NAGARJUNA COLLEGE OF ENGINEERING AND TECHNOLOGY (An Autonomous College under VTU) VenkatagiriKote post, Devanahalli, Bengaluru-562164



Department of CSE (AIML)

Fundamentals of Machine Learning - LABORATORY MANUAL 21CII43

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Course Objectives:

This course will enable students to:

- Understand the basic concepts of machine learning
- Understand the well posed learning techniques.
- Understand decision tree algorithms
- Learn Artificial Neural Networks with multilayer perceptron's.
- Understand Reinforcement learning concept

Course Outcomes:

At the end of the course, students should be able to

- Analyze the models using PAC framework, Rademacher complexity and VC Dimension.
- Solve the problems using support vector machines with suitable kernel models.
- Apply dimensionality reduction methods and reinforcement algorithms to solve the problems
- Implement the suitable regression and boosting algorithms based on the applications.
- Solve multiclass problems and evaluate with various ranking techniques.

Text Books:

- Foundations of machine learning, Mehryar Mohri, Afshin Rostamizadeh, and Ameet Talwalkar.
- Understanding machine learning, Shai Shalev-Shwartz and Shai Ben-David

Reference Books:

- 1. Introduction to Artificial Neural Systems-J.M. Zurada, Jaico Publications 1994.
- 2. Artificial Neural Networks-B. Yegnanarayana, PHI, New Delhi 1998.

LIST OF EXPERIMENTS		
S.No	Title	
1	Design a Simple 3 class dataset with 30 records and the features are represented in 4 columns. Apply rule based classification method to predict the classes in python.	
2	Extract the input and output data from the CSV file using python and split the training and testing data in the ratio of 70:30	
3	Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples. Read the training data from a .CSV file.	
4	For a given set of training data examples stored in a .CSV file, implement and demonstrate the Candidate-Elimination algorithm to output a description of the set of all hypotheses consistent with the training examples.	
5	Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.	
6	Write a python program to demonstrate the working of C4.5 algorithm using a dataset for building the decision tree and validate it.	
7	Build an Artificial neural network for identifying the classes of IRIS dataset and validate the results using confusion matrix in python	
8	Design a back propagation algorithm to predict the class of the input data for a medical problem with multiple classes.	
9	Consider an undirected graph with 8 points from 0 to 7, 0 ->1, 1 ->5, 1->2, 5->4, 5->6, 2->3 and 2->7. The bot is in position 0 and needs to position 7. Design a q-learning model to help the bot to reach the position 7	
10	Design a qlearning based model to help the humanoid bot to reach village near the river. If it finds the desert, it is in wrong direction. The map is represented in an undirected graph as 0->1, 1->5, 5->6, 5->4, 1->2, 2->3 and 2->7, 7->8, 8->9. The bot current position is 0, the river is located in position 2 and the village is in 7. The position 4, 5, 6, 8 and 9 has the desert.	

Design a Simple 3 class dataset with 30 records and the features are represented in 4 columns. Apply rule based classification method to predict the classes in python.

Program

```
import pandas as pd
df = pd.read_csv("Ex1.csv")
#print(df.to_string())
display(df.iloc[1])
for i in range (30):
 if df["Color"].iloc[i] == "White" or "Black" or "BW":
  if df["Sound"].iloc[i] > 79 and df["Sound"].iloc[i] < 101:
   if df["Tail Length"].iloc[i] > 0.6:
    if df["Height"].iloc[i] > 2.9:
      print("Horse")
 if df["Color"].iloc[i] == "White" or "Black" or "BW" or "Brown" or "BBrW":
  if df["Sound"].iloc[i] < 71:
   if df["Tail Length"].iloc[i] < 0.4:
    if df["Height"].iloc[i] < 1:
      print("Cat")
 if df["Color"].iloc[i] == "White" or "Black" or "BW" or "Brown" or "BBrW":
  if df["Sound"].iloc[i] > 100:
   if df["Tail Length"].iloc[i] > 0.4 and df["Tail Length"].iloc[i] < 0.7:
    if df["Height"].iloc[i] > 1 and df["Height"].iloc[i] < 2:
      print("Dog")
```

001101	
Horse	Cat
Horse	Dog
Cat	Dog
Cat	_
Cat	
Cat	
Cat	
Cat	

Extract the input and output data from the CSV file using python and split the training and testing data in the ratio of 70:30

```
import pandas as pd
df = pd.read_csv("Ex1.csv")
from sklearn.model_selection import train_test_split
Features=["Color", "Sound", "Tail Length", "Height"]
X=df.loc[:, Features]
Y=df.loc[:,['Class']]
X_train, X_test, y_train, y_test = train_test_split(X,Y, random_state=104, test_size=0.25, shuffle=True)

print(X_train.head())
print(X_test.head())
print(y_test.head())
```

```
Output
  Color Sound Tail Length Height
17 Black
          55
                 0.2
                      0.5
18 White
          63
                 0.3
                      0.4
9 Black 100
                 1.0
                      3.0
19 Brown
           73
                  0.2 0.2
32 BrW 115
                  0.6 1.5
  Color Sound Tail Length Height
11 Black
          50
                 0.2
                      0.6
30 White 134
                  0.6 1.4
10
    BW
          45
                 0.3
                      0.9
31 Brown
          128
                  0.5 1.3
22 BW
         120
                 0.5
                      1.2
 Class
17 Cat
18 Cat
9 Horse
19 Cat
32 Dog
 Class
11 Cat
30 Dog
10 Cat
31 Dog
22 Dog
```

Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples. Read the training data from a .CSV file.

Program

```
import pandas as pd
import numpy as np
d = pd.read_csv("Tennis.csv")
a = np.array(d)[:,:-1]
print(" The attributes are: ",a)
t = np.array(d)[:,-1]
print("The target is: ",t)
def train(c,t):
for i, val in enumerate(t):
 if val == "Yes":
 specific_hypothesis = c[i].copy()
for i, val in enumerate(c):
 if t[i] == "Yes":
 for x in range(len(specific hypothesis)):
  if val[x] != specific_hypothesis[x]:
   specific hypothesis[x] = '?'
  else:
   pass
 return specific hypothesis
print(" The final hypothesis is:",train(a,t))
```

Output

```
The attributes are: [['Sunny' 'Hot' 'High' 'Weak']
['Sunny' 'Hot' 'High' 'Strong']
['Overcast' 'Hot' 'High' 'Weak']
['Rain' 'Mild' 'High' 'Weak']
['Rain' 'Cool' 'Normal' 'Weak']
['Rain' 'Cool' 'Normal' 'Strong']
['Overcast' 'Cool' 'Normal' 'Strong']
['Sunny' 'Mild' 'High' 'Weak']
['Sunny' 'Cool' 'Normal' 'Weak']
['Rain' 'Mild' 'Normal' 'Weak']
['Sunny' 'Mild' 'Normal' 'Strong']
['Overcast' 'Mild' 'High' 'Strong']
['Overcast' 'Hot' 'Normal' 'Weak']
['Rain' 'Mild' 'High' 'Strong']]
The target is: ['No' 'No' 'Yes' 'Yes' 'Yes' 'No' 'Yes' 'No' 'Yes' 'Yes' 'Yes' 'Yes' 'Yes' 'No']
The final hypothesis is: ['Overcast' 'Hot' '?' 'Weak']
```

For a given set of training data examples stored in a .CSV file, implement and demonstrate the Candidate-Elimination algorithm to output a description of the set of all hypotheses consistent with the training examples.

```
import csv
# open the CSVFile and keep all rows as list of tuples
with open('EnjoySport.csv') as csvFile:
  examples = [tuple(line) for line in csv.reader(csvFile)]
print(examples)
# To obtain the domain of attribute values defined in the instances X
def get_domains(examples):
  # set function returns the unordered collection of items with no duplicates
  d = [set() \text{ for i in examples}[0]]
  for x in examples:
     #Enumerate() function adds a counter to an iterable and returns it in a form of enumerate
object i.e(index,value)
     for i, xi in enumerate(x):
       d[i].add(xi)
  return [list(sorted(x)) for x in d]
# Test the get_domains function
get_domains(examples)
# Repeat the '?' and '0' length of domain no of times
def g_0(n):
  return ('?',)*n
def s_0(n):
  return ('0',)*n
# Function to check generality between two hypothesis
def more_general(h1, h2):
  more_general_parts = []
  for x, y in zip(h1, h2):
     mg = x == '?' \text{ or } (x != '0' \text{ and } (x == y \text{ or } y == '0'))
     more_general_parts.append(mg)
  return all(more_general_parts) # Returns true if all elements of list or tuple are true
# Function to check whether train examples are consistent with hypothesis
def consistent(hypothesis,example):
  return more_general(hypothesis, example)
# Function to add min_generalizations
```

```
def min_generalizations(h, x):
  h_new = list(h)
  for i in range(len(h)):
     if not consistent(h[i:i+1],x[i:i+1]):
       if h[i] != '0':
          h_{new[i]} = '?'
       else:
          h_new[i] = x[i]
  return [tuple(h_new)]
# Function to generalize Specific hypto
def generalize_S(x, G, S):
  S_prev = list(S)
  for s in S_prev:
    if s not in S:
       continue
    if not consistent(s,x):
       S.remove(s)
       Splus = min\_generalizations(s, x)
       # Keep only generalizations that have a counterpart in G
       S.update([h for h in Splus if any([more_general(g,h)
                              for g in G])])
       # Remove from S any hypothesis more general than any other hypothesis in S
       S.difference_update([h for h in S if
                     any([more general(h, h1)
                        for h1 in S if h != h1])])
  return S
# Function to add min specializations
def min_specializations(h, domains, x):
  results = []
  for i in range(len(h)):
     if h[i] == '?':
       for val in domains[i]:
          if x[i] != val:
            h_new = h[:i] + (val_i) + h[i+1:]
            results.append(h_new)
     elif h[i] != '0':
       h_new = h[:i] + ('0',) + h[i+1:]
       results.append(h_new)
  return results
# Function to specialize General hypotheses boundary
def specialize_G(x, domains, G, S):
```

```
G_{prev} = list(G)
  for g in G_prev:
     if g not in G:
        continue
     if consistent(g,x):
        G.remove(g)
        Gminus = min\_specializations(g, domains, x)
        # Keep only specializations that have a counterpart in S
        G.update([h for h in Gminus if any([more_general(h, s)
                                for s in S1)1)
        # Remove hypothesis less general than any other hypothesis in G
        G.difference_update([h for h in G if
                      any([more general(g1, h)
                         for g1 in G if h != g1])])
  return G
# Function to perform CandidateElimination
def candidate_elimination(examples):
  domains = get_domains(examples)[:-1]
  G = set([g_0(len(domains))])
  S = set([s_0(len(domains))])
  i=0
  print('All the hypotheses in General and Specific boundary are:\n')
  print(\n G[\{0\}]:'.format(i),G)
  print(\n S[\{0\}]:'.format(i),S)
  for xcx in examples:
     i=i+1
     x, cx = xcx[:-1], xcx[-1] # Splitting data into attributes and decisions
     if cx=='Yes': # x is positive example
        G = \{g \text{ for } g \text{ in } G \text{ if } consistent(g,x)\}\
        S = generalize S(x, G, S)
     else: # x is negative example
        S = \{s \text{ for } s \text{ in } S \text{ if not consistent}(s,x)\}\
        G = specialize\_G(x, domains, G, S)
     print('\setminus G[\{0\}]:'.format(i),G)
     print(\n S[\{0\}]:'.format(i),S)
  return
candidate_elimination(examples)
```

Output

[('Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same', 'Yes'), ('Sunny', 'Warm', 'High', 'Strong', 'Warm', 'Same', 'Yes'), ('Rainy', 'Cold', 'High', 'Strong', 'Warm', 'Change', 'No'), ('Sunny', 'Warm', 'High', 'Strong', 'Cool', 'Change', 'Yes')]

All the hypotheses in General and Specific boundary are:

Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.

Program

Simple Decision Tree implementation

```
# Load libraries
import pandas as pd
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree Classifier
from sklearn.model_selection import train_test_split # Import train_test_split function
from sklearn import metrics #Import scikit-learn metrics module for accuracy calculation
col_names = ['pregnant', 'glucose', 'bp', 'skin', 'insulin', 'bmi', 'pedigree', 'age', 'label']
# load dataset
pima = pd.read_csv("diabetes.csv", header=None, names=col_names)
#split dataset in features and target variable
feature_cols = ['pregnant', 'insulin', 'bmi', 'age', 'glucose', 'bp', 'pedigree']
X = pima[feature_cols] # Features
y = pima.label # Target variable
# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1) # 70%
training and 30% test
# Create Decision Tree classifer object
clf = DecisionTreeClassifier()
# Train Decision Tree Classifer
clf = clf.fit(X train,y train)
#Predict the response for test dataset
y_pred = clf.predict(X_test)
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

Output

Accuracy: 0.666666666

Write a python program to demonstrate the working of C4.5 algorithm using a dataset for building the decision tree and validate it.

Program

DT using Gini function

```
import numpy as np
import pandas as pd
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
# Function importing Dataset
def importdata():
  balance_data = pd.read_csv(
'https://archive.ics.uci.edu/ml/machine-learning-'+
'databases/balance-scale/balance-scale.data',
  sep=',', header = None
  # Printing the dataswet shape
  print ("Dataset Length: ", len(balance_data))
  print ("Dataset Shape: ", balance_data.shape)
  # Printing the dataset obseravtions
  print ("Dataset: ",balance_data.head())
  return balance data
# Function to split the dataset
def splitdataset(balance_data):
  # Separating the target variable
  X = balance_data.values[:, 1:5]
  Y = balance_data.values[:, 0]
  # Splitting the dataset into train and test
  X train, X test, y train, y test = train test split(
  X, Y, test\_size = 0.3, random\_state = 100)
  return X, Y, X_train, X_test, y_train, y_test
```

```
# Function to perform training with giniIndex.
def train_using_gini(X_train, X_test, y_train):
  # Creating the classifier object
  clf_gini = DecisionTreeClassifier(criterion = "gini",
       random state = 100,max depth=3, min samples leaf=5)
  # Performing training
  clf_gini.fit(X_train, y_train)
  return clf_gini
# Function to perform training with entropy.
def tarin_using_entropy(X_train, X_test, y_train):
  # Decision tree with entropy
  clf_entropy = DecisionTreeClassifier(
       criterion = "entropy", random_state = 100,
       max_depth = 3, min_samples_leaf = 5)
  # Performing training
  clf_entropy.fit(X_train, y_train)
  return clf_entropy
# Function to make predictions
def prediction(X_test, clf_object):
  # Predicton on test with giniIndex
  y_pred = clf_object.predict(X_test)
  print("Predicted values:")
  print(y_pred)
  return y_pred
# Function to calculate accuracy
def cal_accuracy(y_test, y_pred):
  print("Confusion Matrix: ",
     confusion_matrix(y_test, y_pred))
  print ("Accuracy : ",
  accuracy_score(y_test,y_pred)*100)
  print("Report : ",
  classification report(y test, y pred))
```

```
# Driver code
def main():
  # Building Phase
  data = importdata()
  X, Y, X_train, X_test, y_train, y_test = splitdataset(data)
  clf_gini = train_using_gini(X_train, X_test, y_train)
  clf_entropy = tarin_using_entropy(X_train, X_test, y_train)
  # Operational Phase
  print("Results Using Gini Index:")
  # Prediction using gini
  y_pred_gini = prediction(X_test, clf_gini)
  cal_accuracy(y_test, y_pred_gini)
  print("Results Using Entropy:")
  # Prediction using entropy
  y_pred_entropy = prediction(X_test, clf_entropy)
  cal_accuracy(y_test, y_pred_entropy)
# Calling main function
if __name__=="__main___":
main()
```

```
'L' 'R' 'R' 'L' 'L' 'R' 'R' 'R']
Confusion Matrix: [[ 0 6 7]
[ 0 67 18]
[ 0 19 71]]
Accuracy: 73.40425531914893
Report:
          precision recall f1-score support
    В
       0.00
            0.00
                 0.00
                       13
    L
       0.73
            0.79
                 0.76
                       85
    R
       0.74
            0.79
                 0.76
                       90
                 0.73
                      188
 accuracy
 macro avg
          0.49
               0.53
                    0.51
                         188
weighted avg
               0.73
          0.68
                    0.71
                          188
```

```
Results Using Entropy:
Predicted values:
'R' 'R' 'L' 'L' 'L' 'R' 'R' 'R']
Confusion Matrix: [[ 0 6 7]
[ 0 63 22]
[ 0 20 70]]
Accuracy: 70.74468085106383
Report:
      precision recall f1-score support
  В
    0.00
       0.00
          0.00
              13
  L
    0.71
       0.74
          0.72
              85
  R
    0.71
       0.78
          0.74
              90
accuracy
          0.71
             188
macro avg
      0.47
         0.51
           0.49
               188
weighted avg
      0.66
            0.68
               188
         0.71
```

Build an Artificial neural network for identifying the classes of IRIS dataset and validate the results using confusion matrix in python

```
# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn
from sklearn.neural_network import MLPClassifier
from sklearn.neural_network import MLPRegressor
# Import necessary modules
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from math import sqrt
from sklearn.metrics import r2_score
df = pd.read_csv('diabetes.csv')
print(df.shape)
df.describe().transpose()
target column = ['Outcome']
predictors = list(set(list(df.columns))-set(target_column))
df[predictors] = df[predictors]/df[predictors].max()
df.describe().transpose()
X = df[predictors].values
y = df[target_column].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=40)
print(X_train.shape); print(X_test.shape)
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(hidden_layer_sizes=(8,8,8), activation='relu', solver='adam',
max iter=500)
mlp.fit(X_train,y_train)
```

```
predict_train = mlp.predict(X_train)
predict_test = mlp.predict(X_test)
from sklearn.metrics import classification_report,confusion_matrix
print(confusion_matrix(y_train,predict_train))
print(classification report(y train,predict train))
print('Confusion matrix',confusion matrix(y test,predict test))
print(classification_report(y_test,predict_test))
```

```
Output
(768, 9)
(537, 8)
(231, 8)
/usr/local/lib/python3.10/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:1098: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape of y to
(n_samples, ), for example using ravel().
 y = column_or_1d(y, warn=True)
[[318 40]
 [ 70 109]]
        precision recall f1-score support
       0
            0.82
                   0.89
                           0.85
                                    358
       1
            0.73
                   0.61
                           0.66
                                   179
                           0.80
                                   537
  accuracy
  macro avg
                0.78
                        0.75
                               0.76
                                        537
weighted avg
                 0.79
                        0.80
                                0.79
                                        537
Confusion matrix [[123 19]
 [ 39 50]]
        precision recall f1-score support
       0
            0.76
                   0.87
                           0.81
                                    142
       1
            0.72
                   0.56
                           0.63
                                    89
  accuracy
                           0.75
                                   231
                       0.71
  macro avg
                0.74
                               0.72
                                        231
```

weighted avg

0.75

0.75

0.74

231

Design a back propagation algorithm to predict the class of the input data for a medical problem with multiple classes.

Program

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
# reading csv file and extracting class column to y.
x = pd.read_csv("iscxdata2.csv")
a = np.array(x)
X = a[:,1:75]
y = a[:,76] # classes having 0 and 1
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
clf = MLPClassifier(hidden_layer_sizes=(2,7), random_state=5, verbose=True,
learning_rate_init=0.05)
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print(confusion_matrix(y_test,y_pred))
Output
```

[305 11; 15 304]

Consider an undirected graph with 8 points from 0 to 7, 0 ->1, 1 ->5, 1->2, 5->4, 5->6, 2->3 and 2->7. The bot is in position 0 and needs to position 7. Design a q-learning model to help the bot to reach the position 7

```
# -*- coding: utf-8 -*-
Created on Sat Mar 28 12:59:23 2020
Assignment 2 - Agents and Reinforcement Learning
@author: Ronan Murphy - 15397831
import numpy as np
import random
import matplotlib.pyplot as plt
#set the rows and columns length
BOARD ROWS = 5
BOARD\_COLS = 5
#initalise start, win and lose states
START = (0, 0)
WIN\_STATE = (4, 4)
HOLE\_STATE = [(1,0),(3,1),(4,2),(1,3)]
#class state defines the board and decides reward, end and next position
class State:
  def __init__(self, state=START):
    #initalise the state to start and end to false
     self.state = state
    self.isEnd = False
  def getReward(self):
    #give the rewards for each state -5 for loss, +1 for win, -1 for others
    for i in HOLE STATE:
```

```
if self.state == i:
          return -5
     if self.state == WIN_STATE:
       return 1
     else:
       return -1
  def isEndFunc(self):
     #set state to end if win/loss
     if (self.state == WIN_STATE):
       self.isEnd = True
     for i in HOLE_STATE:
       if self.state == i:
          self.isEnd = True
  def nxtPosition(self, action):
     #set the positions from current action - up, down, left, right
     if action == 0:
       nxtState = (self.state[0] - 1, self.state[1]) #up
     elif action == 1:
       nxtState = (self.state[0] + 1, self.state[1]) #down
     elif action == 2:
       nxtState = (self.state[0], self.state[1] - 1) #left
       nxtState = (self.state[0], self.state[1] + 1) #right
     #check if next state is possible
     if (nxtState[0] >= 0) and (nxtState[0] <= 4):
       if (nxtState[1] >= 0) and (nxtState[1] <= 4):
            #if possible change to next state
            return nxtState
     #Return current state if outside grid
     return self.state
#class agent to implement reinforcement learning through grid
class Agent:
  def __init__(self):
```

```
#inialise states and actions
  self.states = []
  self.actions = [0,1,2,3] # up, down, left, right
  self.State = State()
  #set the learning and greedy values
  self.alpha = 0.5
  self.gamma = 0.9
  self.epsilon = 0.1
  self.isEnd = self.State.isEnd
  # array to retain reward values for plot
  self.plot_reward = []
  #initalise Q values as a dictionary for current and new
  self.Q = \{\}
  self.new_Q = \{ \}
  #initalise rewards to 0
  self.rewards = 0
  #initalise all Q values across the board to 0, print these values
  for i in range(BOARD_ROWS):
     for j in range(BOARD_COLS):
       for k in range(len(self.actions)):
          self.Q[(i, j, k)] = 0
          self.new_Q[(i, j, k)] = 0
  print(self.Q)
#method to choose action with Epsilon greedy policy, and move to next state
def Action(self):
  #random value vs epsilon
  rnd = random.random()
  #set arbitraty low value to compare with Q values to find max
  mx_nxt_reward = -10
  action = None
  #9/10 find max Q value over actions
  if(rnd >self.epsilon):
     #iterate through actions, find Q value and choose best
     for k in self.actions:
```

```
i,j = self.State.state
       nxt_reward = self.Q[(i,j,k)]
       if nxt_reward >= mx_nxt_reward:
          action = k
          mx_nxt_reward = nxt_reward
  #else choose random action
  else:
     action = np.random.choice(self.actions)
  #select the next state based on action chosen
  position = self.State.nxtPosition(action)
  return position, action
#Q-learning Algorithm
def Q_Learning(self,episodes):
  x = 0
  #iterate through best path for each episode
  while (x < episodes):
     #check if state is end
     if self.isEnd:
       #get current rewrard and add to array for plot
       reward = self.State.getReward()
       self.rewards += reward
       self.plot_reward.append(self.rewards)
       #get state, assign reward to each Q_value in state
       i,j = self.State.state
       for a in self.actions:
          self.new_Q[(i,j,a)] = round(reward,3)
       #reset state
       self.State = State()
       self.isEnd = self.State.isEnd
       #set rewards to zero and iterate to next episode
       self.rewards = 0
       x+=1
     else:
       #set to arbitrary low value to compare net state actions
```

```
mx_nxt_value = -10
         #get current state, next state, action and current reward
         next state, action = self.Action()
         i,j = self.State.state
         reward = self.State.getReward()
         #add reward to rewards for plot
         self.rewards +=reward
         #iterate through actions to find max Q value for action based on next state action
         for a in self.actions:
            nxtStateAction = (next_state[0], next_state[1], a)
            q_value = (1-self.alpha)*self.Q[(i,j,action)] + self.alpha*(reward +
self.gamma*self.Q[nxtStateAction])
            #find largest Q value
            if q_value >= mx_nxt_value:
              mx_nxt_value = q_value
         #next state is now current state, check if end state
         self.State = State(state=next state)
         self.State.isEndFunc()
         self.isEnd = self.State.isEnd
         #update Q values with max Q value for next state
         self.new_Q[(i,j,action)] = round(mx_nxt_value,3)
       #copy new Q values to Q table
       self.Q = self.new_Q.copy()
    #print final Q table output
     print(self.Q)
  #plot the reward vs episodes
  def plot(self,episodes):
     plt.plot(self.plot_reward)
    plt.show()
  #iterate through the board and find largest Q value in each, print output
  def showValues(self):
    for i in range(0, BOARD_ROWS):
       print('-----')
       out = '| '
```

```
for j in range(0, BOARD_COLS):
         mx_nxt_value = -10
        for a in self.actions:
           nxt\_value = self.Q[(i,j,a)]
           if nxt value >= mx nxt value:
             mx nxt value = nxt value
        out += str(mx_nxt_value).ljust(6) + ' | '
      print(out)
    print('----')
if name == " main ":
  #create agent for 10,000 episdoes implementing a O-learning algorithm plot and show values.
  ag = Agent()
  episodes = 10000
  ag.Q_Learning(episodes)
  ag.plot(episodes)
  ag.showValues()
```

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Design a qlearning based model to help the humanoid bot to reach village near the river. If it finds the desert, it is in wrong direction. The map is represented in an undirected graph as 0->1, 1->5, 5->6, 5->4, 1->2, 2->3 and 2->7, 7->8, 8->9. The bot current position is 0, the river is located in position 2 and the village is in 7. The position 4, 5, 6, 8 and 9 has the desert.

Program

```
from get_dict import get_dict
from get R Q import initial R
from get_R_Q import initial_Q
from get_result import get_result
import pandas as pd
import time
data = pd.read_csv("graph_1.csv")
graph = get dict(data)
A = graph["A"]
Z = graph["Z"]
weight = graph["weight"]
A_Z_{dict} = graph["A_Z_{dict}"]
start = 1
end = [9]
R = initial_R(A,Z,weight,A_Z_dict)
O = initial O(R)
alpha = 0.7 # learning rate
epsilon = 0.1 \#greedy policy
n_{episodes} = 1000
time0 = time.time()
result = get_result(R,Q,alpha,epsilon,n_episodes,start,end)
print("time is:",time.time() - time0)
print(result["ends_find"])
print(result["cost"])
print(result["routes number"])
```

```
loop: 0
nodes: [0, 0, 9]
nodes: [0, 0, 9, 4]
nodes: [0, 0, 9, 4, 4]
nodes: [0, 0, 9, 4, 4, 4]
time is: 0.014706611633300781
[7]
{18: 1}
```