

| Churn_Modelling.csv | | | | | | | | | | | | | | | |
|---------------------|------------|----------|-------------|-----------|---------|--------|--------|---------|---------------|-----------|----------------|-----------------|-----------|---|--|
| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | |
| RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited | | |
| 1 | 1 | 15634602 | Hargrave | 619 | France | Female | 42 | 2 | 0 | 1 | 1 | 101346.88 | 1 | | |
| 2 | 2 | 15647311 | Hill | 609 | Spain | Female | 41 | 1 | 83807.86 | 1 | 0 | 112562.98 | 0 | | |
| 3 | 3 | 15618004 | Otto | 702 | France | Female | 42 | 8 | 159660.9 | 3 | 1 | 113521.97 | 1 | | |
| 4 | 4 | 15701356 | Burn | 695 | France | Female | 39 | 1 | 0 | 2 | 0 | 93616.63 | 0 | | |
| 5 | 5 | 15737868 | Mitchell | 890 | Spain | Female | 43 | 2 | 129510.82 | 1 | 1 | 72084.1 | 0 | | |
| 6 | 6 | 15574012 | Chu | 640 | Spain | Male | 44 | 8 | 113795.78 | 2 | 1 | 149795.71 | 1 | | |
| 7 | 7 | 15592031 | Burke | 822 | France | Male | 55 | 7 | 0 | 2 | 1 | 10082.8 | 0 | | |
| 8 | 8 | 15686148 | Osuna | 378 | Germany | Female | 29 | 4 | 119046.74 | 4 | 1 | 119546.88 | 1 | | |
| 9 | 9 | 15702365 | Ike | 501 | France | Male | 44 | 4 | 142051.07 | 2 | 0 | 74940.5 | 0 | | |
| 10 | 10 | 15692380 | Hy | 684 | France | Male | 27 | 2 | 134809.89 | 1 | 1 | 71726.73 | 0 | | |
| 11 | 11 | 15767621 | Beane | 528 | France | Male | 31 | 6 | 102016.72 | 2 | 0 | 81181.12 | 0 | | |
| 12 | 12 | 15737173 | Andrews | 497 | Spain | Male | 24 | 3 | 0 | 2 | 1 | 0 | 76380.01 | 0 | |
| 13 | 13 | 15612264 | Katz | 476 | France | Female | 34 | 10 | 0 | 2 | 1 | 0 | 26360.96 | 0 | |
| 14 | 14 | 15691463 | Chen | 540 | France | Female | 29 | 9 | 0 | 2 | 0 | 195807.79 | 0 | | |
| 15 | 15 | 15605802 | Scott | 630 | Spain | Female | 30 | 7 | 0 | 2 | 1 | 0 | 65951.60 | 0 | |
| 16 | 16 | 15643866 | Gorkhli | 610 | Germany | Male | 45 | 3 | 143129.41 | 2 | 0 | 1 | 94327.20 | 0 | |
| 17 | 17 | 15737452 | Roman | 603 | Germany | Male | 58 | 1 | 132802.88 | 1 | 1 | 0 | 5097.67 | 1 | |
| 18 | 18 | 15788218 | Henderson | 549 | Spain | Female | 24 | 0 | 0 | 2 | 1 | 1 | 14406.41 | 0 | |
| 19 | 19 | 15681507 | Mulholland | 587 | Spain | Male | 45 | 0 | 0 | 1 | 0 | 0 | 158684.81 | 0 | |
| 20 | 20 | 15688982 | Hsu | 726 | France | Female | 24 | 6 | 0 | 2 | 1 | 1 | 84724.03 | 0 | |
| 21 | 21 | 15577857 | McDonald | 732 | France | Male | 41 | 6 | 0 | 2 | 1 | 1 | 170886.17 | 0 | |
| 22 | 22 | 15597945 | Delucchi | 636 | Spain | Female | 32 | 8 | 0 | 2 | 1 | 0 | 138555.48 | 0 | |
| 23 | 23 | 15683909 | Gerasimov | 510 | Spain | Female | 36 | 4 | 0 | 1 | 1 | 0 | 110815.53 | 1 | |
| 24 | 24 | 15755797 | Nyman | 669 | France | Male | 46 | 3 | 0 | 2 | 0 | 1 | 8487.75 | 0 | |
| 25 | 25 | 15625047 | Van | 944 | France | Female | 38 | 9 | 0 | 1 | 1 | 1 | 187616.16 | 0 | |

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Importing the libraries

[5] import numpy as np
import pandas as pd
import tensorflow as tf

[6] tf.__version__

'2.12.0'


Importing the dataset

Double-click (or enter) to edit

[7] dataset = pd.read_csv('Churn_Modelling.csv')
x = dataset.iloc[:, 3:-1].values
y = dataset.iloc[:, -1].values

[8] print(x)

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print(y)

[1 0 1 ... 1 1 0]

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Encoding the categorical data

[10] from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
x[:, 2] = le.fit_transform(x[:, 2])

[11] print(x)

[[619 'France' 0 ... 1 1 101348.88]
[688 'Spain' 0 ... 0 1 112542.58]
[582 'France' 0 ... 1 0 113931.52]
...
[709 'France' 0 ... 0 1 42005.58]
[772 'Germany' 1 ... 1 0 92888.52]
[792 'France' 0 ... 1 0 38190.78]]

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One hot encoding

[12] from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1])], remainder='passthrough')
x = np.array(ct.fit_transform(x))

[13] print(x)

[[1.0 0.0 0.0 ... 1 1 101340.80]
[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 42005.58]
[0.0 1.0 0.0 ... 1 0 92008.52]
[1.0 0.0 0.0 ... 1 0 10190.78]]

Splitting into training set and test set

[14] from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state = 0)

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Feature scaling

```
[15]: from sklearn.preprocessing import StandardScaler
      sc = StandardScaler()
      X_train = sc.fit_transform(X_train)
      X_test = sc.transform(X_test)

[ ]
```

Part-2 Building the ANN

```
[16]: ann = tf.keras.models.Sequential()

[17]: ann.add(tf.keras.layers.Dense(units=6, activation='relu'))

[18]: ann.add(tf.keras.layers.Dense(units=6, activation='relu'))

[19]: ann.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))
```

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Part-3 Training the ANN

```
[20] ann.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])

[21] ann.fit(X_train, y_train, batch_size = 32, epochs = 100)

Epoch 1/100
250/250 [=====] - 2s 2ms/step - loss: 0.6099 - accuracy: 0.6914
Epoch 2/100
250/250 [=====] - 0s 2ms/step - loss: 0.4746 - accuracy: 0.7956
Epoch 3/100
250/250 [=====] - 0s 2ms/step - loss: 0.4457 - accuracy: 0.7997
Epoch 4/100
250/250 [=====] - 0s 2ms/step - loss: 0.4372 - accuracy: 0.8052
Epoch 5/100
250/250 [=====] - 1s 2ms/step - loss: 0.4285 - accuracy: 0.8144
Epoch 6/100
250/250 [=====] - 1s 3ms/step - loss: 0.4220 - accuracy: 0.8223
Epoch 7/100
250/250 [=====] - 1s 2ms/step - loss: 0.4172 - accuracy: 0.8267
Epoch 8/100
250/250 [=====] - 1s 3ms/step - loss: 0.4137 - accuracy: 0.8265
Epoch 9/100
250/250 [=====] - 1s 3ms/step - loss: 0.4116 - accuracy: 0.8294
Epoch 10/100
250/250 [=====] - 1s 3ms/step - loss: 0.4096 - accuracy: 0.8307
Epoch 11/100
250/250 [=====] - 1s 3ms/step - loss: 0.4081 - accuracy: 0.8305
```

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↳ Predicting the result of single observation

Use our ANN model to predict if the customer with the following informations will leave the bank:
Geography: France
Credit Score: 600
Gender: Male
Age: 40 years old
Tenure: 3 years
Balance: \$ 60000
Number of Products: 2
Does this customer have a credit card? Yes
Is this customer an Active Member: Yes
Estimated Salary: \$ 50000
So, should we say goodbye to that customer?

▶

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

1/1 [=====] - 0s 113ms/step
[[false]]

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Predicting the Test set result

```
[ ] 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]]
```

Making the 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]
 [ 201 204]]
0.863
```

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