Artificial Neural Network

Importing Libraries

```
import numpy as np
import pandas as pd
import tensorflow as tf
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
```

```
tf.__version__
```

```
'2.17.0'
```

Data preprocessing, importing dataset

```
df = pd.read_csv('Churn_Modelling.csv')
df.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Esti
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	

```
x = df.iloc[:,3:-1].values
y = df.iloc[:,-1].values
display(x,y)
```

```
array([[619, 'France', 'Female', ..., 1, 1, 101348.88],
       [608, 'Spain', 'Female', ..., 0, 1, 112542.58],
       [502, 'France', 'Female', ..., 1, 0, 113931.57],
       ...,
       [709, 'France', 'Female', ..., 0, 1, 42085.58],
       [772, 'Germany', 'Male', ..., 1, 0, 92888.52],
       [792, 'France', 'Female', ..., 1, 0, 38190.78]], dtype=object)
array([1, 0, 1, ..., 1, 1, 0])
```

Encoding Categorical Data (Label encoding for the gender column and One hot encoding for geography column)

```
le = LabelEncoder()
x[:,2] = le.fit_transform(x[:,2])
display(x)
he = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1])], remainder='passthrough')
x = np.array(he.fit_transform(x))
display(x)
```

```
array([[619, 'France', 0, ..., 1, 1, 101348.88],
       [608, 'Spain', 0, ..., 0, 1, 112542.58],
       [502, 'France', 0, ..., 1, 0, 113931.57],
       ...,
       [709, 'France', 0, ..., 0, 1, 42085.58],
       [772, 'Germany', 1, ..., 1, 0, 92888.52],
       [792, 'France', 0, ..., 1, 0, 38190.78]], dtype=object)
array([[1.0, 0.0, 0.0, ..., 1, 1, 101348.88],
       [0.0, 0.0, 1.0, ..., 0, 1, 112542.58],
       [1.0, 0.0, 0.0, ..., 1, 0, 113931.57],
       ...,
       [1.0, 0.0, 0.0, ..., 0, 1, 42085.58],
       [0.0, 1.0, 0.0, ..., 1, 0, 92888.52],
       [1.0, 0.0, 0.0, ..., 1, 0, 38190.78]], dtype=object)
```

Splitting dataset into training and test sets

```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=0)
```

Feature Scaling

```
fs = StandardScaler()
x_train = fs.fit_transform(x_train)
x_test = fs.transform(x_test)
```

Building the ANN

```
ann = tf.keras.models.Sequential()
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
ann.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))
```

Compiling and Training the ANN

```
ann.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
ann.fit(x_train, y_train, batch_size=32, epochs=100)
```

```
Epoch 1/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - accuracy: 0.7384 - loss: 0.5810
Epoch 2/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.7936 - loss: 0.4773
Epoch 3/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8076 - loss: 0.4469
Epoch 4/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8005 - loss: 0.4469
Epoch 5/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8017 - loss: 0.4358
Epoch 6/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8012 - loss: 0.4452
Epoch 7/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8135 - loss: 0.4263
Epoch 8/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8142 - loss: 0.4239
Epoch 9/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8092 - loss: 0.4242
Epoch 10/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8137 - loss: 0.4291
Epoch 11/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8213 - loss: 0.4195
Epoch 12/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8277 - loss: 0.4138
Epoch 13/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8159 - loss: 0.4247
Epoch 14/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8334 - loss: 0.4087
Epoch 15/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8270 - loss: 0.4064
Epoch 16/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8354 - loss: 0.3980
Epoch 17/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8260 - loss: 0.4030
Epoch 18/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8424 - loss: 0.3857
Epoch 19/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8495 - loss: 0.3781
Epoch 20/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8553 - loss: 0.3628
Epoch 21/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8547 - loss: 0.3647
Epoch 22/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8572 - loss: 0.3555
Epoch 23/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8640 - loss: 0.3418
Epoch 24/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.8597 - loss: 0.3480
Epoch 25/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8560 - loss: 0.3605
Epoch 26/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.8594 - loss: 0.3483
Epoch 27/100
```

```
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8651 - loss: 0.3349
Epoch 28/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8659 - loss: 0.3334
Epoch 29/100
250/250 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8565 - loss: 0.3508
```

```
ann.summary()
ann.get_weights()
```

```
Model: "sequential"
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape                ┃         Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━┩
│ dense (Dense)                        │ (32, 6)                     │              78 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ dense_1 (Dense)                      │ (32, 6)                     │              42 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ dense_2 (Dense)                      │ (32, 1)                     │               7 │
└──────────────────────────────────────┴─────────────────────────────┴─────────────────┘
 Total params: 383 (1.50 KB)
 Trainable params: 127 (508.00 B)
 Non-trainable params: 0 (0.00 B)
 Optimizer params: 256 (1.00 KB)
[array([[-2.6547974e-01, -2.2832724e-01,  3.3947460e-02,  6.1800456e-01,
          1.9757502e-01,  4.8247880e-01],
        [-4.4663560e-01, -3.7876537e-01, -2.7900496e-01,  3.9352223e-01,
          3.8317564e-01,  6.1381597e-02],
        [ 2.0145959e-01,  4.9254376e-02,  9.8778114e-02, -8.5014361e-01,
          2.2896883e-01, -2.6546156e-01],
        [ 9.4904058e-02,  1.6992192e-03, -7.0457318e-04,  4.1941427e-02,
          3.4490868e-02,  2.9861858e-01],
        [ 3.2151335e-01,  1.7319870e-01,  7.1775697e-02,  1.5637891e-01,
          1.7061082e-01,  4.9185193e-01],
        [ 6.4895773e-01, -1.1502161e+00,  7.3886698e-04, -6.7629224e-01,
          2.8218493e-02,  8.7361646e-01],
        [ 1.9267997e-01,  6.4820093e-03,  2.3088015e-03, -2.1001333e-02,
          9.7534182e-03,  2.2829768e-01],
        [-2.7165353e-01,  2.1154085e-02,  4.0832081e-01, -6.8859205e-02,
         -5.3331554e-01, -3.9900869e-01],
        [ 4.8854563e-01,  9.4737552e-02,  1.4930495e+00,  1.3401368e-01,
         -9.0957826e-01,  5.9874439e-01],
        [ 1.5612599e-01, -1.2398398e-01, -6.1506890e-02, -1.3142451e-02,
         -8.1656553e-02, -5.4847878e-01],
        [ 7.7193528e-01, -7.5546235e-01, -3.1804442e-01, -2.4921866e-01,
         -6.7009574e-01, -5.7402819e-01],
        [-3.9055225e-02,  3.7518330e-02,  2.4187669e-02,  2.9763293e-02,
          2.1161450e-02, -3.6574769e-01]], dtype=float32),
 array([ 0.35869825,  1.203878  , -0.9252916 ,  0.38862708,  0.5144338 ,
        -0.2912554 ], dtype=float32),
 array([[-0.46649447, -0.8127021 ,  0.5988339 ,  0.57124764,  0.588409   ,
         -0.341928  ],
        [-0.25820237,  0.46277976,  0.49570787, -0.5727381 ,  0.6971715 ,
         -0.7083853 ],
        [ 1.1594191 , -1.3149115 , -0.6280865 ,  1.092445  , -0.5458976 ,
          0.1775133 ],
        [-0.33348483,  0.36421648,  0.13765702, -0.7178686 ,  0.1500053 ,
          1.1226299 ],
        [ 0.756339  , -0.3417251 , -0.05422789,  0.59922105, -0.5065279 ,
         -0.07459679],
        [ 0.15852295, -0.5584015 ,  0.52424115,  0.5844732 ,  0.32037237,
         -1.5552546 ]], dtype=float32),
 array([ 0.28626803, -0.1716084 , -0.03814194,  0.02464342,  0.18304493,
         0.19081374], dtype=float32),
 array([[ 0.7051995 ],
        [ 0.9453702 ],
        [-0.97222364],
        [ 0.82407004],
        [-1.0721738 ],
        [-1.6359533 ]], dtype=float32),
 array([0.10697455], dtype=float32)]
```

Predicting result of test set and evaluate the model using confusion matrix

Making the prediction and evaluating the model Predict whether a male customer with active credit card as well as considered an active member (age 40), who lives in France, has credit score of 600, having a 3 years tenure and have a salary of 50000, will leave the bank or not? Breaking down the parameters Geography = France, Credit score = 600, Gender = Male, Age = 40, Tenure = 3, balance = 60000, number of products = 2, have a credit card = yes, an active memeber = yes, salary = 50000 Dollars.

```
print(ann.predict(fs.transform([[1,0,0,600,1,40,3,60000,2,1,1,50000]])) > 0.5)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step
[[False]]
```

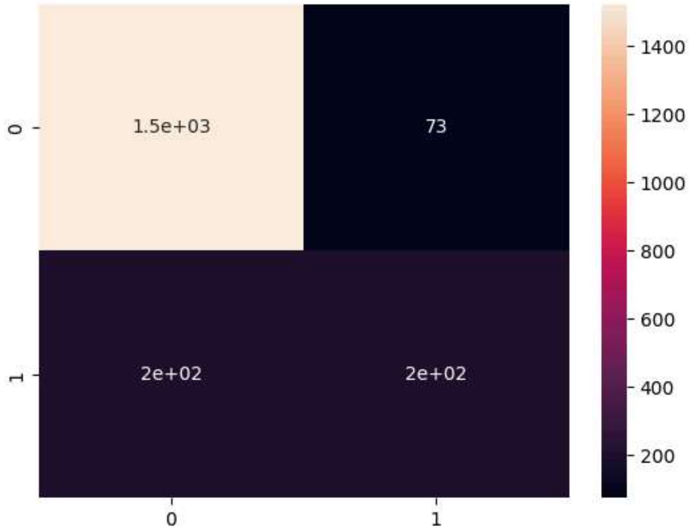
```
y_pred = ann.predict(x_test)
y_pred = (y_pred > 0.5)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
```

```
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
[[0 0]
 [0 1]
 [0 0]
 ...
 [0 0]
 [0 0]
 [0 0]]
```

```
# Confusion Matrix
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[1522   73]
 [ 202  203]]
0.8625
```

```
# Display Confusion Matrix
import seaborn as sns
import matplotlib.pyplot as plt
sns.heatmap(cm, annot=True)
plt.show()
```


1.5e+03
73
2e+02
2e+02
0
1
0
1
1400
1200
1000
800
600
400
200