

COMP6065 – Artificial Intelligence (L5AC)

Final Project Report

Thedy Dinata - 1901531054

Table of Contents

Ι.	Introduction		
II.	Solution Features		
III.	Solution Design Architecture2		
IV.		Program Manual	
	A. Code Snippets2		
	B.	Training & Results	6
	1.	5000 Training – 10 Games	6
	2.	5000 Training – 100 Games	7
	3.	5000 Training – 1000 Games	7
	4.	10000 Training – 10 Games	7
	5.	10000 Training – 100 Games	8
	6.	10000 Training – 1000 Games	8
٧.	Con	Conclusion	
\ /I	Dibliography		

Ι. Introduction

> Since long ago, the interests of games bots have gained lot of attention, especially after Google DeepMind, Alphabet Inc. created AlphaGo, a robot that are capable of

learning and even beating Pro Go player.

This project is a basic learning of what machine learning are capable of for games, for

this project I specially choose Pacman. This program is called Automated Pacman. Based on learning, the pacman will learn and train of best possible move for him to

get the win.

This project is a project that I based on tutorial from Berkeley UC.

11. Solution Features

Automated Pacman uses Reinforcement Learning or QLearning. The model is

made by using Tkinter, python's de-facto standard GUI, and python version 2.x(tested

on python 2.7).

Solution Design Architecture III.

To build this Automated Pacman, I am using Python programming language version

2.7 and Tkinter(python packages). For the machine learning I'm using QLearning, a model-free reinforcement learning technique that can be used to find an optimal

action-selection policy for Markov Decision Process.

The specification of the hardware used to train this program is:

CPU: Intel® Core™ i7-4720HQ

CPU

2.60Ghz

2.59 GHZ

RAM: 12.0 GB

GPU: NVIDIA GeForce GTX 950M

IV. **Program Manual**

A. Code Snippets

Train function

2

```
class QLearningAgent(ReinforcementAgent):
  def __init__(self, **args):
   "You can initialize Q-values here..."
     ReinforcementAgent.__init__(self, **args)
     "*** YOUR CODE HERE ***"
    self.qValues = util.Counter()
print "ALPHA", self.alpha
print "DISCOUNT", self.discount
print "EXPLORATION", self.epsilon
  def getQValue(self, state, action):
     "*** YOUR CODE HERE ***"
    return self.qValues[(state, action)]
  def getValue(self, state):
```

```
"*** YOUR CODE HERE ***"
  possibleStateQValues = util.Counter()
  for action in self.getLegalActions(state):
      possibleStateQValues[action] = self.getQValue(state, action)
  return possibleStateQValues[possibleStateQValues.argMax()]
def getPolicy(self, state):
  "*** YOUR CODE HERE ***"
  possibleStateQValues = util.Counter()
possibleActions = self.getLegalActions(state)
  if len(possibleActions) == 0:
  for action in possibleActions:
      possibleStateQValues[action] = self.getQValue(state, action)
  if possibleStateQValues.totalCount() == 0:
      return random.choice(possibleActions)
      return possibleStateQValues.argMax()
def getAction(self, state):
  legalActions = self.getLegalActions(state)
  action = None
  "*** YOUR CODE HERE ***"
  if len(legalActions) > 0:
    if util.flipCoin(self.epsilon):
         action = random.choice(legalActions)
```

```
return action = self.getPolicy(state)

return action

def update(self, state, action, nextState, reward):

"""

The parent class calls this to observe a state = action => nextState and reward transition.

You should do your Q-Value update here

NOTE: You should never call this function,

it will be called on your behalf

"""

"""

"""

"""

"YOUR CODE HERE ****

print "State: ", state, ", Action: ", action, ", NextState: ", nextState, print "State: ", state, ", Action: ", action) = print "VALUE", self.getQValue(state, action)

print "VALUE", self.getValue(nextState)

self.qvalues((state, action)] = self.getQValue(state, action) + self.alpha = self.getQvalue(state, action) + sel
                                                                                                                                                             action = self.getPolicy(state)
                                                                                       ""** YOUR CODE HERE ***"

print "State: ", state, ", Action: ", action, ", NextState: ", nextState, ", Reward: ", reward

print "QVALUE", self.getQValue(state, action)

print "VALUE", self.getValue(nextState)

self.qValues[(state, action)] = self.getQValue(state, action) + self.alpha * (reward + self.discount * self.getValue(nextState) - self.getQValue(state, action))
                    147
```

```
action = QLearningAgent.getAction(self, state)
self.doAction(state, action)
return action
```

B. Training & Results

1. 5000 Training – 10 Games

```
Reinforcement Learning Status:
Completed 4600 out of 5000 training episodes
Average Rewards over all training: 1094.36
Average Rewards for last 100 episodes: 1038.84
Episode took 43.37 seconds
Reinforcement Learning Status:
Completed 4700 out of 5000 training episodes
                      Average Rewards over all training: 1093.07
Average Rewards for last 100 episodes: 1033.50
Episode took 43.45 seconds
Reinforcement Learning Status:
Completed 4800 out of 5000 training episodes
                      Average Rewards over all training: 1090.88
Average Rewards for last 100 episodes: 988.05
Episode took 45.06 seconds
Reinforcement Learning Status:
Completed 4900 out of 5000 training episodes
Completed 4900 out of 5000 training episodes
Average Rewards over all training: 1093.52
Average Rewards for last 100 episodes: 1220.50
Episode took 47.76 seconds
Reinforcement Learning Status:
Completed 5000 out of 5000 training episodes
Average Rewards over all training: 1091.85
Average Rewards for last 100 episodes: 1009.59
Episode took 43.05 seconds
Training Done (turning off epsilon and alpha)
Pacman emerges victorious! Score: 1924
Pacman emerges victorious! Score: 1543
                                                                                            1543
1524
 Pacman emerges victorious! Score:
Pacman emerges victorious! Score: 1710
Pacman emerges victorious! Score: 1528
Pacman emerges victorious! Score: 1731
Pacman emerges victorious! Score: 1731
Pacman emerges victorious! Score: 1929
Pacman emerges victorious! Score: 1531
Pacman emerges victorious! Score: 1323
Pacman emerges victorious! Score: 1729
Average Score: 1647.2
Scores: 1924, 1543, 1524, 1710, 1528, 1731, 1929, 1531, 1323, 1729
Win Rate: 10/10 (1.00)
 Record:
```

2. 5000 Training – 100 Games

3. 5000 Training – 1000 Games

4. 10000 Training – 10 Games

```
Reinforcement Learning Status:
Completed 9600 out of 10000 training episodes
Average Rewards over all training: 1108.10
Average Rewards for last 100 episodes: 1051.09
Episode took 42.16 seconds
Reinforcement Learning Status:
Completed 9700 out of 10000 training episodes
                   Average Rewards over all training: 1106.60
Average Rewards for last 100 episodes: 963.19
Episode took 40.71 seconds
 Reinforcement Learning Status:
Completed 9800 out of 10000 training episodes
                   Average Rewards over all training: 1106.79
Average Rewards for last 100 episodes: 1124.78
Episode took 46.56 seconds
Reinforcement Learning Status:

Completed 9900 out of 10000 training episodes

Average Rewards over all training: 1106.04

Average Rewards for last 100 episodes: 1032.78

Episode took 43.63 seconds
 Reinforcement Learning Status:
Completed 10000 out of 10000 training episodes
                   Average Rewards over all training: 1105.50
Average Rewards for last 100 episodes: 1052.09
Episode took 42.53 seconds
 Training Done (turning off epsilon and alpha)
Pacman emerges victorious! Score: 1521
Pacman emerges victorious! Score: 1332
Pacman emerges victorious! Score: 1734
Pacman emerges victorious! Score: 1732
Pacman emerges victorious! Score: 1531
Pacman emerges victorious! Score: 1314
Pacman emerges victorious! Score: 1531
Pacman emerges victorious! Score: 1526
Pacman emerges victorious! Score: 1337
Pacman emerges victorious! Score: 1724

Average Score: 1528.2

Scores: 1521, 1332, 1734, 1732, 1531, 1314, 1531, 1526, 1337, 1724

Win Rate: 10/10 (1.00)
                                   Record:
```

5. 10000 Training – 100 Games

6. 10000 Training - 1000 Games

V. Conclusion

In conclusion, training time, code optimization, and the size of the games played are several major factors in optimizing and maximizing the win rate. Even though the size of the learning is quite high, if the code is not optimized and the number of games played is short, the win rate of the game will be affected.

VI. Bibliography

Tutorial Website

http://ai.berkeley.edu/project overview.html

Development Tools

https://www.python.org/download/releases/2.7/