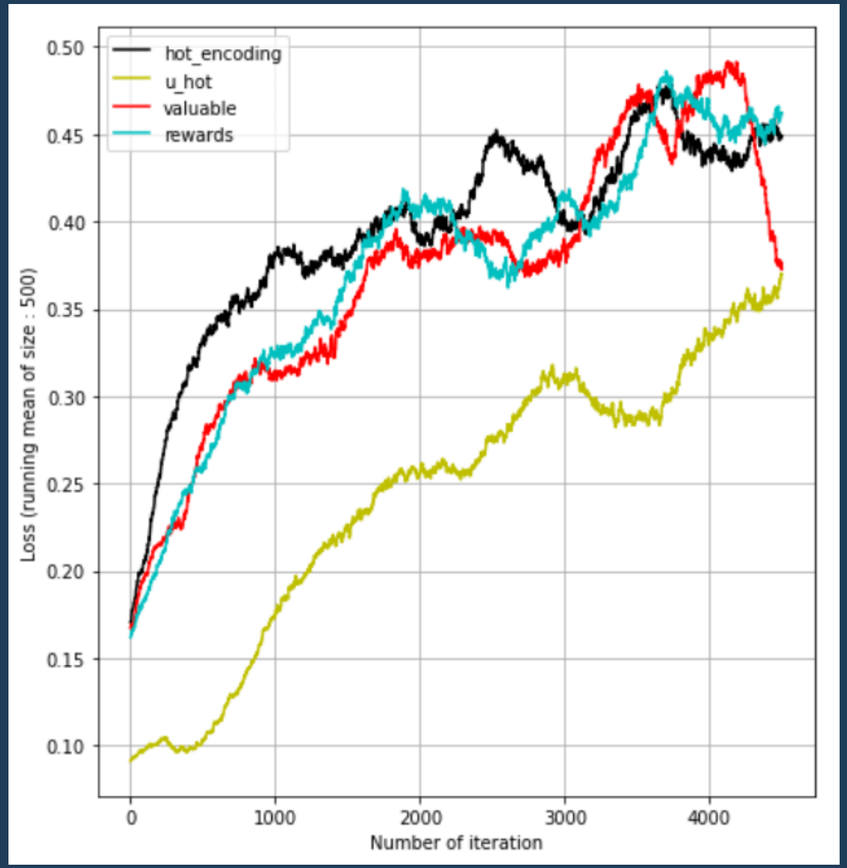
LOSS



Gamma = 0.9

Fully connected model

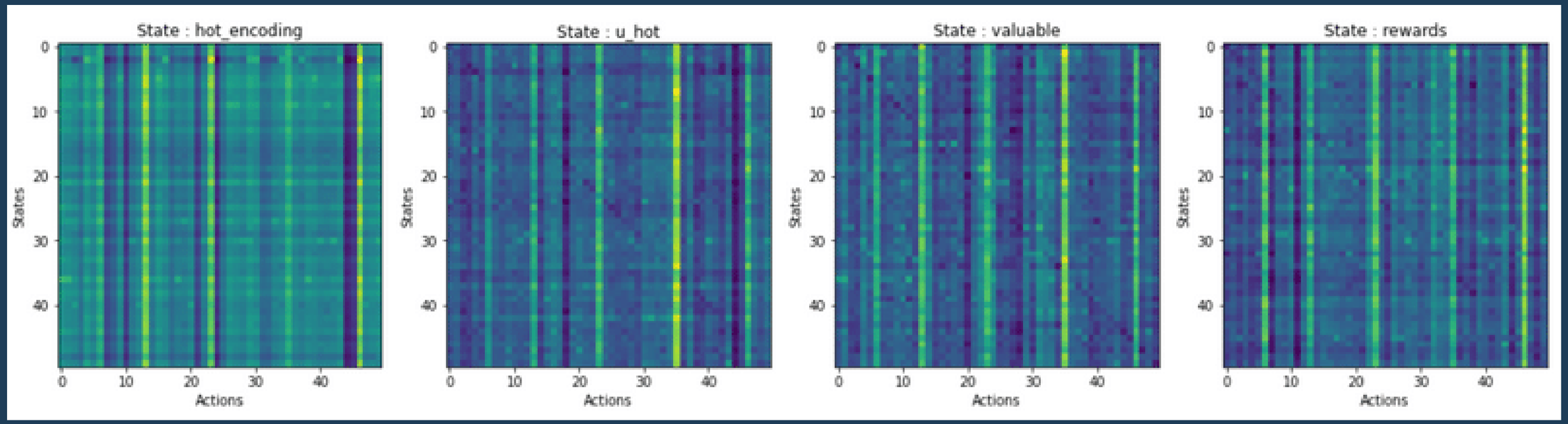
LOSS



Gamma = 0.9

Q-tables for fully connected model

Gamma = 0 .9



Hot encoding U hot encoding Valuable Rewards

Results summary

FINAL REWARDS STILL BELOW THE Q-LEARNING

But it seems the algorithm has converged

LOSS IS INCREASING FOR GAMMA = 0.9

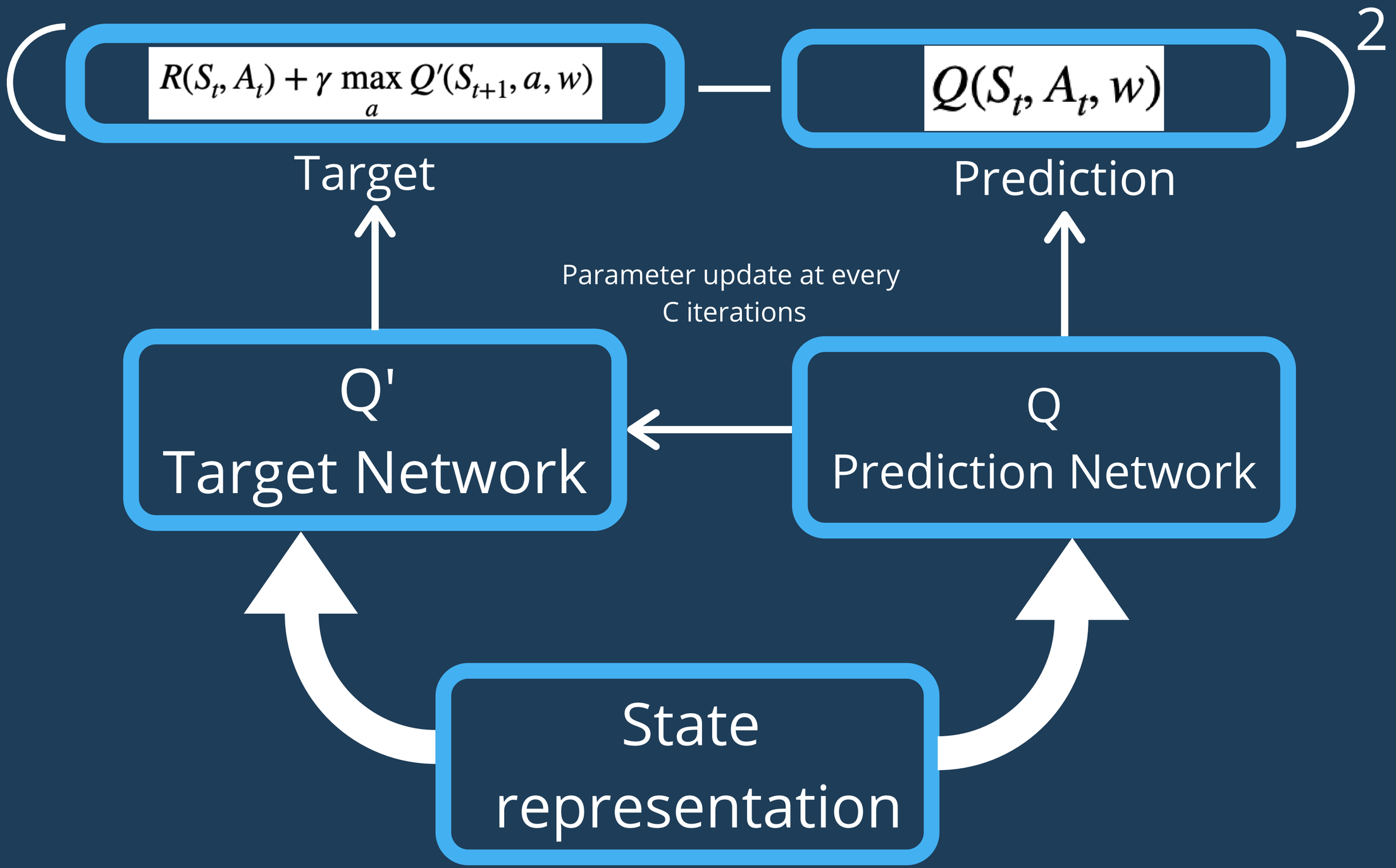
It means it doesn't learn correctly and few errors tend to increase the loss

MORE A TABULAR METHOD

It doesn't seem to approximate something

Double Q-learning

IMPROVEMENTS ?


$R(S_t, A_t) + \gamma \max_a Q'(S_{t+1}, a, w)$
$Q(S_t, A_t, w)$
2
Target
Prediction
Parameter update at every
C iterations
Q'
Target Network
Q
Prediction Network
State
representation

NEW STATE REPRESENTATIONS

MULTIPLE

State i is replaced by :
(a,b,c) for each action with :
- a = 0 if action neither cached not related
- b = 1 if the action is related
-c = 1 if the action is cached

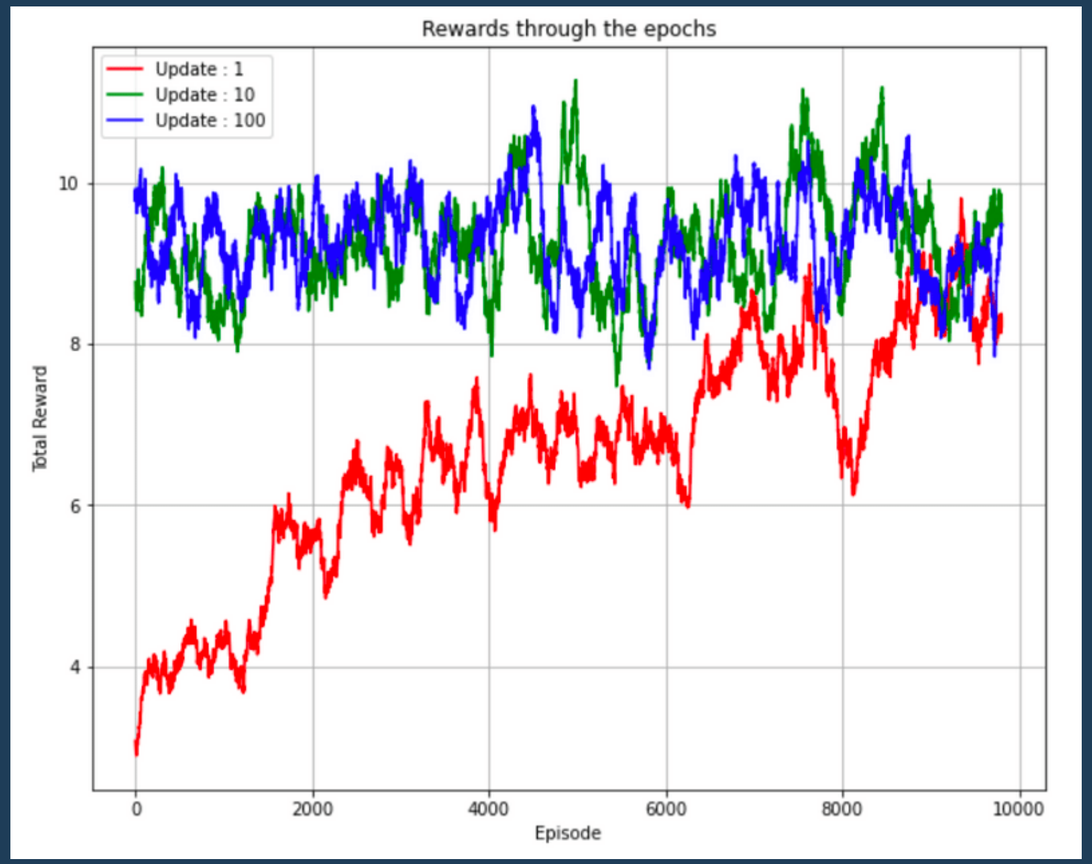
MULTIPLE VALUABLE

State i is replaced by :
(a,b,c,d) for each action with :
-(a,b,c) like multiple representation
-d += 1 if the next action has contents related cached

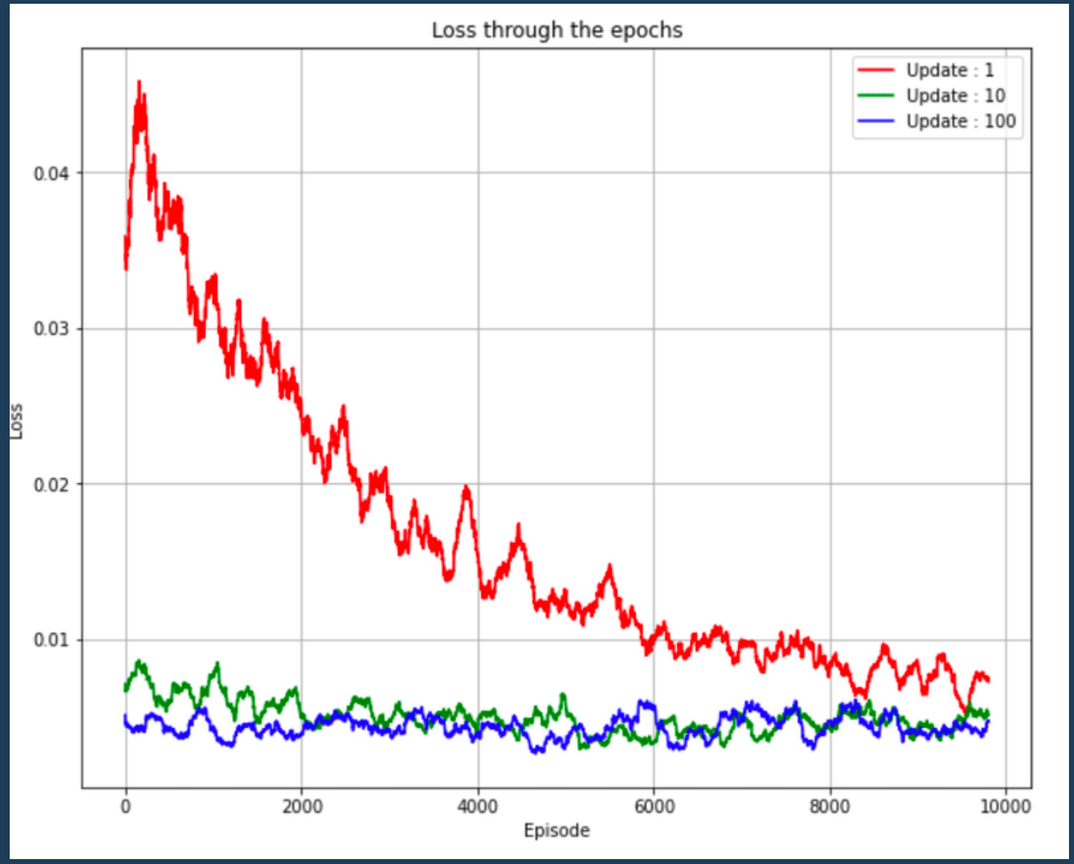
Update hyperparameter

Parameter to update the target and the prediction

Rewards



Loss

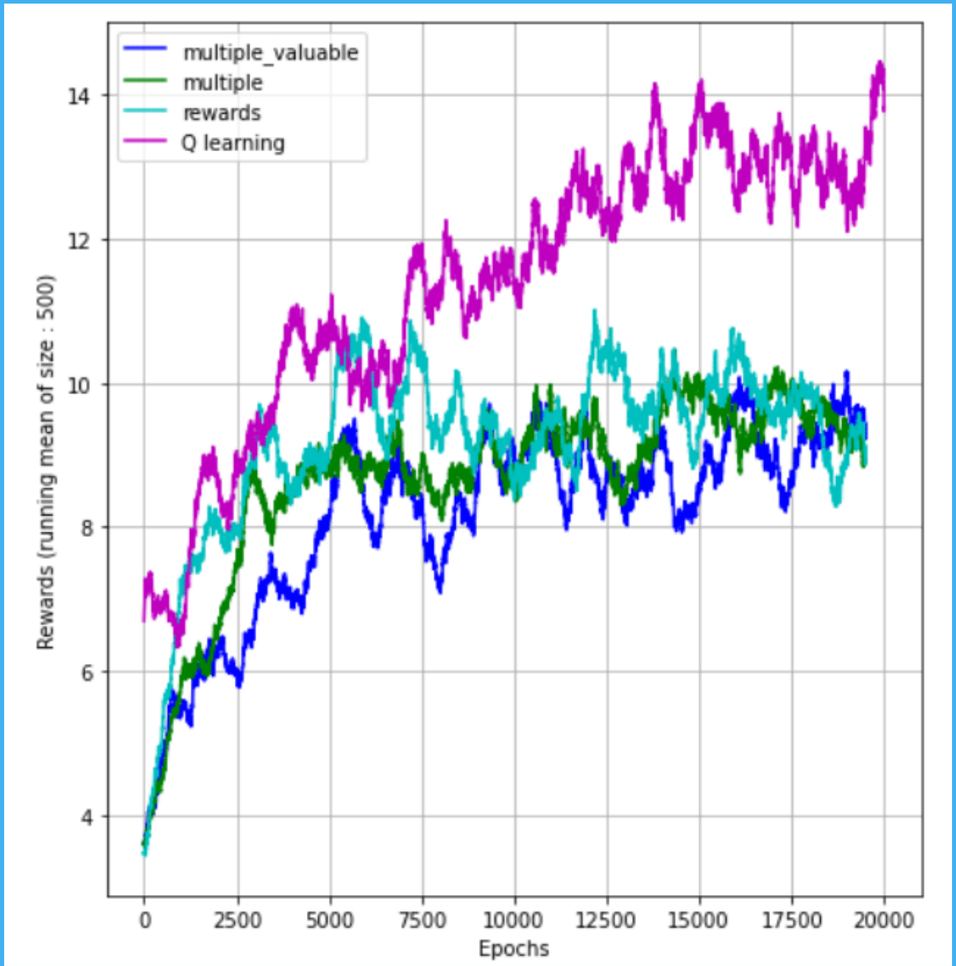


Results

- CATALOGUE OF SIZE 50
-10 RELATED CONTENTS BY STATE
-5 CACHED CONTENTS
-LEARNING RATE : 1E-4
-MEMORY SIZE : 200
-BATCH-SIZE : 20
- NUMBER OF EPOCHS : 20 000
-TARGET UPDATE : 50

Rewards

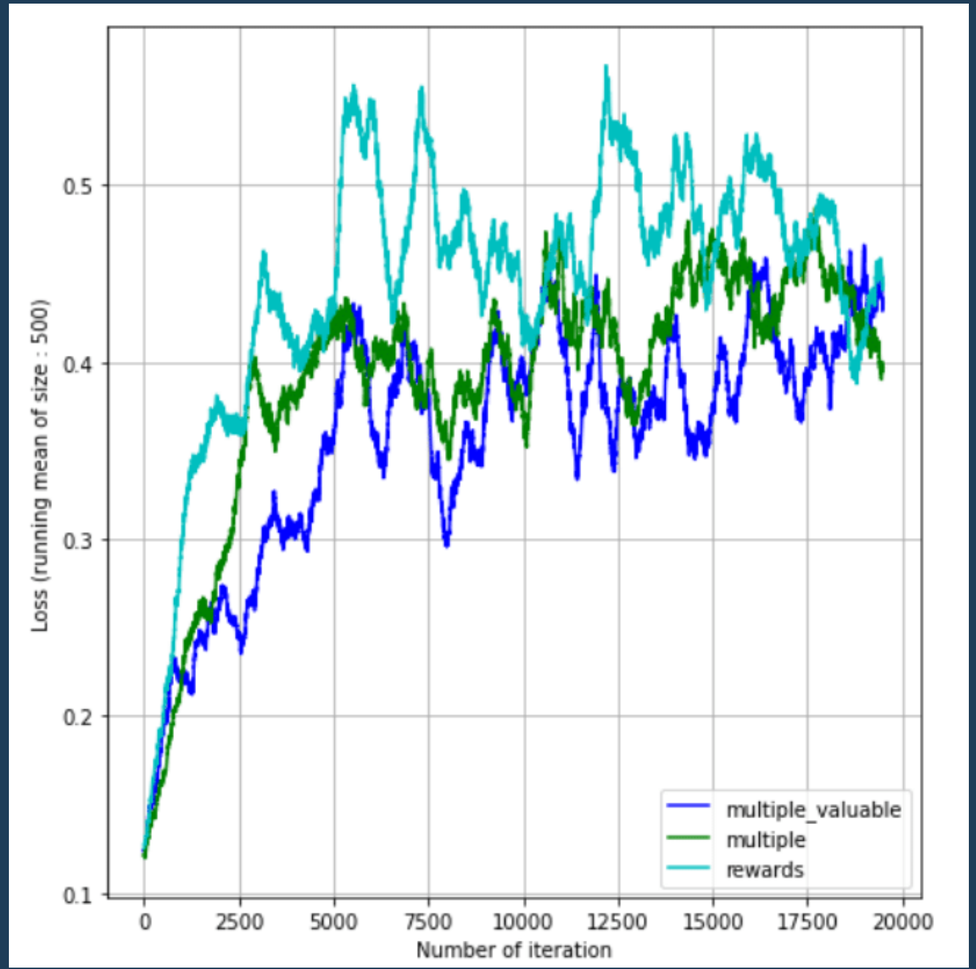
DOUBLE Q-LEARNING



Gamma = 0.9

Loss

DOUBLE Q-LEARNING



Gamma = 0.9

Limits & Conclusions

Limits & Conclusions

STILL TABULAR METHODS

It doesn't approximate enough, due to state representation

DOUBLE Q-LEARNING BETTER

The fact that the target is different from the prediction makes things better

REWARDS PER EPISODE

Still less than the Q-learning algorithm

CONVERGES FASTER

Deep Q-learning and Double Q-learning converges much faster

ADDITIONAL READING

COMPLETE REPORT

https://github.com/clementbernardd/network_friendly/blob/master/FinalReport/ReinforcementLearningFinalReport.pdf

OUR CODE IN GITHUB

https://github.com/clementbernardd/network_friendly

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