Feed forward Neural Networks

Q1)
Criteria 1 [1]:

- Based on the data, draw an expected decision boundary to separate the classes
- Express the decision boundary as a set of lines. Note that the combination of such lines must yield to the decision boundary.
- The number of selected lines represents the number of hidden neurons in the first hidden layer
- To connect the lines created by the previous layer, a new hidden layer is added. A new hidden layer is added each time you need to create connections among the lines in the previous hidden layer.
- The number of hidden neurons in each new hidden layer equals the number of connections to be made

Criteria 2: The trial and error method [3]

It suggests that the decision methods of the optimal number of neurons in the hidden layer have been suggested with information criteria [2], trial and error and so on.

The data are divided into training data and test data of the neural network and after training the neural network, the number of neurons for the hidden layer which has the smallest sum squared error, is adopted into the neural network.

Q2)

	Criteria	Accuracy	Loss
1	3 layers, 1st and 2nd with RELU 3rd layer with sigmoid Error function : binary _cross_entropy	0.5482	0.6858
2	3 layers, 1st and 2nd with RELU 3rd layer with sigmoid Error function : mean_squared_error	0.5482	0.2466
3	3 layers All with sigmoid activation function Error function : binary _cross_entropy	0.6886	0.6328
4	3 layers All with sigmoid activation function Error function : mean_squared_error	0.6886	0.2269
5	2 layers All with sigmoid activation function Error function : binary _cross_entropy	0.6798	0.6551
6	2 layers All with sigmoid activation function Error function : mean_squared_error	0.6930	0.2178

Q3)

Tried out 6 combinations of different loss functions and layers. For the same number of layers of 3 with the same activation function, there was no change in the accuracy when only the loss function was changed.

For loss function with cross entropy, the loss is very high compared to mean squared error. And when the number of layers are reduced from 3 to 2, the accuracy of the model has increased and has the highest when with sigmoid activation function with mean squared error.

Therefore the behaviour shows that the results agrees with the criteria 2 above in the Q1.

[1]: https://towardsdatascience.com/beginners-ask-how-many-hidden-layers-neurons-to-use-in-artificial-neural-networks-51466afa0d3e

[2]: Akaike H. , "A New Look at the Statistical Model Identification", JEEE Transactions on Automatic Control, AC-19, pp. 716-723, 1974

[3]: Kazuhiro Shin-ike, “A Two Phase Method for Determining the Number of Neurons in the Hidden Layer of a 3-Layer Neural Network”, SICE Annual Conference 2010

FNN_script

August 1, 2020

[1]:
```
# import pandas
import pandas as pd

# read the file from google colab
from google.colab import files
uploaded = files.upload()


import io

import tensorflow as tf
from keras.models import Sequential
from keras.layers import Dense
```

```
<IPython.core.display.HTML object>


Saving crx.data to crx.data

Using TensorFlow backend.
```

[2]:
```
df = pd.read_table( io.BytesIO (uploaded['crx.data']), header=None,␣
 ↪delimiter=',')

# read data
print(df.head())
```

```
  0      1      2  3  4  5  6     7  8  9   10 11 12     13   14 15
0  b  30.83  0.000  u  g  w  v  1.25  t  t   1  f  g  00202    0  +
1  a  58.67  4.460  u  g  q  h  3.04  t  t   6  f  g  00043  560  +
2  a  24.50  0.500  u  g  q  h  1.50  t  f   0  f  g  00280  824  +
3  b  27.83  1.540  u  g  w  v  3.75  t  t   5  t  g  00100    3  +
4  b  20.17  5.625  u  g  w  v  1.71  t  f   0  f  s  00120    0  +
```

[3]:
```
print(df.dtypes)

#import numpy
import numpy as np
```

```
# replace mssing values '?' with Na
df = df.replace('?', np.NaN)
```

```
0      object
1      object
2     float64
3      object
4      object
5      object
6      object
7     float64
8      object
9      object
10      int64
11     object
12     object
13     object
14      int64
15     object
dtype: object
```

[4]:
```
# replace the missing values with mean
df.fillna(df.mean(), inplace=True)

# count the number of NaNs to verify that there are no missing values
print(df.isnull().values.sum())
```

```
67
```

[ ]:
```
# still the missing values are present. And those are for non-numeric columns.
# As the mean impuatation does not work for non-numeric values the most␣
↪frequent value from the column, is imputed to missing values for the␣
↪respective columns.
```

[5]:
```
for col in df.columns:

  # first check if the column is of object type
  if df[col].dtypes == 'object':

    #impute the most frequent value
    df = df.fillna(df[col].value_counts().index[0])


# again count the missing values
print(df.isnull().values.sum())
```

```
0
```

```
[ ]: print(df)
```

```
     0      1       2  3  4   5   6     7  8  9  10 11 12     13   14 15
0    b  30.83   0.000  u  g   w   v  1.25  t  t   1  f  g  00202    0  +
1    a  58.67   4.460  u  g   q   h  3.04  t  t   6  f  g  00043  560  +
2    a  24.50   0.500  u  g   q   h  1.50  t  f   0  f  g  00280  824  +
3    b  27.83   1.540  u  g   w   v  3.75  t  t   5  t  g  00100    3  +
4    b  20.17   5.625  u  g   w   v  1.71  t  f   0  f  s  00120    0  +
..  ..    ...     ... .. ..  ..  ..   ... .. ..  .. .. ..    ...  ... ..
685  b  21.08  10.085  y  p   e   h  1.25  f  f   0  f  g  00260    0  -
686  a  22.67   0.750  u  g   c   v  2.00  f  t   2  t  g  00200  394  -
687  a  25.25  13.500  y  p  ff  ff  2.00  f  t   1  t  g  00200    1  -
688  b  17.92   0.205  u  g  aa   v  0.04  f  f   0  f  g  00280  750  -
689  b  35.00   3.375  u  g   c   h  8.29  f  f   0  t  g  00000    0  -

[690 rows x 16 columns]
```

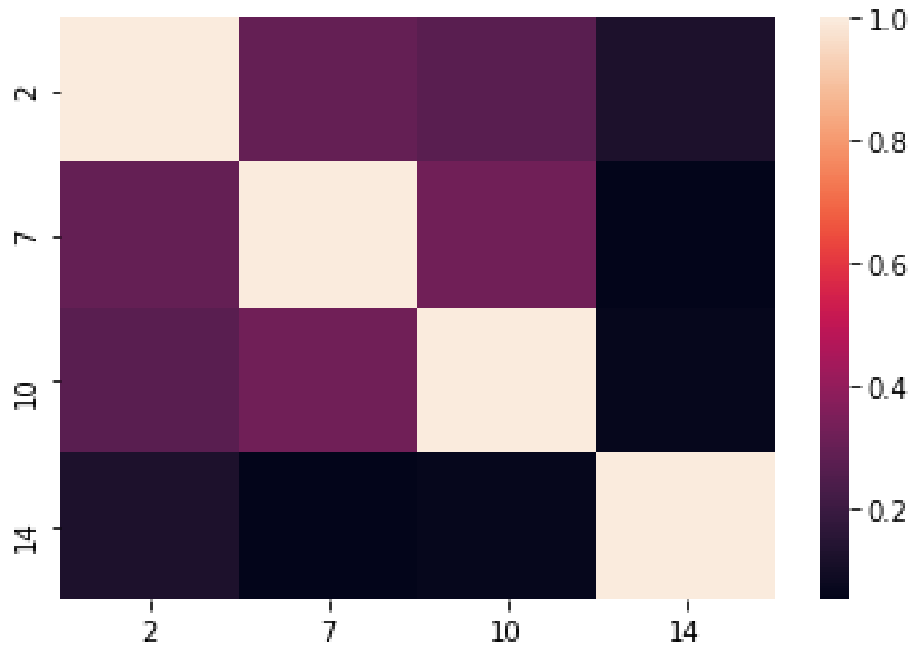
```
[ ]: import seaborn as sns
     import matplotlib as plt

     # get correlation between variables
     corr = df.corr()

     # create a heatmap-type chart to display correlations
     sns.heatmap(corr,
                 xticklabels=corr.columns.values,
                 yticklabels=corr.columns.values)
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the
public API at pandas.testing instead.
  import pandas.util.testing as tm
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7d841f0978>
```



[6]:
```
# Import LabelEncoder
from sklearn.preprocessing import LabelEncoder
# Instantiate LabelEncoder
le=LabelEncoder()

# Iterate over all the values of each column and extract their dtypes
for col in df.columns:
    # Compare if the dtype is object
    if df[col].dtypes=='object':
    # Use LabelEncoder to do the numeric transformation
        df[col]=le.fit_transform(df[col])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 690 entries, 0 to 689
Data columns (total 16 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   0       690 non-null    int64
 1   1       690 non-null    int64
 2   2       690 non-null    float64
 3   3       690 non-null    int64
 4   4       690 non-null    int64
 5   5       690 non-null    int64
 6   6       690 non-null    int64
 7   7       690 non-null    float64
```

```
 8   8       690 non-null    int64
 9   9       690 non-null    int64
 10  10      690 non-null    int64
 11  11      690 non-null    int64
 12  12      690 non-null    int64
 13  13      690 non-null    int64
 14  14      690 non-null    int64
 15  15      690 non-null    int64
dtypes: float64(2), int64(14)
memory usage: 86.4 KB
```

[ ]:
```
print(df)
```

```
     0    1       2   3   4   5   6     7   8   9   10  11  12  13   14  15
0    1  156   0.000   2   1  13   8  1.25   1   1   1   0   0  68    0   0
1    0  328   4.460   2   1  11   4  3.04   1   1   6   0   0  11  560   0
2    0   89   0.500   2   1  11   4  1.50   1   0   0   0   0  96  824   0
3    1  125   1.540   2   1  13   8  3.75   1   1   5   1   0  31    3   0
4    1   43   5.625   2   1  13   8  1.71   1   0   0   0   2  37    0   0
..  ..  …     …  ..  ..  ..  ..   …   ..  ..  ..  ..  ..  ..  …  ..
685  1   52  10.085   3   3   5   4  1.25   0   0   0   0   0  90    0   1
686  0   71   0.750   2   1   2   8  2.00   0   1   2   1   0  67  394   1
687  0   97  13.500   3   3   6   3  2.00   0   1   1   1   0  67    1   1
688  1   20   0.205   2   1   0   8  0.04   0   0   0   0   0  96  750   1
689  1  197   3.375   2   1   2   4  8.29   0   0   0   1   0   0    0   1

[690 rows x 16 columns]
```

[7]:
```
# Import train_test_split
from sklearn.model_selection import train_test_split

# import numpy as np

# Drop the features 11 and 13 and convert the DataFrame to a NumPy array
df = df.drop(columns=[11, 13])
df = df.values

# Segregate features and labels into separate variables
X,y = df[:,0:13] , df[:,13]

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X,
                                y,
                                test_size=0.33,
                                random_state=42)
```

[8]:
```python
# Import MinMaxScaler
from sklearn.preprocessing import MinMaxScaler

# Instantiate MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))

# then use the scaler to rescale X_train and X_test values
rescaledX_train = scaler.fit_transform(X_train)
rescaledX_test = scaler.fit_transform(X_test)
```

Create Keras sequential model

For first two layers, RELU activation function was used and for the third layer sigmoid function was used.

[36]:
```python
from keras.models import Sequential
from keras.layers import Dense

model = Sequential()

model.add(Dense(8, activation='sigmoid', input_shape=(13,)))

# model.add(Dense(8, activation='sigmoid'))

model.add(Dense(1, activation='sigmoid'))
```

complie the neural network.

[37]:
```python
# binary_crossentropy

model.compile(loss='mean_squared_error',
              optimizer='sgd',
              metrics=['accuracy'])

model.fit(X_train, y_train,epochs=10, batch_size=1, verbose=1)
```

```
Epoch 1/10
462/462 [==============================] - 0s 864us/step - loss: 0.2319 -
accuracy: 0.6385
Epoch 2/10
462/462 [==============================] - 0s 805us/step - loss: 0.2262 -
accuracy: 0.6710
Epoch 3/10
462/462 [==============================] - 0s 890us/step - loss: 0.2228 -
accuracy: 0.6818
Epoch 4/10
462/462 [==============================] - 0s 747us/step - loss: 0.2213 -
accuracy: 0.6840
Epoch 5/10
```

```
462/462 [==============================] - 0s 741us/step - loss: 0.2206 -
accuracy: 0.6753
Epoch 6/10
462/462 [==============================] - 0s 739us/step - loss: 0.2209 -
accuracy: 0.6797
Epoch 7/10
462/462 [==============================] - 0s 803us/step - loss: 0.2252 -
accuracy: 0.6558
Epoch 8/10
462/462 [==============================] - 0s 861us/step - loss: 0.2342 -
accuracy: 0.5866
Epoch 9/10
462/462 [==============================] - 0s 832us/step - loss: 0.2291 -
accuracy: 0.6602
Epoch 10/10
462/462 [==============================] - 0s 750us/step - loss: 0.2268 -
accuracy: 0.6818
```

[37]:
```
<keras.callbacks.callbacks.History at 0x7fd5832575f8>
```

[ ]:
```
model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_7 (Dense)              (None, 8)                 112
_________________________________________________________________
dense_8 (Dense)              (None, 8)                 72
_________________________________________________________________
dense_9 (Dense)              (None, 1)                 9
=================================================================
Total params: 193
Trainable params: 193
Non-trainable params: 0
_________________________________________________________________
```

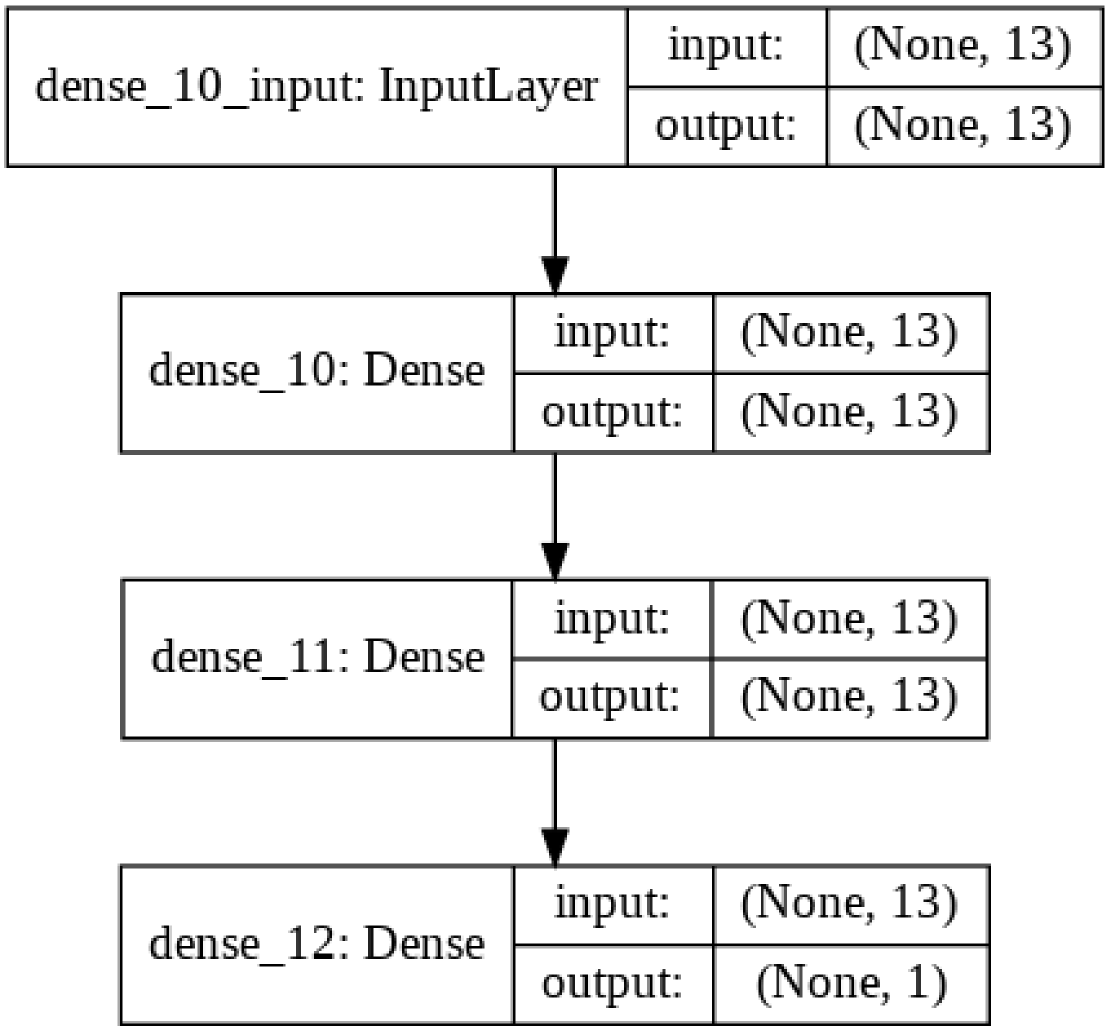
[11]:
```
# print the weights of the model in each layer

for layer in model.layers:
    weights = layer.get_weights()
    # print(weights)
```

[ ]:
```
# plot the layers of the model and the shape

from keras.utils import plot_model
plot_model(model, to_file='/tmp/model.png', show_shapes=True,)
```

[ ]:



[38]:
```
# Evaluate the model with the prediction data
y_pred = model.predict_classes(X_test)
```

[39]:
```
# print the score or the accuracy of the model

score = model.evaluate(X_test, y_test,verbose=1)

print(score)
```

```
228/228 [==============================] - 0s 79us/step
[0.23083383681481345, 0.6666666865348816]
```

Perform 5-fold cross validation