EXERCISE 2:

Changes done in “**phishing_sklearn.py”,** added f1 score, recall, precision code

```python
from warnings import simplefilter

import numpy as np
import pandas as pd
import sklearn
from numpy import genfromtxt
from sklearn import datasets
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (accuracy_score, confusion_matrix, f1_score,
                             precision_score, recall_score)
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler

simplefilter(action='ignore', category=FutureWarning)

###############################################################

feature=genfromtxt('phishing.csv',delimiter=',',usecols=(i for i in range(0,30)),skip_header=1)
target=genfromtxt('phishing.csv',delimiter=',',usecols=(-1),skip_header=1)
sc = StandardScaler()
sc.fit(feature)
target_label = LabelEncoder().fit_transform(target)
feature_std = sc.transform(feature)
test_size_val=0.33
x_train, x_test, y_train, y_test = train_test_split(feature_std, target_label, test_size=test_size_val, random_state=1)

print("Begin with test_size"+str(test_size_val)+":__________________________________")
###################################################
## print stats
precision_scores_list = []
accuracy_scores_list = []

def print_stats_metrics(y_test, y_pred):
    print('Accuracy: %.2f' % accuracy_score(y_test,   y_pred) )
    accuracy_scores_list.append(accuracy_score(y_test,   y_pred) )
    confmat = confusion_matrix(y_true=y_test, y_pred=y_pred)

    print('F1 score: %.2f' % f1_score(y_true=y_test,y_pred=y_pred))
    print('Precision: %.2f' % precision_score(y_true=y_test,y_pred=y_pred))
    print('Recall: %.2f' % recall_score(y_true=y_test,y_pred=y_pred))

    print ("confusion matrix")
    print(confmat)
    print (pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'], margins=True))

########################Logistic Regression##############################
print("########################Logistic Regression##############################")
clfLog = LogisticRegression()
clfLog.fit(x_train,y_train)
predictions = clfLog.predict(x_test)
print_stats_metrics(y_test, predictions)

########################Random Forest##############################
```

```
print("########################Random Forest##############################")
clfRandForest = RandomForestClassifier()
clfRandForest.fit(x_train,y_train)
predictions = clfRandForest.predict(x_test)
print_stats_metrics(y_test, predictions)
#######################Decision Tree######################
print("#######################Decision Tree######################")
clfDT = DecisionTreeRegressor()
clfDT.fit(x_train,y_train)
predictions = clfDT.predict(x_test)
print_stats_metrics(y_test, predictions)
#######################Naive Bayes######################
print("#######################Naive Bayes######################")
clfNB = GaussianNB()
clfNB.fit(x_train,y_train)
predictions = clfNB.predict(x_test)
print_stats_metrics(y_test, predictions)
```

At test_size=0.33

```
########################Logistic Regression##############################
Accuracy: 0.92
F1 score: 0.93
Precision: 0.92
Recall: 0.94
confusion matrix
[[1476  156]
 [ 121 1896]]
Predicted     0     1   All
True
0          1476   156  1632
1           121  1896  2017
All        1597  2052  3649
########################Random Forest##############################
Accuracy: 0.97
F1 score: 0.97
Precision: 0.96
Recall: 0.98
confusion matrix
[[1557   75]
 [  42 1975]]
Predicted     0     1   All
True
0          1557    75  1632
1            42  1975  2017
All        1599  2050  3649
#######################Decision Tree######################
Accuracy: 0.96
F1 score: 0.96
Precision: 0.96
Recall: 0.96
confusion matrix
[[1549   83]
 [  76 1941]]
Predicted   0.0   1.0   All
True
0          1549    83  1632
1            76  1941  2017
All        1625  2024  3649
#######################Naive Bayes######################
Accuracy: 0.62
F1 score: 0.48
Precision: 1.00
```

```
Recall: 0.31
confusion matrix
[[1629    3]
 [1383  634]]
Predicted     0    1   All
True
0          1629    3  1632
1          1383  634  2017
All        3012  637  3649


```

At test_size=0.50

```
Begin with test_size 0.50:___________________________________
########################Logistic Regression##############################
Accuracy: 0.92
F1 score: 0.93
Precision: 0.92
Recall: 0.94
confusion matrix
[[2216  248]
 [ 176 2888]]
Predicted     0     1   All
True
0          2216   248  2464
1           176  2888  3064
All        2392  3136  5528
########################Random Forest##############################
Accuracy: 0.97
F1 score: 0.97
Precision: 0.96
Recall: 0.98
confusion matrix
[[2331  133]
 [  59 3005]]
Predicted     0     1   All
True
0          2331   133  2464
1            59  3005  3064
All        2390  3138  5528
#######################Decision Tree######################
Accuracy: 0.95
F1 score: 0.95
Precision: 0.95
Recall: 0.96
confusion matrix
[[2308  156]
 [ 125 2939]]
Predicted   0.0   1.0   All
True
0          2308   156  2464
1           125  2939  3064
All        2433  3095  5528
#######################Naive Bayes######################
Accuracy: 0.61
F1 score: 0.47
Precision: 0.99
Recall: 0.30
confusion matrix
[[2459    5]
 [2134  930]]
Predicted     0    1   All
```

```
True
0          2459    5  2464
1          2134  930  3064
All        4593  935  5528

```

At test_size=0.20

```
Begin with test_size0.20:__________________________________
########################Logistic Regression##############################
Accuracy: 0.92
F1 score: 0.93
Precision: 0.92
Recall: 0.94
confusion matrix
[[ 895  101]
 [  68 1147]]
Predicted    0     1   All
True
0          895   101   996
1           68  1147  1215
All        963  1248  2211
########################Random Forest##############################
Accuracy: 0.98
F1 score: 0.98
Precision: 0.97
Recall: 0.98
confusion matrix
[[ 963   33]
 [  22 1193]]
Predicted    0     1   All
True
0          963    33   996
1           22  1193  1215
All        985  1226  2211
#######################Decision Tree######################
Accuracy: 0.96
F1 score: 0.96
Precision: 0.97
Recall: 0.96
confusion matrix
[[ 955   41]
 [  46 1169]]
Predicted   0.0   1.0   All
True
0           955    41   996
1            46  1169  1215
All        1001  1210  2211
#######################Naive Bayes######################
Accuracy: 0.62
F1 score: 0.47
Precision: 0.99
Recall: 0.31
confusion matrix
[[993   3]
 [843 372]]
Predicted     0    1   All
True
0           993    3   996
1           843  372  1215
All        1836  375  2211

```

EXERCISE 3:

Learning rate: Itis a tuning parameter in an optimization algorithm that determines the step size at each iteration while moving toward a minimum of a loss function.

Epoch: It's a term used in machine learning and indicates the number of passes of the entire training dataset the algorithm has been completed.

Batch Size: It's a term used in machine learning and refers to the number of training examples utilized in one iteration.

Coded F1 scores, precision, recall

```
import tensorflow.compat.v1 as tf
tf.disable_v2_behavior()
import numpy as np
import pandas as pd
from numpy import genfromtxt
from sklearn import datasets
from sklearn.model_selection import train_test_split
import sklearn
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score, f1_score
import pandas as pd
import matplotlib.pyplot as plt

###############################################################

learning_rate = 0.01
#n_epochs = 5000
n_epochs = 100
batch_size = 10000

def convertOneHot(data):
    y_onehot=[0]*len(data)
    for i,j in enumerate(data):
        y_onehot[i]=[0]*(data.max()+1)
        y_onehot[i][j]=1
    return y_onehot

###############################################################
feature=genfromtxt('phishing.csv',delimiter=',',usecols=(i for i in range(0,31)),skip_header=1)
target=genfromtxt('phishing.csv',delimiter=',',usecols=(-1),skip_header=1)
sc = StandardScaler()
sc.fit(feature)
target_label = LabelEncoder().fit_transform(target)
target_onehot = convertOneHot(target_label)
feature_std = sc.transform(feature)
x_train, x_test, y_train_onehot, y_test_onehot = train_test_split(feature_std, target_onehot, test_size=0.30, random_state=0)
A=x_train.shape[1]
B=len(y_train_onehot[0])
print(len(y_test_onehot[0]))
print(B)
```

```
print("Begin:__________________________________")
######################################################################

def plot_metric_per_epoch():
    x_epochs = []
    y_epochs = []
    for i, val in enumerate(accuracy_scores_list):
        x_epochs.append(i)
        y_epochs.append(val)

    plt.scatter(x_epochs, y_epochs,s=50,c='lightgreen', marker='s', label='score')
    plt.xlabel('epoch')
    plt.ylabel('score')
    plt.title('Score per epoch')
    plt.legend()
    plt.grid()
    plt.show()

####################################################
## print stats
precision_scores_list = []
accuracy_scores_list = []

def print_stats_metrics(y_test, y_pred):
    print('Accuracy: %.2f' % accuracy_score(y_test,   y_pred) )
    #Accuracy: 0.84
    accuracy_scores_list.append(accuracy_score(y_test,   y_pred) )
    confmat = confusion_matrix(y_true=y_test, y_pred=y_pred)

    print('F1 score: %.2f' % f1_score(y_true=y_test,y_pred=y_pred))
    print('Precision: %.2f' % precision_score(y_true=y_test,y_pred=y_pred))
    print('Recall: %.2f' % recall_score(y_true=y_test,y_pred=y_pred))

    print ("confusion matrix")
    print(confmat)
    print (pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'], margins=True))

################################################################
def layer(input, weight_shape, bias_shape):
    weight_stddev = (2.0/weight_shape[0])**0.5
    w_init = tf.random_normal_initializer(stddev=weight_stddev)
    bias_init = tf.constant_initializer(value=0)
    W = tf.get_variable("W", weight_shape, initializer=w_init)
    b = tf.get_variable("b", bias_shape, initializer=bias_init)
    return tf.nn.relu(tf.matmul(input, W) + b)
################################################################
def inference_deep_layers(x_tf, A, B):
    with tf.variable_scope("hidden_1"):
        hidden_1 = layer(x_tf, [A, 15],[15])
    with tf.variable_scope("hidden_2"):
        hidden_2 = layer(hidden_1, [15, 5],[5])
    with tf.variable_scope("output"):
        output = layer(hidden_2, [5, B], [B])
    return output
################################################################
def loss_deep(output, y_tf):
    xentropy = tf.nn.softmax_cross_entropy_with_logits(logits=output, labels=y_tf)
    loss = tf.reduce_mean(xentropy)
    return loss
############################################################

def training(cost):
    optimizer = tf.train.GradientDescentOptimizer(learning_rate)
    train_op = optimizer.minimize(cost)
```

```
    return train_op

################################################################
def evaluate(output, y_tf):
    correct_prediction = tf.equal(tf.argmax(output,1), tf.argmax(y_tf,1))
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
    return accuracy
################################################################

x_tf = tf.placeholder("float",[None,A])
y_tf = tf.placeholder("float",[None,B])
################################################################
output = inference_deep_layers(x_tf,A,B)
cost = loss_deep(output,y_tf)
train_op=training(cost)
eval_op=evaluate(output,y_tf)
################################################################
init = tf.global_variables_initializer()
sess = tf.Session()
sess.run(init)
################################################################
y_p_metrics = tf.argmax(output,1)
################################################################
num_samples_train_set=x_train.shape[0]
num_batches = int(num_samples_train_set/batch_size)

################################################################

for i in range(n_epochs):
    print("epoch %s out of %s"%(i,n_epochs))
    for batch_n in range(num_batches):
        sta = batch_n*batch_size
        end = sta+batch_size
        sess.run(train_op,feed_dict={x_tf:x_train[sta:end],y_tf:y_train_onehot[sta:end]})
    print ("------------------------------------------------------------------------------")
    print ("Accuracy score")
    #result = sess.run(eval_op,feed_dict={x_tf:x_test,y_tf:y_test_onehot})
    result, y_result_metrics = sess.run([eval_op, y_p_metrics], feed_dict={x_tf: x_test, y_tf: y_test_onehot})
    print("Run {},{}".format(i,result))
    y_true = np.argmax(y_test_onehot,1)
    print_stats_metrics(y_true, y_result_metrics)
    if i==n_epochs-1:
        plot_metric_per_epoch()
```

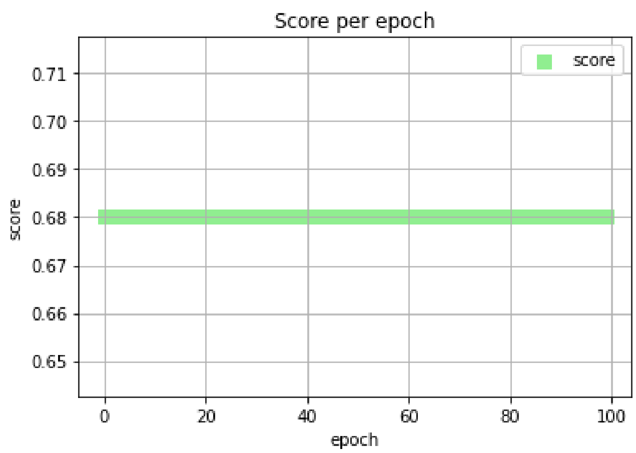
At different epoch, batch size and learning rate

1) At

```
learning_rate = 0.01
n_epochs = 100
batch_size = 10000
```

Output:

```
Accuracy score
Run 99,0.4727163016796112
Accuracy: 0.47
F1 score: 0.09
Precision: 0.85
Recall: 0.05
confusion matrix
[[1483   15]
 [1734   85]]
Predicted     0    1   All
True
0          1483   15  1498
1          1734   85  1819
All        3217  100  3317
```

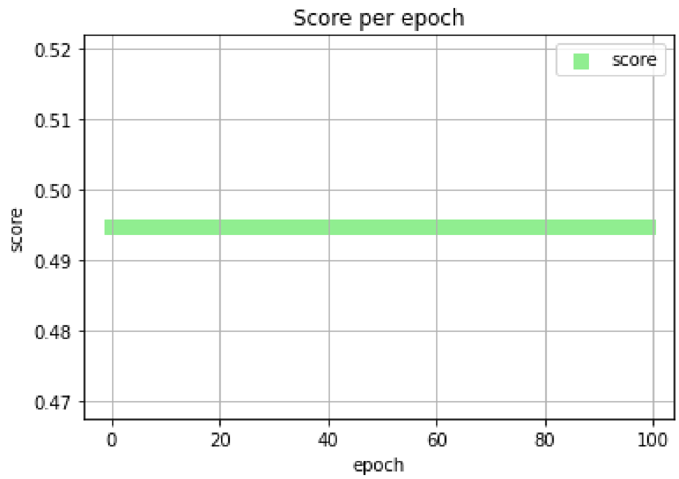


2) At

```
learning_rate = 0.006
n_epochs = 100
batch_size = 10000
```

Output:

```
Accuracy: 0.41
F1 score: 0.20
Precision: 0.39
Recall: 0.13
confusion matrix
[[1127  371]
 [1579  240]]
Predicted     0    1   All
True
0          1127  371  1498
1          1579  240  1819
All        2706  611  3317
```



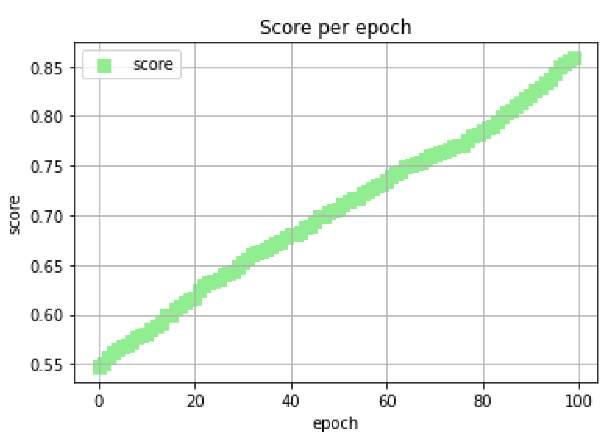
3) At

```
learning_rate = 0.006
n_epochs = 100
batch_size = 1000
```

Output:

```
Accuracy: 0.95
F1 score: 0.95
Precision: 0.94
Recall: 0.96
confusion matrix
[[1390  108]
 [  65 1754]]
Predicted     0     1   All
True
0          1390   108  1498
1            65  1754  1819
All        1455  1862  3317

```



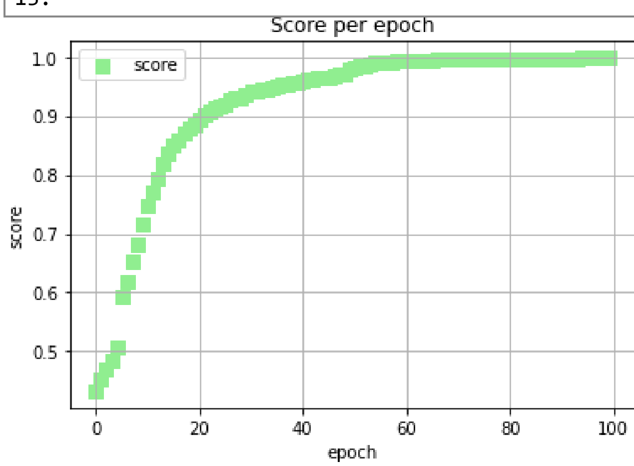
4) At

```
learning_rate = 0.006
n_epochs = 100
batch_size = 128
```

Output:

```
Accuracy: 0.99
F1 score: 0.99
Precision: 0.99
Recall: 1.00
confusion matrix
[[1474   24]
 [   0 1819]]
Predicted     0     1   All
True
0          1474    24  1498
1             0  1819  1819
All        1474  1843  3317

```



Results:
At first we saw that how our dataset looks like, Then we installed weka and opened the CSV data set. Using the Explorer window and. In the classifier tab, we set the classification as different sets. Logistic regression, Naïve Bayes, Random Forest, etc.

Will logged the data by each of them, The output contains the time taken by the model. The confusion matrix the F1 score, precision, accuracy and recall, for the data set over the trained model.

Time taken by model:
- Random Forest: 2.21 s
- LMT: 6.89 s
- Logistic: 0.3
- SGD: 0.49
- Naïve bayes: 0.06

Mean Abs Error:
- Random Forest: 0.049

LMT: 0.034
Logistic: 0.1078
SGD: 0.0705
Naïve bayes: 0.1197

Precision:
Random Forest: 0.970
LMT: 0.967
Logistic: 0.926
SGD: 0.930
Naïve bayes: 0.909

On getting such results we can finally discuss which phising detector performed better in comparison to others, we can see performance on basis of various parameters that Random Forest performed better in comparison to others as it have high precision score and lower Mean Abs Error, but time taken is much higher compared to rest algorithms

In sklearn we implemented the classifier model on the basis of different algorithms like Logistic Regression, Decision Tree, Random Forest, and Naïve Bayes

On the basis of various parameters and accuracy we can see that which model performed better
Accuracy
Logistic Regression:0.92
Random Forest:0.97
Decision Tree:0.96
Naïve Bayes:0.62
F1 score
Logistic Regression:0.93
Random Forest:0.97
Decision Tree:0.96
Naïve Bayes:0.48
Here also we can see the Random Forest worked better in comparison to other

Now, in terms of NN layer, we saw the highest accuracy came out to be 0.99 on slower learning rate and smaller batch size which was even better than earlier attempts.
So we can say that Neural Networks worked better in comparison to others.
We can also say that Neural Networks have the ability to learn and model non-linear and complex relationships , which is really important because in real-life, many of the relationships between inputs and outputs are non-linear as well as complex, so it performed better.