Bank Customer Churn Prediction

Description

This allows you to predict Bank customer churn using Artificial neural network algorithms . Developed with Python and the all codes published on GitHub.

- predict customer churn
- review data analysis

  Dataset: https://www.kaggle.com/code/korfanakis/predicting-customer-churn-with-machine-learning/data?select=Churn_Modelling.csv (https://www.kaggle.com/code/korfanakis/predicting-customer-churn-with-machine-learning/data?select=Churn_Modelling.csv)

Installation and Usage

1. Install all dependencies listed in requirements.txt - all packages are pip-installable.
2. Run Bank_Churn_pred ipynb File.

In [777]:

```
# Importing required modules
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.ticker as mtick
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report,confusion_matrix
import collections
import pickle
```

In [778]:

```
# Reading in dataset/Bank-Churn-data.csv
dataset= pd.read_csv('data\Bank-Churn-data.csv')

#seperating input and output values
x=dataset.iloc[:, 3:-1].values
y=dataset.iloc[:, -1].values
print(x[0])
print(y[0])
```

```
[619 'France' 'Female' 42 2 0.0 1 1 1 101348.88]
1
```

In [779]:

```
print(x[0])
#Changing input string parameters to integer
LE=LabelEncoder()
x[:, 2]=LE.fit_transform(x[:, 2])
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1])], remainder='pas
sthrough')
x=np.array(ct.fit_transform(x))
print(x[0])
```

```
[619 'France' 'Female' 42 2 0.0 1 1 1 101348.88]
[1.0 0.0 0.0 619 0 42 2 0.0 1 1 1 101348.88]
```

Baseline model

In [780]:

```
#Seperating the Train, Test and Validation data
X_train1, X_test1, y_train1, y_test1 = train_test_split(x, y, test_size = 0.3, random_s
tate = 0)
X_test1, X_validation1, y_test1, y_validation1 = train_test_split(X_test1, y_test1, tes
t_size = 0.33, random_state = 0)
```

In [781]:

```
#Standardized Scaling to fit the data in training the model
sc = StandardScaler()
X_train1 = sc.fit_transform(X_train1)
X_test1 = sc.transform(X_test1)
X_validation1=sc.transform(X_validation1)
```

The Baseline model is a Logistic Regression Model

In [782]:

```
#Implementing Logistic Regression
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
result = model.fit(X_train1, y_train1)
from sklearn import metrics
prediction_test = model.predict(X_test1)
# Print the prediction accuracy
results=[]
results.append(metrics.accuracy_score(y_test1, prediction_test))
print(results)
```

```
[0.8099502487562189]
```

In [783]:

```
#Saving the Trained Baseline model
filename = 'data/baseline_model.h5'
pickle.dump(model, open(filename, 'wb'))
```

In [784]:

```
#Showing the Classification Report of Baseline model
y_pred1=model.predict(X_test1)
y_pred1=(y_pred1>0.5)
print(classification_report(y_test1, y_pred1))
```

```
              precision    recall  f1-score   support

           0       0.83      0.96      0.89      1591
           1       0.62      0.23      0.34       419

    accuracy                           0.81      2010
   macro avg       0.72      0.60      0.61      2010
weighted avg       0.78      0.81      0.77      2010
```

Data Exploration

In [785]:

```
#Remove RowNumber from the data set
df2 = dataset.iloc[:,1:]
#Converting all the categorical variables into dummy variables
df_dummies = pd.get_dummies(df2)
df_dummies.head()
```

Out[785]:

	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMe
0	15634602	619	42	2	0.00	1	1	
1	15647311	608	41	1	83807.86	1	0	
2	15619304	502	42	8	159660.80	3	1	
3	15701354	699	39	1	0.00	2	0	
4	15737888	850	43	2	125510.82	1	1	

5 rows × 2947 columns

Senior Citizens, Salarycategory :

Adding a new feature to the dataset. We are considering people above 60 years as Senior Citizens and dividing the Salary type to 3 different categories < 40K , 40K < X < 80K and X > 80K

In [786]:

```
#Adding two new columns to increase the model Accuracy
df2['SeniorCitizen'] =  [1 if x > 60 else 0 for x in df2['Age']]
df2['Salarycategory'] =  [0 if x < 40000 else (1 if x<80000 else 2) for x in df2['Estim
atedSalary']]
column_names = list(df2.columns.values)
print(column_names)
column_names[-3],column_names[-2], column_names[-1] = column_names[-1], column_names[-2
],column_names[-3]
df2=df2.reindex(columns=column_names)
df2.head()
```

```
['CustomerId', 'Surname', 'CreditScore', 'Geography', 'Gender', 'Age', 'Te
nure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'Estimat
edSalary', 'Exited', 'SeniorCitizen', 'Salarycategory']
```

Out[786]:

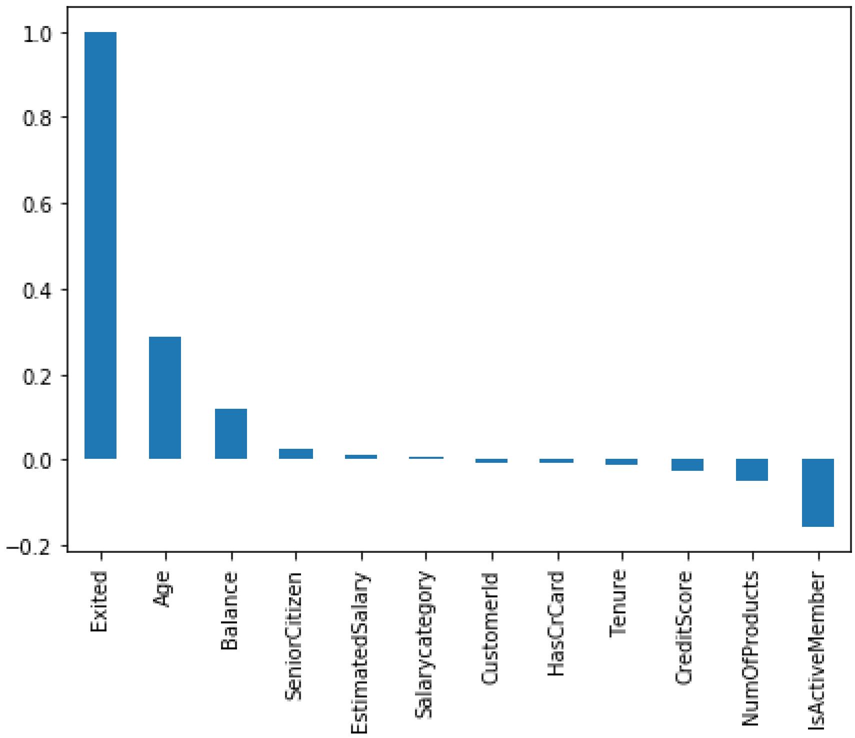
	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfP
0	15634602	Hargrave	619	France	Female	42	2	0.00	
1	15647311	Hill	608	Spain	Female	41	1	83807.86	
2	15619304	Onio	502	France	Female	42	8	159660.80	
3	15701354	Boni	699	France	Female	39	1	0.00	
4	15737888	Mitchell	850	Spain	Female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

In [787]:

```
# Correlation of "Churn" with other variables
plt.figure(figsize=(7,5))
df2.corr()['Exited'].sort_values(ascending = False).plot(kind='bar')
```

Out[787]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1dc37e3e348>
```



Age and Balance seem to be positively correlated with churn.

Interestingly, rest all the features seem to be negatively related to churn.

In [788]:

```
#seperating input and output values after adding new parameters
x=df2.iloc[:, 2:-1].values
y=df2.iloc[:, -1].values
print(x[0])

#Changing input string parameters to integer
LE=LabelEncoder()
x[:, 2]=LE.fit_transform(x[:, 2])
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1])], remainder='pas
sthrough')
x=np.array(ct.fit_transform(x))
df2.isnull().sum()
#Converting all the categorical variables into dummy variables
df_dummies = pd.get_dummies(df2)
df_dummies.head()
print(x[0])
```

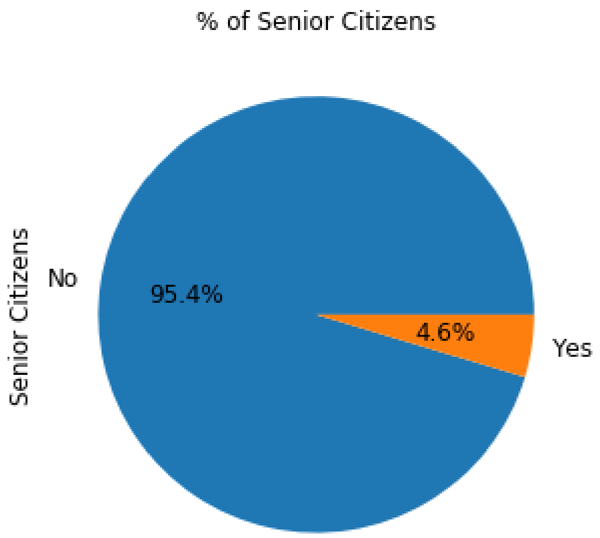
```
[619 'France' 'Female' 42 2 0.0 1 1 1 101348.88 2 0]
[1.0 0.0 0.0 619 0 42 2 0.0 1 1 1 101348.88 2 0]
```

In [789]:

```
# Plotting the % Senior Citizen in dataset
ax = (df2['SeniorCitizen'].value_counts()*100.0 /len(df2))\
.plot.pie(autopct='%.1f%%', labels = ['No', 'Yes'],figsize =(5,5), fontsize = 12 )
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
ax.set_ylabel('Senior Citizens',fontsize = 12)
ax.set_title('% of Senior Citizens', fontsize = 12)
```

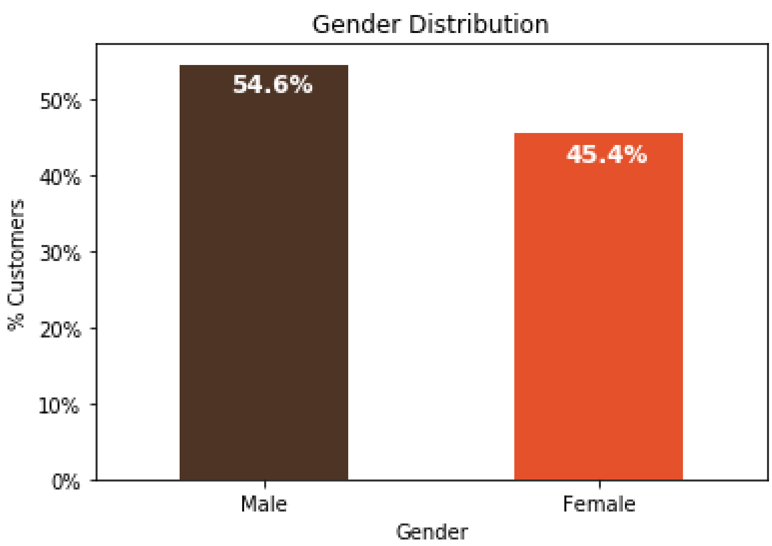
Out[789]:

```
Text(0.5, 1.0, '% of Senior Citizens')
```



In [790]:

```
# Plotting the % Gender in dataset
colors = ['#4D3425','#E4512B']
ax = (df2['Gender'].value_counts()*100.0 /len(df2)).plot(kind='bar',stacked = True,rot
= 0,color = colors)
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
ax.set_ylabel('% Customers')
ax.set_xlabel('Gender')
ax.set_ylabel('% Customers')
ax.set_title('Gender Distribution')

# create a list to collect the plt.patches data
totals = []

# find the values and append to list
for i in ax.patches:
    totals.append(i.get_width())

# set individual bar lables using above list
total = sum(totals)

for i in ax.patches:
    # get_width pulls left or right; get_y pushes up or down
    ax.text(i.get_x()+.15, i.get_height()-3.5, \
            str(round((i.get_height()/total), 1))+'%',
            fontsize=12,
            color='white',
           weight = 'bold')
```

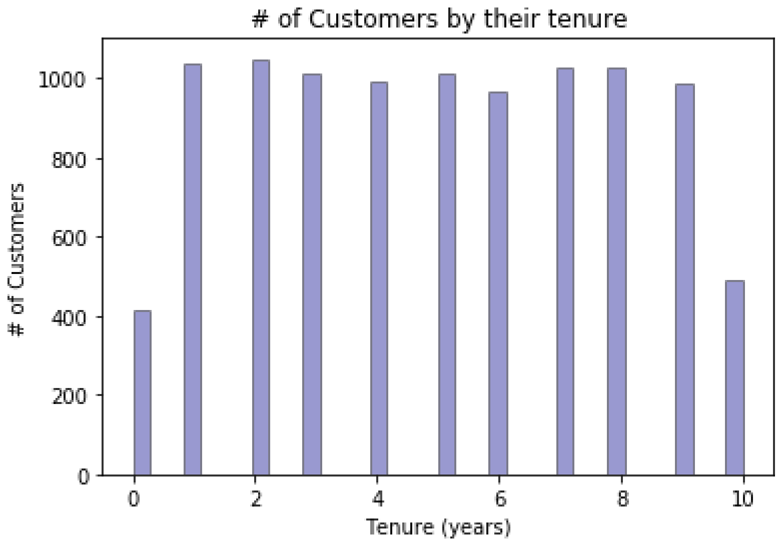


In [791]:

```
# Plotting the Customers by their tenure in dataset
import seaborn as sns
ax = sns.distplot(df2['Tenure'], hist=True, kde=False,
             bins=int(180/5), color = 'darkblue',
             hist_kws={'edgecolor':'black'},
             kde_kws={'linewidth': 4})
ax.set_ylabel('# of Customers')
ax.set_xlabel('Tenure (years)')
ax.set_title('# of Customers by their tenure')
```

Out[791]:

```
Text(0.5, 1.0, '# of Customers by their tenure')
```

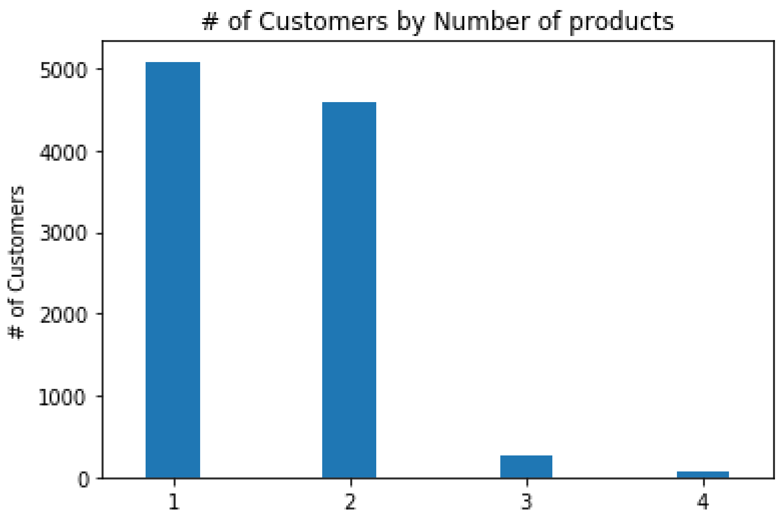


In [792]:

```
# Plotting the Customers by Number of Products in dataset
ax = df2['NumOfProducts'].value_counts().plot(kind = 'bar',rot = 0, width = 0.3)
ax.set_ylabel('# of Customers')
ax.set_title('# of Customers by Number of products')
```

Out[792]:

```
Text(0.5, 1.0, '# of Customers by Number of products')
```

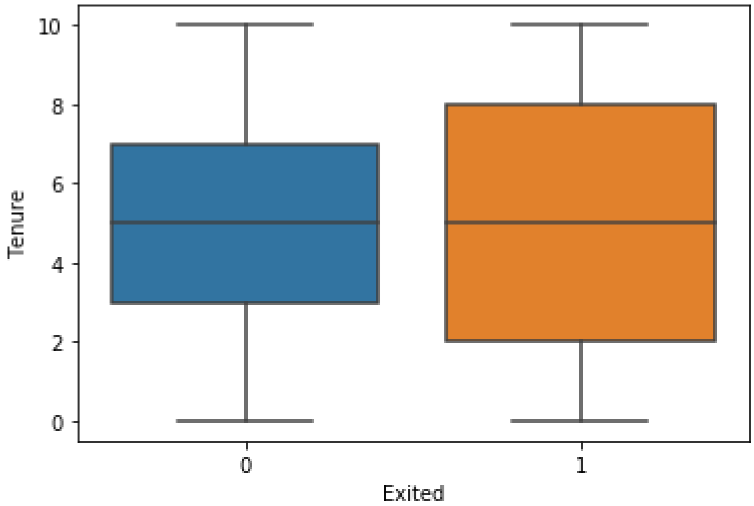


In [793]:

```
# Plotting the Tenure vs Churn
sns.boxplot(x = df2.Exited, y = df2.Tenure)
```

Out[793]:

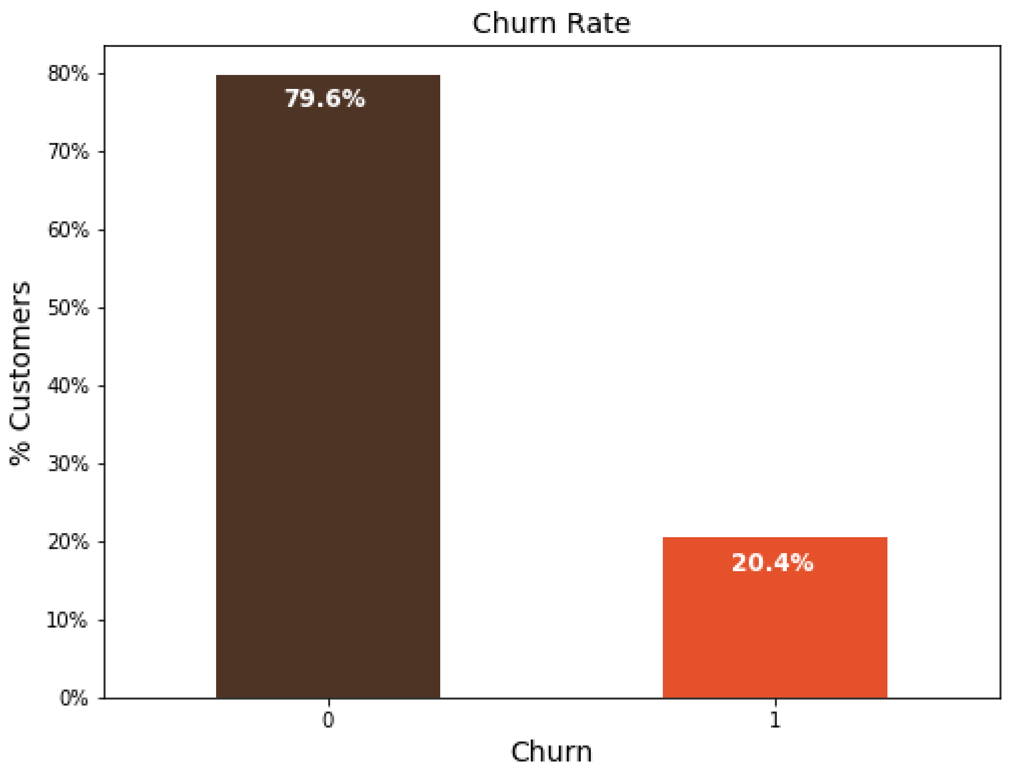
```
<matplotlib.axes._subplots.AxesSubplot at 0x1dc4d350408>
```



Churn vs Tenure: As we can see form the above plot, the customers who do not churn, they tend to stay for a lesser tenure with the Bank.

In [794]:

```
# Plotting the Churn rate in the dataset
colors = ['#4D3425','#E4512B']
ax = (df2['Exited'].value_counts()*100.0 /len(df2)).plot(kind='bar',stacked = True,rot
= 0,color = colors,figsize = (8,6))
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
ax.set_ylabel('% Customers',size = 14)
ax.set_xlabel('Churn',size = 14)
ax.set_title('Churn Rate', size = 14)

# create a list to collect the plt.patches data
totals = []

# find the values and append to list
for i in ax.patches:
    totals.append(i.get_width())

# set individual bar lables using above list
total = sum(totals)

for i in ax.patches:
    # get_width pulls left or right; get_y pushes up or down
    ax.text(i.get_x()+.15, i.get_height()-4.0, \
            str(round((i.get_height()/total), 1))+'%',
            fontsize=12,
            color='white',
           weight = 'bold')
```

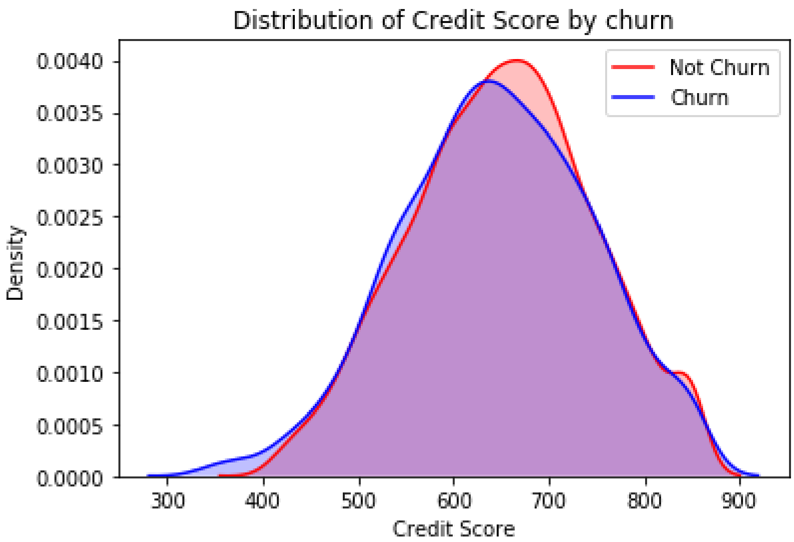


In [795]:

```
#Plotting the Distribution of Credit Score by churn
ax = sns.kdeplot(df2.CreditScore[(df2["Exited"] == 0) ],
                color="Red", shade = True)
ax = sns.kdeplot(df2.CreditScore[(df2["Exited"] == 1) ],
                ax =ax, color="Blue", shade= True)
ax.legend(["Not Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Credit Score')
ax.set_title('Distribution of Credit Score by churn')
```

Out[795]:

```
Text(0.5, 1.0, 'Distribution of Credit Score by churn')
```

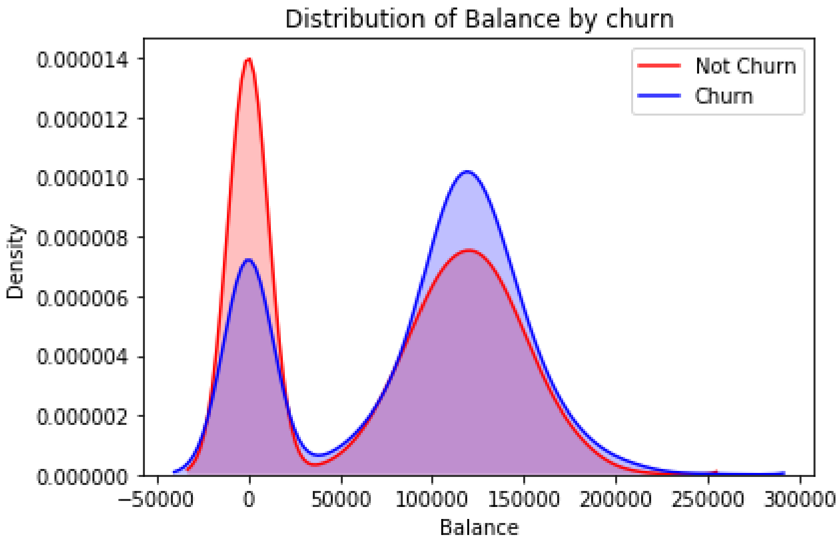


In [796]:

```
#Plotting the Distribution of Credit Score by churn
ax = sns.kdeplot(df2.Balance[(df2["Exited"] == 0) ],
                color="Red", shade = True)
ax = sns.kdeplot(df2.Balance[(df2["Exited"] == 1) ],
                ax =ax, color="Blue", shade= True)
ax.legend(["Not Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Balance')
ax.set_title('Distribution of Balance by churn')
```

Out[796]:

```
Text(0.5, 1.0, 'Distribution of Balance by churn')
```

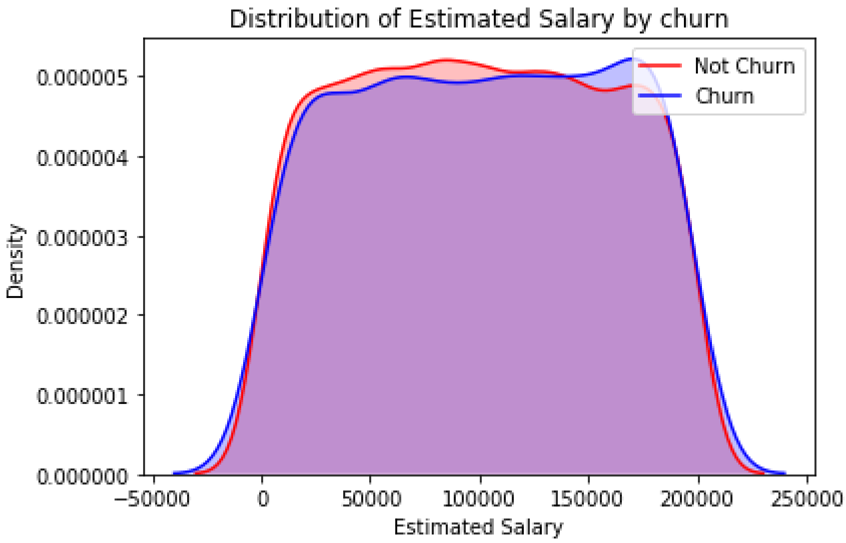


In [797]:

```
#Plotting the Distribution of Estimated Salary by churn
ax = sns.kdeplot(df2.EstimatedSalary[(df2["Exited"] == 0) ],
                color="Red", shade = True)
ax = sns.kdeplot(df2.EstimatedSalary[(df2["Exited"] == 1) ],
                ax =ax, color="Blue", shade= True)
ax.legend(["Not Churn","Churn"],loc='upper right')
ax.set_ylabel('Density')
ax.set_xlabel('Estimated Salary')
ax.set_title('Distribution of Estimated Salary by churn')
```

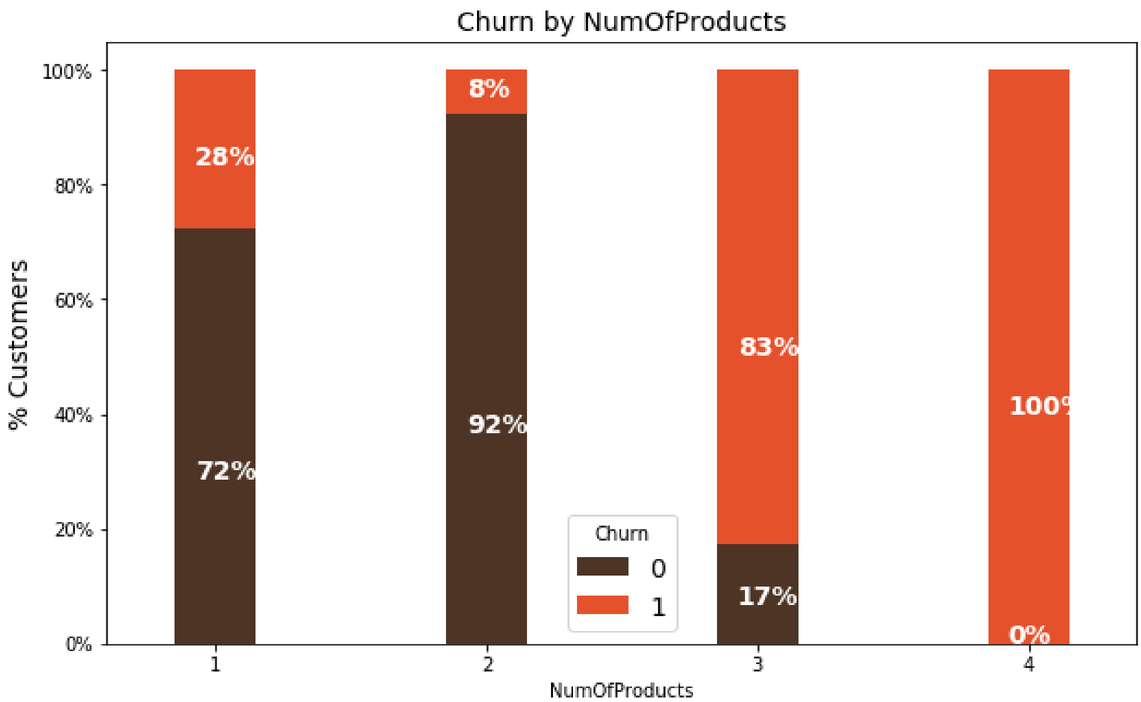
Out[797]:

```
Text(0.5, 1.0, 'Distribution of Estimated Salary by churn')
```



In [798]:

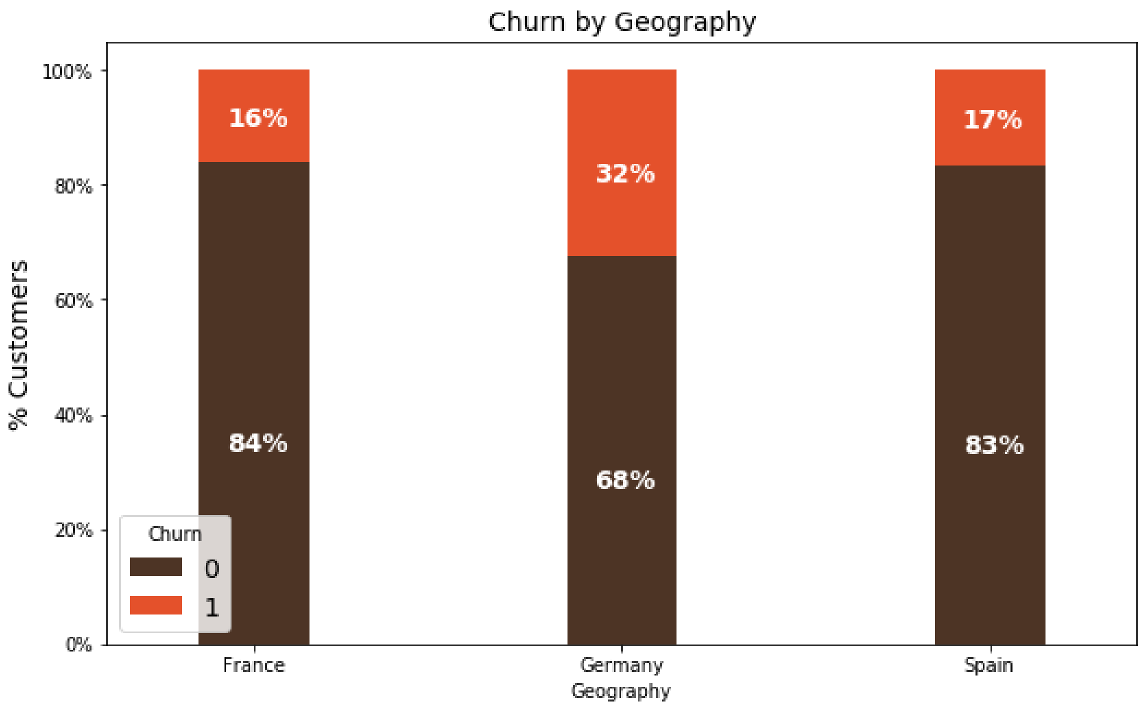
```
# Plotting Churn by NumOfProducts
colors = ['#4D3425','#E4512B']
prod_churn = df2.groupby(['NumOfProducts','Exited']).size().unstack()

ax = (prod_churn.T*100.0 / prod_churn.T.sum()).T.plot(kind='bar',
                                                                width = 0.3,
                                                                stacked = True,
                                                                rot = 0,
                                                                figsize = (10,6),
                                                                color = colors)
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
ax.legend(loc='best',prop={'size':14},title = 'Churn')
ax.set_ylabel('% Customers',size = 14)
ax.set_title('Churn by NumOfProducts',size = 14)

# Code to add the data labels on the stacked bar chart
for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_xy()
    ax.annotate('{:.0f}%'.format(height), (p.get_x()+.25*width, p.get_y()+.4*height),
                color = 'white',
               weight = 'bold',
               size = 14)
```



Churn by Number of products : Similar to what we saw in the correlation plot, the customers who have a more products have a very high churn rate.

In [799]:

```
# Plotting Churn by Geography
colors = ['#4D3425','#E4512B']
prod_churn = df2.groupby(['Geography','Exited']).size().unstack()

ax = (prod_churn.T*100.0 / prod_churn.T.sum()).T.plot(kind='bar',
                                                                width = 0.3,
                                                                stacked = True,
                                                                rot = 0,
                                                                figsize = (10,6),
                                                                color = colors)
ax.yaxis.set_major_formatter(mtick.PercentFormatter())
ax.legend(loc='best',prop={'size':14},title = 'Churn')
ax.set_ylabel('% Customers',size = 14)
ax.set_title('Churn by Geography',size = 14)

for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    x, y = p.get_xy()
    ax.annotate('{:.0f}%'.format(height), (p.get_x()+.25*width, p.get_y()+.4*height),
                 color = 'white',
                weight = 'bold',
                size = 14)
```



Loading data after adding additional features and implementing baseline model

In [800]:

```
#seperating input and output values after adding new parameters
x=df2.iloc[:, 2:-1].values
y=df2.iloc[:, -1].values

#Changing input string parameters to integer
LE=LabelEncoder()
x[:, 2]=LE.fit_transform(x[:, 2])
print(x[5])
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1])], remainder='pas
sthrough')
x=np.array(ct.fit_transform(x))
```

```
[645 'Spain' 1 44 8 113755.78 2 1 0 149756.71 2 0]
```

In [801]:

```
#Seperating the Train, Test and Validation data
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size = 0.3, random_state
= 0)
X_test, X_validation, y_test, y_validation = train_test_split(X_test, y_test, test_size
= 0.33, random_state = 0)
```

In [802]:

```
print(X_validation[3])
print(y_validation[6])
```

```
[0.0 1.0 0.0 706 1 34 0 140641.26 2 1 1 77271.91 1 0]
0
```

In [803]:

```
#Standardized Scaling to fit the data in training the model
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
X_validation=sc.transform(X_validation)
```

In [804]:

```
print(X_validation[0])
```

```
[-1.01525927  1.75478035 -0.5731713   0.1385645   0.92295821  0.01725942
  0.69700901 -0.23836603 -0.92971564  0.64198477 -1.03430227  1.22994458
  0.74920699 -0.21815257]
```

In [805]:

```
# Running logistic regression model
model1 = LogisticRegression()
result = model1.fit(X_train, y_train)
prediction_test = model1.predict(X_test)
# Print the prediction accuracy
results.append(metrics.accuracy_score(y_test, prediction_test))
print(results)
```

```
[0.8099502487562189, 0.8253731343283582]
```

We can see that as we added additional features the accuracy has increased in the baseline model

In [806]:

```
#Printing the modified input of the neural network
print(X_train[0])
```

```
[ 0.98497008 -0.56987189 -0.5731713  -0.09792126  0.92295821 -0.55759842
 -1.03635146  1.13249447  0.81039385  0.64198477  0.96683535 -0.76862426
 -0.51208424 -0.21815257]
```

Artificial neural network:

It is a 5 layer network with Gelu activation function and Adam Optimizer and binary Crossentropy as loss function and with 0.1% dropout after every layer. It is trained with a Batch size of 16 and with 100 Epochs

In [807]:

```
# Artificial Neural Network model
ann=tf.keras.models.Sequential()
ann.add(tf.keras.layers.Dense(units=14,activation='gelu'))
ann.add(tf.keras.layers.Dropout(0.1))
ann.add(tf.keras.layers.Dense(units=16,activation='gelu'))
ann.add(tf.keras.layers.Dropout(0.1))
ann.add(tf.keras.layers.Dense(units=12,activation='gelu'))
ann.add(tf.keras.layers.Dropout(0.1))
ann.add(tf.keras.layers.Dense(units=6,activation='gelu'))
ann.add(tf.keras.layers.Dropout(0.1))
ann.add(tf.keras.layers.Dense(units=1,activation='gelu'))

# Training the ANN model
ann.compile(optimizer='Adam',loss='binary_crossentropy',metrics=['accuracy'])
ann.fit(X_train,y_train,batch_size=16,epochs=100)
```

```
Epoch 1/100
438/438 [==============================] - 5s 3ms/step - loss: 0.8885 - ac
curacy: 0.7761
Epoch 2/100
438/438 [==============================] - 1s 3ms/step - loss: 0.5377 - ac
curacy: 0.7939
Epoch 3/100
438/438 [==============================] - 1s 3ms/step - loss: 0.4898 - ac
curacy: 0.7979
Epoch 4/100
438/438 [==============================] - 1s 3ms/step - loss: 0.4868 - ac
curacy: 0.8007
Epoch 5/100
438/438 [==============================] - 1s 3ms/step - loss: 0.4567 - ac
curacy: 0.8078
Epoch 6/100
438/438 [==============================] - 1s 3ms/step - loss: 0.4444 - ac
curacy: 0.8186
Epoch 7/100
438/438 [==============================] - 1s 3ms/step - loss: 0.4316 - ac
curacy: 0.8249
Epoch 8/100
438/438 [==============================] - 1s 3ms/step - loss: 0.4329 - ac
curacy: 0.8245
Epoch 9/100
438/438 [==============================] - 1s 3ms/step - loss: 0.4045 - ac
curacy: 0.8383
Epoch 10/100
438/438 [==============================] - 1s 3ms/step - loss: 0.4018 - ac
curacy: 0.8421
Epoch 11/100
438/438 [==============================] - 2s 4ms/step - loss: 0.4058 - ac
curacy: 0.8322
Epoch 12/100
438/438 [==============================] - 2s 3ms/step - loss: 0.4108 - ac
curacy: 0.8214
Epoch 13/100
438/438 [==============================] - 2s 3ms/step - loss: 0.4107 - ac
curacy: 0.8324
Epoch 14/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3890 - ac
curacy: 0.8439
Epoch 15/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3738 - ac
curacy: 0.8435
Epoch 16/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3895 - ac
curacy: 0.8361
Epoch 17/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3782 - ac
curacy: 0.8431
Epoch 18/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3854 - ac
curacy: 0.8407
Epoch 19/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3703 - ac
curacy: 0.8466
Epoch 20/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3775 - ac
curacy: 0.8496
Epoch 21/100
```

```
438/438 [==============================] - 1s 3ms/step - loss: 0.3863 - ac
curacy: 0.8243
Epoch 22/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3943 - ac
curacy: 0.8443
Epoch 23/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3886 - ac
curacy: 0.8425
Epoch 24/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3643 - ac
curacy: 0.8462
Epoch 25/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3791 - ac
curacy: 0.8506
Epoch 26/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3944 - ac
curacy: 0.8320
Epoch 27/100
438/438 [==============================] - 2s 4ms/step - loss: 0.3844 - ac
curacy: 0.8469
Epoch 28/100
438/438 [==============================] - 2s 3ms/step - loss: 0.3782 - ac
curacy: 0.8463
Epoch 29/100
438/438 [==============================] - 2s 3ms/step - loss: 0.3885 - ac
curacy: 0.8460
Epoch 30/100
438/438 [==============================] - 2s 4ms/step - loss: 0.3723 - ac
curacy: 0.8523
Epoch 31/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3671 - ac
curacy: 0.8536
Epoch 32/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3619 - ac
curacy: 0.8551
Epoch 33/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3620 - ac
curacy: 0.8589
Epoch 34/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3663 - ac
curacy: 0.8577
Epoch 35/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3754 - ac
curacy: 0.8562
Epoch 36/100
438/438 [==============================] - 2s 4ms/step - loss: 0.3505 - ac
curacy: 0.8571
Epoch 37/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3579 - ac
curacy: 0.8616
Epoch 38/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3791 - ac
curacy: 0.8499
Epoch 39/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3885 - ac
curacy: 0.8510
Epoch 40/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3646 - ac
curacy: 0.8561
Epoch 41/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3812 - ac
```

```
curacy: 0.8437
Epoch 42/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3774 - ac
curacy: 0.8437
Epoch 43/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3748 - ac
curacy: 0.8492
Epoch 44/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3597 - ac
curacy: 0.8493
Epoch 45/100
438/438 [==============================] - 2s 4ms/step - loss: 0.3583 - ac
curacy: 0.8572
Epoch 46/100
438/438 [==============================] - 2s 3ms/step - loss: 0.3496 - ac
curacy: 0.8557
Epoch 47/100
438/438 [==============================] - 2s 4ms/step - loss: 0.3672 - ac
curacy: 0.8421
Epoch 48/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3502 - ac
curacy: 0.8555
Epoch 49/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3734 - ac
curacy: 0.8472
Epoch 50/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3636 - ac
curacy: 0.8525
Epoch 51/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3645 - ac
curacy: 0.8461
Epoch 52/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3677 - ac
curacy: 0.8565
Epoch 53/100
438/438 [==============================] - 2s 4ms/step - loss: 0.3662 - ac
curacy: 0.8509
Epoch 54/100
438/438 [==============================] - 2s 4ms/step - loss: 0.3714 - ac
curacy: 0.8497
Epoch 55/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3710 - ac
curacy: 0.8437
Epoch 56/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3643 - ac
curacy: 0.8570
Epoch 57/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3865 - ac
curacy: 0.8462
Epoch 58/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3505 - ac
curacy: 0.8581
Epoch 59/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3461 - ac
curacy: 0.8566
Epoch 60/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3607 - ac
curacy: 0.8530
Epoch 61/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3610 - ac
curacy: 0.8587
```

```
Epoch 62/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3620 - ac
curacy: 0.8559
Epoch 63/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3622 - ac
curacy: 0.8575
Epoch 64/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3511 - ac
curacy: 0.8603
Epoch 65/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3486 - ac
curacy: 0.8581
Epoch 66/100
438/438 [==============================] - 2s 3ms/step - loss: 0.3661 - ac
curacy: 0.8511
Epoch 67/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3584 - ac
curacy: 0.8573
Epoch 68/100
438/438 [==============================] - 2s 3ms/step - loss: 0.3752 - ac
curacy: 0.8538
Epoch 69/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3450 - ac
curacy: 0.8559
Epoch 70/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3787 - ac
curacy: 0.8376
Epoch 71/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3539 - ac
curacy: 0.8552
Epoch 72/100
438/438 [==============================] - 2s 3ms/step - loss: 0.3497 - ac
curacy: 0.8560
Epoch 73/100
438/438 [==============================] - 2s 3ms/step - loss: 0.3731 - ac
curacy: 0.8540
Epoch 74/100
438/438 [==============================] - 2s 4ms/step - loss: 0.3665 - ac
curacy: 0.8508
Epoch 75/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3690 - ac
curacy: 0.8548
Epoch 76/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3660 - ac
curacy: 0.8563
Epoch 77/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3634 - ac
curacy: 0.8480
Epoch 78/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3520 - ac
curacy: 0.8498
Epoch 79/100
438/438 [==============================] - 2s 3ms/step - loss: 0.3746 - ac
curacy: 0.8457
Epoch 80/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3551 - ac
curacy: 0.8594
Epoch 81/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3587 - ac
curacy: 0.8522
Epoch 82/100
```

```
438/438 [==============================] - 2s 3ms/step - loss: 0.3439 - ac
curacy: 0.8594
Epoch 83/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3589 - ac
curacy: 0.8536
Epoch 84/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3419 - ac
curacy: 0.8598
Epoch 85/100
438/438 [==============================] - 2s 3ms/step - loss: 0.3570 - ac
curacy: 0.8577
Epoch 86/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3706 - ac
curacy: 0.8511
Epoch 87/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3647 - ac
curacy: 0.8499
Epoch 88/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3498 - ac
curacy: 0.8548
Epoch 89/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3464 - ac
curacy: 0.8599
Epoch 90/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3568 - ac
curacy: 0.8591
Epoch 91/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3618 - ac
curacy: 0.8511
Epoch 92/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3445 - ac
curacy: 0.8643
Epoch 93/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3482 - ac
curacy: 0.8593
Epoch 94/100
438/438 [==============================] - 2s 4ms/step - loss: 0.3616 - ac
curacy: 0.8471
Epoch 95/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3516 - ac
curacy: 0.8584
Epoch 96/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3614 - ac
curacy: 0.8544
Epoch 97/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3532 - ac
curacy: 0.8615
Epoch 98/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3494 - ac
curacy: 0.8608
Epoch 99/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3528 - ac
curacy: 0.8614
Epoch 100/100
438/438 [==============================] - 1s 3ms/step - loss: 0.3524 - ac
curacy: 0.8575
```

Out[807]:

```
<tensorflow.python.keras.callbacks.History at 0x1dc4d4ec508>
```

In [818]:

```
#Saving the Trained ANN model
filename = 'data/Updated_model.h5'
ann.save(filename)
```

In [899]:

```
#Showing the Classification Report of Trained ANN Model with test Data
y_pred=ann.predict(X_test)
y_pred=(y_pred>0.51) #Considering prediction accuracy greater then 51%
results.append(metrics.accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.98      0.92      1591
           1       0.84      0.46      0.60       419

    accuracy                           0.87      2010
   macro avg       0.86      0.72      0.76      2010
weighted avg       0.87      0.87      0.85      2010
```

In [900]:

```
#Showing the Classification Report of Trained ANN Model with Validation Data
y_val_pred=ann.predict(X_validation)
y_val_pred=(y_val_pred>0.51) #Considering prediction accuracy greater then 51%
print(classification_report(y_validation, y_val_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.97      0.92       788
           1       0.79      0.42      0.55       202

    accuracy                           0.86       990
   macro avg       0.83      0.70      0.73       990
weighted avg       0.85      0.86      0.84       990
```

In [811]:

```
#Implementing to evaluate with individual inputs
def evaluate_result(a):
    #Encoding Male and Female parameters
    a[2]= 0 if a[2]=='Female' else 1
    # OneHotEncoding geogrophy
    if (a[1]=='France'):
        a.append(1.0)
        a.append(0.0)
        a.append(0.0)
    elif(a[1]=='Spain'):
        a.append(0.0)
        a.append(0.0)
        a.append(1.0)
    else:
        a.append(0.0)
        a.append(1.0)
        a.append(0.0)
    # Removing unwanted attributes
    a.remove(a[1])
    # Fitting to the trained model
    a=collections.deque(a)
    a.rotate(3)
    a=list(a)
    a.append(0 if a[7] < 40000 else (1 if a[7] < 80000 else 2))
    a.append(1 if a[5] > 60 else 0)
    a=np.array([a])
    # Predicting and returning the output as Churn or Not Churn
    y_out=(ann.predict(a) > 0.5)
    if(y_out==1):
        y_out='Churn'
    else:
        y_out='Not Churn'
    return y_out
```

In [812]:

```
# Printing the Implemented to evaluate function
print(evaluate_result([500 ,'Germany' ,'Male' ,43 ,7 ,140641.26 ,2 ,1 ,1 ,77271.91]))
```

Churn

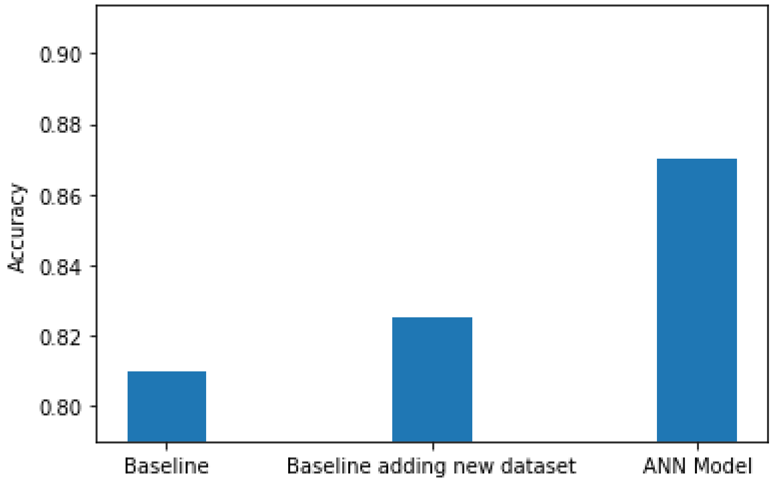
Result Visualisation

In [813]:

```
# Visualization of Results of Baseline model and ANN
plt.bar(['Baseline','Baseline adding new dataset','ANN Model'],results, width = 0.3)
plt.ylabel('Accuracy')
plt.ylim(0.79, None)
```

Out[813]:

(0.79, 0.9136567164179105)

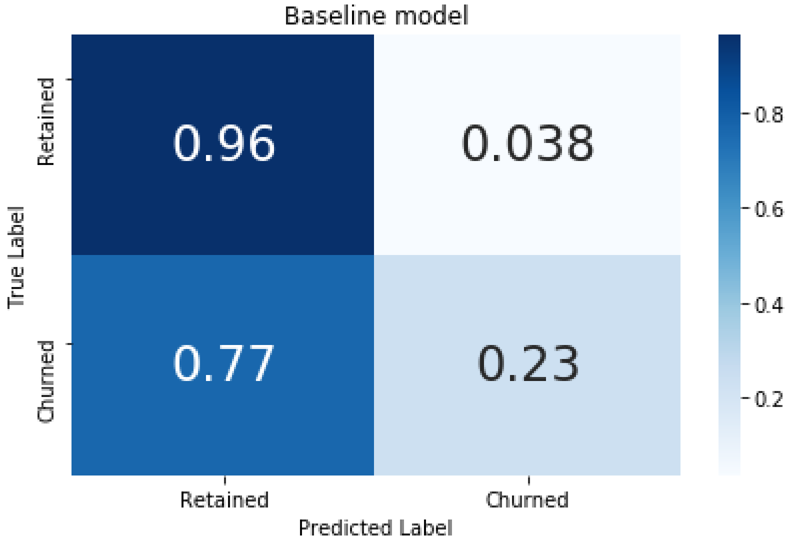


In [896]:

```
# Implementing heatmaps
def model_visualisation(classifier_name,X_test,y_test,y_pred):
    '''Assess the performance on the test set and plot the confusion matrix.'''
    # y_pred = classifier.predict(X_test)
    cm = confusion_matrix(y_test, y_pred, normalize='true')

    ax = sns.heatmap(cm,
                annot=True,
                annot_kws={'fontsize': 24},
                cmap='Blues' )

    ax.set_title(classifier_name)

    ax.set_xlabel('Predicted Label')
    ax.set_xticks([0.5, 1.5])
    ax.set_xticklabels(['Retained', 'Churned'])

    ax.set_ylabel('True Label')
    ax.set_yticks([0.2, 1.4])
    ax.set_yticklabels(['Retained', 'Churned'])
```

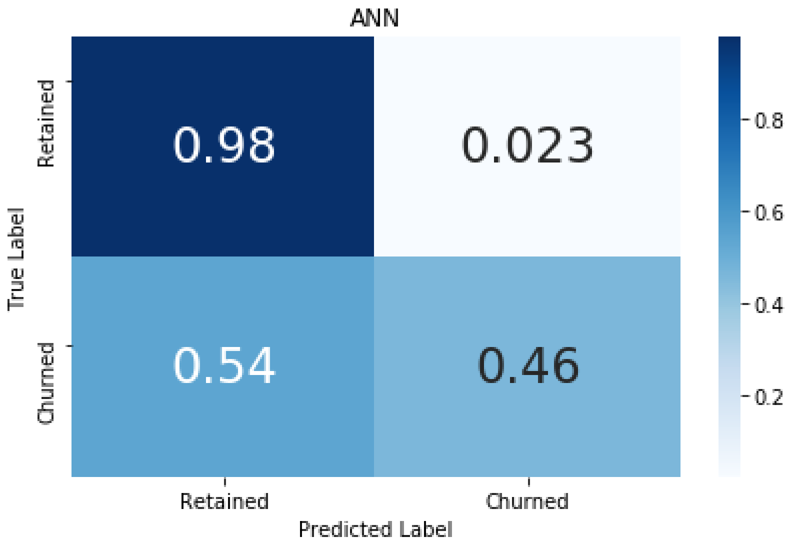
In [897]:

```
# Baseline model Heatmap
model_visualisation('Baseline model',X_test1,y_test1,y_pred1)
plt.tight_layout()
```



In [901]:

```
# ANN model Heatmap
model_visualisation('ANN',X_test,y_test,y_pred)
plt.tight_layout()
```



Conclusions

The foundation of our final bank report should contain two main points:

EDA can help us figure out which characteristics contribute to customer churn. Feature importance analysis can also be used to assess the importance of each feature in predicting churn. Our data suggest that the most critical element is age (older consumers are more prone to churn), followed by the quantity of items (having more products improves a customer's likelihood of leaving). The bank could use our findings to alter and improve its offerings in order to boost satisfaction among clients who are more likely to churn.

We can Build Deep Learning models with a recall of roughly 87 percent, which means they can successfully detect over 90% of churn-prone consumers. Adding additional attributes or records could help us improve our forecasting accuracy. As a result, investing in data collection may benefit the bank.