PROJECT - CHURN MODELLING DATASET

Predicting which set of the customers are gong to churn out from the organization by looking into some of the important attributes and applying Machine Learning and Deep Learning on it.

Customer churn refers to when a customer (player, subscriber, user, etc.) ceases his or her relationship with a company. Online businesses typically treat a customer as churned once a particular amount of time has elapsed since the customer's last interaction with the site or service.

A Predictive Churn Model is a tool that defines the steps and stages of customer churn, or a customer leaving your service or product. ... But with an evolving churn model, you can fight for retention by acting on the metrics as they happen

Customer churn occurs when customers or subscribers stop doing business with a company or service, also known as customer attrition. It is also referred as loss of clients or customers. ... Similar concept with predicting employee turnover, we are going to predict customer churn using telecom dataset.

Importing the libraries

In [1]:

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
```

Importing the Dataset

In [2]:

```
data = pd.read_csv('Churn_Modelling.csv')

data.head(4)
```

Out[2]:

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

In [3]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
RowNumber          10000 non-null int64
CustomerId         10000 non-null int64
Surname            10000 non-null object
CreditScore        10000 non-null int64
Geography          10000 non-null object
Gender             10000 non-null object
Age                10000 non-null int64
Tenure             10000 non-null int64
Balance            10000 non-null float64
NumOfProducts      10000 non-null int64
HasCrCard          10000 non-null int64
IsActiveMember     10000 non-null int64
EstimatedSalary    10000 non-null float64
```

```
Exited             10000 non-null int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

In [4]:

```
data.describe()
```

Out[4]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMe
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.00
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.51
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.49
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.00
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.00
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.00
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.00
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.00

In [5]:

```
data.tail()
```

Out[5]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsA
9995	9996	15606229	Obijiaku	771	France	Male	39	5	0.00	2	1	
9996	9997	15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	
9997	9998	15584532	Liu	709	France	Female	36	7	0.00	1	0	
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75075.31	2	1	
9999	10000	15628319	Walker	792	France	Female	28	4	130142.79	1	1	

In [3]:

```
# Checking if our dataset contains any NULL values

data.isnull().sum()
```

Out[3]:

```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

Data Analysis

In [4]:

```
data['Gender'].value_counts()
```

```
data['Gender'].value_counts()
```

Out[4]:

```
Male      5457
Female    4543
Name: Gender, dtype: int64
```

In [5]:

```
# Plotting the features of the dataset to see the correlation between them

plt.hist(x = data.Gender, bins = 3, color = 'pink')
plt.title('comparison of male and female')
plt.xlabel('Gender')
plt.ylabel('population')
plt.show()
```

In [6]:

```
data['Age'].value_counts()
```

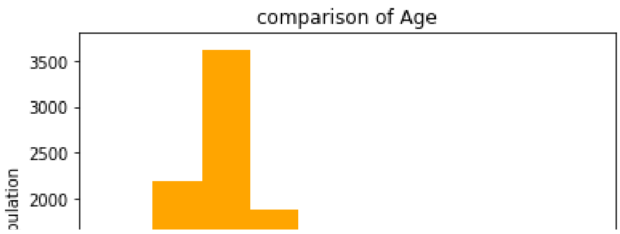
Out[6]:

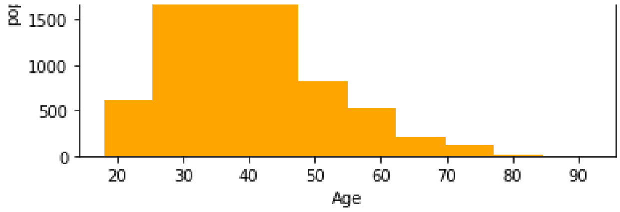
```
37    478
38    477
35    474
36    456
34    447
     ...
92      2
88      1
82      1
85      1
83      1
Name: Age, Length: 70, dtype: int64
```

In [7]:

```
# comparison of age in the dataset

plt.hist(x = data.Age, bins = 10, color = 'orange')
plt.title('comparison of Age')
plt.xlabel('Age')
plt.ylabel('population')
plt.show()
```





In [8]:

```
data['Geography'].value_counts()
```

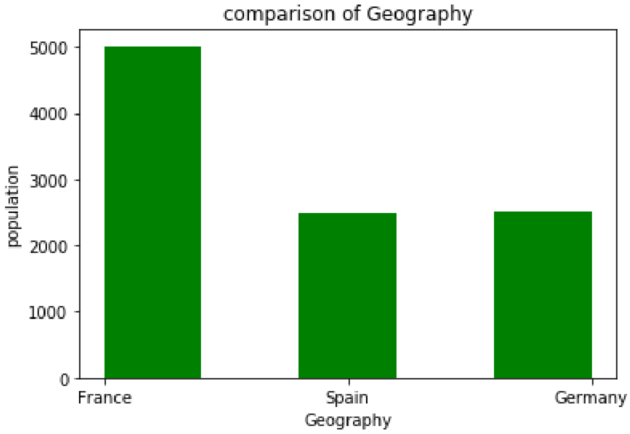
Out[8]:

```
France      5014
Germany     2509
Spain       2477
Name: Geography, dtype: int64
```

In [9]:

```
# comparison of geography

plt.hist(x = data.Geography, bins = 5, color = 'green')
plt.title('comparison of Geography')
plt.xlabel('Geography')
plt.ylabel('population')
plt.show()
```



In [10]:

```
data['HasCrCard'].value_counts()
```

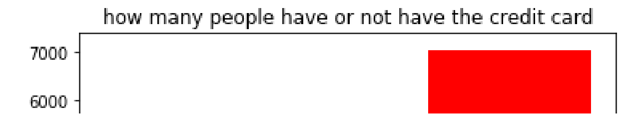
Out[10]:

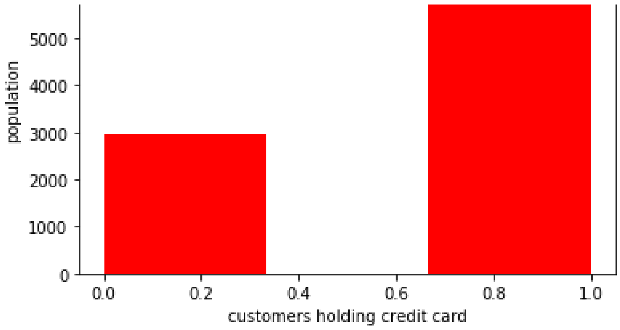
```
1    7055
0    2945
Name: HasCrCard, dtype: int64
```

In [11]:

```
# comparision of how many customers hold the credit card

plt.hist(x = data.HasCrCard, bins = 3, color = 'red')
plt.title('how many people have or not have the credit card')
plt.xlabel('customers holding credit card')
plt.ylabel('population')
plt.show()
```





In [12]:

```
data['IsActiveMember'].value_counts()
```

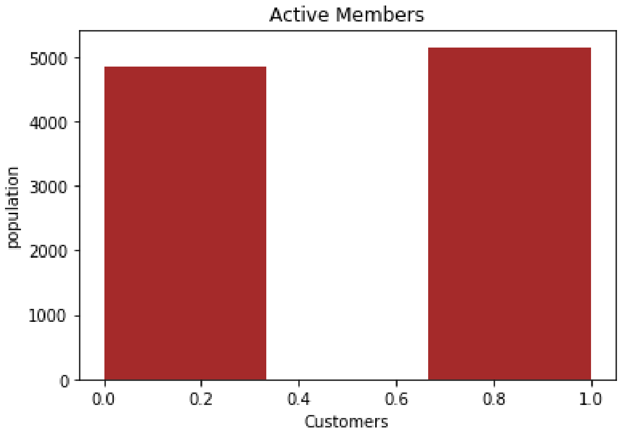
Out[12]:

```
1    5151
0    4849
Name: IsActiveMember, dtype: int64
```

In [13]:

```
# How many active member does the bank have ?

plt.hist(x = data.IsActiveMember, bins = 3, color = 'brown')
plt.title('Active Members')
plt.xlabel('Customers')
plt.ylabel('population')
plt.show()
```



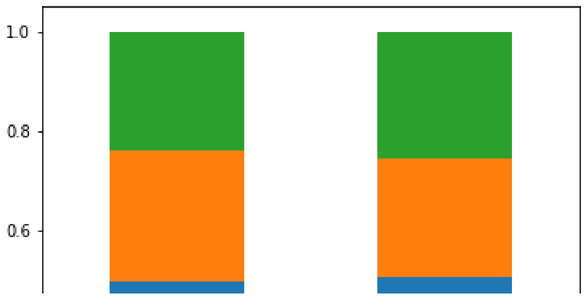
In [14]:

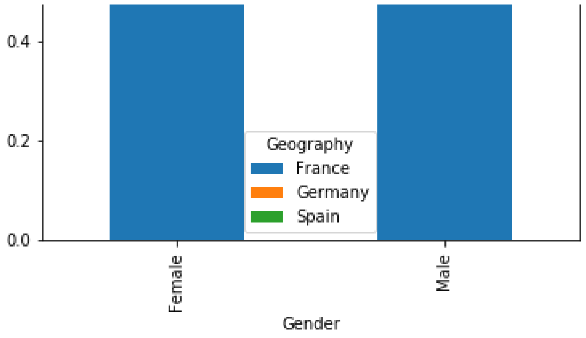
```
# comparison between Geography and Gender

Gender = pd.crosstab(data['Gender'],data['Geography'])
Gender.div(Gender.sum(1).astype(float), axis=0).plot(kind="bar", stacked=True, figsize=(6, 6))
```

Out[14]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x191b39778c8>
```





In [16]:

```
# calculating total balance in france, germany and spain

total_france = data.Balance[data.Geography == 'France'].sum()
total_germany = data.Balance[data.Geography == 'Germany'].sum()
total_spain = data.Balance[data.Geography == 'Spain'].sum()

print("Total Balance in France :",total_france)
print("Total Balance in Germany :",total_germany)
print("Total Balance in Spain :",total_spain)
```

```
Total Balance in France : 311332479.49
Total Balance in Germany : 300402861.38
Total Balance in Spain : 153123552.01
```

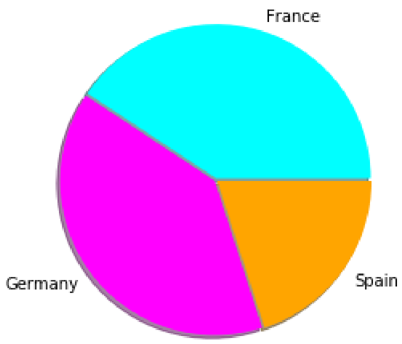
In [17]:

```
# plotting a pie chart

labels = 'France', 'Germany', 'Spain'
colors = ['cyan', 'magenta', 'orange']
sizes =  [311, 300, 153]
explode = [ 0.01, 0.01, 0.01]

plt.pie(sizes, colors = colors, labels = labels, explode = explode, shadow = True)

plt.axis('equal')
plt.show()
```



Data Preprocessing

In [20]:

```
X = data.iloc[:, 3:13].values
y = data.iloc[:, 13].values
```

X is here our Matrix of feature(independent variables) and y (actual value): exited, this is the value we are trying to predict, which means if the customer stays or exit the bank.

Encoding categorical data

In [ ]:

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
labelencoder_X_1 = LabelEncoder()
X[:, 1] = labelencoder_X_1.fit_transform(X[:, 1])
labelencoder_X_2 = LabelEncoder()
X[:, 2] = labelencoder_X_2.fit_transform(X[:, 2])
onehotencoder = OneHotEncoder(categorical_features = [1])
X = onehotencoder.fit_transform(X).toarray()
X = X[:, 1:]
```

In [ ]:

```
# Splitting the dataset into the Training set and Test set
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)
```

In [ ]:

```
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Building of ANN

In [ ]:

```
# Importing the Keras libraries and packages
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout

# Initialising the ANN
classifier = Sequential()

# Adding the input layer and the first hidden layer
classifier.add(Dense(units = 6, kernel_initializer = 'uniform', activation = 'relu', input_dim = 11
))
# classifier.add(Dropout(p = 0.1))

# Adding the second hidden layer
classifier.add(Dense(units = 6, kernel_initializer = 'uniform', activation = 'relu'))
# classifier.add(Dropout(p = 0.1))

# Adding the output layer
classifier.add(Dense(units = 1, kernel_initializer = 'uniform', activation = 'sigmoid'))

# Compiling the ANN
classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])

# Fitting the ANN to the Training set
classifier.fit(X_train, y_train, batch_size = 10, epochs = 100)
```

Epoch 1/100 8000/8000 [==============================] - 2s - loss: 0.4849 - acc: 0.7957
Epoch 2/100 8000/8000 [==============================] - 2s - loss: 0.4271 - acc: 0.7960
Epoch 3/100 8000/8000 [==============================] - 2s - loss: 0.4208 - acc: 0.8016
Epoch 4/100 8000/8000 [==============================] - 2s - loss: 0.4175 - acc: 0.8232
Epoch 5/100 8000/8000 [==============================] - 2s - loss: 0.4155 - acc: 0.8285
Epoch 6/100 8000/8000 [==============================] - 2s - loss: 0.4134 - acc: 0.8309
Epoch 7/100 8000/8000 [==============================] - 2s - loss: 0.4121 - acc: 0.8317
Epoch 8/100 8000/8000 [==============================] - 2s - loss: 0.4107 - acc: 0.8334
Epoch 9/100 8000/8000 [==============================] - 2s - loss: 0.4103 - acc: 0.8346
Epoch 10/100 8000/8000 [==============================] - 2s - loss: 0.4091 - acc: 0.8340
Epoch 11/100 8000/8000 [==============================] - 2s - loss: 0.4078 - acc: 0.8350
Epoch 12/100 8000/8000 [==============================] - 2s - loss: 0.4072 - acc: 0.8340

```
Epoch 12/100 8000/8000 [==============================] - 2s - loss: 0.4072 - acc: 0.8340
Epoch 13/100 8000/8000 [==============================] - 2s - loss: 0.4065 - acc: 0.8344
Epoch 14/100 8000/8000 [==============================] - 2s - loss: 0.4065 - acc: 0.8349
Epoch 15/100 8000/8000 [==============================] - 2s - loss: 0.4057 - acc: 0.8355
Epoch 16/100 8000/8000 [==============================] - 2s - loss: 0.4050 - acc: 0.8340
Epoch 17/100 8000/8000 [==============================] - 2s - loss: 0.4049 - acc: 0.8354
Epoch 18/100 8000/8000 [==============================] - 2s - loss: 0.4040 - acc: 0.8332
Epoch 19/100 8000/8000 [==============================] - 2s - loss: 0.4028 - acc: 0.8352
Epoch 20/100 8000/8000 [==============================] - 2s - loss: 0.4022 - acc: 0.8356
Epoch 21/100 8000/8000 [==============================] - 2s - loss: 0.4013 - acc: 0.8360
Epoch 22/100 8000/8000 [==============================] - 2s - loss: 0.4007 - acc: 0.8352
Epoch 23/100 8000/8000 [==============================] - 2s - loss: 0.3999 - acc: 0.8364
Epoch 24/100 8000/8000 [==============================] - 2s - loss: 0.3999 - acc: 0.8361
Epoch 25/100 8000/8000 [==============================] - 2s - loss: 0.3990 - acc: 0.8344
Epoch 26/100 8000/8000 [==============================] - 2s - loss: 0.3985 - acc: 0.8359
Epoch 27/100 8000/8000 [==============================] - 2s - loss: 0.3977 - acc: 0.8354
Epoch 28/100 8000/8000 [==============================] - 2s - loss: 0.3975 - acc: 0.8351
Epoch 29/100 8000/8000 [==============================] - 2s - loss: 0.3975 - acc: 0.8344
Epoch 30/100 8000/8000 [==============================] - 2s - loss: 0.3975 - acc: 0.8350
Epoch 31/100 8000/8000 [==============================] - 2s - loss: 0.3967 - acc: 0.8354
Epoch 32/100 8000/8000 [==============================] - 2s - loss: 0.3965 - acc: 0.8342
Epoch 33/100 8000/8000 [==============================] - 2s - loss: 0.3964 - acc: 0.8354
Epoch 34/100 8000/8000 [==============================] - 2s - loss: 0.3964 - acc: 0.8359
Epoch 35/100 8000/8000 [==============================] - 2s - loss: 0.3962 - acc: 0.8356
Epoch 36/100 8000/8000 [==============================] - 2s - loss: 0.3958 - acc: 0.8367
Epoch 37/100 8000/8000 [==============================] - 2s - loss: 0.3953 - acc: 0.8364
Epoch 38/100 8000/8000 [==============================] - 2s - loss: 0.3958 - acc: 0.8355
Epoch 39/100 8000/8000 [==============================] - 2s - loss: 0.3954 - acc: 0.8380
Epoch 40/100 8000/8000 [==============================] - 2s - loss: 0.3954 - acc: 0.8366
Epoch 41/100 8000/8000 [==============================] - 2s - loss: 0.3954 - acc: 0.8340
Epoch 42/100 8000/8000 [==============================] - 2s - loss: 0.3952 - acc: 0.8362
Epoch 43/100 8000/8000 [==============================] - 2s - loss: 0.3947 - acc: 0.8350
Epoch 44/100 8000/8000 [==============================] - 2s - loss: 0.3951 - acc: 0.8362
Epoch 45/100 8000/8000 [==============================] - 2s - loss: 0.3945 - acc: 0.8356
Epoch 46/100 8000/8000 [==============================] - 2s - loss: 0.3949 - acc: 0.8354
Epoch 47/100 8000/8000 [==============================] - 2s - loss: 0.3952 - acc: 0.8366
Epoch 48/100 8000/8000 [==============================] - 2s - loss: 0.3950 - acc: 0.8377
Epoch 49/100 8000/8000 [==============================] - 2s - loss: 0.3942 - acc: 0.8359
Epoch 50/100 8000/8000 [==============================] - 2s - loss: 0.3944 - acc: 0.8357
Epoch 51/100 8000/8000 [==============================] - 2s - loss: 0.3947 - acc: 0.8359
Epoch 52/100 8000/8000 [==============================] - 3s - loss: 0.3944 - acc: 0.8379
Epoch 53/100 8000/8000 [==============================] - 3s - loss: 0.3946 - acc: 0.8365
Epoch 54/100 8000/8000 [==============================] - 3s - loss: 0.3946 - acc: 0.8366
Epoch 55/100 8000/8000 [==============================] - 2s - loss: 0.3943 - acc: 0.8356
Epoch 56/100 8000/8000 [==============================] - 2s - loss: 0.3944 - acc: 0.8352
Epoch 57/100 8000/8000 [==============================] - 2s - loss: 0.3948 - acc: 0.8371
Epoch 58/100 8000/8000 [==============================] - 3s - loss: 0.3940 - acc: 0.8371
Epoch 59/100 8000/8000 [==============================] - 3s - loss: 0.3944 - acc: 0.8361
Epoch 60/100 8000/8000 [==============================] - 3s - loss: 0.3941 - acc: 0.8361
Epoch 61/100 8000/8000 [==============================] - 2s - loss: 0.3942 - acc: 0.8367
Epoch 62/100 8000/8000 [==============================] - 2s - loss: 0.3933 - acc: 0.8372
Epoch 63/100 8000/8000 [==============================] - 2s - loss: 0.3940 - acc: 0.8366
Epoch 64/100 8000/8000 [==============================] - 2s - loss: 0.3937 - acc: 0.8362
Epoch 65/100 8000/8000 [==============================] - 2s - loss: 0.3938 - acc: 0.8365
Epoch 66/100 8000/8000 [==============================] - 2s - loss: 0.3929 - acc: 0.8377
Epoch 67/100 8000/8000 [==============================] - 2s - loss: 0.3934 - acc: 0.8361
Epoch 68/100 8000/8000 [==============================] - 2s - loss: 0.3936 - acc: 0.8350
Epoch 69/100 8000/8000 [==============================] - 2s - loss: 0.3930 - acc: 0.8370
Epoch 70/100 8000/8000 [==============================] - 2s - loss: 0.3922 - acc: 0.8376
Epoch 71/100 8000/8000 [==============================] - 2s - loss: 0.3921 - acc: 0.8374
Epoch 72/100 8000/8000 [==============================] - 2s - loss: 0.3919 - acc: 0.8381
Epoch 73/100 8000/8000 [==============================] - 2s - loss: 0.3918 - acc: 0.8375
Epoch 74/100 8000/8000 [==============================] - 2s - loss: 0.3910 - acc: 0.8380
Epoch 75/100 8000/8000 [==============================] - 3s - loss: 0.3907 - acc: 0.8375
Epoch 76/100 8000/8000 [==============================] - 3s - loss: 0.3902 - acc: 0.8386
Epoch 77/100 8000/8000 [==============================] - 2s - loss: 0.3897 - acc: 0.8380
```

Epoch 78/100 8000/8000 [==============================] - 2s - loss: 0.3892 - acc: 0.8386
Epoch 79/100 8000/8000 [==============================] - 2s - loss: 0.3873 - acc: 0.8389
Epoch 80/100 8000/8000 [==============================] - 2s - loss: 0.3848 - acc: 0.8386
Epoch 81/100 8000/8000 [==============================] - 2s - loss: 0.3818 - acc: 0.8377
Epoch 82/100 8000/8000 [==============================] - 2s - loss: 0.3790 - acc: 0.8381
Epoch 83/100 8000/8000 [==============================] - 2s - loss: 0.3749 - acc: 0.8396
Epoch 84/100 8000/8000 [==============================] - 2s - loss: 0.3701 - acc: 0.8419
Epoch 85/100 8000/8000 [==============================] - 2s - loss: 0.3665 - acc: 0.8437
Epoch 86/100 8000/8000 [==============================] - 2s - loss: 0.3641 - acc: 0.8452
Epoch 87/100 8000/8000 [==============================] - 2s - loss: 0.3616 - acc: 0.8467
Epoch 88/100 8000/8000 [==============================] - 2s - loss: 0.3598 - acc: 0.8511
Epoch 89/100 8000/8000 [==============================] - 2s - loss: 0.3583 - acc: 0.8512
Epoch 90/100 8000/8000 [==============================] - 2s - loss: 0.3576 - acc: 0.8530
Epoch 91/100 8000/8000 [==============================] - 2s - loss: 0.3565 - acc: 0.8536
Epoch 92/100 8000/8000 [==============================] - 2s - loss: 0.3554 - acc: 0.8545
Epoch 93/100 8000/8000 [==============================] - 2s - loss: 0.3534 - acc: 0.8545
Epoch 94/100 8000/8000 [==============================] - 2s - loss: 0.3527 - acc: 0.8560
Epoch 95/100 8000/8000 [==============================] - 2s - loss: 0.3514 - acc: 0.8555
Epoch 96/100 8000/8000 [==============================] - 2s - loss: 0.3498 - acc: 0.8557
Epoch 97/100 8000/8000 [==============================] - 2s - loss: 0.3496 - acc: 0.8585
Epoch 98/100 8000/8000 [==============================] - 2s - loss: 0.3489 - acc: 0.8584
Epoch 99/100 8000/8000 [==============================] - 2s - loss: 0.3479 - acc: 0.8589
Epoch 100/100 8000/8000 [==============================] - 2s - loss: 0.3478 - acc: 0.8577

Predicting our Test Results

In [ ]:

```
# Predicting the Test set results
y_pred = classifier.predict(X_test)
y_pred = (y_pred > 0.5)

# Predicting a single new observation
"""Predict if the customer with the following informations will leave the bank:
Geography: France
Credit Score: 600
Gender: Male
Age: 40
Tenure: 3
Balance: 60000
Number of Products: 2
Has Credit Card: Yes
Is Active Member: Yes
Estimated Salary: 50000"""
new_prediction = classifier.predict(sc.transform(np.array([[0.0, 0, 600, 1, 40, 3, 60000, 2, 1, 1, 5
0000]])))
new_prediction = (new_prediction > 0.5)

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

In [ ]:

```
array([[1503,   92],
       [ 189,  216]])
```

Evaluating, Improving and Tuning the ANN

-Using K-Fold Cross validation with Keras

In [ ]:

```
# Evaluating the ANN
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import cross_val_score
from keras.models import Sequential
from keras.layers import Dense
```

```
from keras.layers import Dense
def build_classifier():
    classifier = Sequential()
    classifier.add(Dense(units = 6, kernel_initializer = 'uniform', activation = 'relu', input_dim
= 11))
    classifier.add(Dense(units = 6, kernel_initializer = 'uniform', activation = 'relu'))
    classifier.add(Dense(units = 1, kernel_initializer = 'uniform', activation = 'sigmoid'))
    classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
    return classifier
classifier = KerasClassifier(build_fn = build_classifier, batch_size = 10, epochs = 100)
mean = accuracies.mean()
variance = accuracies.std()
```

In [ ]:

```
mean = 0.
```

Drop out regularization: A solution for overfitting - high variance

At each iteration of training, some neurons of your artificial neural network are randomly disabled to prevent them from being too dependent on each other when they learn the correlations Therefore, by overwriting these neurons, the ANN learn several independent correlations in the data because each time there is not the same configuration of the neurons. The fact that we get these independent correlations of the data, meaning the neurons work more independently, that prevents the neuron from learning too much and therefore overfitting. Using Dropout() argument:

p: the fraction of the input units you want to drop/disable at each iteration. For example: if we have 10 neurons, p=0.1 (10%), this means at each iteration, 1 neuron will be disabled.

In [ ]:

```
# Improving the ANN
# Dropout Regularization to reduce overfitting if needed

# Tuning the ANN
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout

def build_classifier(optimizer):
    classifier = Sequential()
    classifier.add(Dense(units = 6, kernel_initializer = 'uniform', activation = 'relu', input_dim
= 11))
    # classifier.add(Dropout(p = 0.1))
    classifier.add(Dense(units = 6, kernel_initializer = 'uniform', activation = 'relu'))
    # classifier.add(Dropout(p = 0.1))
    classifier.add(Dense(units = 1, kernel_initializer = 'uniform', activation = 'sigmoid'))
    classifier.compile(optimizer = optimizer, loss = 'binary_crossentropy', metrics = ['accuracy'])
    return classifier
classifier = KerasClassifier(build_fn = build_classifier)
parameters = {'batch_size': [25, 32],
              'epochs': [100, 500],
              'optimizer': ['adam', 'rmsprop']}
grid_search = GridSearchCV(estimator = classifier,
                           param_grid = parameters,
                           scoring = 'accuracy',
                           cv = 10)
grid_search = grid_search.fit(X_train, y_train)
best_parameters = grid_search.best_params_
best_accuracy = grid_search.best_score_
```

In [ ]:

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best_accuracy = 0.85348
best_parameters="batch_size"=25,"epochs"=500, "optimizer"=rmsprop
```

THANK YOU