tensorflow_submission

June 14, 2020

1 Objective:

Given a Bank customer, build a neural network based classifier that can determine whether they will leave or not in the next 6 months.

1.0.1 Context:

Businesses like banks which provide service have to worry about problem of 'Churn' i.e. customers leaving and joining another service provider. It is important to understand which aspects of the service influence a customer's decision in this regard. Management can concentrate efforts on improvement of service, keeping in mind these priorities.

Drop the columns which are unique for all users like IDs (5 points)

2 1.0 Load libraries and dataset

2.1 1.1 Libraries and raw data analysis

[2]:
```
# Load the required libraries

%matplotlib inline
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.pipeline import Pipeline
from matplotlib import pyplot as plt
import warnings
warnings.filterwarnings("ignore")

raw_bank_data = pd.read_csv("bank.csv") # read a cvs file that contains the␣
 ↪dataset for a bank
raw_bank_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
```

```
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  int64
 11  IsActiveMember   10000 non-null  int64
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

[3]:
```
raw_bank_data.head()
```

[3]:
```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age  \
0          1    15634602  Hargrave          619    France  Female   42
1          2    15647311      Hill          608     Spain  Female   41
2          3    15619304      Onio          502    France  Female   42
3          4    15701354      Boni          699    France  Female   39
4          5    15737888  Mitchell          850     Spain  Female   43

   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
4       2  125510.82              1          1               1

   EstimatedSalary  Exited
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

2.2 1.2 Feature Engineering

We notice that RowNumber, CustomerId and Surname do not appear be more than weak correlation to the exit outcome of customers. Therefore, they should be dropped.

[4]:
```
bank_data = raw_bank_data.drop(columns=["RowNumber", "CustomerId", "Surname"])
```

[5]:
```
bank_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CreditScore      10000 non-null  int64
 1   Geography        10000 non-null  object
 2   Gender           10000 non-null  object
 3   Age              10000 non-null  int64
 4   Tenure           10000 non-null  int64
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  int64
 7   HasCrCard        10000 non-null  int64
 8   IsActiveMember   10000 non-null  int64
 9   EstimatedSalary  10000 non-null  float64
 10  Exited           10000 non-null  int64
dtypes: float64(2), int64(7), object(2)
memory usage: 859.5+ KB
```

The data type of Geography and gender needs to be converted to categorical type because they are in 'object' type right now.

[6]:
```
bank_data['Geography'] = bank_data['Geography'].astype('category') # Convert␣
↪Geography data into categorical type
bank_data['Gender'] = bank_data['Gender'].astype('category') # Convert Gender␣
↪data into categorical type
```

[7]:
```
bank_data.describe()
```

[7]:
```
        CreditScore           Age        Tenure        Balance  NumOfProducts  \
count  10000.000000  10000.000000  10000.000000   10000.000000   10000.000000
mean     650.528800     38.921800      5.012800   76485.889288       1.530200
std       96.653299     10.487806      2.892174   62397.405202       0.581654
min      350.000000     18.000000      0.000000       0.000000       1.000000
25%      584.000000     32.000000      3.000000       0.000000       1.000000
50%      652.000000     37.000000      5.000000   97198.540000       1.000000
75%      718.000000     44.000000      7.000000  127644.240000       2.000000
max      850.000000     92.000000     10.000000  250898.090000       4.000000

         HasCrCard  IsActiveMember  EstimatedSalary        Exited
count  10000.00000    10000.000000     10000.000000  10000.000000
mean       0.70550        0.515100    100090.239881      0.203700
std        0.45584        0.499797     57510.492818      0.402769
min        0.00000        0.000000        11.580000      0.000000
25%        0.00000        0.000000     51002.110000      0.000000
50%        1.00000        1.000000    100193.915000      0.000000
75%        1.00000        1.000000    149388.247500      0.000000
max        1.00000        1.000000    199992.480000      1.000000
```

2.3 1.3 Convert categorical data to integer data

[8]:
```
bank_data_clean = pd.get_dummies(bank_data) # convert object data to␣
↪categorical
bank_data_clean.describe()
```

[8]:
```
        CreditScore           Age        Tenure        Balance  NumOfProducts  \
count  10000.000000  10000.000000  10000.000000   10000.000000   10000.000000
mean     650.528800     38.921800      5.012800   76485.889288       1.530200
std       96.653299     10.487806      2.892174   62397.405202       0.581654
min      350.000000     18.000000      0.000000       0.000000       1.000000
25%      584.000000     32.000000      3.000000       0.000000       1.000000
50%      652.000000     37.000000      5.000000   97198.540000       1.000000
75%      718.000000     44.000000      7.000000  127644.240000       2.000000
max      850.000000     92.000000     10.000000  250898.090000       4.000000

         HasCrCard  IsActiveMember  EstimatedSalary        Exited  \
count  10000.00000    10000.000000     10000.000000  10000.000000
mean       0.70550        0.515100    100090.239881      0.203700
std        0.45584        0.499797     57510.492818      0.402769
min        0.00000        0.000000        11.580000      0.000000
25%        0.00000        0.000000     51002.110000      0.000000
50%        1.00000        1.000000    100193.915000      0.000000
75%        1.00000        1.000000    149388.247500      0.000000
max        1.00000        1.000000    199992.480000      1.000000

       Geography_France  Geography_Germany  Geography_Spain  Gender_Female  \
count      10000.000000       10000.000000     10000.000000   10000.000000
mean           0.501400           0.250900         0.247700       0.454300
std            0.500023           0.433553         0.431698       0.497932
min            0.000000           0.000000         0.000000       0.000000
25%            0.000000           0.000000         0.000000       0.000000
50%            1.000000           0.000000         0.000000       0.000000
75%            1.000000           1.000000         0.000000       1.000000
max            1.000000           1.000000         1.000000       1.000000

        Gender_Male
count  10000.000000
mean       0.545700
std        0.497932
min        0.000000
25%        0.000000
50%        1.000000
75%        1.000000
max        1.000000
```

3 2.0 Create feature and target set

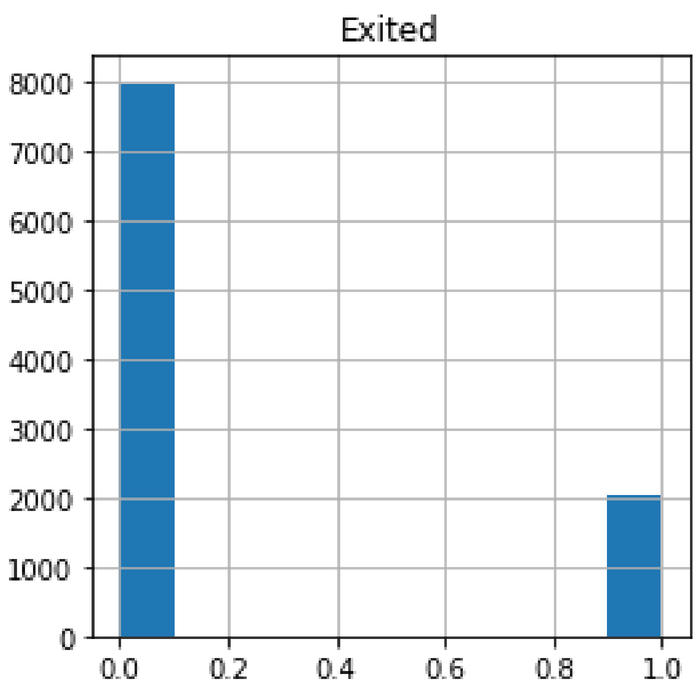
3.1 2.1 Create feature and target set

Distinguish the feature and target set (5 points)

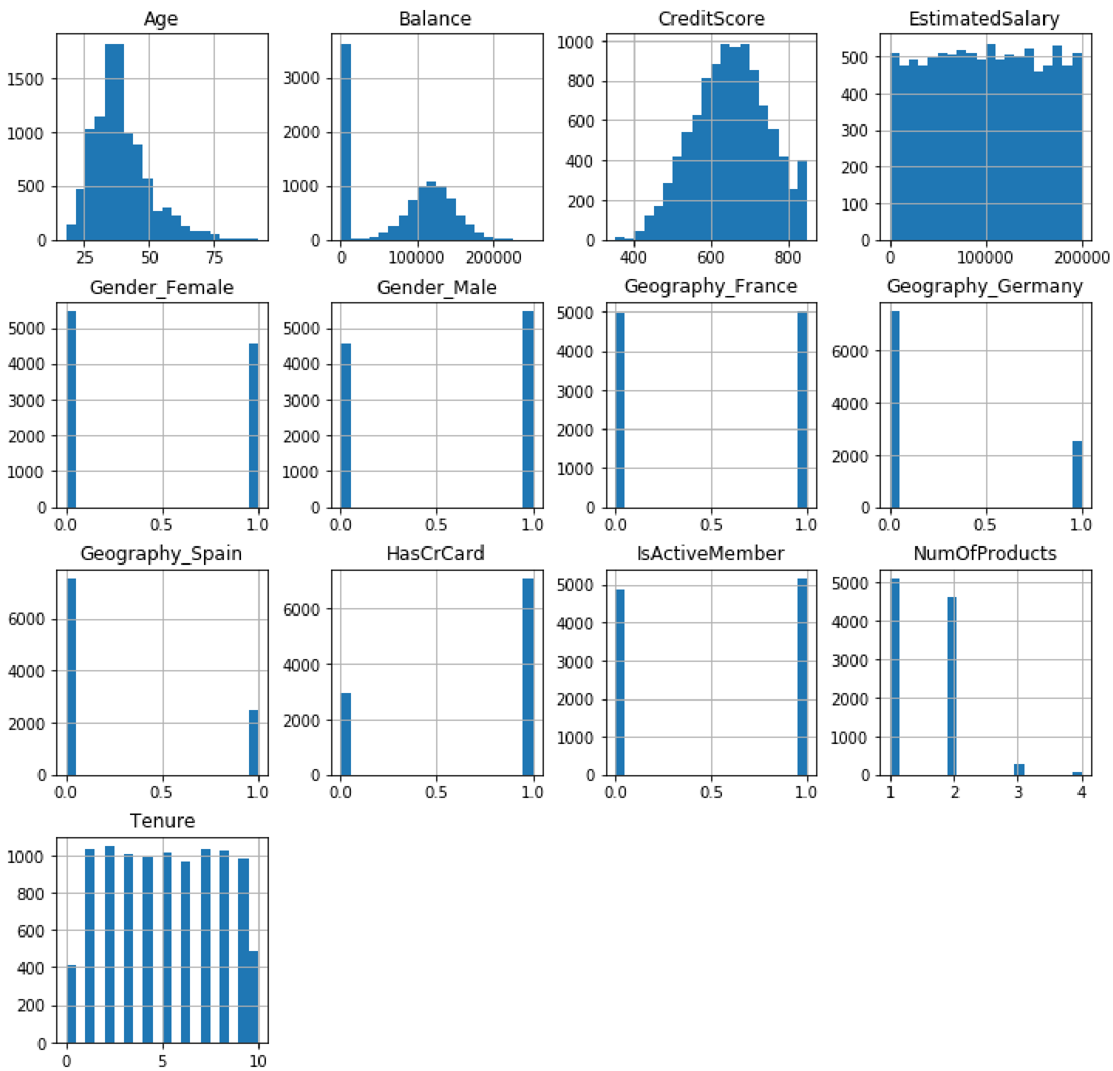
[9]:
```
X = bank_data_clean.drop(columns=['Exited']) # Distinguish the feature and␣
↪target set
y = bank_data_clean[['Exited']]
```

[10]:
```
y.hist(stacked=False, figsize=(4, 4)) # There is an imbalance count of Exited␣
↪and Stayed data in the dataset
print(y.groupby('Exited')['Exited'].count())  # The imbalance
print(f"% of stayed count of {y[y['Exited']==0].shape[0]/y.shape[0]*100}%")
```

```
Exited
0    7963
1    2037
Name: Exited, dtype: int64
% of stayed count of 79.63%
```

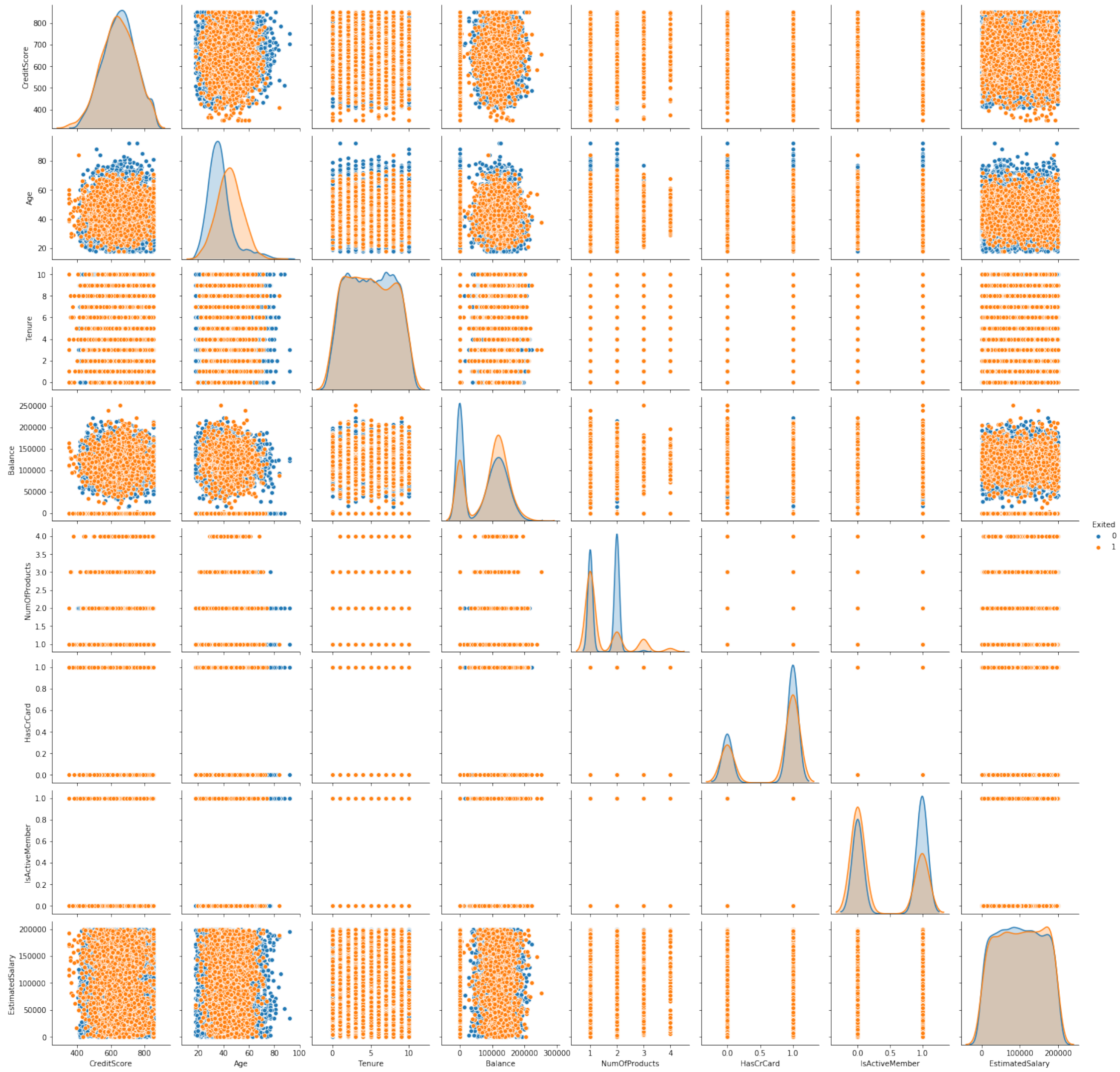


[11]:
```
X.hist(stacked=False, bins=20, figsize=(12, 12)); # Generate graphs to study␣
↪the distribution of data
```



[12]:
```
sns.pairplot(bank_data, hue="Exited") # Generate pairplot graphs that are␣
↪classified by
```

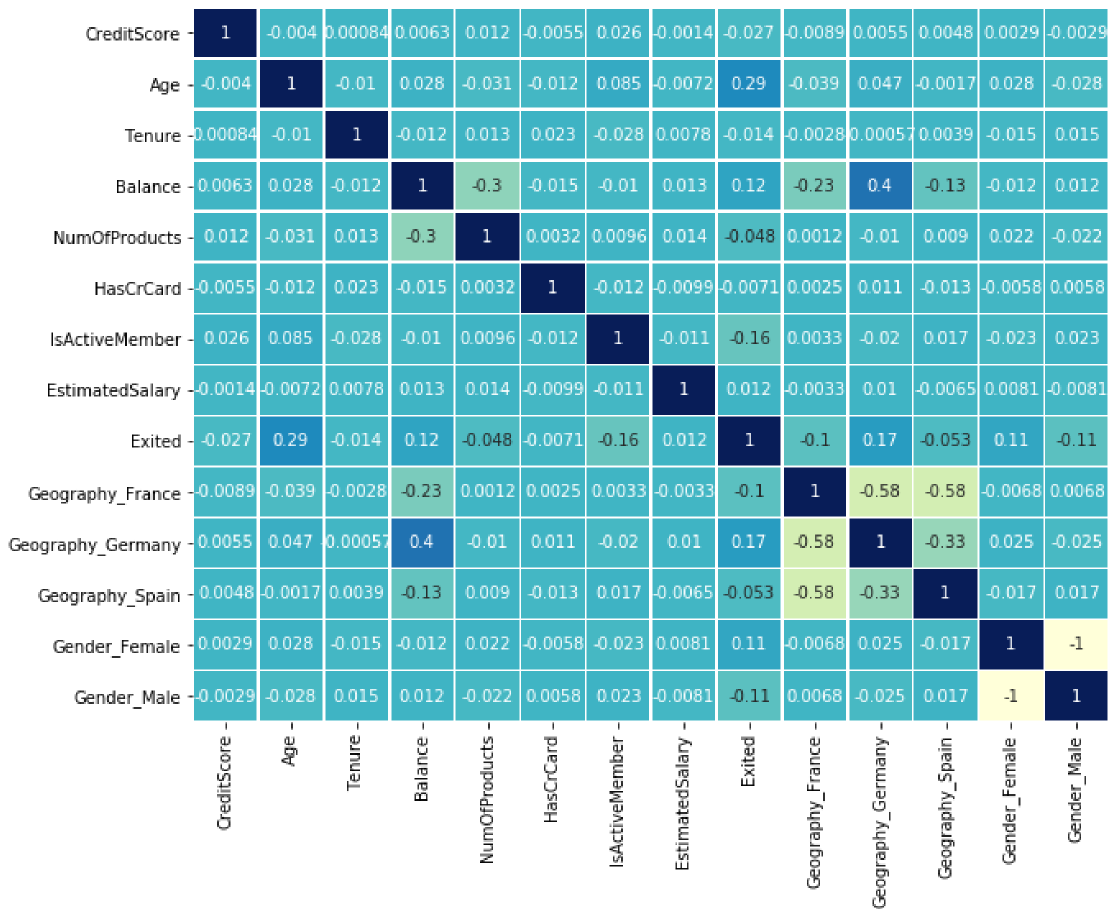
[12]: <seaborn.axisgrid.PairGrid at 0x15d18862c48>



There is a balance dataset that is right skewed with high number of count at 0. Otherwise, there is no other datasets with significant outliers that require further data cleansing.

[13]:
```
plt.figure(figsize=(10,8))

# Generate correlation matrix and show it using heat map
sns.heatmap(
    bank_data_clean.corr(),
    annot=True,
    linewidths=.5,
    center=0,
    cbar=False,
    cmap="YlGnBu"
)
```

```
plt.show()
```



We discover that Age, and to some extend balance have positive and linearly correlation with Exited members.

4 3.0 Setup training and test sets

Divide the data set into training and test sets (5 points)

[14]:
```
from sklearn import linear_model
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score

X_train, X_test, y_train, y_test = train_test_split(X.values, y.values,␣
↪test_size = 0.30, random_state=0) # Split the feature and target data to 70%␣
↪train and 30% test data
```

[15]:
```
type(X_train) # Check to make sure that it's a numpy array
```

[15]:
```
numpy.ndarray
```

[16]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape # check the row and
↪column sizes
```

[16]:
```
((7000, 13), (3000, 13), (7000, 1), (3000, 1))
```

The shapes of training and test data show that the dataset is split according to a 70% and 30% rule.

[17]:
```
X_train
```

[17]:
```
array([[641.,  33.,   2., …,   0.,   0.,   1.],
       [541.,  39.,   7., …,   0.,   0.,   1.],
       [590.,  76.,   5., …,   0.,   1.,   0.],
       …,
       [738.,  35.,   5., …,   0.,   0.,   1.],
       [590.,  38.,   9., …,   1.,   1.,   0.],
       [623.,  48.,   1., …,   0.,   1.,   0.]])
```

5 4.0 Normalize the train and test data (10points)

Normalize the train and test data (10 points)

[18]:
```
from sklearn.preprocessing import StandardScaler

# Define the scaler
scaler = StandardScaler().fit(X_train)

# Scale the train set
X_train_scaled = scaler.transform(X_train)

# Scale the test set
X_test_scaled = scaler.transform(X_test)
```

[19]:
```
pd.DataFrame(X_test_scaled).describe() # verify that the dataset is properly
↪scaled to similar mininum and maximum values
```

[19]:
```
                 0            1            2            3            4  \
count  3000.000000  3000.000000  3000.000000  3000.000000  3000.000000
mean      0.000179     0.032557     0.027007     0.068122    -0.023699
std       0.979136     1.015659     1.008509     0.983048     1.039743
min      -2.935750    -1.994743    -1.729696    -1.199755    -0.929716
25%      -0.663431    -0.653408    -0.689679    -1.199755    -0.929716
50%       0.004899    -0.174360     0.003665     0.389573    -0.929716
```

```
75%       0.652664     0.496308     1.043681     0.857160     0.810394
max       2.051015     5.095170     1.737025     2.802861     4.290613

                 5            6            7            8            9  \
count  3000.000000  3000.000000  3000.000000  3000.000000  3000.000000
mean     -0.019378    -0.011721     0.002957    -0.041148     0.044611
std       1.008815     1.000493     0.997101     0.999943     1.025290
min      -1.557669    -1.034302    -1.736420    -1.015259    -0.569872
25%      -1.557669    -1.034302    -0.849583    -1.015259    -0.569872
50%       0.641985     0.966835     0.011807    -1.015259    -0.569872
75%       0.641985     0.966835     0.843292     0.984970     1.754780
max       0.641985     0.966835     1.736116     0.984970     1.754780

                10           11           12
count  3000.000000  3000.000000  3000.000000
mean      0.003201    -0.038122     0.038122
std       1.002035     0.996373     0.996373
min      -0.573171    -0.922958    -1.083473
25%      -0.573171    -0.922958    -1.083473
50%      -0.573171    -0.922958     0.922958
75%      -0.573171     1.083473     0.922958
max       1.744679     1.083473     0.922958
```

[20]:
```
pd.DataFrame(X_train_scaled).describe() # verify that the dataset is properly
 ↪scaled to similar mininum and maximum values
```

[20]:
```
                  0             1             2             3             4  \
count  7.000000e+03  7.000000e+03  7.000000e+03  7.000000e+03  7.000000e+03
mean  -4.388315e-16 -2.175879e-16  2.534481e-17 -1.829013e-16  2.445663e-17
std    1.000071e+00  1.000071e+00  1.000071e+00  1.000071e+00  1.000071e+00
min   -3.089980e+00 -1.994743e+00 -1.729696e+00 -1.199755e+00 -9.297156e-01
25%   -6.942767e-01 -6.534081e-01 -1.036351e+00 -1.199755e+00 -9.297156e-01
50%    1.518062e-02 -1.743599e-01  3.664819e-03  3.293472e-01 -9.297156e-01
75%    7.040739e-01  4.963076e-01  6.970090e-01  8.278490e-01  8.103938e-01
max    2.051015e+00  4.424503e+00  1.737025e+00  2.603279e+00  4.290613e+00

                  5             6             7             8             9  \
count  7.000000e+03  7.000000e+03  7.000000e+03  7.000000e+03  7.000000e+03
mean  -7.035642e-16  3.368417e-16 -1.399301e-15  3.160646e-16  4.130347e-16
std    1.000071e+00  1.000071e+00  1.000071e+00  1.000071e+00  1.000071e+00
min   -1.557669e+00 -1.034302e+00 -1.737784e+00 -1.015259e+00 -5.698719e-01
25%   -1.557669e+00 -1.034302e+00 -8.535116e-01 -1.015259e+00 -5.698719e-01
50%    6.419848e-01  9.668353e-01 -1.471948e-03  9.849701e-01 -5.698719e-01
75%    6.419848e-01  9.668353e-01  8.604335e-01  9.849701e-01 -5.698719e-01
max    6.419848e-01  9.668353e-01  1.736493e+00  9.849701e-01  1.754780e+00

                 10            11            12
```

```
count  7.000000e+03  7.000000e+03  7.000000e+03
mean   6.907173e-17  1.636152e-16 -1.681829e-16
std    1.000071e+00  1.000071e+00  1.000071e+00
min   -5.731713e-01 -9.229582e-01 -1.083473e+00
25%   -5.731713e-01 -9.229582e-01 -1.083473e+00
50%   -5.731713e-01 -9.229582e-01  9.229582e-01
75%   -5.731713e-01  1.083473e+00  9.229582e-01
max    1.744679e+00  1.083473e+00  9.229582e-01
```

All datasets are properly scaled with mean values at 0.

6 5.0 Initialize and build a model

Initialize & build the model. Identify the points of improvement and implement some models. (20p)

6.1 5.1 Build a model

[21]:
```
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
import tensorflow as tf

def build_tf_model(param, optimizer, X_train_scaled_local, y_train_local):

    # Build a neural network model with 1 input layer and 1 hidden layer
    model = tf.keras.Sequential([
    tf.keras.layers.Dense(param['nodes1'], activation='relu',␣
↪input_shape=param['input_shape']),
    tf.keras.layers.Dropout(rate=0.01),
    tf.keras.layers.Dense(param['nodes2'], activation='tanh'),
    tf.keras.layers.Dropout(rate=0.01),
    tf.keras.layers.Dense(1, activation='sigmoid') # Use sigmoid activation for␣
↪binary status
    ])

    # Compile a model based on model parameters
    model.compile(optimizer=optimizer, loss='binary_crossentropy',␣
↪metrics=param['matrix'])

    # Fit the independent variables to the Neural Network
    history = model.fit(
    X_train_scaled_local, y_train_local, batch_size=1000,
    epochs=param['epochs'], validation_split = 0.3, verbose=0)
    #callbacks=[tfdocs.modeling.EpochDots()])

    return model, history
```

[22]:
```
import decimal

param = {}
model = []
history = []
parameters = []

for lr in [x / 1000.0 for x in range(1, 10, 4)]: # generate learning rate
    for node in range(16, 130, 64): # generate node number

        # Use ADAM optimizer
        optimizer = tf.keras.optimizers.Adam(lr=lr)
        param['input_shape'] = (X_train_scaled.shape[1],) # Define the input␣
 ↪shape
        param['nodes1'] = node # Define the number of node for input and hidden␣
 ↪layers
        param['nodes2'] = node/2
        param['epochs'] = 100
        param['matrix'] = ['accuracy']

        model_temp, history_temp = build_tf_model(param, optimizer,␣
 ↪X_train_scaled, y_train) # Train the model using neural network of Tensor␣
 ↪Flow

        model = [model_temp] + model
        history = [history_temp] + history
        parameters = [{'node':node, 'lr':lr }] + parameters # Save the␣
 ↪parameter result
#history = model.fit(
#X_train_scaled, y_train, batch_size=700
#epochs=param['epochs'], validation_split = 0.2, verbose=1)
```

Use various learning rates and node numbers to train models so that we can choose the best one among them.

6.2 5.2 Verify the model

[23]:
```
results = model[0].evaluate(X_test_scaled, y_test, verbose=0) # Evaluate the␣
 ↪validation accuracy
print(f"Loss = {results[0]}, validation accuracy = {results[1]}")
```

```
Loss = 0.4129222445487976, validation accuracy = 0.8500000238418579
```

[24]:
```
X_test_scale_1 = StandardScaler().fit_transform(X_test) # Try to scale the data␣
 ↪using fit transform
results = model[0].evaluate(X_test_scale_1, y_test, verbose=0)
print(f"Loss = {results[0]}, validation accuracy = {results[1]}")
```

```
Loss = 0.41256663354237877, validation accuracy = 0.8483333587646484
```

[25]:
```
y_test_pred = model[0].predict_proba(X_test_scaled)
pred_result = pd.DataFrame(data=y_test_pred, columns=['prediction'])
pred_result['actual'] = y_test
pred_result[pred_result['prediction']>0.5].head(10) # Visually inspect the
 ↪prediction result that is more than 0.5
```

[25]:

	prediction	actual
5	0.997594	1
9	0.939753	1
14	0.980497	1
20	0.838080	0
25	0.629889	0
28	0.549933	0
34	0.554633	0
40	0.594962	0
41	0.661089	1
44	0.759709	0

A visual analysis of 10 sample result shows that actual count of its exited status is more than stayed status when the prediction is more than 0.5.

[26]:
```
y_test_pred = model[0].predict_proba(X_test_scaled)
pred_result = pd.DataFrame(data=y_test_pred, columns=['prediction'])
pred_result['actual'] = y_test
pred_result[pred_result['prediction']<0.5].head(10) # Visually inspect the
 ↪prediction result that is more than 0.5
```

[26]:

	prediction	actual
0	0.290940	0
1	0.094995	1
2	0.018003	0
3	0.065938	0
4	0.005092	0
6	0.000793	0
7	0.154344	0
8	0.086716	1
10	0.000626	0
11	0.016103	0

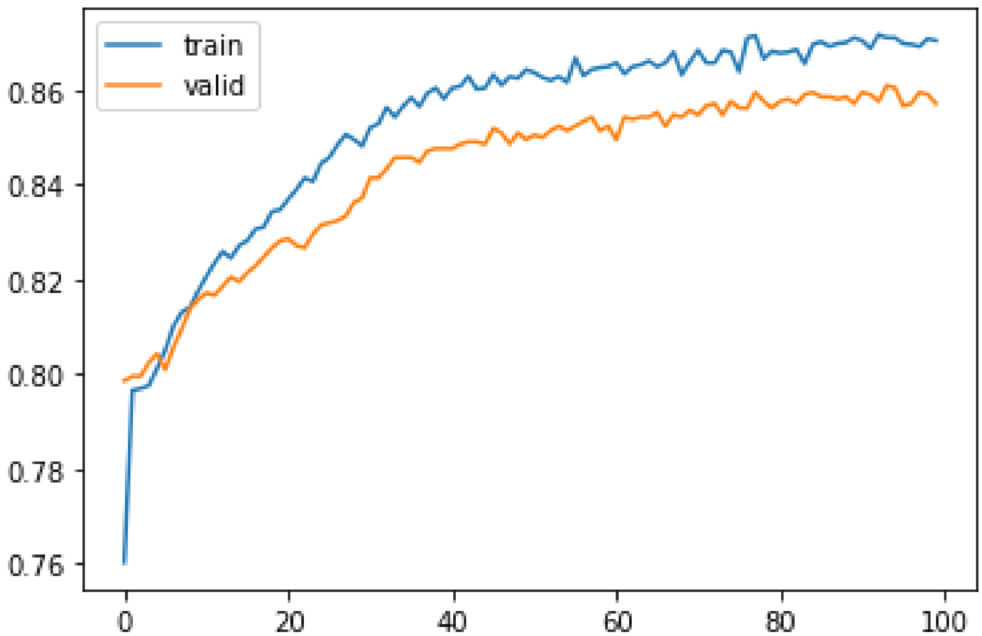
A visual analysis of 20 sample result shows that actual count of its Exited status is significantly less than stayed status when the prediction is less than 0.5.

[27]:
```
results
```

[27]:
```
[0.41256663354237877, 0.84833336]
```

[28]:
```
hist  = pd.DataFrame(history[4].history)
hist['epoch'] = history[4].epoch

import matplotlib.pyplot as plt

plt.plot(hist['accuracy'])
plt.plot(hist['val_accuracy'])
plt.legend(("train" , "valid") , loc =0)
```

[28]: <matplotlib.legend.Legend at 0x15d2a16bc08>



The neural network model seems to slightly overfit after 40 epoches. However, accuracy values still keep increasing, although not significantly, until about 100 epoches.

7 5.3 Recall score

Since the objective of the business is for banks to focus on problem of 'Churn' i.e. customers leaving and joining another service provider. It is also important to build a model to optimize recall, which is based on True Positive/(True Positive and False Negative). For higher recall, the higher the confidence for the model to predict all the customers who may be leaving in a new dataset with similar independent and dependent variables.

[29]:
```
param = {}
recall_model = []
recall_history = []
recall_parameters = []
```

```
for lr in [x / 1000.0 for x in range(1, 10, 4)]: # generate learning rate
    for node in range(16, 48, 16): # generate node number
        optimizer = tf.keras.optimizers.Adam(lr=lr)
        param['input_shape'] = (X_train_scaled.shape[1],)
        param['nodes1'] = node
        param['nodes2'] = node/2
        param['epochs'] = 100
        param['matrix'] = [tf.keras.metrics.Recall()]

        model_temp, history_temp = build_tf_model(param, optimizer,␣
 ↪X_train_scaled, y_train) # Train the model using neural network of Tensor␣
 ↪Flow

        recall_model = [model_temp] + recall_model
        recall_history = [history_temp] + recall_history
        recall_parameters = [{'node':node, 'lr':lr }] + recall_parameters #␣
 ↪Save the parameter result
```

8 6.0 Evaluate the model

Predict the results using 0.5 as a threshold (10points)

8.1 6.1 Choose the best model based on accuracy among many models

[30]:
```
pd_matrix = pd.DataFrame()

for index in range(0, len(model)):
    #print("----------------------")
    # Recall the accuracy of the training dataset and validation dataset
    pd_accuracy = history[index].history['accuracy'][-1]
    pd_val_accuracy = history[index].history['val_accuracy'][-1]

    # Evaluate the results of the trained model
    results = model[index].evaluate(X_test_scaled, y_test, verbose=0)

    # Save the results in a dataframe for further comparison
    pd_temp = pd.DataFrame(data=[[str(parameters[index]), pd_accuracy,␣
 ↪pd_val_accuracy, results[0], results[1]]], columns=['name', 'accuracy',␣
 ↪'val_accuracy', 'loss', 'test_accuracy'])

    pd_matrix = pd_matrix.append(pd_temp)

pd_matrix.reset_index(drop=True).head(20).sort_values(by=["test_accuracy"],␣
 ↪ascending=False)
```

[30]:

	name	accuracy	val_accuracy	loss	test_accuracy
1	{'node': 16, 'lr': 0.009}	0.871224	0.857143	0.342753	0.859000
4	{'node': 80, 'lr': 0.001}	0.870408	0.857143	0.341255	0.855667
3	{'node': 16, 'lr': 0.005}	0.867143	0.857143	0.346940	0.853000
0	{'node': 80, 'lr': 0.009}	0.920000	0.844286	0.412922	0.850000
2	{'node': 80, 'lr': 0.005}	0.894286	0.850952	0.378299	0.847000
5	{'node': 16, 'lr': 0.001}	0.848776	0.836190	0.368543	0.846000

{'node': 16, 'lr': 0.005} has the best test accuracy at 0.857333

8.2 6.2 Predict the results using 0.5 as a threshold

[31]:

```
from sklearn.metrics import accuracy_score
pd_matrix = pd.DataFrame()

for index in range(0, len(model)):
    # Predict the probability of exited status based on feature values
    y_test_pred = model[index].predict_proba(X_test_scaled)

    y_test_pred_pd = pd.DataFrame(y_test_pred, columns=['pred']).
 ↪reset_index(drop=True)

    # Predict the results using 0.5 as a treshold
    y_test_pred_pd = y_test_pred_pd['pred'].map(lambda x : 1 if x>0.5 else 0)

    accuracy = accuracy_score(y_test, y_test_pred_pd)

    pd_temp = pd.DataFrame(data=[[str(parameters[index]), accuracy]],␣
 ↪columns=['name', 'test accuracy at 0.5'])

    pd_matrix = pd_matrix.append(pd_temp)

pd_matrix.reset_index(drop=True).head(20)
```

[31]:

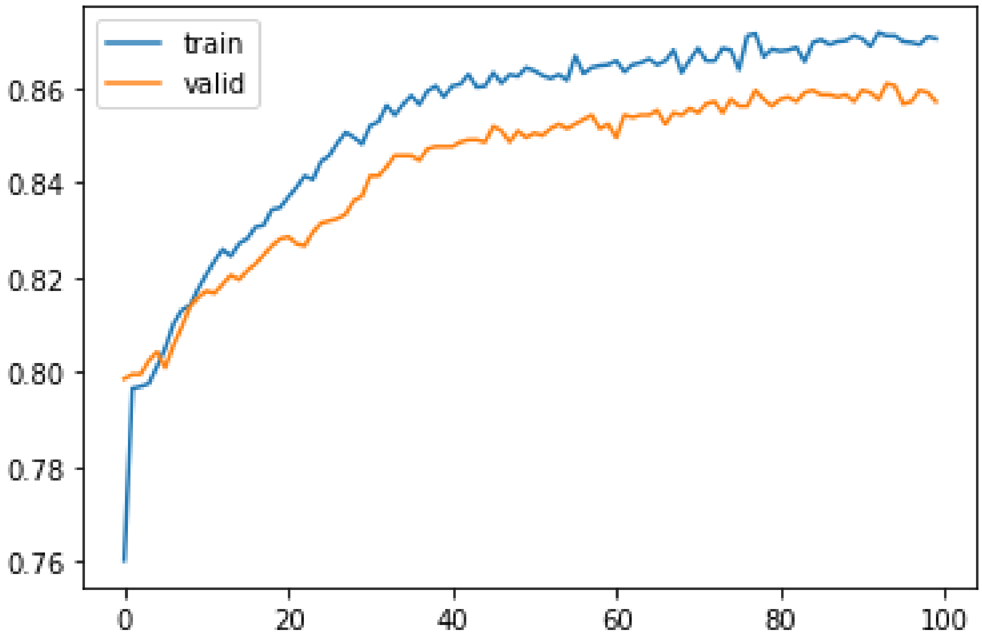
	name	test accuracy at 0.5
0	{'node': 80, 'lr': 0.009}	0.850000
1	{'node': 16, 'lr': 0.009}	0.859000
2	{'node': 80, 'lr': 0.005}	0.847000
3	{'node': 16, 'lr': 0.005}	0.853000
4	{'node': 80, 'lr': 0.001}	0.855667
5	{'node': 16, 'lr': 0.001}	0.846000

[32]:

```
hist  = pd.DataFrame(history[4].history)
hist['epoch'] = history[4].epoch

import matplotlib.pyplot as plt
```

```
plt.plot(hist['accuracy'])
plt.plot(hist['val_accuracy'])
plt.legend(("train" , "valid") , loc =0)
```

[32]: <matplotlib.legend.Legend at 0x15d3486cfc8>



The neural network model seems to slightly overfit after 40 epoches. However, accuracy values still keep increasing until about 100 epoches.

8.3 6.2 Choose the best model based on recall among many models

[33]:
```
pd_matrix = pd.DataFrame()
index = 4
pd_recall = recall_history[index].history['recall_1'][-1]
pd_val_recall = recall_history[index].history['val_recall_1'][-1]

results = recall_model[index].evaluate(X_test_scaled, y_test, verbose=0)

pd_temp = pd.DataFrame(data=[[str(parameters[index]), pd_recall, pd_val_recall,␣
↪results[0], results[1]]], columns=['name', 'recall', 'val_recall', 'loss',␣
↪'test_recall'])

pd_matrix_recall = pd_matrix.append(pd_temp)

pd_matrix_recall.reset_index(drop=True).head(20).
↪sort_values(by=["test_recall"], ascending=False)
```

[33]:
```
                        name    recall  val_recall      loss  test_recall
0  {'node': 80, 'lr': 0.001}  0.471357    0.427553  0.356272     0.489533
```

The recall value of 0.472 is not high enough to be used to predict which customers will be leaving for another service provider.

9 7.0 Accuracy score and confusion matrix

Print the Accuracy score and confusion matrix (5 points)

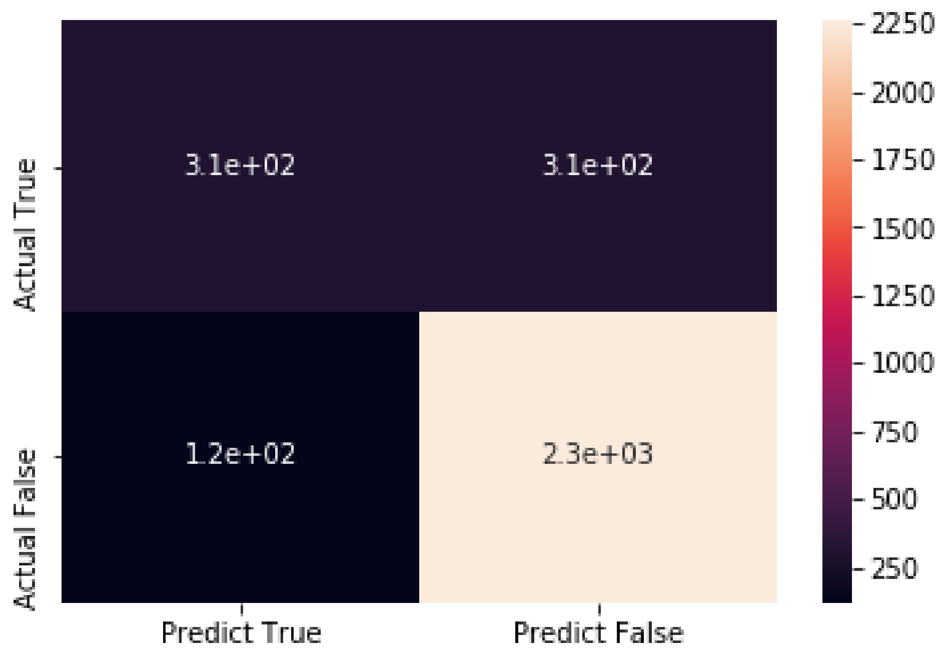
9.1 7.1 Confusion matrix

[34]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sn
import pandas as pd
import matplotlib.pyplot as plt

# Use model 4, which is the best model in terms of accuracy, to predict␣
↪probability of customers to exit
y_test_pred = model[4].predict_proba(X_test_scaled)

y_test_pred_pd = pd.DataFrame(y_test_pred, columns=['pred']).
↪reset_index(drop=True)
y_test_pred_result = (y_test_pred_pd>0.5)
print(y_test_pred_result)

# Predict the result using the probability of 0.5 as a threshold
y_test_pred_pd = y_test_pred_pd['pred'].map(lambda x : 1 if x>0.5 else 0)

tn, fp, fn, tp  = confusion_matrix(y_test, y_test_pred_pd).ravel()
print(tn, fp, fn, tp)

df_cm = pd.DataFrame([[tp, fn], [fp, tn]], index = ["Actual True", "Actual␣
↪False"],
                  columns = ["Predict True", "Predict False"])

plt.figure(figsize = (6,4))
sn.heatmap(df_cm, annot=True)
```

```
       pred
0     False
1     False
2     False
3     False
4     False
…       …
2995  False
```

```
2996  False
2997  False
2998  False
2999   True

[3000 rows x 1 columns]
2258 121 312 309
```

[34]: <matplotlib.axes._subplots.AxesSubplot at 0x15d34892b88>



[38]:
```
df_cm
```

[38]:

	Predict True	Predict False
Actual True	314	307
Actual False	124	2255

The accuracy of the model, using a 0.5 probability treshold is reasonable at 0.855

9.2 7.2 Optimizing for different business objectives

[37]:
```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import accuracy_score

y_test_pred = model[4].predict_proba(X_test_scaled)
```

```
# Use different probability tresholds to predict outcomes
for pred_prob in [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9]:
    y_test_pred_pd = pd.DataFrame(y_test_pred, columns=['pred']).
 ↪reset_index(drop=True)

    # Convert probability values to outcome values
    y_test_pred_pd = y_test_pred_pd['pred'].map(lambda x : 1 if x>pred_prob␣
 ↪else 0)

    recall  = recall_score(y_test, y_test_pred_pd).ravel()
    precision  = precision_score(y_test, y_test_pred_pd).ravel()
    accuracy = accuracy_score(y_test, y_test_pred_pd).ravel()

    print(f"for probability below {pred_prob}, the recall = {recall}, precision␣
 ↪= {precision}, accuracy = {accuracy}")
```

```
for probability below 0.1, the recall = [0.8921095], precision = [0.36114733],
accuracy = [0.651]
for probability below 0.2, the recall = [0.784219], precision = [0.47558594],
accuracy = [0.77633333]
for probability below 0.3, the recall = [0.66988728], precision = [0.56908345],
accuracy = [0.82666667]
for probability below 0.4, the recall = [0.57809984], precision = [0.64684685],
accuracy = [0.84733333]
for probability below 0.5, the recall = [0.50563607], precision = [0.71689498],
accuracy = [0.85633333]
for probability below 0.6, the recall = [0.44766506], precision = [0.8057971],
accuracy = [0.86333333]
for probability below 0.7, the recall = [0.36553945], precision = [0.8697318],
accuracy = [0.85733333]
for probability below 0.8, the recall = [0.25442834], precision = [0.93491124],
accuracy = [0.842]
for probability below 0.9, the recall = [0.12721417], precision = [0.97530864],
accuracy = [0.81866667]
```

We can choose from a wide range of recall, precision or accuracy values, as show on the table above, that best match our business objectives.

we will use a probability threshold that has lower accuracy but high recall, for marketing campaign that is low cost, but the cost of losing the customers is high.

We may also use upsampling of dataset for minority class, which is Exited data set in this case, to retrain the data and potentially improve recall accuracy.

[ ]:

```
```