

Deep Learning

Naval Mine Detector Application

In this use case, they have been provided with a SONAR data set which contains the data about 208 patterns obtained by bouncing sonar signals off a metal cylinder (naval mine) and a rock at various angles and under various conditions.

Now, as we know, a naval mine is a self-contained explosive device placed in water to damage or destroy surface ships or submarines.

So, our goal is to build a model that can predict whether the object is a naval mine or rock based on our data set.



```

1 import numpy as np
2 import pandas as pd
3 import tensorflow as tf
4 import matplotlib.pyplot as plt
5 from sklearn.utils import shuffle
6 from sklearn.preprocessing import LabelEncoder
7 from sklearn.model_selection import train_test_split
8
9 ##########
10
11 # Reading the dataset
12 def read_dataset():
13     df = pd.read_csv("sonar.csv")
14     print("Marvellous Infosystems : Dataset loaded successfully")
15     print("Marvellous Infosystems : Number of columns: ",len(df.columns))
16
17 #Fetures of dataset
18 X = df[df.columns[0:60]].values
19
20 #Label of dataset
21 y = df[df.columns[60]]
22
23 # Encode the dependant variable
24 encoder = LabelEncoder()
25
26 # Encode character labeles into integer ie 1 or 0 (One hot encode)
27 encoder.fit(y)
28 y = encoder.transform(y)
29 Y = one_hot_encode(y)
30
31 print("Marvellous Infosystems : X.shape",X.shape)
32
33 return (X,Y)
34
35 #####
36
37 # Define the encoder function to set M => 1, R => 0
38 def one_hot_encode(labels):
39     n_labels = len(labels)
40     n_unique_labels = len(np.unique(labels))
41     one_hot_encode = np.zeros((n_labels,n_unique_labels))
42     one_hot_encode[np.arange(n_labels),labels] = 1
43     return one_hot_encode
44
45 #####
46
47 # Model for training
48 def multilayer_perceptron(x, weights, biases):
49
50     # Hidden layer with RELU activations

```

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51 # First layer performs matrix multiplication of input with weights
52 layer_1 = tf.add(tf.matmul(x, weights['h1']), biases['b1'])
53 layer_1 = tf.nn.relu(layer_1)
54
55 # Hidden layer with sigmoid activations
56 # Second layer performs matrix multiplication of layer1 with weights
57 layer_2 = tf.add(tf.matmul(layer_1, weights['h2']), biases['b2'])
58 layer_2 = tf.nn.sigmoid(layer_2)
59
60 # Hidden layer with sigmoid activations
61 # Third layer performs matrix multiplication of layer2 with weights
62 layer_3 = tf.add(tf.matmul(layer_2, weights['h3']), biases['b3'])
63 layer_3 = tf.nn.sigmoid(layer_3)
64
65 # Hidden layer with RELU activations
66 # Forth layer performs matrix multiplication of layer3 with weights
67 layer_4 = tf.add(tf.matmul(layer_3, weights['h4']), biases['b4'])
68 layer_4 = tf.nn.relu(layer_4)
69
70 # Output layer with linear activations
71 out_layer = tf.matmul(layer_4, weights['out']) + biases['out']
72 return out_layer
73
74 ######
75
76 def main():
77   # Read the dataset
78   X, Y = read_dataset()
79
80   # Shuffle the dataset to mix up the rows
81   X, Y = shuffle(X, Y, random_state=1)
82
83   # Convert the dataset into train and test datasets
84   # For testing we use 10% and for training we use 90%
85   train_x, test_x, train_y, test_y = train_test_split(X, Y, test_size=0.30, random_state=415)
86
87   # Inspect the shape of the train and test datasets
88   print("Marvellous Infosystems : train_x.shape",train_x.shape)
89   print("Marvellous Infosystems : train_y.shape",train_y.shape)
90   print("Marvellous Infosystems : test_x.shape",test_x.shape)
91   print("Marvellous Infosystems : test_y.shape",test_y.shape)
92
93   # Define the parameters which are required for tensors ie hyperparameters
94
95   # Change in a variable in each iteration
96   learning_rate = 0.3
97
98   # Total number of iterations to minimize the error
99   training_epochs = 1000
100

```

```

101 cost_history = np.empty(shape=[1], dtype=float)
102
103 # Number of features <=> number of columns
104 n_dim = X.shape[1]
105 print("Number of columens are n_dim",n_dim)
106
107 # As we have tow classess as R and M
108 n_class = 2
109
110 # Path which contains model files
111 model_path = "Marvellous"
112
113 # Define the number of hidden layers an the
114 # number of neurons for each layer
115
116 # Number of hidden layers are 4
117 # NNeurons in each layer are 60
118 n_hidden_1 = 60
119 n_hidden_2 = 60
120 n_hidden_3 = 60
121 n_hidden_4 = 60
122
123 # Placeholder to store Inputs
124 x = tf.compat.v1.placeholder(tf.float32,[None, n_dim])
125
126 # Placeholder to store Outputs
127 y_ = tf.compat.v1.placeholder(tf.float32,[None, n_class])
128
129 # Model parameters
130 W = tf.Variable(tf.zeros([n_dim,n_class]))
131 b = tf.Variable(tf.zeros([n_class]))
132
133 # define the weights and the biases for each layer
134 # Create variable which contens random values
135 weights = {
136     'h1': tf.Variable(tf.random.truncated_normal([n_dim, n_hidden_1])),
137     'h2': tf.Variable(tf.random.truncated_normal([n_hidden_1, n_hidden_2])),
138     'h3': tf.Variable(tf.random.truncated_normal([n_hidden_2, n_hidden_3])),
139     'h4': tf.Variable(tf.random.truncated_normal([n_hidden_3, n_hidden_4])),
140     'out': tf.Variable(tf.random.truncated_normal([n_hidden_4, n_class]))  },
141 }
142
143 # Create variable which contens random values
144 biases = {
145     'b1': tf.Variable(tf.random.truncated_normal([n_hidden_1])),
146     'b2': tf.Variable(tf.random.truncated_normal([n_hidden_2])),
147     'b3': tf.Variable(tf.random.truncated_normal([n_hidden_3])),
148     'b4': tf.Variable(tf.random.truncated_normal([n_hidden_4])),
149     'out': tf.Variable(tf.random.truncated_normal([n_class])),
150   }

```

```

176 cost = sess.run(cost_function,feed_dict={x:train_x, y_:train_y})
177 cost_history = np.append(cost_history, cost)
178 correct_prediction = tf.equal(tf.argmax(y,1),tf.argmax(y_,1))
179 accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
180 pred_y = sess.run(y,feed_dict={x:test_x} )
181 mse = tf.reduce_mean(tf.square(pred_y - test_y))
182 mse_ = sess.run(mse)
183 accuracy = (sess.run(accuracy,feed_dict={x:train_x, y_:train_y}))
184 accuracy_history.append(accuracy)
185 print('epoch: ', epoch, ' - ', 'cost: ', cost, " - MSE: ", mse_, "- Train Accuracy: ", accuracy)
186
187 # Model gets saved in the file
188 save_path = saver.save(sess, model_path)
189 print("Model saved in file: %s", save_path)
190
191 # Display graph for accuracy history
192 plt.plot(accuracy_history)
193 plt.title("Marvellous Infosystems : Accuracy History")
194 plt.xlabel('Epoch')
195 plt.ylabel('Accuracy')
196 plt.show()
197
198 # Display graph for Loss calculation
199 plt.plot(range(len(cost_history)),cost_history)
200 plt.title("Marvellous Infosystems : Loss calculation")
201 plt.axis([0,training_epochs,0,np.max(cost_history)/100])
202 plt.xlabel('Epoch')
203 plt.ylabel('Loss')
204 plt.show()
205
206 # Print the final mean square error
207 correct_prediction = tf.equal(tf.argmax(y, 1), tf.argmax(y_, 1))
208 accuracy = tf.reduce_mean(tf.square(pred_y - test_y))
209 print("Test Accuracy: ", (sess.run(y, feed_dict={x:test_x, y_:test_y} )))
210
211 # Print the final mean square error
212 pred_y = sess.run(y, feed_dict={x:test_x})
213 mse = tf.reduce_mean(tf.square(pred_y- test_y))
214 print("Mean Square Error : %.4f" % sess.run(mse))
215
216 if __name__ == "__main__":
217   main()

```