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Batch : C32

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In [1]:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder,MinMaxScaler
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import classification_report,confusion_matrix,ConfusionMatrixDisplay
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
dataset = pd.read_csv('churn.csv')
dataset
```

Out[2]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estin
0	619	France	Female	42	2	0.00	1	1	1	
1	608	Spain	Female	41	1	83807.86	1	0	1	
2	502	France	Female	42	8	159660.80	3	1	0	
3	699	France	Female	39	1	0.00	2	0	0	
4	850	Spain	Female	43	2	125510.82	1	1	1	
...	...	...	...	...	...	...	...	...	...	
9995	771	France	Male	39	5	0.00	2	1	0	
9996	516	France	Male	35	10	57369.61	1	1	1	
9997	709	France	Female	36	7	0.00	1	0	1	
9998	772	Germany	Male	42	3	75075.31	2	1	0	
9999	792	France	Female	28	4	130142.79	1	1	0	

10000 rows × 11 columns

In [3]:

```
# EDA

print('Columns : ',list(dataset.columns))
print()
print('Number of missing values : ',dataset.isnull().sum().sum())
print()
dataset.describe()
```

```
Columns :  ['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProduc
ts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary', 'Exited']

Number of missing values :  0
```

Out[3]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Esti

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Esti
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	1
mean	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	1(
std	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	5
min	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	
25%	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	5
50%	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	1(
75%	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	14
max	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	19

In [4]:

```
# Data Analysis

print(dataset['Geography'].unique())
print(dataset['Gender'].unique())
```

```
['France' 'Spain' 'Germany']
['Female' 'Male']
```

In [5]:

```
# Data Preprocessing

le = LabelEncoder()
dataset['Gender'] = le.fit_transform(dataset['Gender'])

dataset = pd.get_dummies(dataset,columns = ['Geography'])
dataset
```

Out[5]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	0	42	2	0.00	1	1	1	101348.88
1	608	0	41	1	83807.86	1	0	1	112542.58
2	502	0	42	8	159660.80	3	1	0	113931.57
3	699	0	39	1	0.00	2	0	0	93826.63
4	850	0	43	2	125510.82	1	1	1	79084.10
...	...	...	...	...	...	...	...	...	...
9995	771	1	39	5	0.00	2	1	0	96270.64
9996	516	1	35	10	57369.61	1	1	1	101699.77
9997	709	0	36	7	0.00	1	0	1	42085.58
9998	772	1	42	3	75075.31	2	1	0	92888.52
9999	792	0	28	4	130142.79	1	1	0	38190.78

10000 rows × 13 columns

In [6]:

```
dataset[['Geography_France','Geography_Germany',
        'Geography_Spain','EstimatedSalary','Exited']]
```

Out[6]:

	Geography_France	Geography_Germany	Geography_Spain	EstimatedSalary	Exited

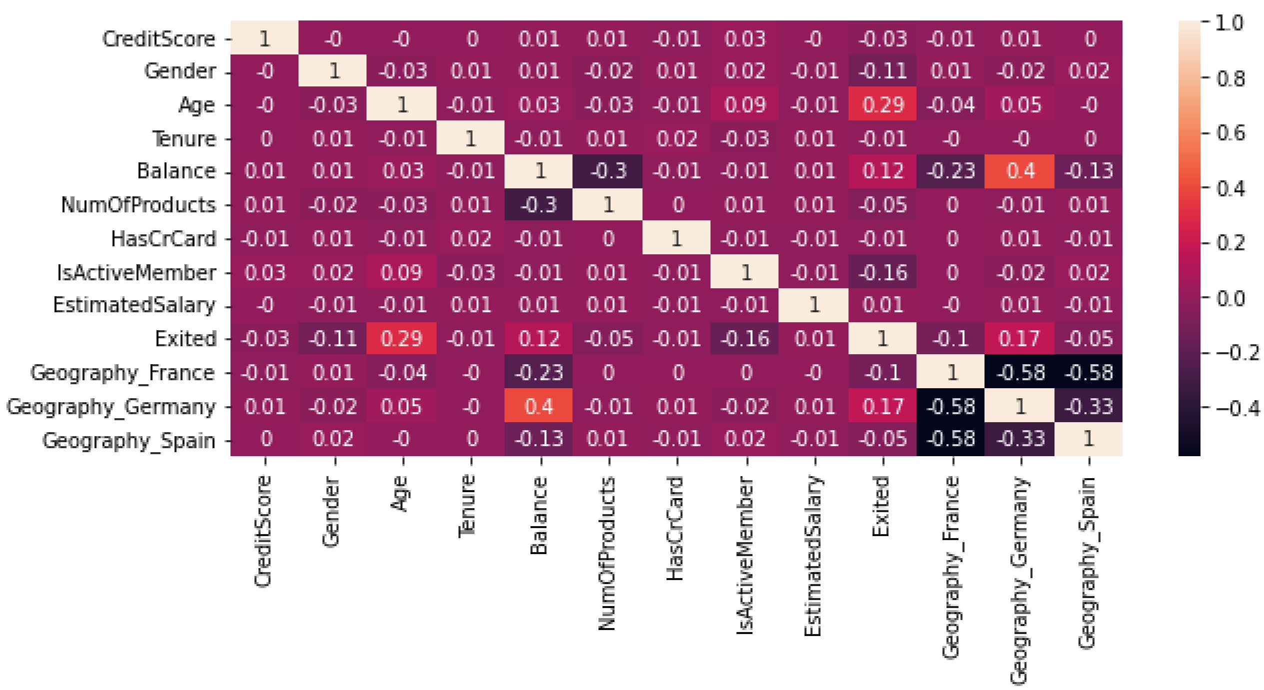
	Geography_France	Geography_Germany	Geography_Spain	EstimatedSalary	Exited
0	1	0	0	101348.88	1
1	0	0	1	112542.58	0
2	1	0	0	113931.57	1
3	1	0	0	93826.63	0
4	0	0	1	79084.10	0
...	...	...	...	...	...
9995	1	0	0	96270.64	0
9996	1	0	0	101699.77	0
9997	1	0	0	42085.58	1
9998	0	1	0	92888.52	1
9999	1	0	0	38190.78	0

10000 rows × 5 columns

In [7]:

```
# Feature Importance

plt.figure(figsize=(10, 4))
correl_matrix = dataset.corr().round(2)
sns.heatmap(data=correl_matrix, annot=True)
plt.show()
```



Hence we can see that most important features for predicting class label 'Exited' are : Age, Geography_Germany, isActiveMember, Balance, Gender

In [8]:

```
X = dataset[['Age','Geography_Germany','IsActiveMember','Balance','Gender']]
y = dataset['Exited']

X
```

Out[8]:

	Age	Geography_Germany	IsActiveMember	Balance	Gender
0	42	0	1	0.00	0
1	41	0	1	83807.86	0
2	42	0	0	159660.80	0
3	39	0	0	0.00	0
4	43	0	1	125510.82	0
...	...	...	...	...	...
9995	39	0	0	0.00	1
9996	35	0	1	57369.61	1
9997	36	0	1	0.00	0
9998	42	1	0	75075.31	1
9999	28	0	0	130142.79	0

10000 rows × 5 columns

In [9]:

```
y
```

Out[9]:

```
0       1
1       0
2       1
3       0
4       0
       ..
9995    0
9996    0
9997    1
9998    1
9999    0
Name: Exited, Length: 10000, dtype: int64
```

In [34]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,
                                                    random_state=13)
X_train
```

Out[34]:

	Age	Geography_Germany	IsActiveMember	Balance	Gender
4847	23	0	1	104822.45	0
9992	36	0	0	0.00	1
4621	43	0	0	115643.58	1
5774	31	1	0	117020.08	1
9294	36	0	1	133889.35	1
...	...	...	...	...	...
5876	39	0	0	111525.02	1
866	38	0	1	88293.13	1
7696	39	1	1	125997.22	0
74	36	0	1	0.00	1

	Age	Geography_Germany	IsActiveMember	Balance	Gender
338	39	0	0	165272.13	0

7000 rows × 5 columns

In [35]:

```
# Scaling

scaler = MinMaxScaler()
X_train[['Age','Balance']] = scaler.fit_transform(
    X_train[['Age','Balance']])
X_test[['Age','Balance']] = scaler.transform(
    X_test[['Age','Balance']])
X_train
```

Out[35]:

	Age	Geography_Germany	IsActiveMember	Balance	Gender
4847	0.067568	0	1	0.439714	0
9992	0.243243	0	0	0.000000	1
4621	0.337838	0	0	0.485107	1
5774	0.175676	1	0	0.490882	1
9294	0.243243	0	1	0.561646	1
...	...	...	...	...	...
5876	0.283784	0	0	0.467831	1
866	0.270270	0	1	0.370376	1
7696	0.283784	1	1	0.528539	0
74	0.243243	0	1	0.000000	1
338	0.283784	0	0	0.693292	0

7000 rows × 5 columns

SVM - RBF

In [12]:

```
svc_rbf1 = SVC(kernel='rbf',random_state=13,C=1)
svc_rbf1.fit(X_train,y_train)
y_pred_rbf1 = svc_rbf1.predict(X_test)

print('Model performance on Training Set : \n')
print(classification_report(y_train,svc_rbf1.predict(X_train)))
print()
print()
print('Model performance on Test Set : \n')
print(classification_report(y_test,y_pred_rbf1))
print()
print()
```

```
Model performance on Training Set :

              precision    recall  f1-score   support

           0       0.83      0.99      0.90      5591
           1       0.81      0.21      0.33      1409
```

```
    accuracy                           0.83      7000
   macro avg       0.82      0.60      0.62      7000
weighted avg       0.83      0.83      0.79      7000



Model performance on Test Set :

              precision    recall  f1-score   support

           0       0.82      0.99      0.90      2372
           1       0.85      0.20      0.32       628

    accuracy                           0.82      3000
   macro avg       0.83      0.60      0.61      3000
weighted avg       0.83      0.82      0.78      3000
```

In [13]:

```
svc_rbf2 = SVC(kernel='rbf',random_state=13,C=10)
svc_rbf2.fit(X_train,y_train)
y_pred_rbf2 = svc_rbf2.predict(X_test)

print('Model performance on Training Set : \n')
print(classification_report(y_train,svc_rbf2.predict(X_train)))
print()
print()
print('Model performance on Test Set : \n')
print(classification_report(y_test,y_pred_rbf2))
print()
print()
```

```
Model performance on Training Set :

              precision    recall  f1-score   support

           0       0.84      0.99      0.91      5591
           1       0.81      0.24      0.37      1409

    accuracy                           0.84      7000
   macro avg       0.82      0.61      0.64      7000
weighted avg       0.83      0.84      0.80      7000



Model performance on Test Set :

              precision    recall  f1-score   support

           0       0.83      0.99      0.90      2372
           1       0.84      0.23      0.36       628

    accuracy                           0.83      3000
   macro avg       0.83      0.61      0.63      3000
weighted avg       0.83      0.83      0.79      3000
```

In [14]:

```
svc_rbf3 = SVC(kernel='rbf',random_state=13,C=100)
svc_rbf3.fit(X_train,y_train)
y_pred_rbf3 = svc_rbf3.predict(X_test)
```

```
print('Model performance on Training Set : \n')
print(classification_report(y_train,svc_rbf3.predict(X_train)))
print()
print()
print('Model performance on Test Set : \n')
print(classification_report(y_test,y_pred_rbf3))
print()
print()
```

```
Model performance on Training Set :

              precision    recall  f1-score   support

           0       0.84      0.98      0.91      5591
           1       0.80      0.25      0.38      1409

    accuracy                           0.84      7000
   macro avg       0.82      0.62      0.64      7000
weighted avg       0.83      0.84      0.80      7000



Model performance on Test Set :

              precision    recall  f1-score   support

           0       0.83      0.99      0.90      2372
           1       0.84      0.23      0.36       628

    accuracy                           0.83      3000
   macro avg       0.83      0.61      0.63      3000
weighted avg       0.83      0.83      0.79      3000
```

Conclusion : Best SVM with RBF kernel obtained by setting C=10 or C=100

SVM - Polynomial

In [15]:

```
svc_poly1 = SVC(kernel='poly',random_state=13,C=1)
svc_poly1.fit(X_train,y_train)
y_pred_poly1 = svc_poly1.predict(X_test)

print('Model performance on Training Set : \n')
print(classification_report(y_train,svc_poly1.predict(X_train)))
print()
print()
print('Model performance on Test Set : \n')
print(classification_report(y_test,y_pred_poly1))
print()
print()
```

```
Model performance on Training Set :

              precision    recall  f1-score   support

           0       0.83      0.99      0.90      5591
           1       0.80      0.18      0.29      1409

    accuracy                           0.83      7000
   macro avg       0.81      0.58      0.60      7000
```

```
weighted avg       0.82      0.83      0.78      7000



Model performance on Test Set :

              precision    recall  f1-score   support

           0       0.82      0.99      0.90      2372
           1       0.83      0.16      0.27       628

    accuracy                           0.82      3000
   macro avg       0.82      0.57      0.58      3000
weighted avg       0.82      0.82      0.76      3000
```

In [16]:

```
svc_poly2 = SVC(kernel='poly',random_state=13,C=10)
svc_poly2.fit(X_train,y_train)
y_pred_poly2 = svc_poly2.predict(X_test)

print('Model performance on Training Set : \n')
print(classification_report(y_train,svc_poly2.predict(X_train)))
print()
print()
print('Model performance on Test Set : \n')
print(classification_report(y_test,y_pred_poly2))
print()
print()
```

```
Model performance on Training Set :

              precision    recall  f1-score   support

           0       0.83      0.99      0.90      5591
           1       0.80      0.21      0.33      1409

    accuracy                           0.83      7000
   macro avg       0.81      0.60      0.62      7000
weighted avg       0.82      0.83      0.79      7000



Model performance on Test Set :

              precision    recall  f1-score   support

           0       0.82      0.99      0.90      2372
           1       0.86      0.19      0.32       628

    accuracy                           0.82      3000
   macro avg       0.84      0.59      0.61      3000
weighted avg       0.83      0.82      0.78      3000
```

In [17]:

```
svc_poly3 = SVC(kernel='poly',random_state=13,C=100)
svc_poly3.fit(X_train,y_train)
y_pred_poly3 = svc_poly3.predict(X_test)

print('Model performance on Training Set : \n')
print(classification_report(y_train,svc_poly3.predict(X_train)))
```

```
print()
print()
print('Model performance on Test Set : \n')
print(classification_report(y_test,y_pred_poly3))
print()
print()
```

```
Model performance on Training Set :

              precision    recall  f1-score   support

           0       0.83      0.99      0.90      5591
           1       0.79      0.22      0.34      1409

    accuracy                           0.83      7000
   macro avg       0.81      0.60      0.62      7000
weighted avg       0.83      0.83      0.79      7000



Model performance on Test Set :

              precision    recall  f1-score   support

           0       0.82      0.99      0.90      2372
           1       0.86      0.20      0.33       628

    accuracy                           0.83      3000
   macro avg       0.84      0.60      0.61      3000
weighted avg       0.83      0.83      0.78      3000
```

Conclusion : Best SVM with Polynomial kernel obtained by setting C=100

SVM - Linear

In [18]:

```
svc_lin1 = SVC(kernel='linear',random_state=13,C=1)
svc_lin1.fit(X_train,y_train)
y_pred_lin1 = svc_lin1.predict(X_test)

print('Model performance on Training Set : \n')
print(classification_report(y_train,svc_lin1.predict(X_train)))
print()
print()
print('Model performance on Test Set : \n')
print(classification_report(y_test,y_pred_lin1))
print()
print()
```

```
Model performance on Training Set :

              precision    recall  f1-score   support

           0       0.80      1.00      0.89      5591
           1       0.00      0.00      0.00      1409

    accuracy                           0.80      7000
   macro avg       0.40      0.50      0.44      7000
weighted avg       0.64      0.80      0.71      7000
```

```
Model performance on Test Set :

              precision    recall  f1-score   support

           0       0.79      1.00      0.88      2372
           1       0.00      0.00      0.00       628

    accuracy                           0.79      3000
   macro avg       0.40      0.50      0.44      3000
weighted avg       0.63      0.79      0.70      3000
```

In [19]:

```python
svc_lin2 = SVC(kernel='linear',random_state=13,C=10)
svc_lin2.fit(X_train,y_train)
y_pred_lin2 = svc_lin2.predict(X_test)

print('Model performance on Training Set : \n')
print(classification_report(y_train,svc_lin2.predict(X_train)))
print()
print()
print('Model performance on Test Set : \n')
print(classification_report(y_test,y_pred_lin2))
print()
print()
```

```
Model performance on Training Set :

              precision    recall  f1-score   support

           0       0.80      1.00      0.89      5591
           1       0.00      0.00      0.00      1409

    accuracy                           0.80      7000
   macro avg       0.40      0.50      0.44      7000
weighted avg       0.64      0.80      0.71      7000


Model performance on Test Set :

              precision    recall  f1-score   support

           0       0.79      1.00      0.88      2372
           1       0.00      0.00      0.00       628

    accuracy                           0.79      3000
   macro avg       0.40      0.50      0.44      3000
weighted avg       0.63      0.79      0.70      3000
```

In [20]:

```python
svc_lin3 = SVC(kernel='linear',random_state=13,C=100)
svc_lin3.fit(X_train,y_train)
y_pred_lin3 = svc_lin3.predict(X_test)

print('Model performance on Training Set : \n')
print(classification_report(y_train,svc_lin3.predict(X_train)))
print()
print()
print('Model performance on Test Set : \n')
```

```
print(classification_report(y_test,y_pred_lin3))
print()
print()
```

```
Model performance on Training Set :

              precision    recall  f1-score   support

           0       0.80      1.00      0.89      5591
           1       0.00      0.00      0.00      1409

    accuracy                           0.80      7000
   macro avg       0.40      0.50      0.44      7000
weighted avg       0.64      0.80      0.71      7000



Model performance on Test Set :

              precision    recall  f1-score   support

           0       0.79      1.00      0.88      2372
           1       0.00      0.00      0.00       628

    accuracy                           0.79      3000
   macro avg       0.40      0.50      0.44      3000
weighted avg       0.63      0.79      0.70      3000
```

Conclusion : Best SVM with Linear kernel obtained by setting C=1 or C=10 or C=100

Comparing performance of the SVMs

In [21]:

```
result = pd.DataFrame({'rbf':[0.83,0.84,0.84],
                       'polynomial':[0.83,0.83,0.83],
                       'linear':[0.80,0.80,0.80]},
                       index=['C=1','C=10','C=100'])
print('Comparing Performance on Training set : \n')
result
```

```
Comparing Performance on Training set :
```

Out[21]:

	rbf	polynomial	linear
C=1	0.83	0.83	0.8
C=10	0.84	0.83	0.8
C=100	0.84	0.83	0.8

In [22]:

```
result = pd.DataFrame({'rbf':[0.82,0.83,0.83],
                       'polynomial':[0.82,0.82,0.83],
                       'linear':[0.79,0.79,0.79]},
                       index=['C=1','C=10','C=100'])
print('Comparing Performance on Test set : \n')
result
```

```
Comparing Performance on Test set :
```

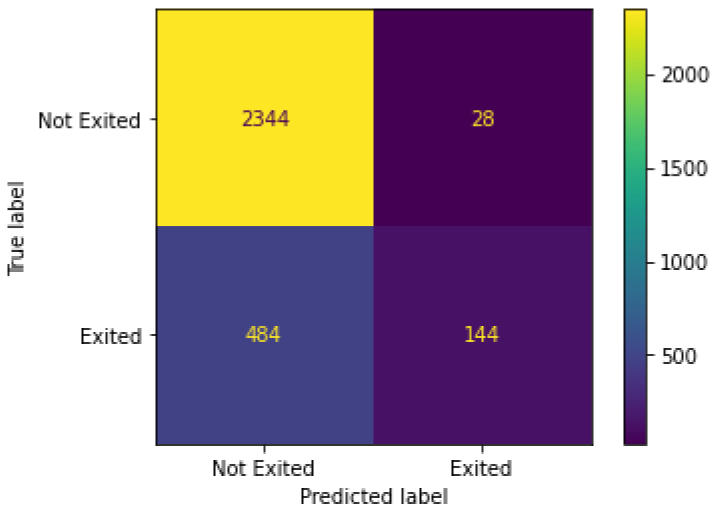
Out[22]:

	rbf	polynomial	linear
C=1	0.82	0.82	0.79
C=10	0.83	0.82	0.79
C=100	0.83	0.83	0.79

In [23]:

```
# Displaying Confusion Matrix for best SVM model obtained
# kernel = RBF and C = 100

cm_display = ConfusionMatrixDisplay.from_estimator(
             svc_rbf3, X_test, y_test,
             display_labels=['Not Exited','Exited'])
plt.show()
```



In [41]:

```
# Taking user input for prediction

X_ip = list(map(float,
       input("Enter Age, Geography_Germany, isActiveMember, Balance, Gender : ")
                .split()))[:5]
X_test = X_test.reset_index(drop=True)
X_test[['Age','Balance']] = scaler.inverse_transform(X_test[['Age','Balance']])
X_test.loc[len(X_test.index)] = X_ip
X_test[['Age','Balance']] = scaler.transform(X_test[['Age','Balance']])
print('Predicted class : ',svc_rbf3.predict(X_test.iloc[[-1]])[0])
X_test.drop(index=X_test.index[-1], axis=0,inplace=True)
```

```
Enter Age, Geography_Germany, isActiveMember, Balance, Gender : 36 0 1 57000 1
Predicted class :  0
```

Conclusion : Best SVM Model Obtained via kernel=RBF and C=10 (or C=100), with 84% accuracy on training set and 83% accuracy on test set