

# Week 1: Multiple Output Models using the Keras Functional API

Welcome to the first programming assignment of the course! Your task will be to use the Keras functional API to train a model to predict two outputs. For this lab, you will use the [Wine Quality Dataset](#) from the **UCI machine learning repository**. It has separate datasets for red wine and white wine.

Normally, the wines are classified into one of the quality ratings specified in the attributes. In this exercise, you will combine the two datasets to predict the wine quality and whether the wine is red or white solely from the attributes.

You will model wine quality estimations as a regression problem and wine type detection as a binary classification problem.

Please complete sections that are marked (TODO)

## Imports

In [1]:

```
import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Input

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
import itertools

import utils
```

## Load Dataset

You will now download the dataset from the [UCI Machine Learning Repository](#).

## Pre-process the white wine dataset (TODO)

You will add a new column named `is_red` in your dataframe to indicate if the wine is white or red.

- In the white wine dataset, you will fill the column `is_red` with zeros (0).

In [4]:

```
## Please uncomment all lines in this cell and replace those marked with `# YOUR CODE HERE`.
## You can select all lines in this code cell with Ctrl+A (Windows/Linux) or Cmd+A (Mac), then pre
ss Ctrl+/ (Windows/Linux) or Cmd+/ (Mac) to uncomment.

# URL of the white wine dataset
URL = 'http://archive.ics.uci.edu/ml/machine-learning-databases/wine-quality/winequality-
white.csv'

# load the dataset from the URL
white_df = pd.read_csv(URL, sep=";")

# fill the `is_red` column with zeros.
white_df["is_red"] = 0

# keep only the first of duplicate items
white_df = white_df.drop_duplicates(keep='first')
```

In [5]:

```
# You can click `File -> Open` in the menu above and open the `utils.py` file
# in case you want to inspect the unit tests being used for each graded function.
```

```
utils.test_white_df(white_df)
```

All public tests passed

In [6]:

```
print(white_df.alcohol[0])
print(white_df.alcohol[100])
```

```
# EXPECTED OUTPUT
# 8.8
# 9.1
```

8.8

9.1

## Pre-process the red wine dataset (TODO)

- In the red wine dataset, you will fill in the column `is_red` with ones (1).

In [7]:

```
## Please uncomment all lines in this cell and replace those marked with `# YOUR CODE HERE`.
## You can select all lines in this code cell with Ctrl+A (Windows/Linux) or Cmd+A (Mac), then press Ctrl+/ (Windows/Linux) or Cmd+/ (Mac) to uncomment.
```

```
# URL of the red wine dataset
```

```
URL = 'http://archive.ics.uci.edu/ml/machine-learning-databases/wine-quality/winequality-red.csv'
```

```
# load the dataset from the URL
```

```
red_df = pd.read_csv(URL, sep=";")
```

```
# fill the `is_red` column with ones.
```

```
red_df["is_red"] = 1
```

```
# keep only the first of duplicate items
```

```
red_df = red_df.drop_duplicates(keep='first')
```

In [8]:

```
utils.test_red_df(red_df)
```

All public tests passed

In [9]:

```
print(red_df.alcohol[0])
print(red_df.alcohol[100])
```

```
# EXPECTED OUTPUT
# 9.4
# 10.2
```

9.4

10.2

## Concatenate the datasets

Next, concatenate the red and white wine dataframes.

In [10]:

```
df = pd.concat([red_df, white_df], ignore_index=True)
```

In [11]:

```
print(df.alcohol[0])
print(df.alcohol[100])
```

```
# EXPECTED OUTPUT
# 9.4
# 9.5
```

9.4  
9.5

In [13]:

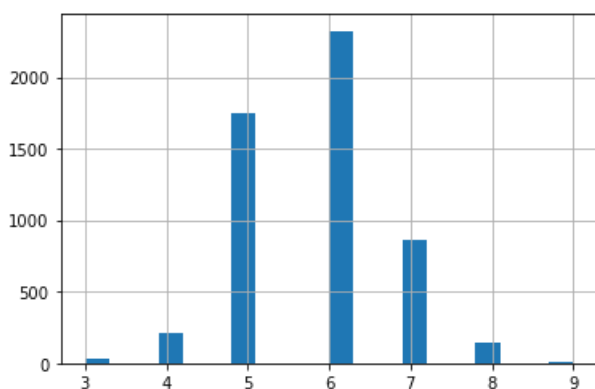
```
# NOTE: In a real-world scenario, you should shuffle the data.
# YOU ARE NOT going to do that here because we want to test
# with deterministic data. But if you want the code to do it,
# it's in the commented line below:
```

```
#df = df.iloc[np.random.permutation(len(df))]
```

This will chart the quality of the wines.

In [14]:

```
df['quality'].hist(bins=20);
```



## Imbalanced data (TODO)

You can see from the plot above that the wine quality dataset is imbalanced.

- Since there are very few observations with quality equal to 3, 4, 8 and 9, you can drop these observations from your dataset.
- You can do this by removing data belonging to all classes except those  $> 4$  and  $< 8$ .

In [15]:

```
# Please uncomment all lines in this cell and replace those marked with `# YOUR CODE HERE`.
# You can select all lines in this code cell with Ctrl+A (Windows/Linux) or Cmd+A (Mac), then pres
s Ctrl+/- (Windows/Linux) or Cmd+/- (Mac) to uncomment.
```

```
# get data with wine quality greater than 4 and less than 8
df = df[(df['quality'] > 4) & (df['quality'] < 8)]
```

```
# reset index and drop the old one
df = df.reset_index(drop=True)
```

In [16]:

```
utils.test_df_drop(df)
```

All public tests passed

In [17]:

```
print(df.alcohol[0])
print(df.alcohol[100])
```

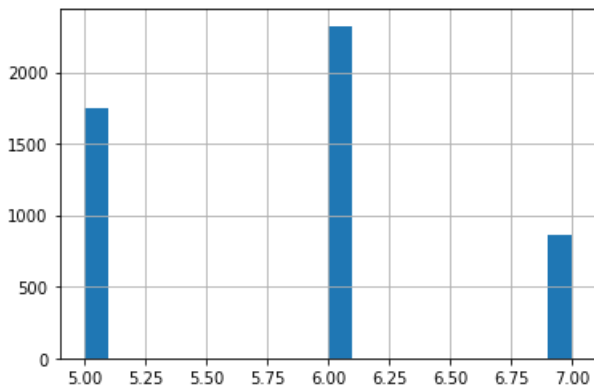
```
# EXPECTED OUTPUT
# 9.4
# 10.9
```

```
9.4
10.9
```

You can plot again to see the new range of data and quality

In [18]:

```
df['quality'].hist(bins=20);
```



## Train Test Split (TODO)

Next, you can split the datasets into training, test and validation datasets.

- The data frame should be split 80:20 into `train` and `test` sets.
- The resulting `train` should then be split 80:20 into `train` and `val` sets.
- The `train_test_split` parameter `test_size` takes a float value that ranges between 0. and 1, and represents the proportion of the dataset that is allocated to the test set. The rest of the data is allocated to the training set.

In [19]:

```
# Please uncomment all lines in this cell and replace those marked with `# YOUR CODE HERE`.
# You can select all lines in this code cell with Ctrl+A (Windows/Linux) or Cmd+A (Mac), then press
# Ctrl+/ (Windows/Linux) or Cmd+/ (Mac) to uncomment.
```

```
# Please do not change the random_state parameter. This is needed for grading.
```

```
# split df into 80:20 train and test sets
train, test = train_test_split(df, test_size=.2, random_state = 1)
```

```
# split train into 80:20 train and val sets
train, val = train_test_split(train, test_size=.2, random_state = 1)
```

In [20]:

```
utils.test_data_sizes(train.size, test.size, val.size)
```

All public tests passed

Here's where you can explore the training stats. You can pop the labels 'is\_red' and 'quality' from the data as these will be used as the labels

In [21]:

```
train_stats = train.describe()
train_stats.pop('is_red')
train_stats.pop('quality')
train_stats = train_stats.transpose()
```

Explore the training stats!

In [22]:

```
train_stats
```

Out[22]:

	count	mean	std	min	25%	50%	75%	max
<b>fixed acidity</b>	3155.0	7.221616	1.325297	3.80000	6.40000	7.00000	7.7000	15.60000
<b>volatile acidity</b>	3155.0	0.338929	0.162476	0.08000	0.23000	0.29000	0.4000	1.24000
<b>citric acid</b>	3155.0	0.321569	0.147970	0.00000	0.25000	0.31000	0.4000	1.66000
<b>residual sugar</b>	3155.0	5.155911	4.639632	0.60000	1.80000	2.80000	7.6500	65.80000
<b>chlorides</b>	3155.0	0.056976	0.036802	0.01200	0.03800	0.04700	0.0660	0.61100
<b>free sulfur dioxide</b>	3155.0	30.388590	17.236784	1.00000	17.00000	28.00000	41.0000	131.00000
<b>total sulfur dioxide</b>	3155.0	115.062282	56.706617	6.00000	75.00000	117.00000	156.0000	344.00000
<b>density</b>	3155.0	0.994633	0.003005	0.98711	0.99232	0.99481	0.9968	1.03898
<b>pH</b>	3155.0	3.223201	0.161272	2.72000	3.11000	3.21000	3.3300	4.01000
<b>sulphates</b>	3155.0	0.534051	0.149149	0.22000	0.43000	0.51000	0.6000	1.95000
<b>alcohol</b>	3155.0	10.504466	1.154654	8.50000	9.50000	10.30000	11.3000	14.00000

## Get the labels (TODO)

The features and labels are currently in the same dataframe.

- You will want to store the label columns `is_red` and `quality` separately from the feature columns.
- The following function, `format_output`, gets these two columns from the dataframe (it's given to you).
- `format_output` also formats the data into numpy arrays.
- Please use the `format_output` and apply it to the `train`, `val` and `test` sets to get dataframes for the labels.

In [23]:

```
def format_output(data):
    is_red = data.pop('is_red')
    is_red = np.array(is_red)
    quality = data.pop('quality')
    quality = np.array(quality)
    return (quality, is_red)
```

In [24]:

```
# Please uncomment all lines in this cell and replace those marked with `# YOUR CODE HERE`.
# You can select all lines in this code cell with Ctrl+A (Windows/Linux) or Cmd+A (Mac), then pres
s Ctrl+/ (Windows/Linux) or Cmd+/ (Mac) to uncomment.

# format the output of the train set
train_Y = format_output(train)

# format the output of the val set
val_Y = format_output(val)
```

```
# format the output of the test set
test_Y = format_output(test)
```

In [25]:

```
utils.test_format_output(df, train_Y, val_Y, test_Y)
```

All public tests passed

Notice that after you get the labels, the `train`, `val` and `test` dataframes no longer contain the label columns, and contain just the feature columns.

- This is because you used `.pop` in the `format_output` function.

In [26]:

```
train.head()
```

Out[26]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
225	7.5	0.65	0.18	7.0	0.088	27.0	94.0	0.99915	3.38	0.77	9.4
3557	6.3	0.27	0.29	12.2	0.044	59.0	196.0	0.99782	3.14	0.40	8.8
3825	8.8	0.27	0.25	5.0	0.024	52.0	99.0	0.99250	2.87	0.49	11.4
1740	6.4	0.45	0.07	1.1	0.030	10.0	131.0	0.99050	2.97	0.28	10.8
1221	7.2	0.53	0.13	2.0	0.058	18.0	22.0	0.99573	3.21	0.68	9.9

## Normalize the data (TODO)

Next, you can normalize the data,  $x$ , using the formula:  $x_{\text{norm}} = \frac{x - \mu}{\sigma}$

- The `norm` function is defined for you.
- Please apply the `norm` function to normalize the dataframes that contains the feature columns of `train`, `val` and `test` sets.

In [27]:

```
def norm(x):
    return (x - train_stats['mean']) / train_stats['std']
```

In [28]:

```
# Please uncomment all lines in this cell and replace those marked with `# YOUR CODE HERE`.
# You can select all lines in this code cell with Ctrl+A (Windows/Linux) or Cmd+A (Mac), then press Ctrl+/ (Windows/Linux) or Cmd+/ (Mac) to uncomment.

# # normalize the train set
norm_train_X = norm(train)

# # normalize the val set
norm_val_X = norm(val)

# # normalize the test set
norm_test_X = norm(test)
```

In [29]:

```
utils.test_norm(norm_train_X, norm_val_X, norm_test_X, train, val, test)
```

All public tests passed

## Define the Model (TODO)

Define the model using the functional API. The base model will be 2 `Dense` layers of 128 neurons each, and have the `'relu'` activation.

- Check out the documentation for [tf.keras.layers.Dense](https://keras.io/layers/dense/)

In [30]:

```
# Please uncomment all lines in this cell and replace those marked with `# YOUR CODE HERE`.
# You can select all lines in this code cell with Ctrl+A (Windows/Linux) or Cmd+A (Mac), then press Ctrl+/ (Windows/Linux) or Cmd+/ (Mac) to uncomment.

def base_model(inputs):

    # connect a Dense layer with 128 neurons and a relu activation
    x = Dense(128, activation='relu')(inputs)

    # connect another Dense layer with 128 neurons and a relu activation
    x = Dense(128, activation='relu')(x)
    return x
```

In [31]:

```
utils.test_base_model(base_model)
```

All public tests passed

## Define output layers of the model (TODO)

You will add output layers to the base model.

- The model will need two outputs.

One output layer will predict wine quality, which is a numeric value.

- Define a `Dense` layer with 1 neuron.
- Since this is a regression output, the activation can be left as its default value `None`.

The other output layer will predict the wine type, which is either red `1` or not red `0` (white).

- Define a `Dense` layer with 1 neuron.
- Since there are two possible categories, you can use a sigmoid activation for binary classification.

Define the `Model`

- Define the `Model` object, and set the following parameters:
  - `inputs`: pass in the inputs to the model as a list.
  - `outputs`: pass in a list of the outputs that you just defined: wine quality, then wine type.
  - **Note:** please list the wine quality before wine type in the outputs, as this will affect the calculated loss if you choose the other order.

In [34]:

```
# Please uncomment all lines in this cell and replace those marked with `# YOUR CODE HERE`.
# You can select all lines in this code cell with Ctrl+A (Windows/Linux) or Cmd+A (Mac), then press Ctrl+/ (Windows/Linux) or Cmd+/ (Mac) to uncomment.

def final_model(inputs):

    # get the base model
    x = base_model(inputs)

    # connect the output Dense layer for regression
    wine_quality = Dense(units='1', name='wine_quality')(x)
```

```
# connect the output Dense layer for classification. this will use a sigmoid activation.
wine_type = Dense(units='1', activation='sigmoid', name='wine_type')(x)

# define the model using the input and output layers
model = Model(inputs=inputs, outputs=[wine_quality, wine_type])

return model
```

In [35]:

```
utils.test_final_model(final_model)
```

All public tests passed

## Compiling the Model

Next, compile the model. When setting the loss parameter of `model.compile`, you're setting the loss for each of the two outputs (wine quality and wine type).

To set more than one loss, use a dictionary of key-value pairs.

- You can look at the docs for the losses [here](#).
  - Note:** For the desired spelling, please look at the "Functions" section of the documentation and not the "classes" section on that same page.
- wine\_type: Since you will be performing binary classification on wine type, you should use the binary crossentropy loss function for it. Please pass this in as a string.
  - Hint,** this should be all lowercase. In the documentation, you'll see this under the "Functions" section, not the "Classes" section.
- wine\_quality: since this is a regression output, use the mean squared error. Please pass it in as a string, all lowercase.
  - Hint:** You may notice that there are two aliases for mean squared error. Please use the shorter name.

You will also set the metric for each of the two outputs. Again, to set metrics for two or more outputs, use a dictionary with key value pairs.

- The metrics documentation is linked [here](#).
- For the wine type, please set it to accuracy as a string, all lowercase.
- For wine quality, please use the root mean squared error. Instead of a string, you'll set it to an instance of the class [RootMeanSquaredError](#), which belongs to the `tf.keras.metrics` module.

**Note:** If you see the error message

```
Exception: wine quality loss function is incorrect.
```

- Please also check your other losses and metrics, as the error may be caused by the other three key-value pairs and not the wine quality loss.

In [39]:

```
# Please uncomment all lines in this cell and replace those marked with `# YOUR CODE HERE`.
# You can select all lines in this code cell with Ctrl+A (Windows/Linux) or Cmd+A (Mac), then pres
s Ctrl+/ (Windows/Linux) or Cmd+/ (Mac) to uncomment.

inputs = tf.keras.layers.Input(shape=(11,))
rms = tf.keras.optimizers.RMSprop(lr=0.0001)
model = final_model(inputs)

model.compile(optimizer=rms,
              loss = {'wine_type' : 'binary_crossentropy',
                     'wine_quality': 'mse'
                     },
              metrics = {'wine_type' : 'accuracy',
                        'wine_quality': tf.keras.metrics.RootMeanSquaredError()
                        }
              )
```

In [40]:



```
utils.test_model_compile(model)
```

All public tests passed

## Training the Model

Fit the model to the training inputs and outputs.

- Check the documentation for [model.fit](#).
- Remember to use the normalized training set as inputs.
- For the validation data, please use the normalized validation set.

In [42]:

```
# Please uncomment all lines in this cell and replace those marked with `# YOUR CODE HERE`.
# You can select all lines in this code cell with Ctrl+A (Windows/Linux) or Cmd+A (Mac), then press Ctrl+/ (Windows/Linux) or Cmd+/ (Mac) to uncomment.
```

```
history = model.fit(norm_train_X, train_Y,
                    epochs = 180, validation_data=(norm_val_X, val_Y))
```

Train on 3155 samples, validate on 789 samples

Epoch 1/180

```
3155/3155 [=====] - 1s 321us/sample - loss: 24.7157 - wine_quality_loss: 23.9919 - wine_type_loss: 0.6763 - wine_quality_root_mean_squared_error: 4.9030 - wine_type_accuracy: 0.5971 - val_loss: 16.0329 - val_wine_quality_loss: 15.4115 - val_wine_type_loss: 0.6436 - val_wine_quality_root_mean_squared_error: 3.9230 - val_wine_type_accuracy: 0.7529
```

Epoch 2/180

```
3155/3155 [=====] - 0s 94us/sample - loss: 10.0501 - wine_quality_loss: 9.4268 - wine_type_loss: 0.5990 - wine_quality_root_mean_squared_error: 3.0742 - wine_type_accuracy: 0.7930 - val_loss: 5.4150 - val_wine_quality_loss: 4.9202 - val_wine_type_loss: 0.5619 - val_wine_quality_root_mean_squared_error: 2.2032 - val_wine_type_accuracy: 0.8200
```

Epoch 3/180

```
3155/3155 [=====] - 0s 93us/sample - loss: 3.7703 - wine_quality_loss: 3.2639 - wine_type_loss: 0.5019 - wine_quality_root_mean_squared_error: 1.8078 - wine_type_accuracy: 0.8390 - val_loss: 2.8972 - val_wine_quality_loss: 2.5012 - val_wine_type_loss: 0.4544 - val_wine_quality_root_mean_squared_error: 1.5632 - val_wine_type_accuracy: 0.8504
```

Epoch 4/180

```
3155/3155 [=====] - 0s 93us/sample - loss: 2.6140 - wine_quality_loss: 2.2134 - wine_type_loss: 0.3981 - wine_quality_root_mean_squared_error: 1.4885 - wine_type_accuracy: 0.8764 - val_loss: 2.3650 - val_wine_quality_loss: 2.0381 - val_wine_type_loss: 0.3648 - val_wine_quality_root_mean_squared_error: 1.4144 - val_wine_type_accuracy: 0.8872
```

Epoch 5/180

```
3155/3155 [=====] - 0s 93us/sample - loss: 2.1533 - wine_quality_loss: 1.8403 - wine_type_loss: 0.3148 - wine_quality_root_mean_squared_error: 1.3558 - wine_type_accuracy: 0.9242 - val_loss: 2.0153 - val_wine_quality_loss: 1.7500 - val_wine_type_loss: 0.2877 - val_wine_quality_root_mean_squared_error: 1.3145 - val_wine_type_accuracy: 0.9392
```

Epoch 6/180

```
3155/3155 [=====] - 0s 91us/sample - loss: 1.8729 - wine_quality_loss: 1.6217 - wine_type_loss: 0.2504 - wine_quality_root_mean_squared_error: 1.2737 - wine_type_accuracy: 0.9601 - val_loss: 1.7766 - val_wine_quality_loss: 1.5615 - val_wine_type_loss: 0.2285 - val_wine_quality_root_mean_squared_error: 1.2443 - val_wine_type_accuracy: 0.9708
```

Epoch 7/180

```
3155/3155 [=====] - 0s 92us/sample - loss: 1.6665 - wine_quality_loss: 1.4650 - wine_type_loss: 0.1995 - wine_quality_root_mean_squared_error: 1.2112 - wine_type_accuracy: 0.9743 - val_loss: 1.5879 - val_wine_quality_loss: 1.4140 - val_wine_type_loss: 0.1821 - val_wine_quality_root_mean_squared_error: 1.1857 - val_wine_type_accuracy: 0.9823
```

Epoch 8/180

```
3155/3155 [=====] - 0s 75us/sample - loss: 1.5094 - wine_quality_loss: 1.3456 - wine_type_loss: 0.1608 - wine_quality_root_mean_squared_error: 1.1613 - wine_type_accuracy: 0.9797 - val_loss: 1.4438 - val_wine_quality_loss: 1.3006 - val_wine_type_loss: 0.1486 - val_wine_quality_root_mean_squared_error: 1.1381 - val_wine_type_accuracy: 0.9848
```

Epoch 9/180

```
3155/3155 [=====] - 0s 89us/sample - loss: 1.3875 - wine_quality_loss: 1.2534 - wine_type_loss: 0.1330 - wine_quality_root_mean_squared_error: 1.1201 - wine_type_accuracy: 0.9851 - val_loss: 1.3339 - val_wine_quality_loss: 1.2139 - val_wine_type_loss: 0.1224 - val_wine_quality_root_mean_squared_error: 1.1007 - val_wine_type_accuracy: 0.9873
```

Epoch 10/180

3155/3155 [=====] - 0s 75us/sample - loss: 1.2831 - wine\_quality\_loss: 1.1710 - wine\_type\_loss: 0.1123 - wine\_quality\_root\_mean\_squared\_error: 1.0820 - wine\_type\_accuracy: 0.9864 - val\_loss: 1.2373 - val\_wine\_quality\_loss: 1.1344 - val\_wine\_type\_loss: 0.1038 - val\_wine\_quality\_root\_mean\_squared\_error: 1.0647 - val\_wine\_type\_accuracy: 0.9899  
Epoch 11/180  
3155/3155 [=====] - 0s 76us/sample - loss: 1.1990 - wine\_quality\_loss: 1.1008 - wine\_type\_loss: 0.0968 - wine\_quality\_root\_mean\_squared\_error: 1.0498 - wine\_type\_accuracy: 0.9873 - val\_loss: 1.1451 - val\_wine\_quality\_loss: 1.0553 - val\_wine\_type\_loss: 0.0903 - val\_wine\_quality\_root\_mean\_squared\_error: 1.0270 - val\_wine\_type\_accuracy: 0.9911  
Epoch 12/180  
3155/3155 [=====] - 0s 90us/sample - loss: 1.1213 - wine\_quality\_loss: 1.0349 - wine\_type\_loss: 0.0850 - wine\_quality\_root\_mean\_squared\_error: 1.0179 - wine\_type\_accuracy: 0.9880 - val\_loss: 1.0753 - val\_wine\_quality\_loss: 0.9959 - val\_wine\_type\_loss: 0.0796 - val\_wine\_quality\_root\_mean\_squared\_error: 0.9978 - val\_wine\_type\_accuracy: 0.9911  
Epoch 13/180  
3155/3155 [=====] - 0s 73us/sample - loss: 1.0498 - wine\_quality\_loss: 0.9796 - wine\_type\_loss: 0.0761 - wine\_quality\_root\_mean\_squared\_error: 0.9867 - wine\_type\_accuracy: 0.9883 - val\_loss: 1.0020 - val\_wine\_quality\_loss: 0.9310 - val\_wine\_type\_loss: 0.0711 - val\_wine\_quality\_root\_mean\_squared\_error: 0.9648 - val\_wine\_type\_accuracy: 0.9911  
Epoch 14/180  
3155/3155 [=====] - 0s 88us/sample - loss: 0.9848 - wine\_quality\_loss: 0.9159 - wine\_type\_loss: 0.0689 - wine\_quality\_root\_mean\_squared\_error: 0.9570 - wine\_type\_accuracy: 0.9886 - val\_loss: 0.9426 - val\_wine\_quality\_loss: 0.8775 - val\_wine\_type\_loss: 0.0641 - val\_wine\_quality\_root\_mean\_squared\_error: 0.9372 - val\_wine\_type\_accuracy: 0.9911  
Epoch 15/180  
3155/3155 [=====] - 0s 88us/sample - loss: 0.9242 - wine\_quality\_loss: 0.8611 - wine\_type\_loss: 0.0630 - wine\_quality\_root\_mean\_squared\_error: 0.9280 - wine\_type\_accuracy: 0.9895 - val\_loss: 0.8936 - val\_wine\_quality\_loss: 0.8334 - val\_wine\_type\_loss: 0.0586 - val\_wine\_quality\_root\_mean\_squared\_error: 0.9137 - val\_wine\_type\_accuracy: 0.9924  
Epoch 16/180  
3155/3155 [=====] - 0s 75us/sample - loss: 0.8696 - wine\_quality\_loss: 0.8104 - wine\_type\_loss: 0.0582 - wine\_quality\_root\_mean\_squared\_error: 0.9007 - wine\_type\_accuracy: 0.9905 - val\_loss: 0.8345 - val\_wine\_quality\_loss: 0.7788 - val\_wine\_type\_loss: 0.0544 - val\_wine\_quality\_root\_mean\_squared\_error: 0.8831 - val\_wine\_type\_accuracy: 0.9924  
Epoch 17/180  
3155/3155 [=====] - 0s 90us/sample - loss: 0.8166 - wine\_quality\_loss: 0.7630 - wine\_type\_loss: 0.0544 - wine\_quality\_root\_mean\_squared\_error: 0.8730 - wine\_type\_accuracy: 0.9908 - val\_loss: 0.7855 - val\_wine\_quality\_loss: 0.7332 - val\_wine\_type\_loss: 0.0510 - val\_wine\_quality\_root\_mean\_squared\_error: 0.8569 - val\_wine\_type\_accuracy: 0.9924  
Epoch 18/180  
3155/3155 [=====] - 0s 87us/sample - loss: 0.7705 - wine\_quality\_loss: 0.7207 - wine\_type\_loss: 0.0514 - wine\_quality\_root\_mean\_squared\_error: 0.8479 - wine\_type\_accuracy: 0.9908 - val\_loss: 0.7378 - val\_wine\_quality\_loss: 0.6882 - val\_wine\_type\_loss: 0.0480 - val\_wine\_quality\_root\_mean\_squared\_error: 0.8304 - val\_wine\_type\_accuracy: 0.9924  
Epoch 19/180  
3155/3155 [=====] - 0s 75us/sample - loss: 0.7293 - wine\_quality\_loss: 0.6794 - wine\_type\_loss: 0.0487 - wine\_quality\_root\_mean\_squared\_error: 0.8249 - wine\_type\_accuracy: 0.9914 - val\_loss: 0.7013 - val\_wine\_quality\_loss: 0.6539 - val\_wine\_type\_loss: 0.0456 - val\_wine\_quality\_root\_mean\_squared\_error: 0.8096 - val\_wine\_type\_accuracy: 0.9924  
Epoch 20/180  
3155/3155 [=====] - 0s 90us/sample - loss: 0.6922 - wine\_quality\_loss: 0.6449 - wine\_type\_loss: 0.0466 - wine\_quality\_root\_mean\_squared\_error: 0.8035 - wine\_type\_accuracy: 0.9924 - val\_loss: 0.6591 - val\_wine\_quality\_loss: 0.6139 - val\_wine\_type\_loss: 0.0436 - val\_wine\_quality\_root\_mean\_squared\_error: 0.7844 - val\_wine\_type\_accuracy: 0.9924  
Epoch 21/180  
3155/3155 [=====] - 0s 88us/sample - loss: 0.6545 - wine\_quality\_loss: 0.6091 - wine\_type\_loss: 0.0447 - wine\_quality\_root\_mean\_squared\_error: 0.7809 - wine\_type\_accuracy: 0.9918 - val\_loss: 0.6263 - val\_wine\_quality\_loss: 0.5824 - val\_wine\_type\_loss: 0.0420 - val\_wine\_quality\_root\_mean\_squared\_error: 0.7642 - val\_wine\_type\_accuracy: 0.9924  
Epoch 22/180  
3155/3155 [=====] - 0s 74us/sample - loss: 0.6224 - wine\_quality\_loss: 0.5790 - wine\_type\_loss: 0.0433 - wine\_quality\_root\_mean\_squared\_error: 0.7610 - wine\_type\_accuracy: 0.9921 - val\_loss: 0.5972 - val\_wine\_quality\_loss: 0.5548 - val\_wine\_type\_loss: 0.0406 - val\_wine\_quality\_root\_mean\_squared\_error: 0.7459 - val\_wine\_type\_accuracy: 0.9924  
Epoch 23/180  
3155/3155 [=====] - 0s 89us/sample - loss: 0.5938 - wine\_quality\_loss: 0.5512 - wine\_type\_loss: 0.0418 - wine\_quality\_root\_mean\_squared\_error: 0.7430 - wine\_type\_accuracy: 0.9924 - val\_loss: 0.5759 - val\_wine\_quality\_loss: 0.5344 - val\_wine\_type\_loss: 0.0393 - val\_wine\_quality\_root\_mean\_squared\_error: 0.7323 - val\_wine\_type\_accuracy: 0.9924  
Epoch 24/180  
3155/3155 [=====] - 0s 88us/sample - loss: 0.5649 - wine\_quality\_loss: 0.5246 - wine\_type\_loss: 0.0407 - wine\_quality\_root\_mean\_squared\_error: 0.7241 - wine\_type\_accuracy: 0.9924 - val\_loss: 0.5440 - val\_wine\_quality\_loss: 0.5037 - val\_wine\_type\_loss: 0.0384 - val\_wine\_quality\_root\_mean\_squared\_error: 0.7108 - val\_wine\_type\_accuracy: 0.9937  
Epoch 25/180  
3155/3155 [=====] - 0s 76us/sample - loss: 0.5398 - wine\_quality\_loss: 0.5004 - wine\_type\_loss: 0.0395 - wine\_quality\_root\_mean\_squared\_error: 0.7072 - wine\_type\_accuracy:

0.9930 - val\_loss: 0.5194 - val\_wine\_quality\_loss: 0.4801 - val\_wine\_type\_loss: 0.0375 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.6939 - val\_wine\_type\_accuracy: 0.9937  
Epoch 26/180  
3155/3155 [=====] - 0s 87us/sample - loss: 0.5179 - wine\_quality\_loss: 0.  
4791 - wine\_type\_loss: 0.0388 - wine\_quality\_root\_mean\_squared\_error: 0.6922 - wine\_type\_accuracy:  
0.9933 - val\_loss: 0.4963 - val\_wine\_quality\_loss: 0.4575 - val\_wine\_type\_loss: 0.0367 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.6777 - val\_wine\_type\_accuracy: 0.9937  
Epoch 27/180  
3155/3155 [=====] - 0s 73us/sample - loss: 0.4974 - wine\_quality\_loss: 0.  
4586 - wine\_type\_loss: 0.0377 - wine\_quality\_root\_mean\_squared\_error: 0.6779 - wine\_type\_accuracy:  
0.9933 - val\_loss: 0.4864 - val\_wine\_quality\_loss: 0.4481 - val\_wine\_type\_loss: 0.0361 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.6708 - val\_wine\_type\_accuracy: 0.9937  
Epoch 28/180  
3155/3155 [=====] - 0s 89us/sample - loss: 0.4785 - wine\_quality\_loss: 0.  
4414 - wine\_type\_loss: 0.0370 - wine\_quality\_root\_mean\_squared\_error: 0.6644 - wine\_type\_accuracy:  
0.9937 - val\_loss: 0.4711 - val\_wine\_quality\_loss: 0.4335 - val\_wine\_type\_loss: 0.0353 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.6599 - val\_wine\_type\_accuracy: 0.9949  
Epoch 29/180  
3155/3155 [=====] - 0s 89us/sample - loss: 0.4642 - wine\_quality\_loss: 0.  
4271 - wine\_type\_loss: 0.0363 - wine\_quality\_root\_mean\_squared\_error: 0.6540 - wine\_type\_accuracy:  
0.9940 - val\_loss: 0.4579 - val\_wine\_quality\_loss: 0.4208 - val\_wine\_type\_loss: 0.0349 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.6501 - val\_wine\_type\_accuracy: 0.9949  
Epoch 30/180  
3155/3155 [=====] - 0s 74us/sample - loss: 0.4494 - wine\_quality\_loss: 0.  
4137 - wine\_type\_loss: 0.0357 - wine\_quality\_root\_mean\_squared\_error: 0.6431 - wine\_type\_accuracy:  
0.9940 - val\_loss: 0.4363 - val\_wine\_quality\_loss: 0.3998 - val\_wine\_type\_loss: 0.0344 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.6337 - val\_wine\_type\_accuracy: 0.9949  
Epoch 31/180  
3155/3155 [=====] - 0s 90us/sample - loss: 0.4350 - wine\_quality\_loss: 0.  
3998 - wine\_type\_loss: 0.0351 - wine\_quality\_root\_mean\_squared\_error: 0.6323 - wine\_type\_accuracy:  
0.9940 - val\_loss: 0.4273 - val\_wine\_quality\_loss: 0.3911 - val\_wine\_type\_loss: 0.0340 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.6269 - val\_wine\_type\_accuracy: 0.9949  
Epoch 32/180  
3155/3155 [=====] - 0s 89us/sample - loss: 0.4234 - wine\_quality\_loss: 0.  
3903 - wine\_type\_loss: 0.0348 - wine\_quality\_root\_mean\_squared\_error: 0.6235 - wine\_type\_accuracy:  
0.9943 - val\_loss: 0.4175 - val\_wine\_quality\_loss: 0.3820 - val\_wine\_type\_loss: 0.0337 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.6193 - val\_wine\_type\_accuracy: 0.9949  
Epoch 33/180  
3155/3155 [=====] - 0s 75us/sample - loss: 0.4157 - wine\_quality\_loss: 0.  
3814 - wine\_type\_loss: 0.0341 - wine\_quality\_root\_mean\_squared\_error: 0.6176 - wine\_type\_accuracy:  
0.9943 - val\_loss: 0.4090 - val\_wine\_quality\_loss: 0.3739 - val\_wine\_type\_loss: 0.0332 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.6128 - val\_wine\_type\_accuracy: 0.9949  
Epoch 34/180  
3155/3155 [=====] - 0s 89us/sample - loss: 0.4057 - wine\_quality\_loss: 0.  
3716 - wine\_type\_loss: 0.0341 - wine\_quality\_root\_mean\_squared\_error: 0.6098 - wine\_type\_accuracy:  
0.9943 - val\_loss: 0.4136 - val\_wine\_quality\_loss: 0.3785 - val\_wine\_type\_loss: 0.0330 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.6167 - val\_wine\_type\_accuracy: 0.9949  
Epoch 35/180  
3155/3155 [=====] - 0s 73us/sample - loss: 0.4000 - wine\_quality\_loss: 0.  
3671 - wine\_type\_loss: 0.0334 - wine\_quality\_root\_mean\_squared\_error: 0.6054 - wine\_type\_accuracy:  
0.9943 - val\_loss: 0.3999 - val\_wine\_quality\_loss: 0.3651 - val\_wine\_type\_loss: 0.0327 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.6057 - val\_wine\_type\_accuracy: 0.9949  
Epoch 36/180  
3155/3155 [=====] - 0s 88us/sample - loss: 0.3912 - wine\_quality\_loss: 0.  
3578 - wine\_type\_loss: 0.0331 - wine\_quality\_root\_mean\_squared\_error: 0.5984 - wine\_type\_accuracy:  
0.9940 - val\_loss: 0.3885 - val\_wine\_quality\_loss: 0.3544 - val\_wine\_type\_loss: 0.0324 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.5965 - val\_wine\_type\_accuracy: 0.9949  
Epoch 37/180  
3155/3155 [=====] - 0s 87us/sample - loss: 0.3870 - wine\_quality\_loss: 0.  
3542 - wine\_type\_loss: 0.0327 - wine\_quality\_root\_mean\_squared\_error: 0.5953 - wine\_type\_accuracy:  
0.9943 - val\_loss: 0.3805 - val\_wine\_quality\_loss: 0.3465 - val\_wine\_type\_loss: 0.0322 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.5899 - val\_wine\_type\_accuracy: 0.9949  
Epoch 38/180  
3155/3155 [=====] - 0s 75us/sample - loss: 0.3802 - wine\_quality\_loss: 0.  
3472 - wine\_type\_loss: 0.0324 - wine\_quality\_root\_mean\_squared\_error: 0.5898 - wine\_type\_accuracy:  
0.9940 - val\_loss: 0.3800 - val\_wine\_quality\_loss: 0.3465 - val\_wine\_type\_loss: 0.0320 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.5897 - val\_wine\_type\_accuracy: 0.9949  
Epoch 39/180  
3155/3155 [=====] - 0s 87us/sample - loss: 0.3773 - wine\_quality\_loss: 0.  
3448 - wine\_type\_loss: 0.0320 - wine\_quality\_root\_mean\_squared\_error: 0.5876 - wine\_type\_accuracy:  
0.9940 - val\_loss: 0.3773 - val\_wine\_quality\_loss: 0.3438 - val\_wine\_type\_loss: 0.0317 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.5875 - val\_wine\_type\_accuracy: 0.9949  
Epoch 40/180  
3155/3155 [=====] - 0s 74us/sample - loss: 0.3721 - wine\_quality\_loss: 0.  
3400 - wine\_type\_loss: 0.0317 - wine\_quality\_root\_mean\_squared\_error: 0.5835 - wine\_type\_accuracy:  
0.9946 - val\_loss: 0.3696 - val\_wine\_quality\_loss: 0.3364 - val\_wine\_type\_loss: 0.0314 -  
val\_wine\_quality\_root\_mean\_squared\_error: 0.5812 - val\_wine\_type\_accuracy: 0.9949

```
3155/3155 [=====] - 0s 88us/sample - loss: 0.3684 - wine_quality_loss: 0.  
3365 - wine_type_loss: 0.0313 - wine_quality_root_mean_squared_error: 0.5805 - wine_type_accuracy:  
0.9946 - val_loss: 0.3706 - val_wine_quality_loss: 0.3373 - val_wine_type_loss: 0.0313 -  
val_wine_quality_root_mean_squared_error: 0.5821 - val_wine_type_accuracy: 0.9949  
Epoch 42/180  
3155/3155 [=====] - 0s 86us/sample - loss: 0.3631 - wine_quality_loss: 0.  
3320 - wine_type_loss: 0.0310 - wine_quality_root_mean_squared_error: 0.5762 - wine_type_accuracy:  
0.9946 - val_loss: 0.3709 - val_wine_quality_loss: 0.3378 - val_wine_type_loss: 0.0311 -  
val_wine_quality_root_mean_squared_error: 0.5826 - val_wine_type_accuracy: 0.9949  
Epoch 43/180  
3155/3155 [=====] - 0s 74us/sample - loss: 0.3618 - wine_quality_loss: 0.  
3302 - wine_type_loss: 0.0309 - wine_quality_root_mean_squared_error: 0.5753 - wine_type_accuracy:  
0.9946 - val_loss: 0.3727 - val_wine_quality_loss: 0.3401 - val_wine_type_loss: 0.0311 -  
val_wine_quality_root_mean_squared_error: 0.5842 - val_wine_type_accuracy: 0.9949  
Epoch 44/180  
3155/3155 [=====] - 0s 89us/sample - loss: 0.3591 - wine_quality_loss: 0.  
3289 - wine_type_loss: 0.0305 - wine_quality_root_mean_squared_error: 0.5731 - wine_type_accuracy:  
0.9946 - val_loss: 0.3683 - val_wine_quality_loss: 0.3358 - val_wine_type_loss: 0.0308 -  
val_wine_quality_root_mean_squared_error: 0.5806 - val_wine_type_accuracy: 0.9949  
Epoch 45/180  
3155/3155 [=====] - 0s 72us/sample - loss: 0.3558 - wine_quality_loss: 0.  
3248 - wine_type_loss: 0.0303 - wine_quality_root_mean_squared_error: 0.5704 - wine_type_accuracy:  
0.9946 - val_loss: 0.3609 - val_wine_quality_loss: 0.3285 - val_wine_type_loss: 0.0307 -  
val_wine_quality_root_mean_squared_error: 0.5743 - val_wine_type_accuracy: 0.9949  
Epoch 46/180  
3155/3155 [=====] - 0s 90us/sample - loss: 0.3531 - wine_quality_loss: 0.  
3228 - wine_type_loss: 0.0300 - wine_quality_root_mean_squared_error: 0.5684 - wine_type_accuracy:  
0.9949 - val_loss: 0.3585 - val_wine_quality_loss: 0.3264 - val_wine_type_loss: 0.0306 -  
val_wine_quality_root_mean_squared_error: 0.5723 - val_wine_type_accuracy: 0.9949  
Epoch 47/180  
3155/3155 [=====] - 0s 88us/sample - loss: 0.3503 - wine_quality_loss: 0.  
3202 - wine_type_loss: 0.0299 - wine_quality_root_mean_squared_error: 0.5660 - wine_type_accuracy:  
0.9946 - val_loss: 0.3582 - val_wine_quality_loss: 0.3261 - val_wine_type_loss: 0.0305 -  
val_wine_quality_root_mean_squared_error: 0.5721 - val_wine_type_accuracy: 0.9949  
Epoch 48/180  
3155/3155 [=====] - 0s 75us/sample - loss: 0.3486 - wine_quality_loss: 0.  
3194 - wine_type_loss: 0.0296 - wine_quality_root_mean_squared_error: 0.5647 - wine_type_accuracy:  
0.9949 - val_loss: 0.3607 - val_wine_quality_loss: 0.3287 - val_wine_type_loss: 0.0303 -  
val_wine_quality_root_mean_squared_error: 0.5744 - val_wine_type_accuracy: 0.9949  
Epoch 49/180  
3155/3155 [=====] - 0s 90us/sample - loss: 0.3460 - wine_quality_loss: 0.  
3166 - wine_type_loss: 0.0294 - wine_quality_root_mean_squared_error: 0.5626 - wine_type_accuracy:  
0.9943 - val_loss: 0.3602 - val_wine_quality_loss: 0.3286 - val_wine_type_loss: 0.0302 -  
val_wine_quality_root_mean_squared_error: 0.5741 - val_wine_type_accuracy: 0.9949  
Epoch 50/180  
3155/3155 [=====] - 0s 90us/sample - loss: 0.3456 - wine_quality_loss: 0.  
3164 - wine_type_loss: 0.0291 - wine_quality_root_mean_squared_error: 0.5625 - wine_type_accuracy:  
0.9949 - val_loss: 0.3549 - val_wine_quality_loss: 0.3232 - val_wine_type_loss: 0.0302 -  
val_wine_quality_root_mean_squared_error: 0.5695 - val_wine_type_accuracy: 0.9949  
Epoch 51/180  
3155/3155 [=====] - 0s 74us/sample - loss: 0.3433 - wine_quality_loss: 0.  
3150 - wine_type_loss: 0.0290 - wine_quality_root_mean_squared_error: 0.5606 - wine_type_accuracy:  
0.9946 - val_loss: 0.3551 - val_wine_quality_loss: 0.3236 - val_wine_type_loss: 0.0301 -  
val_wine_quality_root_mean_squared_error: 0.5698 - val_wine_type_accuracy: 0.9949  
Epoch 52/180  
3155/3155 [=====] - 0s 89us/sample - loss: 0.3408 - wine_quality_loss: 0.  
3119 - wine_type_loss: 0.0287 - wine_quality_root_mean_squared_error: 0.5585 - wine_type_accuracy:  
0.9952 - val_loss: 0.3577 - val_wine_quality_loss: 0.3263 - val_wine_type_loss: 0.0299 -  
val_wine_quality_root_mean_squared_error: 0.5722 - val_wine_type_accuracy: 0.9949  
Epoch 53/180  
3155/3155 [=====] - 0s 89us/sample - loss: 0.3392 - wine_quality_loss: 0.  
3109 - wine_type_loss: 0.0286 - wine_quality_root_mean_squared_error: 0.5573 - wine_type_accuracy:  
0.9952 - val_loss: 0.3550 - val_wine_quality_loss: 0.3236 - val_wine_type_loss: 0.0298 -  
val_wine_quality_root_mean_squared_error: 0.5700 - val_wine_type_accuracy: 0.9949  
Epoch 54/180  
3155/3155 [=====] - 0s 73us/sample - loss: 0.3390 - wine_quality_loss: 0.  
3117 - wine_type_loss: 0.0284 - wine_quality_root_mean_squared_error: 0.5573 - wine_type_accuracy:  
0.9952 - val_loss: 0.3543 - val_wine_quality_loss: 0.3230 - val_wine_type_loss: 0.0297 -  
val_wine_quality_root_mean_squared_error: 0.5693 - val_wine_type_accuracy: 0.9949  
Epoch 55/180  
3155/3155 [=====] - 0s 90us/sample - loss: 0.3375 - wine_quality_loss: 0.  
3090 - wine_type_loss: 0.0281 - wine_quality_root_mean_squared_error: 0.5562 - wine_type_accuracy:  
0.9952 - val_loss: 0.3550 - val_wine_quality_loss: 0.3240 - val_wine_type_loss: 0.0296 -  
val_wine_quality_root_mean_squared_error: 0.5701 - val_wine_type_accuracy: 0.9949  
Epoch 56/180  
3155/3155 [=====] - 0s 89us/sample - loss: 0.3362 - wine quality loss: 0.
```

[illegible]

[illegible]

[illegible]

[illegible]



[illegible]

[illegible]

[illegible]

[illegible]

```

2010 - wine_type_loss: 0.0170 - wine_quality_loss: 0.3170 - wine_quality_root_mean_squared_error: 0.5512 - wine_type_accuracy:
0.9962 - val_loss: 0.3440 - val_wine_quality_loss: 0.3171 - val_wine_type_loss: 0.0260 -
val_wine_quality_root_mean_squared_error: 0.5636 - val_wine_type_accuracy: 0.9937
Epoch 180/180
3155/3155 [=====] - 0s 75us/sample - loss: 0.2678 - wine_quality_loss: 0.
2505 - wine_type_loss: 0.0189 - wine_quality_root_mean_squared_error: 0.5005 - wine_type_accuracy:
0.9962 - val_loss: 0.3397 - val_wine_quality_loss: 0.3129 - val_wine_type_loss: 0.0260 -
val_wine_quality_root_mean_squared_error: 0.5597 - val_wine_type_accuracy: 0.9937

```

In [43]:

```
utils.test_history(history)
```

All public tests passed

In [44]:

```

# Gather the training metrics
loss, wine_quality_loss, wine_type_loss, wine_quality_rmse, wine_type_accuracy = model.evaluate(x=norm_val_X, y=val_Y)

print()
print(f'loss: {loss}')
print(f'wine_quality_loss: {wine_quality_loss}')
print(f'wine_type_loss: {wine_type_loss}')
print(f'wine_quality_rmse: {wine_quality_rmse}')
print(f'wine_type_accuracy: {wine_type_accuracy}')

# EXPECTED VALUES
# ~ 0.30 - 0.38
# ~ 0.30 - 0.38
# ~ 0.018 - 0.030
# ~ 0.50 - 0.62
# ~ 0.97 - 1.0

# Example:
#0.3657050132751465
#0.3463745415210724
#0.019330406561493874
#0.5885359048843384
#0.9974651336669922

```

```

789/789 [=====] - 0s 93us/sample - loss: 0.3397 - wine_quality_loss: 0.31
29 - wine_type_loss: 0.0260 - wine_quality_root_mean_squared_error: 0.5597 - wine_type_accuracy: 0
.9937

```

```

loss: 0.339655585766443
wine_quality_loss: 0.31292524933815
wine_type_loss: 0.026018548756837845
wine_quality_rmse: 0.5597356557846069
wine_type_accuracy: 0.9936628937721252

```

## Analyze the Model Performance

Note that the model has two outputs. The output at index 0 is quality and index 1 is wine type

So, round the quality predictions to the nearest integer.

In [45]:

```

predictions = model.predict(norm_test_X)
quality_pred = predictions[0]
type_pred = predictions[1]

```

In [46]:

```

print(quality_pred[0])

# EXPECTED OUTPUT
# 5.6 - 6.0

```

```
[5.7119555]
```

```
In [47]:
```

```
print(type_pred[0])
print(type_pred[944])

# EXPECTED OUTPUT
# A number close to zero
# A number close to or equal to 1
```

```
[0.00012767]
[0.999998]
```

## Plot Utilities

We define a few utilities to visualize the model performance.

```
In [48]:
```

```
def plot_metrics(metric_name, title, ylim=5):
    plt.title(title)
    plt.ylim(0,ylim)
    plt.plot(history.history[metric_name],color='blue',label=metric_name)
    plt.plot(history.history['val_' + metric_name],color='green',label='val_' + metric_name)
```

```
In [49]:
```

```
def plot_confusion_matrix(y_true, y_pred, title='', labels=[0,1]):
    cm = confusion_matrix(y_true, y_pred)
    fig = plt.figure()
    ax = fig.add_subplot(111)
    cax = ax.matshow(cm)
    plt.title('Confusion matrix of the classifier')
    fig.colorbar(cax)
    ax.set_xticklabels([''] + labels)
    ax.set_yticklabels([''] + labels)
    plt.xlabel('Predicted')
    plt.ylabel('True')
    fmt = 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="black" if cm[i, j] > thresh else "white")
    plt.show()
```

```
In [50]:
```

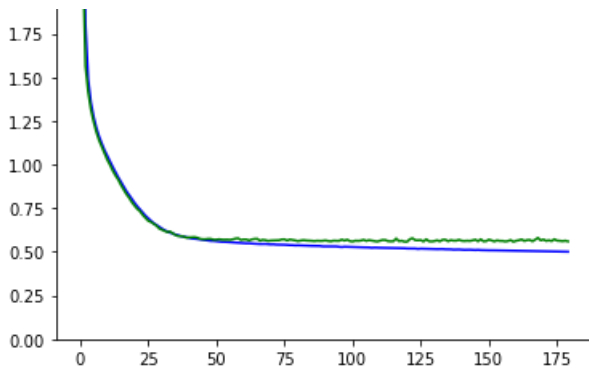
```
def plot_diff(y_true, y_pred, title = '' ):
    plt.scatter(y_true, y_pred)
    plt.title(title)
    plt.xlabel('True Values')
    plt.ylabel('Predictions')
    plt.axis('equal')
    plt.axis('square')
    plt.plot([-100, 100], [-100, 100])
    return plt
```

## Plots for Metrics

```
In [51]:
```

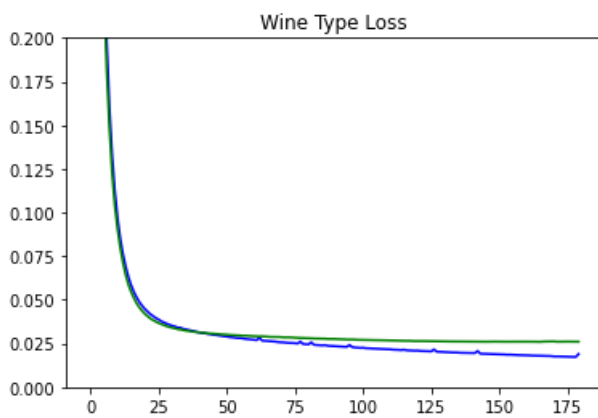
```
plot_metrics('wine_quality_root_mean_squared_error', 'RMSE', ylim=2)
```





In [52]:

```
plot_metrics('wine_type_loss', 'Wine Type Loss', ylim=0.2)
```

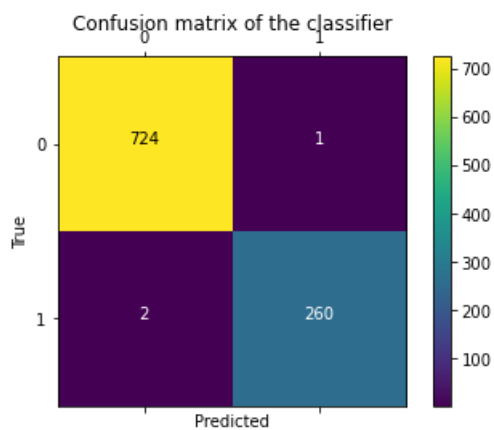


## Plots for Confusion Matrix

Plot the confusion matrices for wine type. You can see that the model performs well for prediction of wine type from the confusion matrix and the loss metrics.

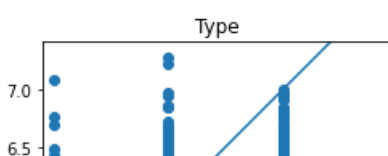
In [53]:

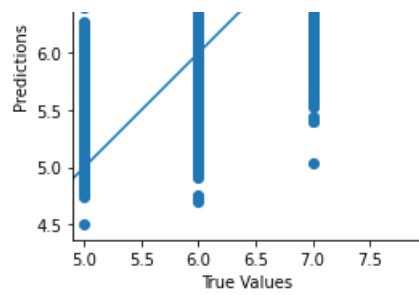
```
plot_confusion_matrix(test_Y[1], np.round(type_pred), title='Wine Type', labels = [0, 1])
```



In [54]:

```
scatter_plot = plot_diff(test_Y[0], quality_pred, title='Type')
```





In [ ]: