

```
# Chaitanya Mangla AI - DS B1
# Bank Customer Attrition Prediction ML Project
# Use Classification to predict which bank custoers are likely to close their accounts

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

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```
# Generating a synthetic dataset
np.random.seed(42)
n_samples = 5000

data = pd.DataFrame({
    'CustomerID' : np.arange(1, n_samples+1),
    'Age': np.random.randint(18,70,n_samples),
    'Gender' : np.random.choice(['Male', 'Female'], n_samples),
    'Geography' : np.random.choice(['France', 'Spain', 'Germany'], n_samples),
    'Tenure' : np.random.randint(0,10,n_samples),
    'Balance' : np.random.uniform(0, 25000, n_samples),
    'NumOfProducts': np.random.randint(1, 4, n_samples),
    'HasCreditCard': np.random.choice([0,1], n_samples),
    'IsActiveMember': np.random.choice([0,1], n_samples),
    'EstimatedSalary': np.random.uniform(10000, 150000, n_samples)
})
```

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```
data # the whole data has been printed here in tabular form
```

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Python

	CustomerID	Age	Gender	Geography	Tenure	Balance	NumOfProducts	HasCreditCard	IsActiveMember	EstimatedSalary
0	1	56	Male	Spain	7	1883.872406	2	0	0	55175.683538
1	2	69	Female	France	8	23958.714591	2	1	0	79148.195594
2	3	46	Female	France	5	10875.298186	3	0	0	27944.499818
3	4	32	Male	Germany	9	15581.437742	3	0	0	140171.961319
4	5	60	Male	Spain	1	16657.633078	2	0	1	54631.448347
...	...	...	...	...	...	...	...	...	...	...
4995	4996	24	Male	Spain	6	12854.704523	3	0	1	111433.488481
4996	4997	66	Female	Germany	8	10156.870014	2	1	1	27934.085674
4997	4998	26	Female	Spain	8	1120.407767	1	1	1	27274.455181
4998	4999	53	Female	Germany	0	23937.288947	2	0	1	135390.809391
4999	5000	36	Female	Germany	0	23821.738009	3	1	0	124731.573523

5000 rows × 10 columns

```

# Simulate the churn probability based on some rules
data['Exited'] = (
    (data['Age'] > 50).astype(int) +
    (data['Balance'] < 50000).astype(int) +
    (1 - data['IsActiveMember']) +
    (data['NumOfProducts'] == 1).astype(int)
)
data['Exited'] = (data['Exited'] > 2).astype(int)
data

# Here one more column of the exited is added which shows that if there are more than 2 risk factors ten exited is labelled as 1 otherwise 0

```

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Python

	CustomerID	Age	Gender	Geography	Tenure	Balance	NumOfProducts	HasCreditCard	IsActiveMember	EstimatedSalary	Exited
0	1	56	Male	Spain	7	1883.872406	2	0	0	55175.683538	1
1	2	69	Female	France	8	23958.714591	2	1	0	79148.195594	1
2	3	46	Female	France	5	10875.298186	3	0	0	27944.499818	0
3	4	32	Male	Germany	9	15581.437742	3	0	0	140171.961319	0
4	5	60	Male	Spain	1	16657.633078	2	0	1	54631.448347	0
...	...	...	...	...	...	...	...	...	...	...	...
4995	4996	24	Male	Spain	6	12854.704523	3	0	1	111433.488481	0
4996	4997	66	Female	Germany	8	10156.870014	2	1	1	27934.085674	0
4997	4998	26	Female	Spain	8	1120.407767	1	1	1	27274.455181	0
4998	4999	53	Female	Germany	0	23937.288947	2	0	1	135390.809391	0
4999	5000	36	Female	Germany	0	23821.738009	3	1	0	124731.573523	0

5000 rows × 11 columns

```
▶ data = pd.get_dummies(data, columns=['Gender', 'Geography'], drop_first=True)  
data
```

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Python

	CustomerID	Age	Tenure	Balance	NumOfProducts	HasCreditCard	IsActiveMember	EstimatedSalary	Exited	Gender_Male	Geography_
0	1	56	7	1883.872406	2	0	0	55175.683538	1	True	
1	2	69	8	23958.714591	2	1	0	79148.195594	1	False	
2	3	46	5	10875.298186	3	0	0	27944.499818	0	False	
3	4	32	9	15581.437742	3	0	0	140171.961319	0	True	
4	5	60	1	16657.633078	2	0	1	54631.448347	0	True	
...	...	...	...	...	...	...	...	...	...	...	...
4995	4996	24	6	12854.704523	3	0	1	111433.488481	0	True	
4996	4997	66	8	10156.870014	2	1	1	27934.085674	0	False	
4997	4998	26	8	1120.407767	1	1	1	27274.455181	0	False	
4998	4999	53	0	23937.288947	2	0	1	135390.809391	0	False	
4999	5000	36	0	23821.738009	3	1	0	124731.573523	0	False	

5000 rows × 12 columns

```
# Separating the independent and dependent feature  
X = data.drop(['CustomerID', 'Exited'], axis = 1)  
y = data['Exited']
```

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Python

```
X # Here the Customer ID and Exited has been removed from the tabular data
```

[251]

Python

	Age	Tenure	Balance	NumOfProducts	HasCreditCard	IsActiveMember	EstimatedSalary	Gender_Male	Geography_Germany	Geography
0	56	7	1883.872406	2	0	0	55175.683538	True		False
1	69	8	23958.714591	2	1	0	79148.195594	False		False
2	46	5	10875.298186	3	0	0	27944.499818	False		False
3	32	9	15581.437742	3	0	0	140171.961319	True		True
4	60	1	16657.633078	2	0	1	54631.448347	True		False
...	...	...	...	...	...	...	...	...	...	...
4995	24	6	12854.704523	3	0	1	111433.488481	True		False
4996	66	8	10156.870014	2	1	1	27934.085674	False		True
4997	26	8	1120.407767	1	1	1	27274.455181	False		False
4998	53	0	23937.288947	2	0	1	135390.809391	False		True
4999	36	0	23821.738009	3	1	0	124731.573523	False		True

5000 rows × 10 columns

▷ ▾

```
y # Here only theExited column is shown here
```

[252]

```
... 0 1  
1 1  
2 0  
3 0  
4 0  
..  
4995 0  
4996 0  
4997 0  
4998 0  
4999 0
```

Name: Exited, Length: 5000, dtype: int64

```
from sklearn.model_selection import train_test_split  
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state= 42)
```

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```
x_train # Data on which the model is trained
```

Python

	Age	Tenure	Balance	NumOfProducts	HasCreditCard	IsActiveMember	EstimatedSalary	Gender_Male	Geography_Germany	Geography
1840	30	2	7682.341081	3	0	1	83951.481132	True		True
2115	31	3	16693.900630	3	0	1	145626.197657	False		True
4437	24	6	14600.966446	2	1	1	99265.808698	True		True
1146	46	2	3731.547425	1	1	0	143817.185177	True		True
2486	48	5	7977.383497	2	0	0	71938.726078	True		False
...	...	...	...	...	...	...	...	...	...	...
4426	37	0	18829.692596	1	0	0	66588.115359	True		False
466	23	3	8913.905592	3	0	0	136848.154681	True		False
3092	51	9	9037.210749	2	1	1	80960.825673	False		True
3772	19	0	24414.683480	1	1	0	31219.135913	False		False
860	51	2	19726.849572	2	0	0	139517.948121	False		True

3500 rows × 10 columns

```
X_test # Data oj which model is tested
```

[255]

Python

	Age	Tenure	Balance	NumOfProducts	HasCreditCard	IsActiveMember	EstimatedSalary	Gender_Male	Geography_Germany	Geography
1501	59	0	23105.942520	3	0	1	15779.468084	True		False
2586	25	1	13699.194920	3	0	0	26190.226929	False		False
2653	38	6	19939.138813	2	1	0	40558.872348	False		True
1055	48	0	20789.237459	3	1	1	48412.009314	True		False
705	53	2	24216.572829	3	1	0	119282.139769	True		False
...	...	...	...	...	...	...	...	...	...	...
3563	31	6	17389.629358	3	0	1	136490.004802	True		False
1538	46	5	19995.736351	3	0	0	87995.387695	False		False
1837	50	5	10216.442055	3	1	1	109677.077967	False		True
2380	41	9	18946.157323	3	1	1	135940.788038	True		False
1912	39	1	19371.246163	1	1	0	100846.629798	True		False

1500 rows × 10 columns

```
▷ ▾      y_train # Data on which model is trained  
[256]  
  
... 1840    0  
2115    0  
4437    0  
1146    1  
2486    0  
..  
4426    1  
466     0  
3092    0  
3772    1  
860     1  
Name: Exited, Length: 3500, dtype: int64
```

```
      y_test # Data on which model is tested  
[257]  
  
... 1501    0  
2586    0  
2653    0  
1055    0  
705     1  
..  
3563    0  
1538    0  
1837    0  
2380    0  
1912    1  
Name: Exited, Length: 1500, dtype: int64
```

```
# Feature Scaling by Standard Scaler
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

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```
X_train_scaled
```

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```
... array([[-0.91132783, -0.85978882, -0.68281905, ..., 1.00515615,
       1.41755363, -0.68419354],
       [-0.84481864, -0.51133341,  0.56149103, ..., -0.9948703 ,
       1.41755363, -0.68419354],
       [-1.31038292,  0.5340328 ,  0.27250009, ..., 1.00515615,
       1.41755363, -0.68419354],
       ...,
       [ 0.48536501,  1.579399 , -0.49573956, ..., -0.9948703 ,
       1.41755363, -0.68419354],
       [-1.64292884, -1.55669962,  1.62757153, ..., -0.9948703 ,
       -0.70544068,  1.46157474],
       [ 0.48536501, -0.85978882,  0.98027858, ..., -0.9948703 ,
       1.41755363, -0.68419354]], shape=(3500, 10))
```

```
▶ Generate ▶ Code ▶ Markdown ▶ Run All ▶ Restart ▶ Clear All Outputs ▶ Hide python variables ▶ Outline
```

▶ X\_test\_scaled  
[260]

```
... array([[ 1.01743848, -1.55669962,  1.44686146, ... ,  1.00515615,
   -0.70544068,  1.46157474],
   [-1.24387374, -1.20824422,  0.14798408, ... , -0.9948703 ,
   -0.70544068, -0.68419354],
   [-0.37925436,  0.5340328 ,  1.00959134, ... , -0.9948703 ,
   1.41755363, -0.68419354],
   ... ,
   [ 0.41885583,  0.18557739, -0.33291209, ... , -0.9948703 ,
   1.41755363, -0.68419354],
   [-0.17972681,  1.579399 ,  0.87248112, ... ,  1.00515615,
   -0.70544068,  1.46157474],
   [-0.31274518, -1.20824422,  0.9311771 , ... ,  1.00515615,
   -0.70544068,  1.46157474]], shape=(1500, 10))
```

▶ from sklearn.ensemble import RandomForestClassifier  
model = RandomForestClassifier(n\_estimators = 100, random\_state = 42)  
model.fit(X\_train\_scaled, y\_train)  
[261]

...

### RandomForestClassifier

Parameters

n_estimators	100
criterion	'gini'
max_depth	None
min_samples_split	2
min_samples_leaf	1
min_weight_fraction_leaf	0.0
max_features	'sqrt'
max_leaf_nodes	None
min_impurity_decrease	0.0
bootstrap	True
oob_score	False
n_jobs	None
random_state	42
verbose	0
warm_start	False
class_weight	None
ccp_alpha	0.0
max_samples	None
monotonic_cst	None

```
# Evaluating the model  
y pred = model.predict(x test scaled)
```

```
# Evaluating the model
```

```
y_pred = model.predict(X_test_scaled)
```

```
y_prob = model.predict_proba(X_test_scaled)[:,1]
```

```
y_pred # It prints all the predictions in the form of the low risk or high risk
```

```
... array([0, 0, 0, ..., 0, 0, 1], shape=(1500,))
```

```
y_prob # It shows all the probabilities in order of the data
```

```
... array([0.06, 0. , 0. , ..., 0. , 0. , 0.99], shape=(1500,))
```

```
# Importing the metrics for evaluation
```

```
from sklearn.metrics import classification_report, roc_auc_score, confusion_matrix
```

```
# calculation of ROC-AUC score
```

```
print("ROC-AUC Score:", roc_auc_score(y_test,y_prob))
```

```
# The ROC AUC Score is near to 1 showing good accuracy
```

```
[ ]
```

```
... ROC-AUC Score: 1.0
```

```
[ ] # Making the ClassificationReport  
print("Classification Report\n", classification_report(y_test, y_pred))  
# Here the classification report is being printed  
# f1 score is the harmonic mean of precision and recall  
# Support is total number of occurrences of specific class in ground truth dataset
```

[ ] ... classification Report

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	1.00	1.00	1.00	967
1	1.00	1.00	1.00	533

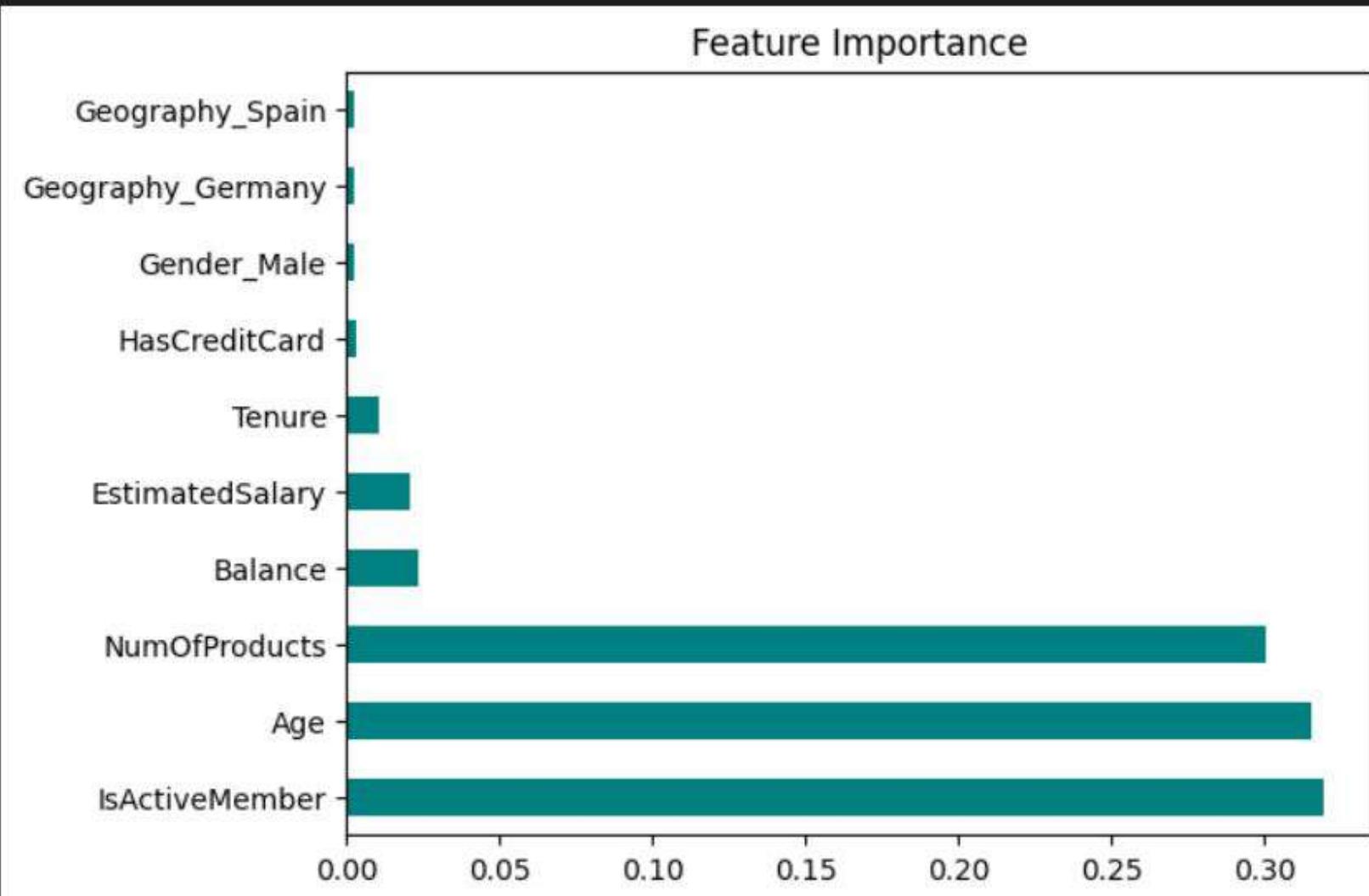
accuracy			1.00	1500
macro avg	1.00	1.00	1.00	1500
weighted avg	1.00	1.00	1.00	1500

```
[270] # Printing of the confusion Matrix  
print("Confusion Matrix\n", confusion_matrix(y_test, y_pred))
```

[270] ... Confusion Matrix

[[967 0]
[ 0 533]]

```
# Feature importance  
importances = pd.Series(model.feature_importances_, index=X.columns)  
importances.nlargest(10).plot(kind='barh', color='teal')  
plt.title("Feature Importance")  
plt.show()
```



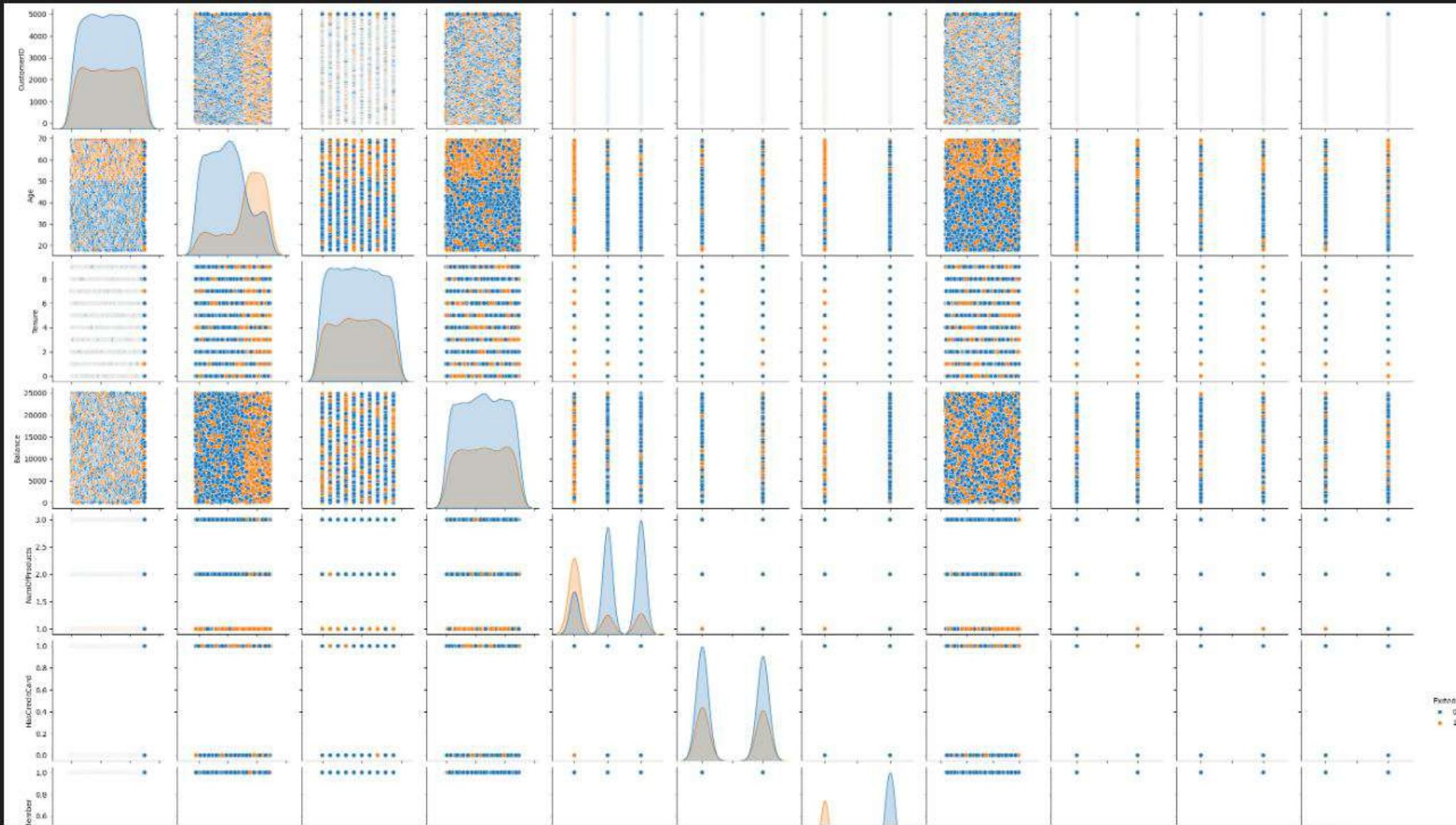


```
sns.pairplot(data, hue='Exited')
```

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Python

... <seaborn.axisgrid.PairGrid at 0x256137cb230>

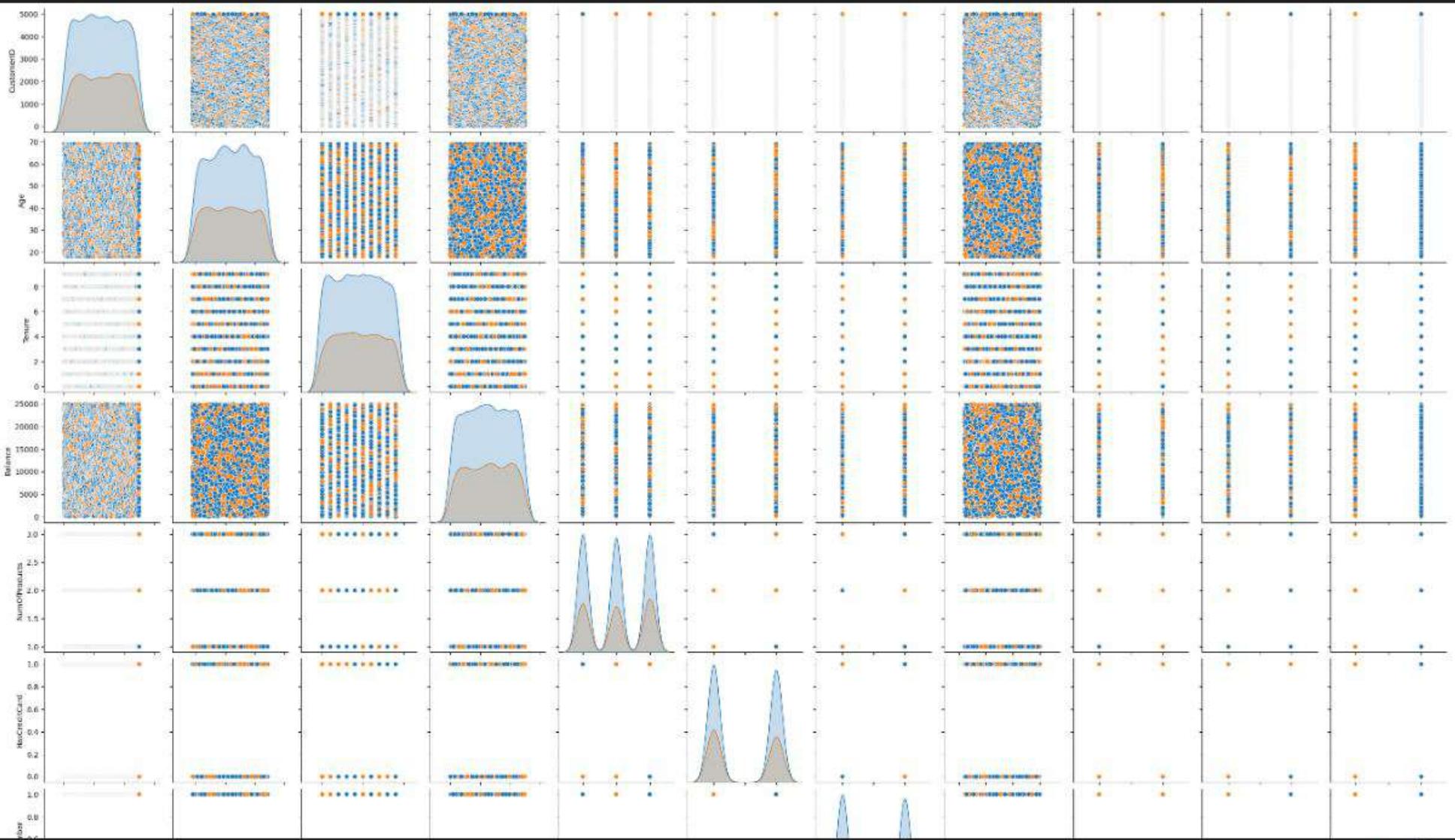


```
sns.pairplot(data, hue='Geography_Germany')
```

[274]

Python

```
... <seaborn.axisgrid.PairGrid at 0x256158f7ed0>
```

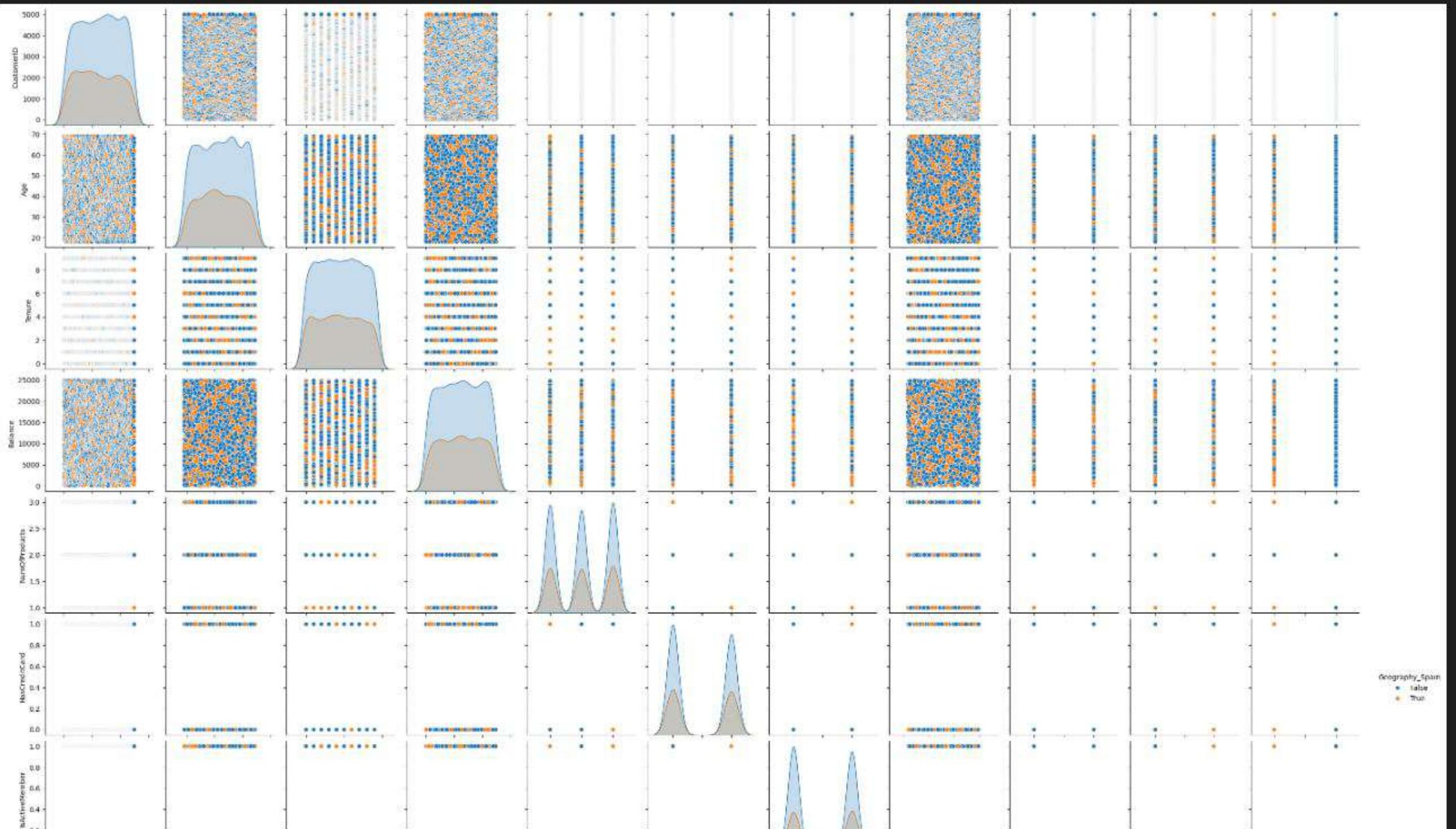


```
sns.pairplot(data, hue='Geography_Spain')
```

[275]

Python

... <seaborn.axisgrid.PairGrid at 0x2562df4ca50>



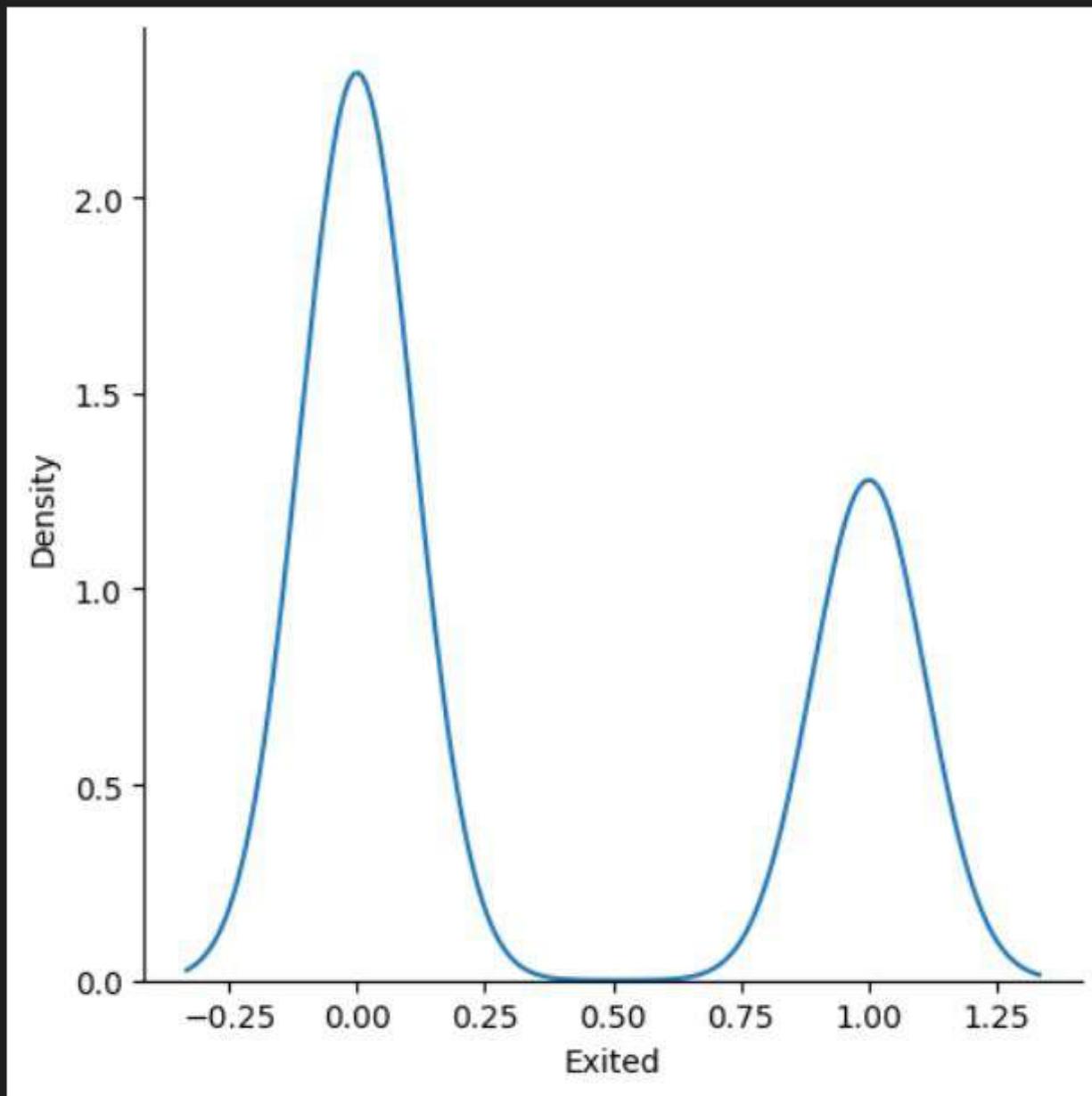


```
sns.displot(y_test, kind='kde')
```

[280]

... <seaborn.axisgrid.FacetGrid at 0x2563cb3f750>

...



```
    'Geography': ['France', 'Germany'],
    'Tenure': [4, 8],
    'Balance': [65000, 30000],
    'NumOfProducts': [2, 1],
    'HasCreditCard': [1, 1],
    'IsActiveMember': [1, 0],
    'EstimatedSalary': [70000, 120000]
})
```

```
new_data = pd.get_dummies(new_data, columns=['Gender', 'Geography'], drop_first=True)

# Align columns with training data
new_data = new_data.reindex(columns=X.columns, fill_value=0)

new_data_scaled = scaler.transform(new_data)
pred_labels = model.predict(new_data_scaled)
pred_probs = model.predict_proba(new_data_scaled)[:, 1]

new_data['Predicted_Exited'] = pred_labels
new_data['Churn_Probability'] = pred_probs
print(new_data)
```

```
[ ]
```

```
...   Age  Tenure  Balance  NumOfProducts  HasCreditCard  IsActiveMember  \
0    43        4     65000            2                  1                  1
1    60        8     30000            1                  1                  0

  EstimatedSalary  Gender_Male  Geography_Germany  Geography_Spain  \
0          70000      False           False                   0
1         120000      True            True                   0

  Predicted_Exited  Churn_Probability
0                  0                 0.00
1                  1                 0.98
```