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RA: 20.83984-7

Data: https://www.kaggle.com/uciml/red-wine-quality-cortez-et-al-2009

## **Imports**

```
In [1]:
```

```
import tensorflow as tf
from tensorflow import keras
import matplotlib as mpl
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import sklearn
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
```

#### In [2]:

```
file_path = '/content/drive/MyDrive/Education/IMT/Pós Graduação/IA com Deep Learning/Deve
loping Neural Network Tools/Atividade 2/winequality-red.csv'

#Checking the file encoder
with open(file_path) as f:
    print(f)
```

<\_io.TextIOWrapper name='/content/drive/MyDrive/Education/IMT/Pós Graduação/IA com Deep L earning/Developing Neural Network Tools/Atividade 2/winequality-red.csv' mode='r' encodin g='UTF-8'>

#### In [3]:

```
df = pd.read_csv(file_path)
df.head()
```

#### Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

### In [4]:

#### df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
                       Non-Null Count Dtype
# Column
                       1599 non-null float64
0 fixed acidity
1 volatile acidity
                       1599 non-null float64
                        1599 non-null float64
  citric acid
 3
  residual sugar
                       1599 non-null float64
  chlorides
                        1599 non-null float64
```

```
free sulfur dioxide
                           1599 non-null
                                            float.64
    total sulfur dioxide 1599 non-null
                                            float64
 7
                           1599 non-null
                                            float64
    density
 8
                           1599 non-null
                                            float64
    рΗ
 9
    sulphates
                           1599 non-null
                                            float64
 10
    alcohol
                           1599 non-null
                                            float64
    quality
                           1599 non-null
                                            int64
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
In [5]:
df.describe()
Out[5]:
```

```
volatile
                                                                             free sulfur
                                                                                          total sulfur
                                                    residual
                                                                                                                             рΗ
       fixed acidity
                                    citric acid
                                                                chlorides
                                                                                                           density
                          acidity
                                                                               dioxide
                                                                                             dioxide
                                                      sugar
count 1599.000000 1599.000000 1599.000000 1599.000000
                                                             1599.000000
                                                                           1599.000000
                                                                                         1599.000000 1599.000000 1599.000000
                        0.527821
                                                   2.538806
                                                                                           46.467792
                                                                                                         0.996747
mean
          8.319637
                                     0.270976
                                                                0.087467
                                                                             15.874922
                                                                                                                       3.311113
          1.741096
                        0.179060
                                     0.194801
                                                   1.409928
                                                                0.047065
                                                                             10.460157
                                                                                           32.895324
                                                                                                         0.001887
                                                                                                                       0.154386
  std
 min
          4.600000
                        0.120000
                                     0.000000
                                                   0.900000
                                                                0.012000
                                                                              1.000000
                                                                                            6.000000
                                                                                                         0.990070
                                                                                                                       2.740000
                                     0.090000
                                                                0.070000
                                                                                                         0.995600
 25%
          7.100000
                        0.390000
                                                   1.900000
                                                                              7.000000
                                                                                           22,000000
                                                                                                                       3.210000
 50%
          7.900000
                        0.520000
                                     0.260000
                                                   2.200000
                                                                 0.079000
                                                                             14.000000
                                                                                           38.000000
                                                                                                         0.996750
                                                                                                                       3.310000
 75%
          9.200000
                        0.640000
                                     0.420000
                                                   2.600000
                                                                 0.090000
                                                                             21.000000
                                                                                           62.000000
                                                                                                         0.997835
                                                                                                                       3.400000
 max
         15.900000
                        1.580000
                                      1.000000
                                                  15.500000
                                                                0.611000
                                                                             72.000000
                                                                                          289.000000
                                                                                                         1.003690
                                                                                                                       4.010000
```

```
In [6]:
```

```
# Data dimensions
print('Dimensões dos dados =', df.shape)

Dimensões dos dados = (1599, 12)

In [7]:
```

```
#Defining graphic colors
colors = plt.rcParams['axes.prop_cycle'].by_key()['color']
```

# Changing the 'quality' column

In this work, we will classify the wines as Good or Bad. Let's consider a wine bad if it's score quality is <= 5 and good if quality > 5

After creating a new column with this boolean classification, lets just remove the 'quality' column since we don't need it anymore (for this study).

```
In [8]:
```

Out[8]:

```
df_wines = df.copy()

#Creating and replacing the 'quality' column with 0 or 1 (for a classification problem)
df_wines['quality_bool'] = np.where(df_wines['quality'] <= 5 , 0, np.where(df_wines['quality'] > 5, 1 , "")).astype('float64')

#Removing the Quality Data
df_wines.pop('quality')
df_wines.head()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	quality_bool
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	0.0
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	0.0
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	0.0
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	1.0
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	0.0

#### In [9]:

```
#Checking if the new class is inballanced
df_wines['quality_bool'].value_counts(normalize=True)
```

#### Out[9]:

```
1.0 0.534709
0.0 0.465291
Name: quality bool, dtype: float64
```

Considering we have almost 50% of 0 and 1, I don't think this will represent a problem when creating the model.

## **Splitting the Data**

```
In [10]:
```

```
# Splitting (80% - 20%)
train_df, test_df = train_test_split(df_wines, test_size=0.2)
test_df, val_df = train_test_split(test_df, test_size=0.5)

# Spliting the outputs and transforming them in numpy tensors
train_labels = np.array(train_df.pop('quality_bool'))
val_labels = np.array(val_df.pop('quality_bool'))
test_labels = np.array(test_df.pop('quality_bool'))

# Transforming the inputs in numpy tensors
train_features = np.array(train_df)
val_features = np.array(val_df)
test_features = np.array(test_df)
```

# Normalizing

```
In [11]:
```

```
# Calculates the mean and standard deviation for each training data column
mean = np.mean(train_features, axis=0)
std = np.std(train_features, axis=0)

# Normalizes training data, validation and test using the mean and standard deviation fro
m the training data
train_features = (train_features - mean)/std
val_features = (val_features - mean)/std
test_features = (test_features - mean)/std

print('Training Output Dimensions:', train_labels.shape)
print('Validation Output Dimensions:', val_labels.shape)
print('Training Input Dimensions:', test_labels.shape)
print('Training Input Dimensions:', train_features.shape)
print('Validation Input Dimensions:', val_features.shape)
print('Test Input Dimensions:', test_features.shape)
```

```
Training Output Dimensions: (1279,)
Validation Output Dimensions: (160,)
Test Output Dimensions: (160,)
Training Input Dimensions: (1279, 11)
```

```
Validation Input Dimensions: (160, 11)
Test Input Dimensions: (160, 11)
```

# **Building the RNA**

### **RNA** definition and Metrics

```
In [12]:
```

```
# Import model classes and layers from Keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
# Define metrics
METRICS = [
keras.metrics.TruePositives(name='tp'),
keras.metrics.FalsePositives(name='fp'),
keras.metrics.TrueNegatives(name='tn'),
keras.metrics.FalseNegatives(name='fn'),
keras.metrics.BinaryAccuracy(name='accuracy'),
keras.metrics.Precision(name='precision'),
keras.metrics.Recall(name='recall'),
keras.metrics.AUC(name='auc')]
# Function to create and compile the RNA
def make model(METRICS, INPUT DIM):
  # Network Setting
 rna = Sequential()
 rna.add(Dense(units= 32, activation= 'relu', input dim= INPUT DIM))
 rna.add(Dense(units= 16, activation= 'relu'))
 rna.add(Dense(units= 1, activation= 'sigmoid'))
 rna.compile(optimizer = keras.optimizers.Adam(learning rate = 0.001),
 loss = keras.losses.BinaryCrossentropy(),
 metrics = METRICS)
 return rna
```

#### In [13]:

```
# feature numbers
features_shape = train_features.shape[1]
print('Dimensão dos dados de entrada =', features_shape)

# Compiled RNA (Create)
rna = make_model(METRICS, features_shape)
rna.summary()
```

Dimensão dos dados de entrada = 11 Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 32)	384
dense_1 (Dense)	(None, 16)	528
dense_2 (Dense)	(None, 1)	17
Total params: 929 Trainable params: 929 Non-trainable params: 0		

## **Training**

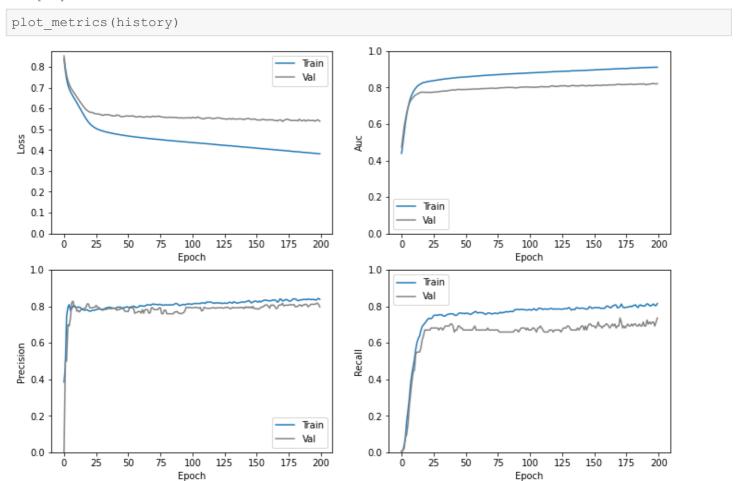
In [14]:

# **Analysing the Results**

In [15]:

```
# Define function to create a graph from some metrics
def plot metrics(history):
   metrics = ['loss', 'auc', 'precision', 'recall']
   plt.figure(figsize=(12,8))
    for n, metric in enumerate(metrics):
        name = metric.replace(" ", " ").capitalize()
        plt.subplot (2, 2, n+1)
        plt.plot(history.epoch, history.history[metric], color = colors[0], label = 'Tra
in')
        plt.plot(history.epoch, history.history['val '+metric], color = 'grey', label =
'Val')
       plt.xlabel('Epoch')
        plt.ylabel(name)
        if metric == 'loss':
            plt.ylim([0, plt.ylim()[1]])
        elif metric == 'auc':
            plt.ylim([0,1])
        else:
            plt.ylim([0,1])
        plt.legend()
```

#### In [16]:



## **Evaluating the Results**

```
In [17]:
print('Number of positive examples from test set =', len(test_labels[test_labels> 0.9]))
Number of positive examples from test set = 91
In [18]:
#Test Evaluation
base_results = rna.evaluate(test_features, test_labels, batch_size = BATCH_SIZE, verbose
for name, value in zip(rna.metrics_names, base_results):
   print(name, ': ', value)
print()
loss: 0.4563659727573395
tp: 67.0
fp : 11.0
tn : 58.0
fn : 24.0
accuracy : 0.78125
precision: 0.8589743375778198
recall: 0.7362637519836426
auc: 0.8671762943267822
In [19]:
#Train Evaluation
base results = rna.evaluate(train features, train labels, batch size = BATCH SIZE, verbo
se = 0)
for name, value in zip(rna.metrics names, base results):
    print(name, ': ', value)
print()
loss: 0.38123831152915955
tp: 552.0
fp : 106.0
tn : 500.0
fn : 121.0
accuracy: 0.8225175738334656
precision: 0.8389057517051697
recall: 0.8202080130577087
auc: 0.9122960567474365
In [20]:
#Output Test Examples
train pred base = rna.predict(train features, batch size = BATCH SIZE)
test pred base = rna.predict(test features, batch size = BATCH SIZE)
print('Test examples outputs:')
print(test_pred_base[:10])
Test examples outputs:
[[0.1557236]
 [0.6854476]
 [0.21633586]
 [0.41808015]
 [0.5309093]
 [0.9153248]
 [0.5450209 ]
 [0.130543
 [0.06034201]
 [0.9518492]]
```

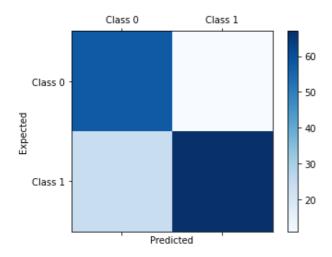
### **Confusion Matrix**

```
In [21]:
#Test
conf_mat = confusion_matrix(y_true= test_labels, y_pred= np.round(test_pred_base))
print('COnfusion Matrix\n', conf_mat)

labels = ['Class 0', 'Class 1']
plt.figure(figsize=(6,6))
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(conf_mat, cmap=plt.cm.Blues)
fig.colorbar(cax)
ax.set_xticklabels([''] + labels)
ax.set_yticklabels([''] + labels)
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

```
COnfusion Matrix [[58 11] [24 67]]
```

<Figure size 432x432 with 0 Axes>



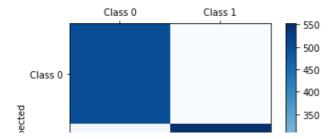
#### In [22]:

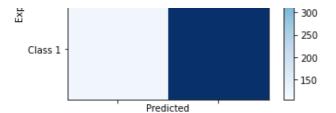
```
#Train
conf_mat = confusion_matrix(y_true= train_labels, y_pred= np.round(train_pred_base))
print('COnfusion Matrix\n', conf_mat)

labels = ['Class 0', 'Class 1']
plt.figure(figsize=(6,6))
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(conf_mat, cmap=plt.cm.Blues)
fig.colorbar(cax)
ax.set_xticklabels([''] + labels)
ax.set_yticklabels([''] + labels)
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

COnfusion Matrix [[500 106] [121 552]]

<Figure size 432x432 with 0 Axes>

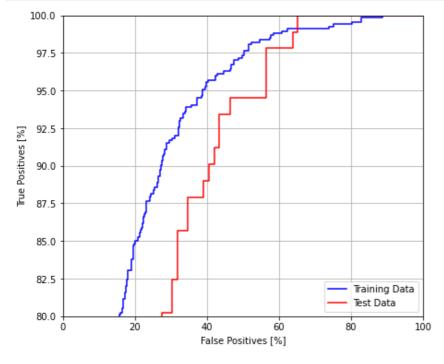




### **ROC Curve**

#### In [23]:

```
fp_train, tp_train, _ = sklearn.metrics.roc_curve(train_labels, train_pred_base)
fp_test, tp_test, _ = sklearn.metrics.roc_curve(test_labels, test_pred_base)
plt.figure(figsize=(7, 6))
plt.plot(100*fp_train, 100*tp_train, 'b', label= 'Training Data')
plt.plot(100*fp_test, 100*tp_test, 'r', label= 'Test Data')
plt.xlabel('False Positives [%]')
plt.ylabel('True Positives [%]')
plt.xlim([0,100])
plt.ylim([80,100])
plt.grid(True)
ax = plt.gca()
plt.legend(loc='lower right')
plt.show()
```



## **Real and Predicted Classes**

```
In [24]:
```

```
y_pred = rna.predict(test_features)
classes = np.round(y_pred)
```

#### In [25]:

```
# Real and Predicted Classes
plt.figure(figsize=(16, 4))
plt.plot(val_labels, 'ro', label='Real Classes')
plt.plot(classes, 'bo', label='Predicted Classes')
plt.title('Real and Predicted Classes')
plt.xlabel('Examples')
plt.ylabel('Classes')
plt.legend()
plt.show()
```

