SE 4050 – Deep Learning

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Lab Assignment 3

Lasal Sandeepa Hettiarachchi

IT19132310

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Department of Computer Science and Software Engineering

Sri Lanka Institute of Information Technology
Sri Lanka

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1. MODEL-BASED ALGORITHMS (VALUE ITERATION APPROACH)

Model-based algorithms require a model of the environment in that it incoperates the knowledge of the transition process from one state to another.

1.1 valueIterationAgents.py

```
2
    # Write value iteration code here
3
         "*** YOUR CODE HERE ***"
4
5
         for _ in range(iterations):
6
            current_values = self.values.copy() #Getting a copy of the
7
            states = self.mdp.getStates()
8
            for state in states: # iterating through each state
9
              if self.mdp.isTerminal(state):
10
                 continue
11
              # get value for best possible action for changing state
12
              actions = self.mdp.getPossibleActions(state)
13
              val_arr = []
14
              for a in actions:
                 val_arr.append(self.getQValue(state, a))
15
16
              best_value = max(val_arr)
17
              current_values[state] = best_value
18
19
            self.values = current_values
  def computeQValueFromValues(self, state, action):
      Compute the Q-value of action in state from the
      value function stored in self.values.
     "*** YOUR CODE HERE ***"
     qValue = 0
     # go through every possible outcome of the action
     t_state_probs = self.mdp.getTransitionStatesAndProbs(state, action)
     for nextState, probability in t_state_probs:
       # add reward & future reward (=V) * probability of the outcome
```

```
reward = self.mdp.getReward(state, action, nextState)
       discount = self.discount
       val = self.values[nextState]
       qValue = qValue + probability * (reward + discount * val)
     return qValue
     util.raiseNotDefined()
def computeActionFromValues(self, state):
      The policy is the best action in the given state
      according to the values currently stored in self.values.
      You may break ties any way you see fit. Note that if
      there are no legal actions, which is the case at the
      terminal state, you should return None.
     "*** YOUR CODE HERE ***"
     # retreive the best possible action for the state
     policies = util.Counter()
     pos_actions = self.mdp.getPossibleActions(state)
     for action in pos_actions:
       # how good is an action = q-value (which considers all possible outcomes)
       policies[action] = self.getQValue(state, action)
     # return the best action, e.g. 'north'
     return policies.argMax()
     util.raiseNotDefined()
1.2 analysis.py
2
    def question2():
       answerDiscount = 0.9
3
       answerNoise = 0
4
5
       return answerDiscount, answerNoise
6
7
    def question3a():
```

```
8
      answerDiscount = 0.1
9
      answerNoise = 0
10
      answerLivingReward = 0.7 # give a negative penalty for moving
11
      return answerDiscount, answerNoise, answerLivingReward
12
13 def question3b():
14
      answerDiscount = 0.1
15
      answerNoise = 0.1
16
      answerLivingReward = 0.7
17
      return answerDiscount, answerNoise, answerLivingReward
18
19 def question3c():
20
      answerDiscount = 0.5
21
      answerNoise = 0
22
      answerLivingReward = 0.5
23
      return answerDiscount, answerNoise, answerLivingReward
24
25 def question3d():
26
      answerDiscount = 0.9
27
      answerNoise = 0.1
28
      answerLivingReward = 0.2
29
      return answerDiscount, answerNoise, answerLivingReward
30
31 def question3e():
32
      answerDiscount = 0
33
      answerNoise = 0
34
      answerLivingReward = 0
35
      return answerDiscount, answerNoise, answerLivingReward
36
37 def question6():
38
      answerEpsilon = None
39
      answerLearningRate = None
40
      # return answerEpsilon, answerLearningRate
      # If not possible, return 'NOT POSSIBLE'
41
42
      return 'NOT POSSIBLE'
43
44 if __name__ == '__main__':
45
      print 'Answers to analysis questions:'
46
      import analysis
47
      for q in [q for q in dir(analysis) if q.startswith('question')]:
```

```
48 response = getattr(analysis, q)()
49 print ' Question %s:\t%s' % (q, str(response))
```

2. MODEL-FREE ALGORITHMS (Q-LEARNING)

In reinforcement learning, a model-free algorithm is an algorithm which does not use the transition probability distribution associated

2.1 qlearningAgents.py

33

Instance variables you have access to

```
3
    # qlearningAgents.py
4
    # Licensing Information: You are free to use or extend these projects for
6
   # educational purposes provided that (1) you do not distribute or publish
7
    # solutions, (2) you retain this notice, and (3) you provide clear
   # attribution to UC Berkeley, including a link to http://ai.berkeley.edu.
8
9
10 # Attribution Information: The Pacman AI projects were developed at UC Berkeley.
11 # The core projects and autograders were primarily created by John DeNero
12 # (denero@cs.berkeley.edu) and Dan Klein (klein@cs.berkeley.edu).
13 # Student side autograding was added by Brad Miller, Nick Hay, and
14 # Pieter Abbeel (pabbeel@cs.berkeley.edu).
15
16 from game import *
17 from learningAgents import ReinforcementAgent
18 from featureExtractors import *
19
20 import random, util, math
21
22 class QLearningAgent(ReinforcementAgent):
23
24
       Q-Learning Agent
25
26
        Functions you should fill in:
27
         - computeValueFromQValues
28
         - computeActionFromQValues
29
         - getQValue
30
         - getAction
31
         - update
32
```

```
34
         - self.epsilon (exploration prob)
35
         - self.alpha (learning rate)
36
         - self.discount (discount rate)
37
38
        Functions you should use
39
         - self.getLegalActions(state)
40
           which returns legal actions for a state
41
42
       def __init__(self, **args):
43
         "You can initialize Q-values here..."
44
         ReinforcementAgent.__init__(self, **args)
45
         "*** YOUR CODE HERE ***"
46
47
         self.values = util.Counter()
48
49
       def getQValue(self, state, action):
50
51
           Returns Q(state, action)
52
          Should return 0.0 if we have never seen a state
53
          or the Q node value otherwise
54
         "*** YOUR CODE HERE ***"
55
56
         return self.values[(state, action)]
         util.raiseNotDefined()
57
58
59
       def computeValueFromQValues(self, state):
60
           Returns max_action Q(state,action)
61
62
          where the max is over legal actions. Note that if
63
          there are no legal actions, which is the case at the
64
          terminal state, you should return a value of 0.0.
65
         "*** YOUR CODE HERE ***"
66
67
         maxQ = float('-inf')
         for action in self.getLegalActions(state):
68
69
            maxQ = max(maxQ, self.getQValue(state, action))
70
         return maxQ if maxQ != float('-inf') else 0.0
71
         util.raiseNotDefined()
72
73
       def computeActionFromQValues(self, state):
```

```
74
75
           Compute the best action to take in a state. Note that if there
76
           are no legal actions, which is the case at the terminal state,
77
          you should return None.
78
79
         "*** YOUR CODE HERE ***"
80
         if len(self.getLegalActions(state)) == 0:
81
            return None
82
83
         bestQ = self.computeValueFromQValues(state)
84
         bestActions = []
85
         for action in self.getLegalActions(state):
86
            if bestQ == self.getQValue(state, action):
87
              bestActions.append(action)
88
89
         return random.choice(bestActions)
90
         util.raiseNotDefined()
91
92
       def getAction(self, state):
93
94
           Compute the action to take in the current state. With
95
           probability self.epsilon, we should take a random action and
96
           take the best policy action otherwise. Note that if there are
97
           no legal actions, which is the case at the terminal state, you
98
           should choose None as the action.
99
100
          HINT: You might want to use util.flipCoin(prob)
101
          HINT: To pick randomly from a list, use random.choice(list)
102
103
         # Pick Action
104
         legalActions = self.getLegalActions(state)
         action = None
105
         "*** YOUR CODE HERE ***"
106
107
         if util.flipCoin(self.epsilon):
108
            action = random.choice(legalActions)
109
         else:
            action = self.computeActionFromQValues(state)
110
111
112
         return action
113
         util.raiseNotDefined()
```

```
114
115
      def update(self, state, action, nextState, reward):
116
117
          The parent class calls this to observe a
118
          state = action => nextState and reward transition.
119
          You should do your Q-Value update here
120
121
          NOTE: You should never call this function,
122
          it will be called on your behalf
123
         "*** YOUR CODE HERE ***"
124
         oldValue = self.values[(state, action)]
125
126
         newValue = reward + (self.discount * self.computeValueFromQValues(nextState))
127
128
         self.values[(state, action)] = (1 - self.alpha) * oldValue + self.alpha * newValue
         #util.raiseNotDefined()
129
130
      def getPolicy(self, state):
131
132
         return self.computeActionFromQValues(state)
133
134
      def getValue(self, state):
135
         return self.computeValueFromQValues(state)
136
137 class PacmanQAgent(QLearningAgent):
138
      "Exactly the same as QLearningAgent, but with different default parameters"
139
140
      def __init__(self, epsilon=0.05,gamma=0.8,alpha=0.2, numTraining=0, **args):
141
142
         These default parameters can be changed from the pacman.py command line.
143
         For example, to change the exploration rate, try:
144
           python pacman.py -p PacmanQLearningAgent -a epsilon=0.1
145
146
         alpha - learning rate
147
         epsilon - exploration rate
148
         gamma - discount factor
149
         numTraining - number of training episodes, i.e. no learning after these many episodes
150
151
         args['epsilon'] = epsilon
         args['gamma'] = gamma
152
153
         args['alpha'] = alpha
```

```
154
         args['numTraining'] = numTraining
155
         self.index = 0 # This is always Pacman
156
         QLearningAgent.__init__(self, **args)
157
158
      def getAction(self, state):
159
160
         Simply calls the getAction method of QLearningAgent and then
161
         informs parent of action for Pacman. Do not change or remove this
162
         method.
163
164
         action = QLearningAgent.getAction(self,state)
165
         self.doAction(state,action)
166
         return action
167
168 class ApproximateQAgent(PacmanQAgent):
      .....
169
170
        ApproximateQLearningAgent
171
172
        You should only have to overwrite getQValue
173
        and update. All other QLearningAgent functions
174
        should work as is.
175
176
      def __init__(self, extractor='IdentityExtractor', **args):
177
         self.featExtractor = util.lookup(extractor, globals())()
178
         PacmanQAgent.__init__(self, **args)
179
         self.weights = util.Counter()
180
181
      def getWeights(self):
182
         return self.weights
183
184
      def getQValue(self, state, action):
185
186
          Should return Q(state,action) = w * featureVector
187
          where * is the dotProduct operator
188
         "*** YOUR CODE HERE ***"
189
190
         features = self.featExtractor.getFeatures(state, action)
191
192
         sum = 0
193
         for feature, value in features.iteritems():
```

```
194
            sum += self.weights[feature] * value
195
         return
         util.raiseNotDefined()
196
197
198
       def update(self, state, action, nextState, reward):
199
200
           Should update your weights based on transition
201
         "*** YOUR CODE HERE ***"
202
203
         newValue = reward + self.discount * self.computeValueFromQValues(nextState)
204
         oldValue = self.getQValue(state, action)
205
         difference = newValue - oldValue
206
207
         features = self.featExtractor.getFeatures(state, action)
208
         for feature, value in features.iteritems():
209
          self.weights[feature] += self.alpha * difference * features[feature]
210
         #util.raiseNotDefined()
211
212
       def final(self, state):
213
         "Called at the end of each game."
214
         # call the super-class final method
215
         PacmanQAgent.final(self, state)
216
217
         # did we finish training?
218
         if self.episodesSoFar == self.numTraining:
219
            # you might want to print your weights here for debugging
            "*** YOUR CODE HERE ***"
220
221
            pass
222
```

3. AUTOGRADER TOOL RESULTS

3.1 Question 1

3.2 Question 2

3.3 Question 3

3.4 Question 4

3.5 Question 5

3.6 Question 6

3.7 Question 7

```
Average Score: 500.2
Scores: 495.0, 499.0, 503.0, 503.0, 503.0, 503.0, 503.0, 503.0, 503.0, 503.0, 503.0, 503.0, 503.0, 503.0, 503.0, 495.0, 503.0, 495.0, 503.0, 495.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 503.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 499.0, 4
```

4. APPENDIX



