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1 import pandas as pd
2 import numpy as np
3 import sys
4 import random as rd
5
6 #insert an all-one column as the first column
7 def addAllOneColumn(matrix):
8     n = matrix.shape[0] #total of data points
9     p = matrix.shape[1] #total number of attributes
10
11     newMatrix = np.zeros((n,p+1))
12     newMatrix[:,1:] = matrix
13     newMatrix[:,0] = np.ones(n)
14
15     return newMatrix
16
17 # Reads the data from CSV files, converts it into Dataframe and returns x and y
18 # dataframes
19 def getDataframe(filePath):
20     dataframe = pd.read_csv(filePath)
21     y = dataframe['y']
22     x = dataframe.drop('y', axis=1)
23     return x, y
24
25 # train_x and train_y are numpy arrays
26 # function returns value of beta calculated using (0) the formula  $\beta = (X^T X)^{-1} (X^T Y)$ 
27 def getBeta(train_x, train_y):
28     n = train_x.shape[0] #total of data points
29     p = train_x.shape[1] #total number of attributes
30
31     beta = np.zeros(p)
32     #=====#
33     # STRART YOUR CODE HERE #
34     #=====#
35
36     x_transpose = np.transpose(train_x)
37     left_operand = np.linalg.inv(np.matmul(x_transpose, train_x))
38     right_operand = np.matmul(x_transpose, train_y)
39     beta = np.matmul(left_operand, right_operand)
40
41     #=====#
42     # END YOUR CODE HERE #
43     #=====#
44     return beta
45
46 # train_x and train_y are numpy arrays
47 # lr (learning rate) is a scalar
48 # function returns value of beta calculated using (1) batch gradient descent
49 def getBetaBatchGradient(train_x, train_y, lr, num_iter):
50     beta = np.random.rand(train_x.shape[1])
51
52     n = train_x.shape[0] #total of data points
53     p = train_x.shape[1] #total number of attributes
54
55     beta = np.random.rand(p)
56     #update beta iteratively
57     for iter in range(0, num_iter):
58         deriv = np.zeros(p)

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59     for i in range(n):
60         #=====#
61         # STRART YOUR CODE HERE #
62         #=====#
63
64         # gradient of OLS(1/2 (yi-xi)^2)
65         cur_deriv = train_x[i] * (np.dot(beta, np.transpose(train_x[i])) -
train_y[i])
66         deriv = np.add(deriv, cur_deriv)
67
68         #=====#
69         #   END YOUR CODE HERE   #
70         #=====#
71     deriv = deriv / n
72     beta = beta - deriv.dot(lr)
73     return beta
74
75 # train_x and train_y are numpy arrays
76 # lr (learning rate) is a scalar
77 # function returns value of beta calculated using (2) stochastic gradient descent
78 def getBetaStochasticGradient(train_x, train_y, lr):
79     n = train_x.shape[0] #total of data points
80     p = train_x.shape[1] #total number of attributes
81
82     beta = np.random.rand(p)
83
84     epoch = 100
85     for iter in range(epoch):
86         indices = list(range(n))
87         rd.shuffle(indices)
88         for i in range(n):
89             idx = indices[i]
90             #=====#
91             # STRART YOUR CODE HERE #
92             #=====#
93
94             # use np.multiply instead of * here to avoid overflow
95             # needs to multiply lr first to avoid overflow
96             coefficient = lr * (train_y[idx] - np.dot(np.transpose(train_x[idx]),
beta))
97             cur_update = np.multiply(coefficient, train_x[idx])
98             beta = np.add(beta, cur_update)
99
100            #=====#
101            #   END YOUR CODE HERE   #
102            #=====#
103    return beta
104
105
106 # Linear Regression implementation
107 class LinearRegression(object):
108     # Initializes by reading data, setting hyper-parameters, and forming linear model
109     # Forms a linear model (learns the parameter) according to type of beta (0 -
closed form, 1 - batch gradient, 2 - stochastic gradient)
110     # Performs z-score normalization if z_score is 1
111     def __init__(self, lr=0.005, num_iter=1000):
112         self.lr = lr
113         self.num_iter = num_iter
114         self.train_x = pd.DataFrame()
115         self.train_y = pd.DataFrame()

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116     self.test_x = pd.DataFrame()
117     self.test_y = pd.DataFrame()
118     self.algType = 0
119     self.isNormalized = 0
120
121     def load_data(self, train_file, test_file):
122         self.train_x, self.train_y = getDataframe(train_file)
123         self.test_x, self.test_y = getDataframe(test_file)
124
125     def normalize(self):
126         # Applies z-score normalization to the dataframe and returns a normalized
dataframe
127         self.isNormalized = 1
128         means = self.train_x.mean(0)
129         std = self.train_x.std(0)
130         self.train_x = (self.train_x - means).div(std)
131         self.test_x = (self.test_x - means).div(std)
132
133         # Gets the beta according to input
134     def train(self, algType):
135         self.algType = algType
136         newTrain_x = addAllOneColumn(self.train_x.values) #insert an all-one column
as the first column
137         print('Learning Algorithm Type: ', algType)
138         if(algType == '0'):
139             beta = getBeta(newTrain_x, self.train_y.values)
140             #print('Beta: ', beta)
141
142         elif(algType == '1'):
143             beta = getBetaBatchGradient(newTrain_x, self.train_y.values, self.lr,
self.num_iter)
144             #print('Beta: ', beta)
145         elif(algType == '2'):
146             # change learning rate to 0.0005 to converge
147             beta = getBetaStochasticGradient(newTrain_x, self.train_y.values, 0.0005)
148             #print('Beta: ', beta)
149         else:
150             print('Incorrect beta_type! Usage: 0 - closed form solution, 1 - batch
gradient descent, 2 - stochastic gradient descent')
151
152
153         return beta
154
155     # Predicts the y values on given data and learned beta
156     def predict(self, x, beta):
157         newTest_x = addAllOneColumn(x)
158         self.predicted_y = newTest_x.dot(beta)
159         return self.predicted_y
160
161
162     # predicted_y and y are the predicted and actual y values respectively as numpy
arrays
163     # function returns the mean squared error (MSE) value for the test dataset
164     def compute_mse(self, predicted_y, y):
165         mse = np.sum((predicted_y - y)**2)/predicted_y.shape[0]
166         return mse
167
168
169

```