Exploratory data analysis

A fictitious datasets of a financial institution is given in the "data" folder.

The dataset called "Churn_clients" is composed by 10,000 rows and 13 columns of features, where one is the "Exited" column, composed by binary data: "1" if the client had left the bank, "0" if it had not.

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

plt.rcParams.update({'font.size': 14})
```

In [2]:
```
df = pd.read_csv("data/Churn_clients.csv")
```

Understanding the data structure

In the cells below, the data description shows that there are 5 numerical features worth looking at: Age, Balance, CreditScore, EstimatedSalary, and Tenure.

The Gender, Geography, NumOfProducts, IsActiveMember, HasCrCard, and Exited are categorical variables. By observing the statistics further below, only the Geography feature has more than two categories, i.e., France, Spain, and Germany.

There are no duplicates or null values in this dataset.

In [3]:
```
df.shape          # Rows and columns
df.info()         # Data types, non-null counts
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        10000 non-null  object 
 5   Gender           10000 non-null  object 
 6   Age              10000 non-null  int64  
 7   Tenure           10000 non-null  int64  
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

In [4]:
```
df.head()        # Show first 5 rows
```

Out[4]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure
0	1	15634602	Hargrave	619	France	Female	42	2
1	2	15647311	Hill	608	Spain	Female	41	1
2	3	15619304	Onio	502	France	Female	42	8
3	4	15701354	Boni	699	France	Female	39	1
4	5	15737888	Mitchell	850	Spain	Female	43	2

In [5]:
```
df['Geography'].unique()
```

Out[5]:
```
array(['France', 'Spain', 'Germany'], dtype=object)
```

In [6]:
```
df['Gender'].unique()
```

Out[6]:
```
array(['Female', 'Male'], dtype=object)
```

In [7]:
```
df.tail()
```

Out[7]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Ten
9995	9996	15606229	Obijiaku	771	France	Male	39	
9996	9997	15569892	Johnstone	516	France	Male	35	
9997	9998	15584532	Liu	709	France	Female	36	
9998	9999	15682355	Sabbatini	772	Germany	Male	42	
9999	10000	15628319	Walker	792	France	Female	28	

In [8]:
```
df.dtypes
```

Out[8]:
```
RowNumber            int64
CustomerId           int64
Surname             object
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

In [9]:
```
df.isnull().sum()         # Total missing per column
```

Out[9]:
```
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
```

In [10]:
```
df.duplicated().sum()
```

Out[10]:
```
0
```

Summary Statistics

It seems that there aren't any data points that are worth eliminating, because the maximum and minimum values of Balance and EstimatedSalary, for instance, make sense.

In [11]:
```
df.describe()
```

Out[11]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Bal
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.00
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.88
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.40
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.00
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.00
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.54
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.24
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.09

The plots below show that most clients are from France, but most clients from Germany are the ones leaving the bank.

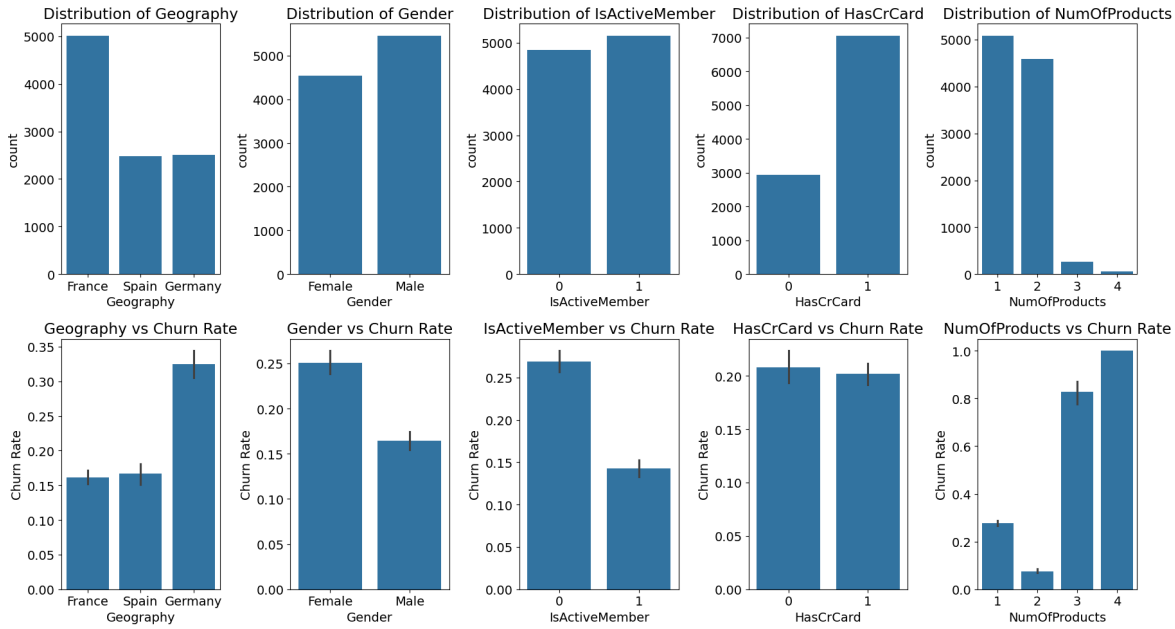
There are more Male clients, but the proportion of Female is higher.

The number of members that aren't active are the ones that tend to leave the financial institution the more.

People that have more product in the bank tend to churn. Having 2 products seems to be the optimal for the bank.

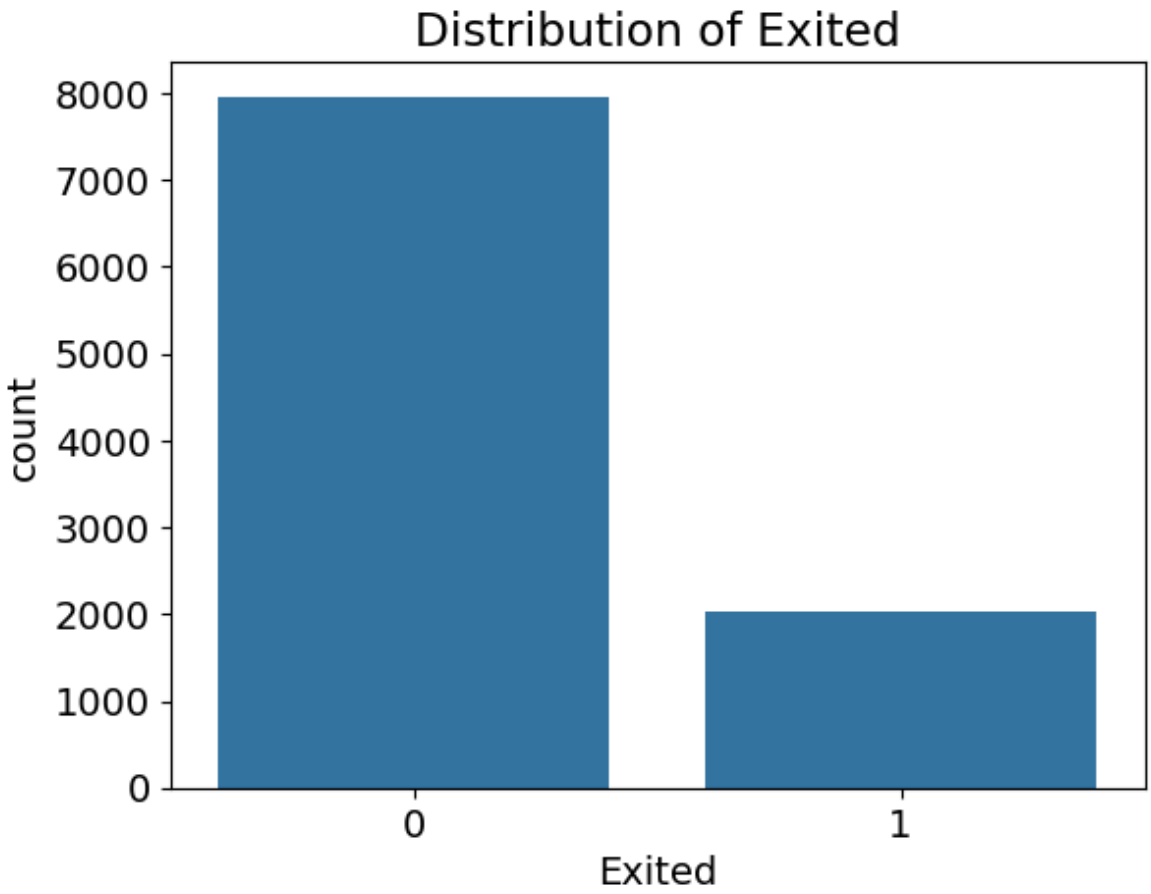
Nonlinear relationships between these variables can be investigated to see how they are related. A predictor such as a deep neural network can model these relationships, or a feature engineering can be applied.

In [12]:
```
fig, axes = plt.subplots(2, 5, figsize=(18, 10))

cat_features = ['Geography', 'Gender', 'IsActiveMember', 'HasCrCard', 'NumOfProd

for idx_axis, col in enumerate(cat_features):
    # Plot 1: Distribuição do atributo
    sns.countplot(data=df, x=col, ax=axes[0, idx_axis])
    axes[0, idx_axis].set_title(f'Distribution of {col}')

    # Plot 2: Taxa de churn por categoria
    if col != 'Exited':
        sns.barplot(data=df, x=col, y='Exited', ax=axes[1, idx_axis])
        axes[1, idx_axis].set_title(f'{col} vs Churn Rate')
        axes[1, idx_axis].set_ylabel("Churn Rate")
    else:
        axes[1, idx_axis].axis('off')

plt.tight_layout()
plt.show()
```



In [13]:
```
sns.countplot(data=df, x='Exited')
plt.title('Distribution of Exited')
```

Out[13]:
```
Text(0.5, 1.0, 'Distribution of Exited')
```



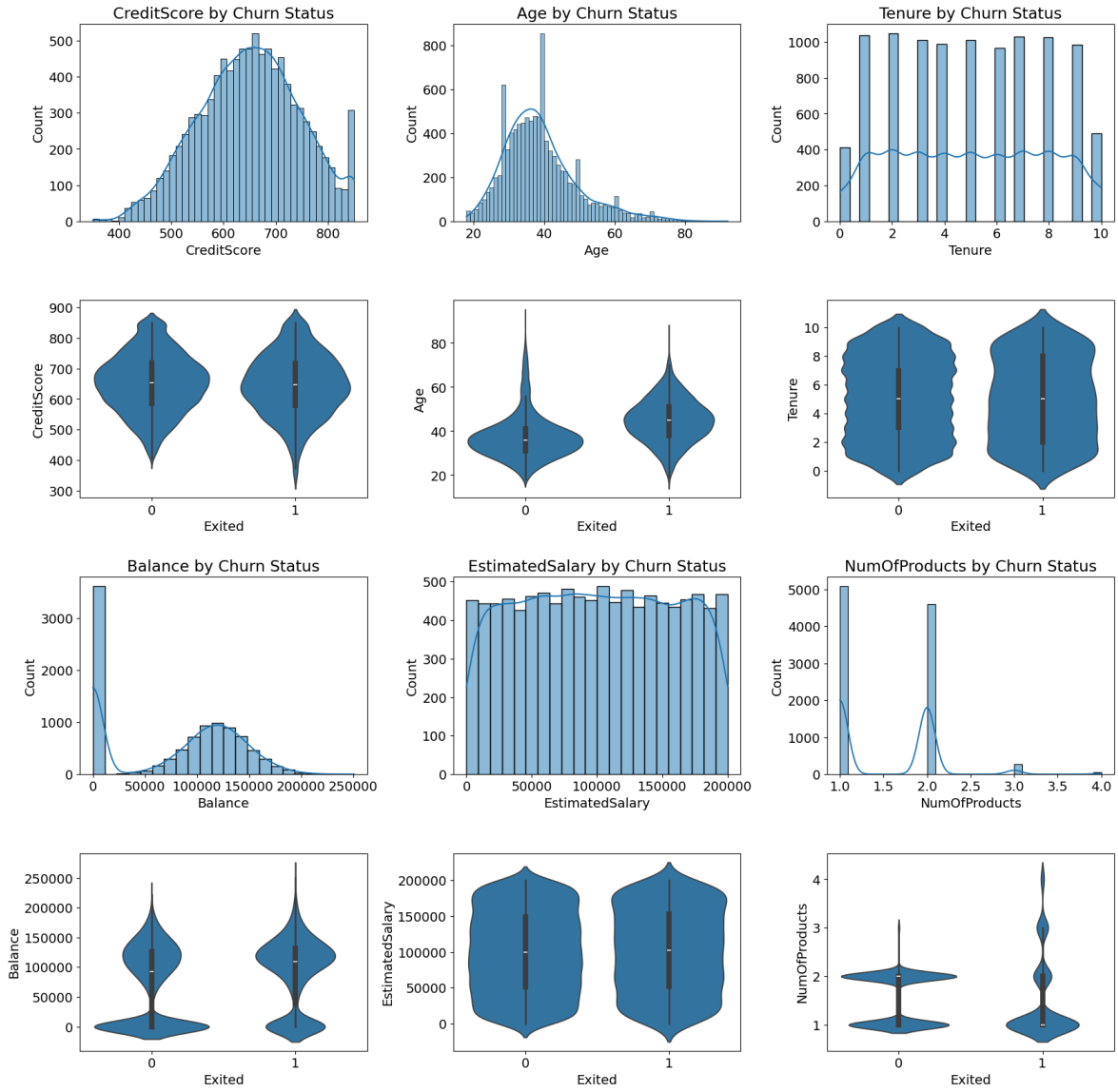
People slightly older are leaving, around 51 to 60 years old.

The average of the Balance of the people who left is slightly higher than the average of the ones who stayed.

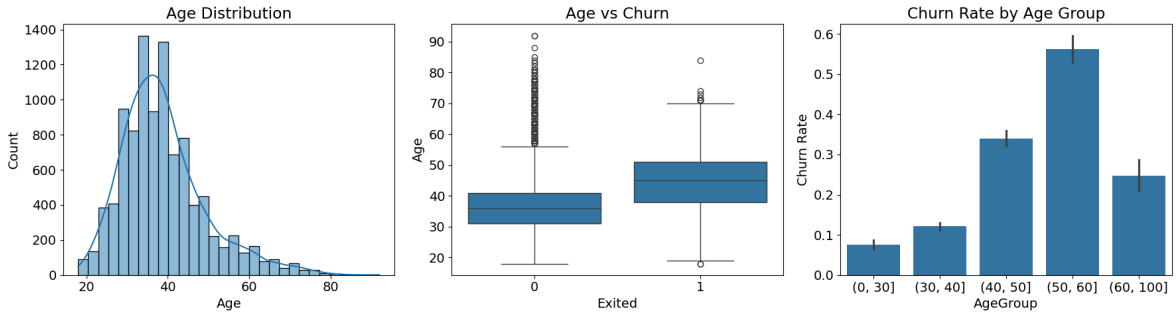
The other variables show some minor impact. Maybe it is worth considering them since they may strong influence when combined with others.

A library with auto feature engineering may reveal important aspects. A sensitivity analysis can also show how important each feature is on the output.

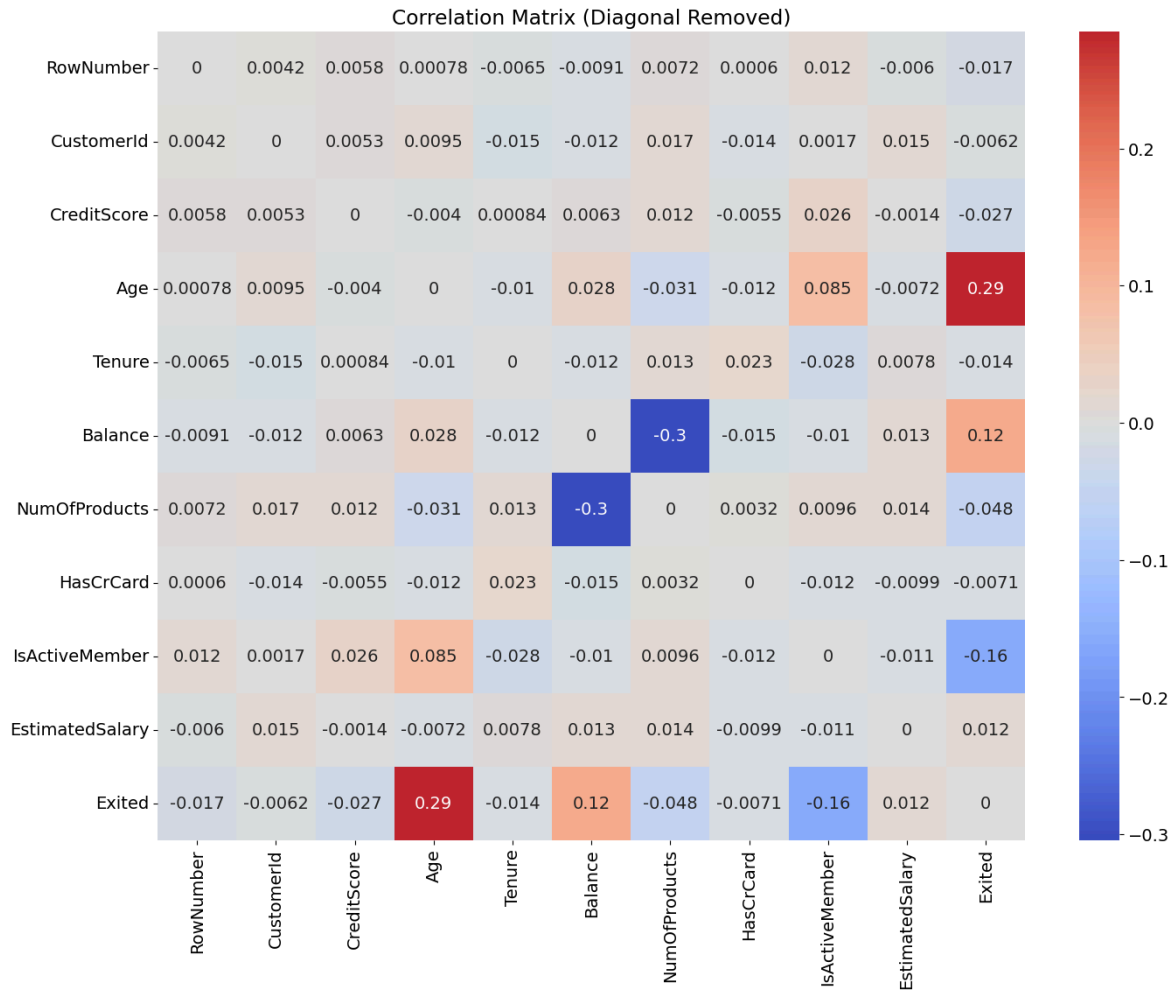
In [14]:
```
# Select numerical features for analysis
num_features = ['CreditScore', 'Age', 'Tenure', 'Balance', 'EstimatedSalary', 'N
n = len(num_features)

# Create subplot grid
fig, axes = plt.subplots(4, int(n/2), figsize=(20, 20))
plt.subplots_adjust(hspace=0.4, wspace=0.3)

# Univariate and Bivariate Analysis
for i, feature in enumerate(num_features):
    # Univariate analysis (top row)
    sns.histplot(df[feature], ax=axes[0+int(i>2)*2, i%3], kde=True)
    axes[0+int(i>2)*2, i%3].set_title(f'Distribution of {feature}')

    # Bivariate analysis (bottom row)
    sns.violinplot(x='Exited', y=feature, data=df, ax=axes[1+int(i>2)*2, i%3])
    axes[0+int(i>2)*2, i%3].set_title(f'{feature} by Churn Status')

plt.show()
```



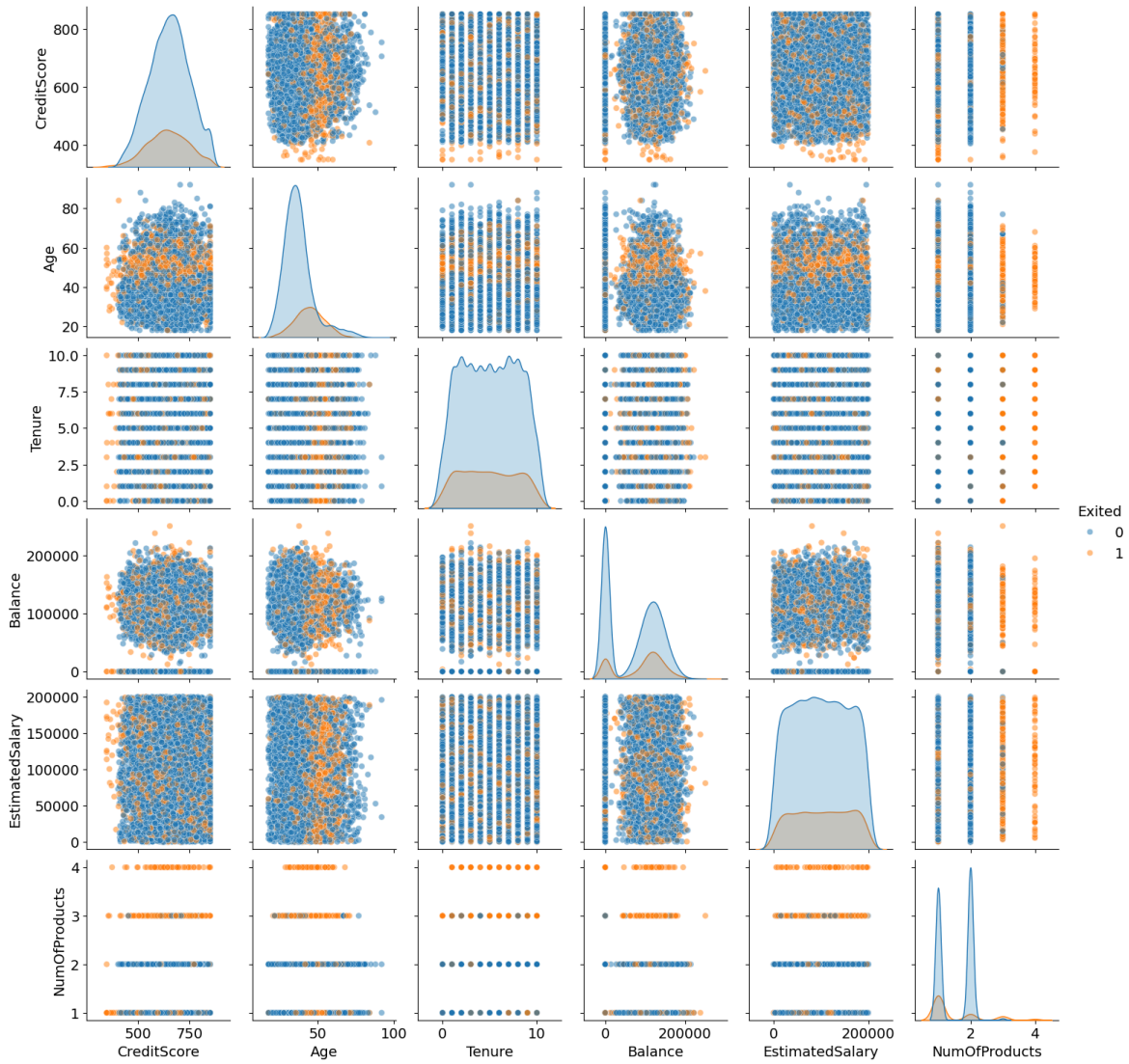
In [15]:
```
# Binned features
df['AgeGroup'] = pd.cut(df['Age'], bins=[0, 30, 40, 50, 60, 100])
df['BalanceTier'] = pd.cut(df['Balance'], bins=[-1, 0, 50000, 100000, 200000, fl
df['EstimatedSalaryTier'] = pd.cut(df['Balance'], bins=[0, 50000, 100000, 200000
df['CreditScoreTier'] = pd.cut(df['CreditScore'], bins=[300, 500, 600, 700, 800,

# Criação dos subplots
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# Gráfico 1: Distribuição de Idades
sns.histplot(df['Age'], kde=True, bins=30, ax=axes[0])
axes[0].set_title('Age Distribution')

# Gráfico 2: Idade vs Churn
sns.boxplot(data=df, x='Exited', y='Age', ax=axes[1])
axes[1].set_title('Age vs Churn')

# Gráfico 3: Churn por Faixa Etária
sns.barplot(data=df, x='AgeGroup', y='Exited', ax=axes[2])
axes[2].set_title('Churn Rate by Age Group')
axes[2].set_ylabel('Churn Rate')

plt.tight_layout()
plt.show()
```



In [16]:
```
# Calcula a matriz de correlação
corr = df.corr(numeric_only=True)

# Zera a diagonal
np.fill_diagonal(corr.values, 0)

# Plota a matriz de correlação com diagonal zerada
plt.figure(figsize=(16, 12))
sns.heatmap(corr, annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Matrix (Diagonal Removed)')
plt.show()
```



In [17]:
```
sns.pairplot(df, vars=num_features, hue='Exited', diag_kind='kde', plot_kws={'al
plt.show()
```

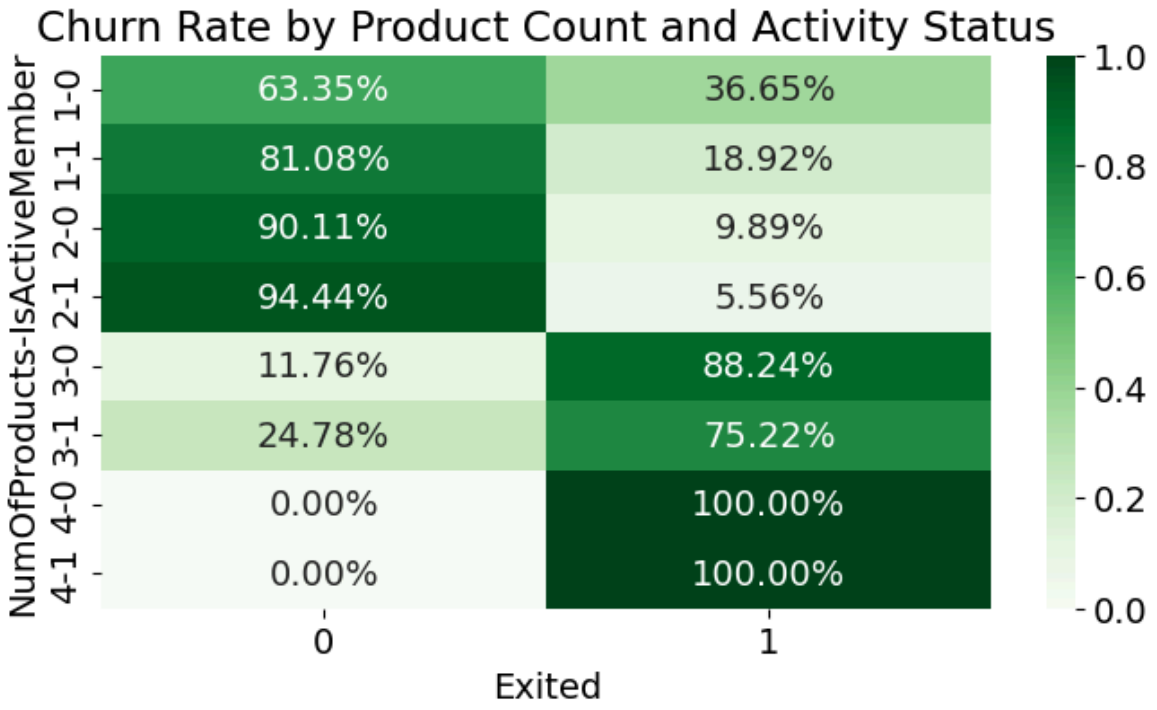


It can be seen that the Age is a very important feature, because people with around 50 y.o. are leaving the bank.

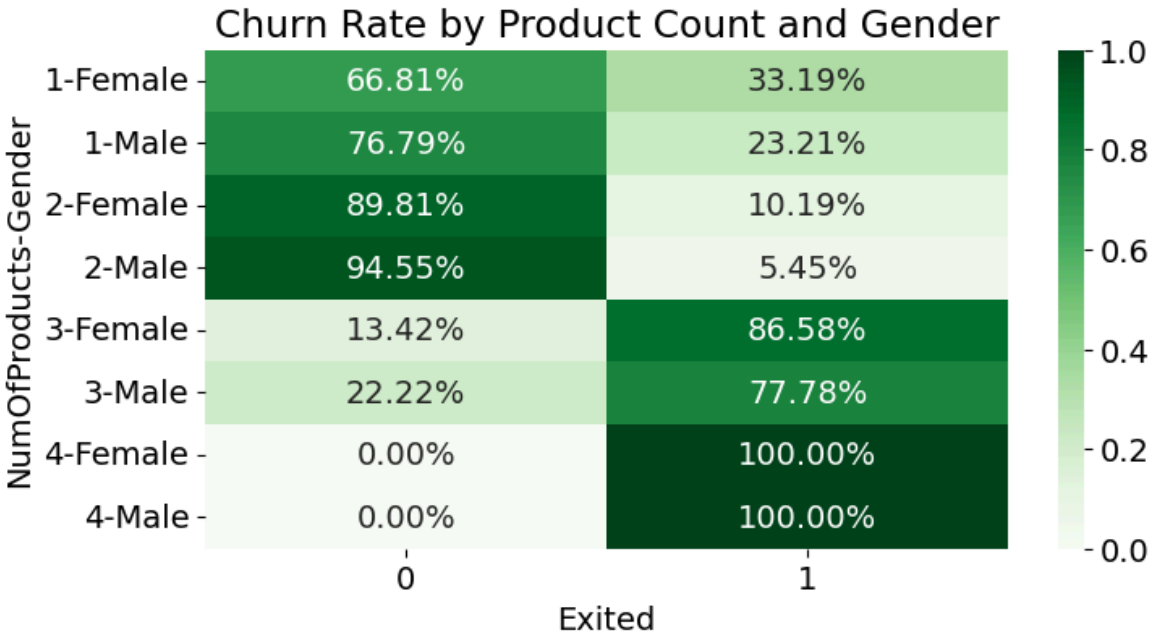
The Balance and Number of Products are features that may influence Churn.

This can be investigated further in more details, as it will be done down below.

In [18]:
```
ct2 = pd.crosstab(index=[df['NumOfProducts'], df['IsActiveMember']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(8,4))
sns.heatmap(ct2, annot=True, fmt='.2%', cmap='Greens')
plt.title('Churn Rate by Product Count and Activity Status')
plt.show()
```

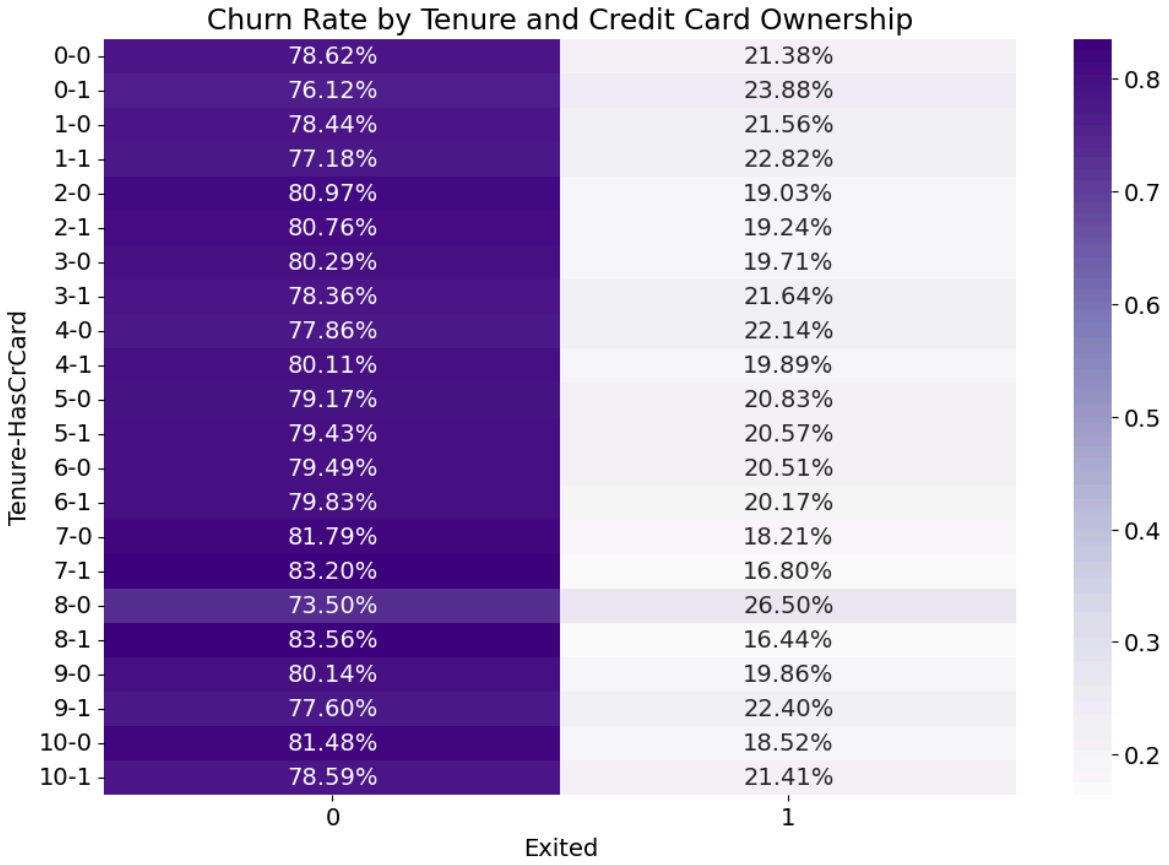


In [19]:
```
ct2 = pd.crosstab(index=[df['NumOfProducts'], df['Gender']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(8,4))
sns.heatmap(ct2, annot=True, fmt='.2%', cmap='Greens')
plt.title('Churn Rate by Product Count and Gender')
plt.show()
```



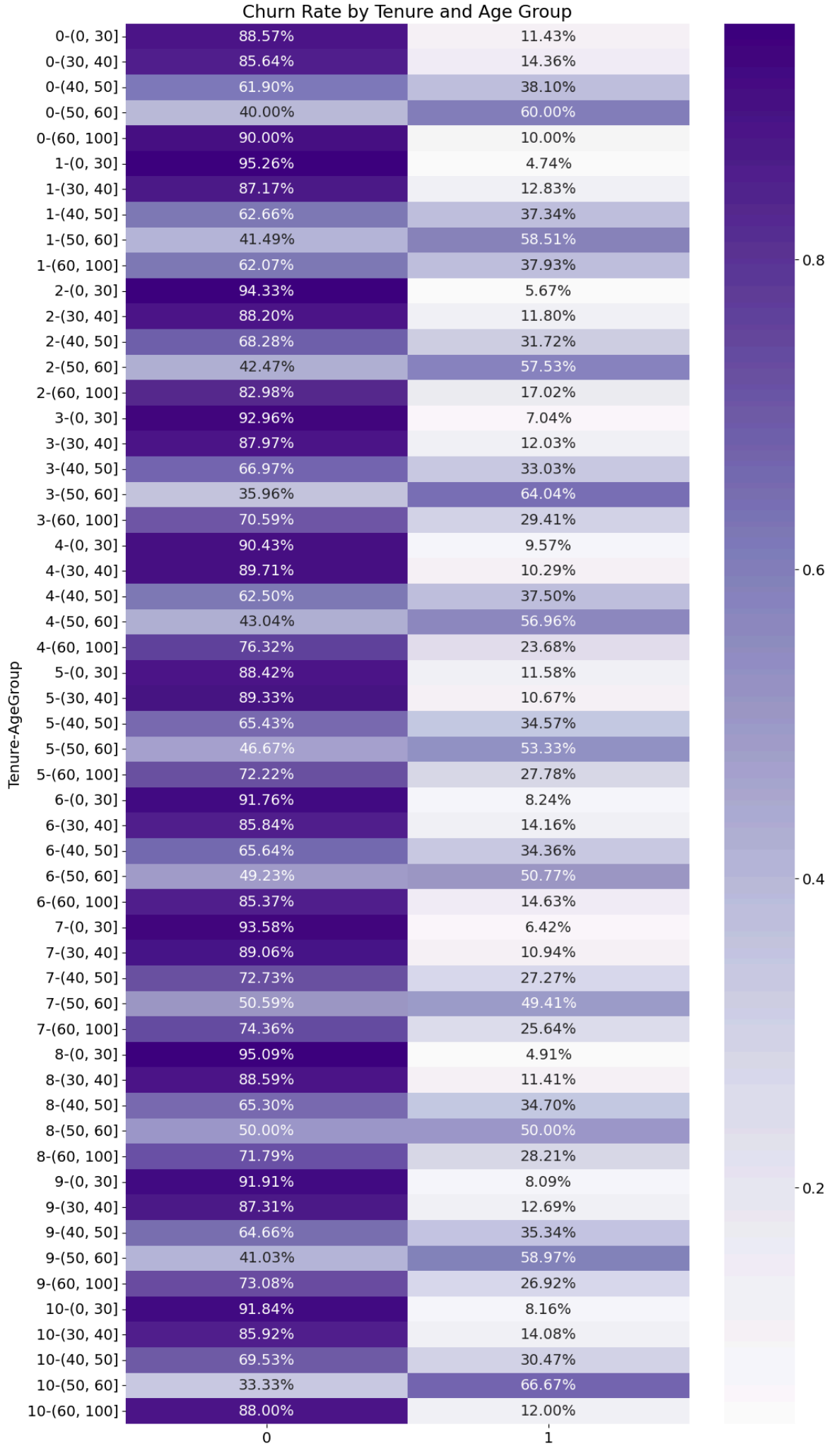
Being inactive seems to increase the Churn possibility. And having more products is also a factor. Having 2 products is optimal for the bank, as seen before.

In [20]:
```
ct3 = pd.crosstab(index=[df['Tenure'], df['HasCrCard']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(12,8))
sns.heatmap(ct3, annot=True, fmt='.2%', cmap='Purples')
plt.title('Churn Rate by Tenure and Credit Card Ownership')
plt.show()
```



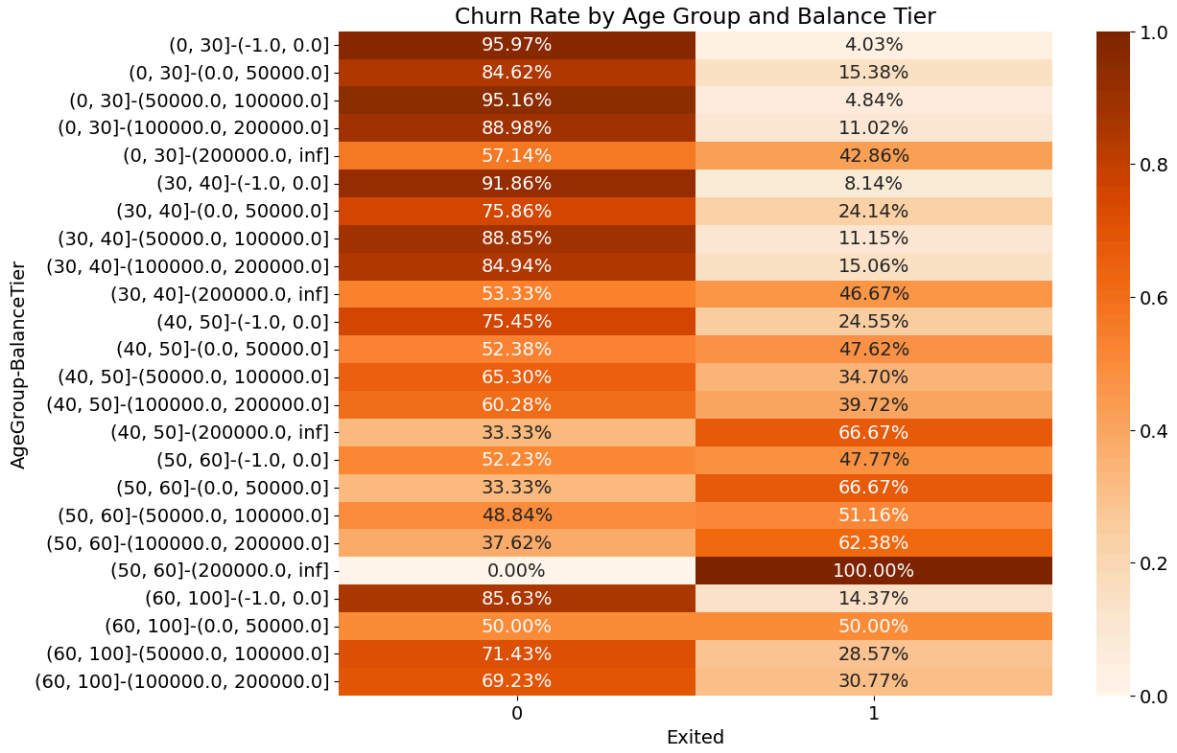
Tenure does not seem to matter much. Looking at age, only older people can have more Tenure. Thus, Age is a more important feature and probably that's why the Churn is concentrated a bit more with a Tenure of 8 years. Having a credit card has a nonlinear impact, but it influences the Churn very little.

In [21]:
```
ct3 = pd.crosstab(index=[df['Tenure'], df['AgeGroup']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(12,24))
sns.heatmap(ct3, annot=True, fmt='.2%', cmap='Purples')
plt.title('Churn Rate by Tenure and Age Group')
plt.show()
```

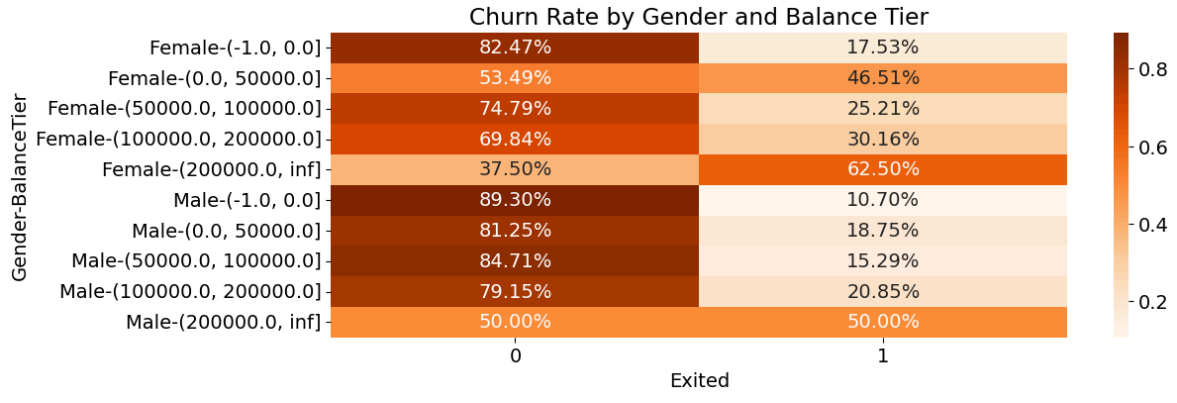

Churn Rate by Tenure and Age Group
Tenure-AgeGroup
0-(0, 30] 88.57% 11.43%
0-(30, 40] 85.64% 14.36%
0-(40, 50] 61.90% 38.10%
0-(50, 60] 40.00% 60.00%
0-(60, 100] 90.00% 10.00%
1-(0, 30] 95.26% 4.74%
1-(30, 40] 87.17% 12.83%
1-(40, 50] 62.66% 37.34%
1-(50, 60] 41.49% 58.51%
1-(60, 100] 62.07% 37.93%
2-(0, 30] 94.33% 5.67%
2-(30, 40] 88.20% 11.80%
2-(40, 50] 68.28% 31.72%
2-(50, 60] 42.47% 57.53%
2-(60, 100] 82.98% 17.02%
3-(0, 30] 92.96% 7.04%
3-(30, 40] 87.97% 12.03%
3-(40, 50] 66.97% 33.03%
3-(50, 60] 35.96% 64.04%
3-(60, 100] 70.59% 29.41%
4-(0, 30] 90.43% 9.57%
4-(30, 40] 89.71% 10.29%
4-(40, 50] 62.50% 37.50%
4-(50, 60] 43.04% 56.96%
4-(60, 100] 76.32% 23.68%
5-(0, 30] 88.42% 11.58%
5-(30, 40] 89.33% 10.67%
5-(40, 50] 65.43% 34.57%
5-(50, 60] 46.67% 53.33%
5-(60, 100] 72.22% 27.78%
6-(0, 30] 91.76% 8.24%
6-(30, 40] 85.84% 14.16%
6-(40, 50] 65.64% 34.36%
6-(50, 60] 49.23% 50.77%
6-(60, 100] 85.37% 14.63%
7-(0, 30] 93.58% 6.42%
7-(30, 40] 89.06% 10.94%
7-(40, 50] 72.73% 27.27%
7-(50, 60] 50.59% 49.41%
7-(60, 100] 74.36% 25.64%
8-(0, 30] 95.09% 4.91%
8-(30, 40] 88.59% 11.41%
8-(40, 50] 65.30% 34.70%
8-(50, 60] 50.00% 50.00%
8-(60, 100] 71.79% 28.21%
9-(0, 30] 91.91% 8.09%
9-(30, 40] 87.31% 12.69%
9-(40, 50] 64.66% 35.34%
9-(50, 60] 41.03% 58.97%
9-(60, 100] 73.08% 26.92%
10-(0, 30] 91.84% 8.16%
10-(30, 40] 85.92% 14.08%
10-(40, 50] 69.53% 30.47%
10-(50, 60] 33.33% 66.67%
10-(60, 100] 88.00% 12.00%
0
1
0.8
0.6
0.4
0.2

Exited

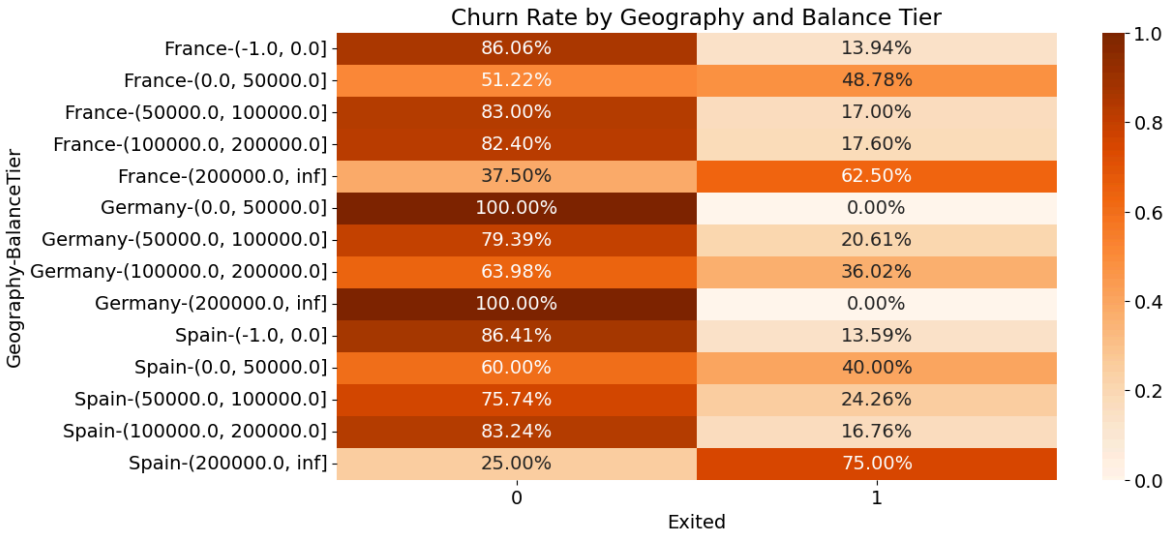
In [22]:
```
ct4 = pd.crosstab(index=[df['AgeGroup'], df['BalanceTier']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(12,9))
sns.heatmap(ct4, annot=True, fmt='.2%', cmap='Oranges')
plt.title('Churn Rate by Age Group and Balance Tier')
plt.show()
```



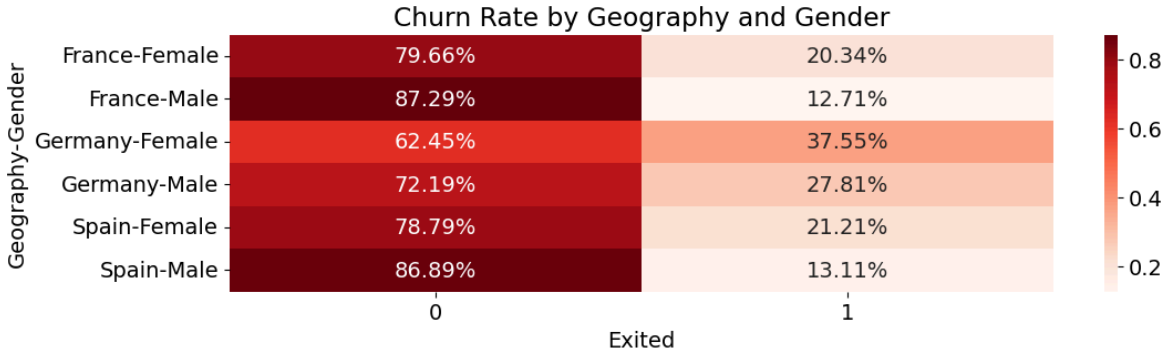
In [23]:
```
ct4 = pd.crosstab(index=[df['Gender'], df['BalanceTier']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(12,4))
sns.heatmap(ct4, annot=True, fmt='.2%', cmap='Oranges')
plt.title('Churn Rate by Gender and Balance Tier')
plt.show()
```



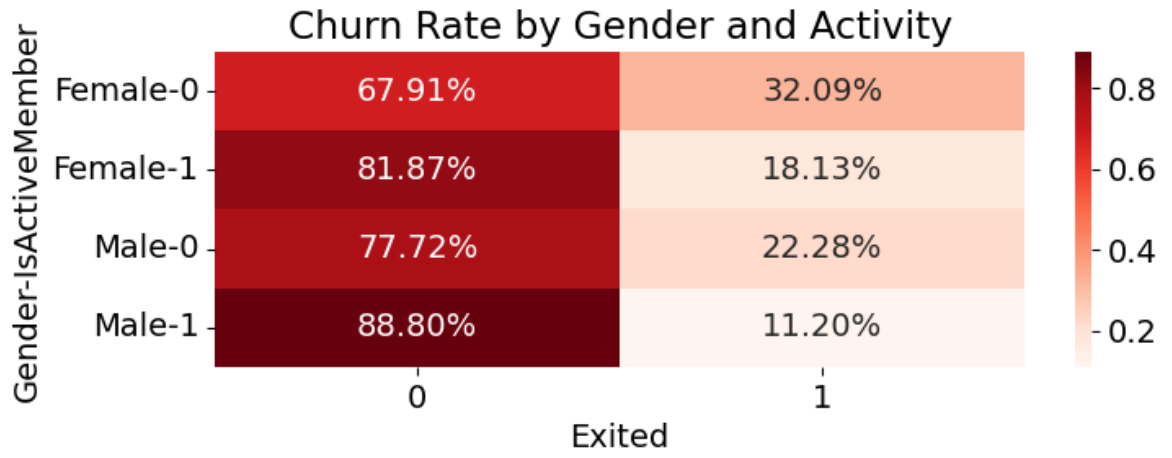
In [24]:
```
ct4 = pd.crosstab(index=[df['Geography'], df['BalanceTier']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(12,6))
sns.heatmap(ct4, annot=True, fmt='.2%', cmap='Oranges')
plt.title('Churn Rate by Geography and Balance Tier')
plt.show()
```



In [25]:
```
ct4 = pd.crosstab(index=[df['Geography'], df['Gender']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(12,3))
sns.heatmap(ct4, annot=True, fmt='.2%', cmap='Reds')
plt.title('Churn Rate by Geography and Gender')
plt.show()
```

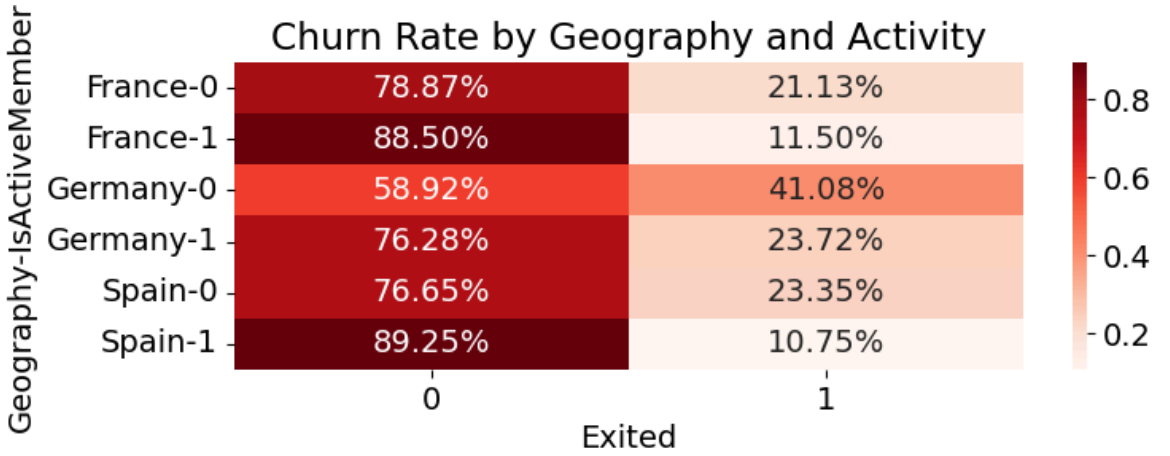


In [26]:
```
ct2 = pd.crosstab(index=[df['Gender'], df['IsActiveMember']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(8,2.5))
sns.heatmap(ct2, annot=True, fmt='.2%', cmap='Reds')
plt.title('Churn Rate by Gender and Activity')
plt.show()
```

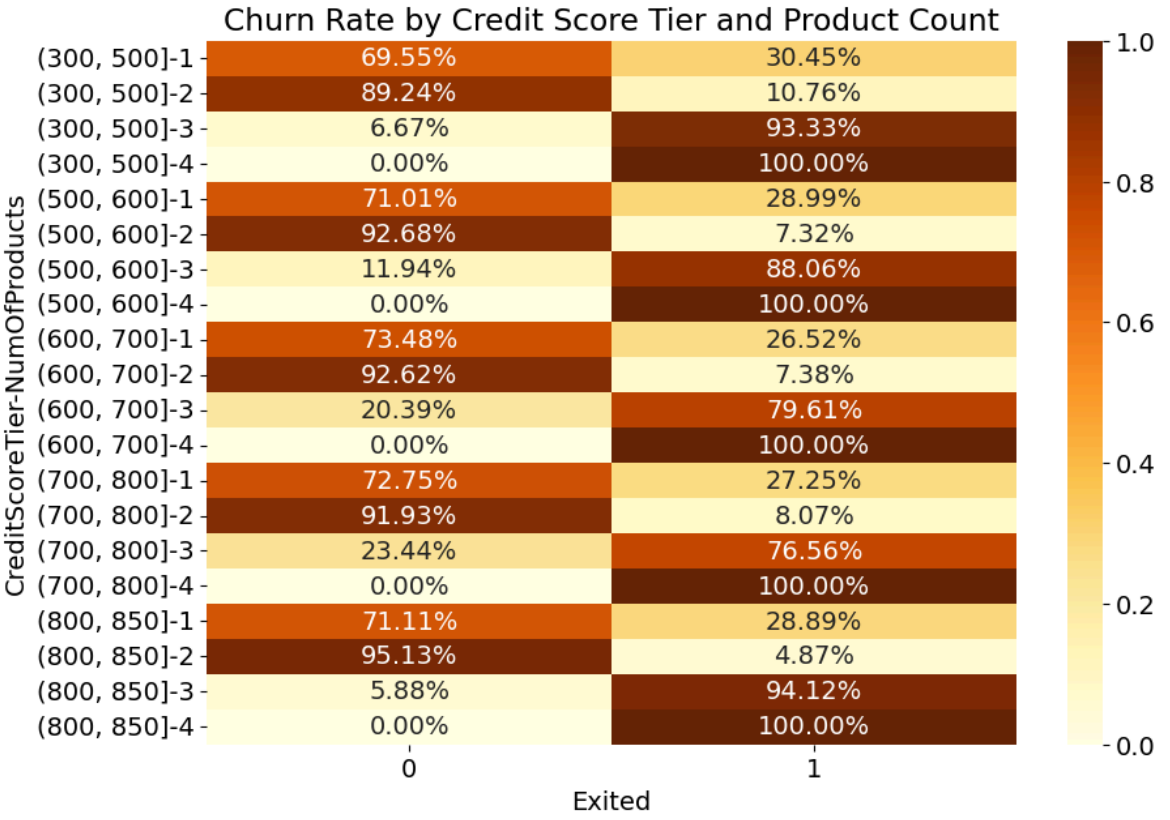


In [27]:
```
ct2 = pd.crosstab(index=[df['Geography'], df['IsActiveMember']],
                  columns=df['Exited'], normalize='index')
```

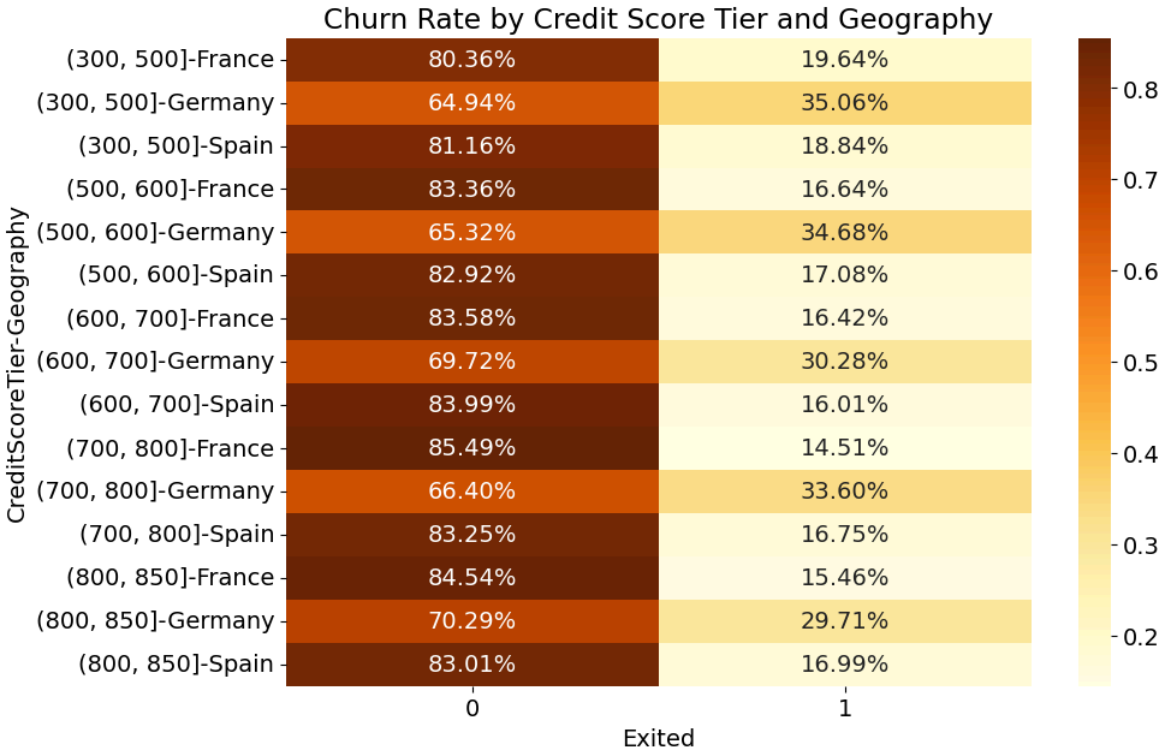
```
plt.figure(figsize=(8,2.5))
sns.heatmap(ct2, annot=True, fmt='.2%', cmap='Reds')
plt.title('Churn Rate by Geography and Activity')
plt.show()
```



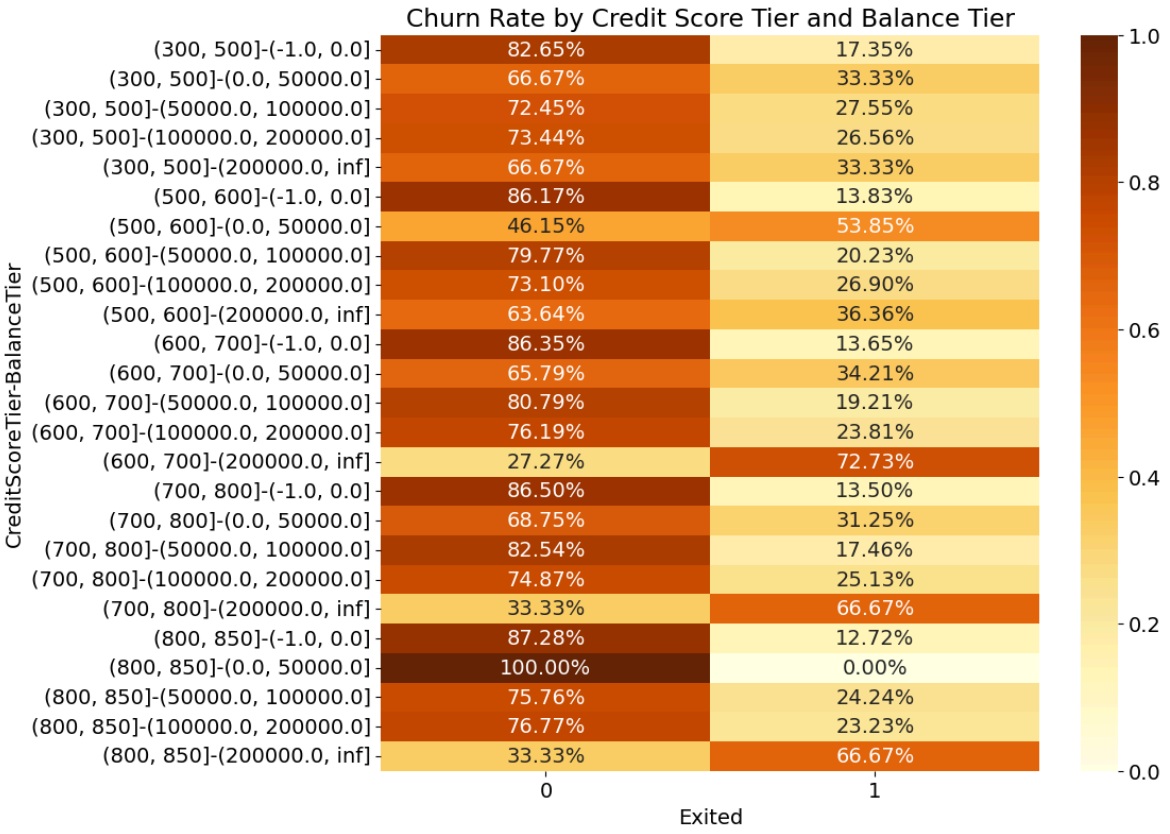
In [28]:
```
ct5 = pd.crosstab(index=[df['CreditScoreTier'], df['NumOfProducts']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(10,7))
sns.heatmap(ct5, annot=True, fmt='.2%', cmap='YlOrBr')
plt.title('Churn Rate by Credit Score Tier and Product Count')
plt.show()
```



In [29]:
```
ct5 = pd.crosstab(index=[df['CreditScoreTier'], df['Geography']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(10,7))
sns.heatmap(ct5, annot=True, fmt='.2%', cmap='YlOrBr')
plt.title('Churn Rate by Credit Score Tier and Geography')
plt.show()
```

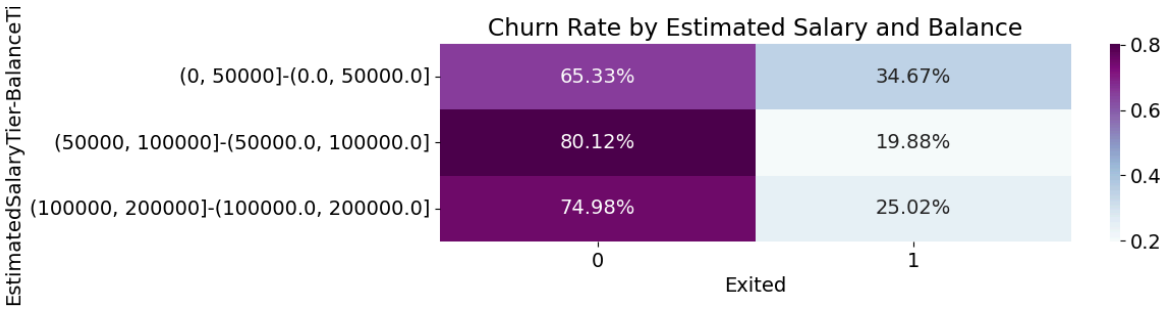


In [30]:
```
ct5 = pd.crosstab(index=[df['CreditScoreTier'], df['BalanceTier']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(10,9))
sns.heatmap(ct5, annot=True, fmt='.2%', cmap='YlOrBr')
plt.title('Churn Rate by Credit Score Tier and Balance Tier')
plt.show()
```

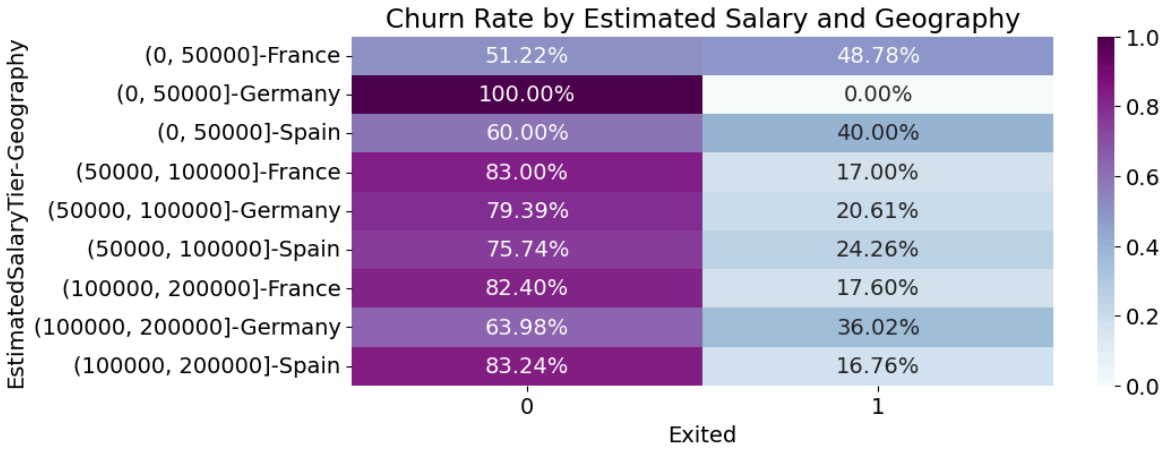


In [31]:
```
ct5 = pd.crosstab(index=[df['EstimatedSalaryTier'], df['BalanceTier']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(10,2.5))
sns.heatmap(ct5, annot=True, fmt='.2%', cmap='BuPu')
```

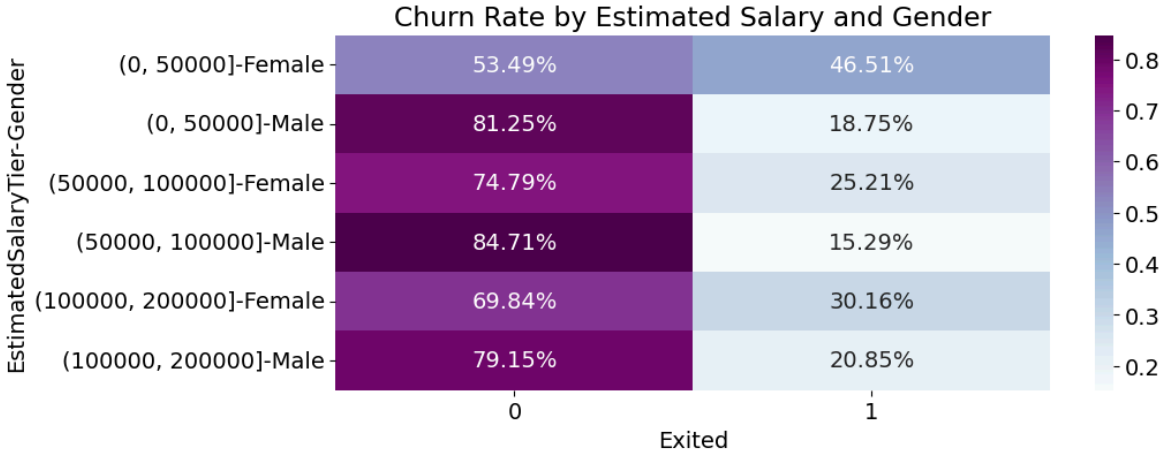
```
plt.title('Churn Rate by Estimated Salary and Balance')
plt.show()
```



In [32]:
```
ct5 = pd.crosstab(index=[df['EstimatedSalaryTier'], df['Geography']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(10,4))
sns.heatmap(ct5, annot=True, fmt='.2%', cmap='BuPu')
plt.title('Churn Rate by Estimated Salary and Geography')
plt.show()
```



In [33]:
```
ct5 = pd.crosstab(index=[df['EstimatedSalaryTier'], df['Gender']],
                  columns=df['Exited'], normalize='index')
plt.figure(figsize=(10,4))
sns.heatmap(ct5, annot=True, fmt='.2%', cmap='BuPu')
plt.title('Churn Rate by Estimated Salary and Gender')
plt.show()
```



Conclusions:

- Having higher Balance and higher Age, around 50 y.o., seems to increase Churn.

- Also, having between 0 (not included) and 50k in Balance increases the chance of Churn.
- Although, in Germany the pattern shifts a bit, where having between 50k and 200k of Balance concentrates the Churn. So Geography is a very important feature and it relates to other variables differently, impacting Churn.
- If the member is inactive, it basically doubles the Churn.
- Having more products is also a factor. Having 2 products is optimal for the bank, as seen before.
- It seems that there is a range within CreditScore where there is more Churn.
- Finally, in Spain and France people that have a smaller Estimated Salary tend to leave more, while in Germany it is people who tend to earn more that leave.
- Geography, Balance, Activity, Age, NumOfProducts, CreditScore, Estimated Salary, and Gender are important features to use for training a predictive model.

Feature importance

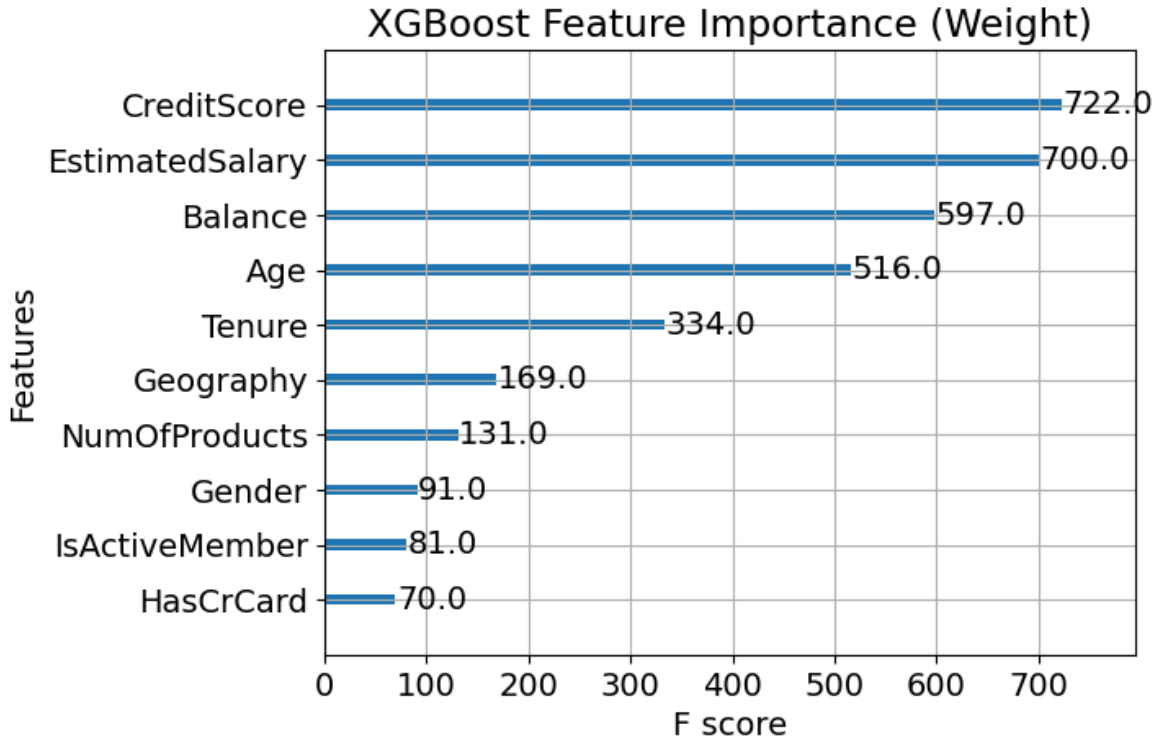
Data preparation

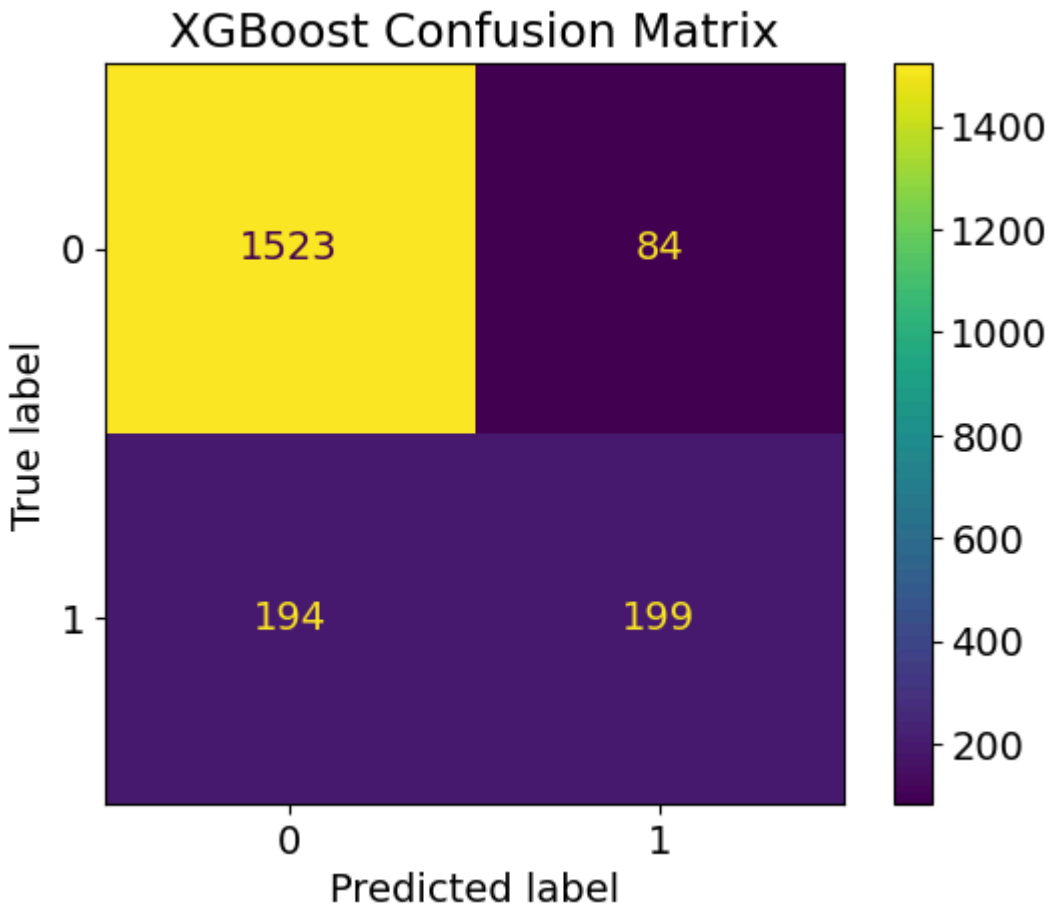
In [34]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, roc_auc_score, ConfusionMatrixDispla

df = pd.read_csv('data/Churn_clients.csv')

# Encode categorical variables
label_encoders = {}
for col in ['Geography', 'Gender']:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le

# Define features and target
X = df.drop(['RowNumber', 'CustomerId', 'Surname', 'Exited'], axis=1)
y = df['Exited']

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

In [35]:
```
import xgboost as xgb
from xgboost import plot_importance

# Train XGBoost model
model = xgb.XGBClassifier(random_state=42, eval_metric='logloss')
model.fit(X_train, y_train)

# Evaluate
```

```
y_pred = model.predict(X_test)
print(f"XGBoost Accuracy: {accuracy_score(y_test, y_pred):.4f}")
print(f"XGBoost ROC AUC: {roc_auc_score(y_test, model.predict_proba(X_test)[:,1]

# Feature importance
plt.figure(figsize=(10, 6))
plot_importance(model, max_num_features=15, importance_type='weight')
plt.title('XGBoost Feature Importance (Weight)')
plt.show()

# Confusion matrix
ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
plt.title('XGBoost Confusion Matrix')
plt.show()
```

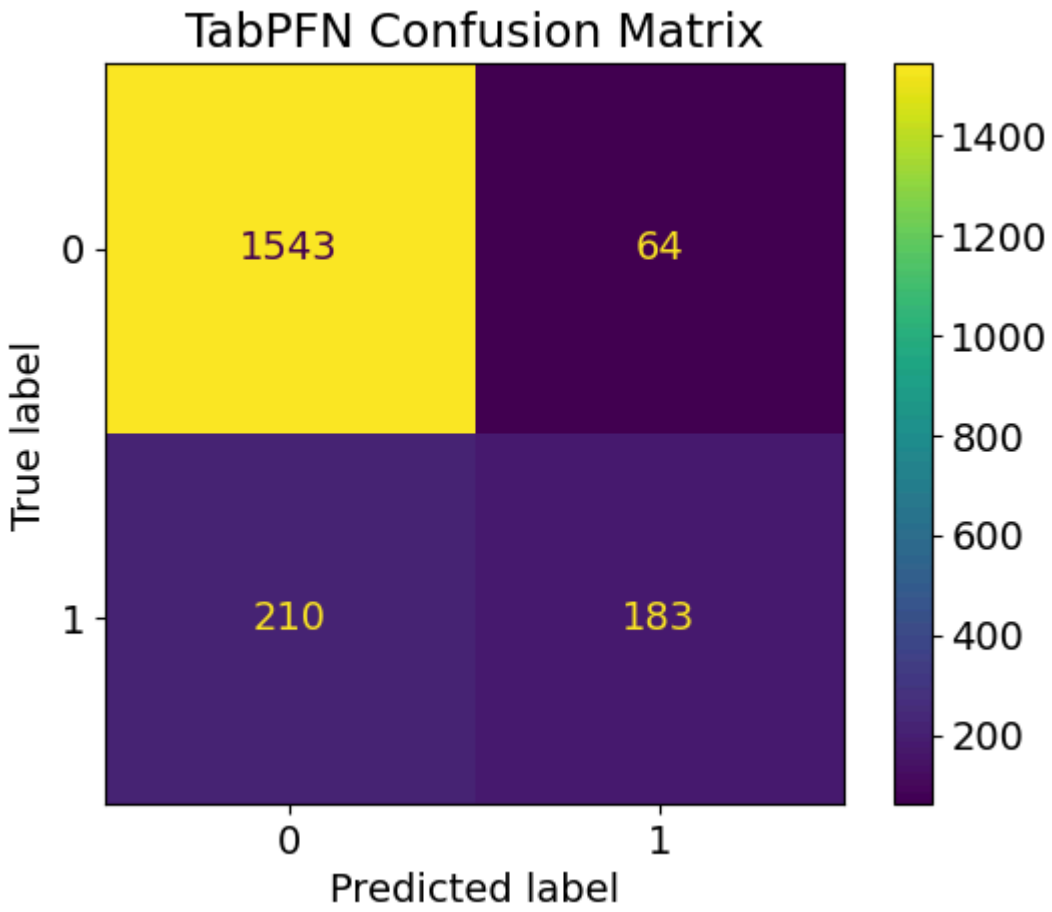
```
XGBoost Accuracy: 0.8610
XGBoost ROC AUC: 0.8467
<Figure size 1000x600 with 0 Axes>
```





In [36]:
```python
from tabpfn import TabPFNClassifier

# Initialize TabPFN (works best with <1000 samples)
n_samples = min(1000, len(X_train))  # TabPFN limitation
X_train_tabpfn = X_train[:n_samples].values
y_train_tabpfn = y_train[:n_samples].values

# Train TabPFN
tabpfn = TabPFNClassifier(device='cpu')
tabpfn.fit(X_train_tabpfn, y_train_tabpfn)

# Evaluate
tabpfn_probs = tabpfn.predict_proba(X_test.values)[:, 1]
tabpfn_preds = (tabpfn_probs > 0.5).astype(int)
print(f"\nTabPFN Accuracy: {accuracy_score(y_test, tabpfn_preds):.4f}")
print(f"TabPFN ROC AUC: {roc_auc_score(y_test, tabpfn_probs):.4f}")

# Confusion matrix
ConfusionMatrixDisplay.from_predictions(y_test, tabpfn_preds)
plt.title('TabPFN Confusion Matrix')
plt.show()
```

```
c:\Users\CORE\AppData\Local\Programs\Python\Python39\lib\site-packages\tabpfn\classifier.py:431: UserWarning: Running on CPU with more than 200 samples may be slow.
Consider using a GPU or the tabpfn-client API: https://github.com/PriorLabs/tabpfn-client
  check_cpu_warning(self.device, X)
TabPFN Accuracy: 0.8630
TabPFN ROC AUC: 0.8652
```

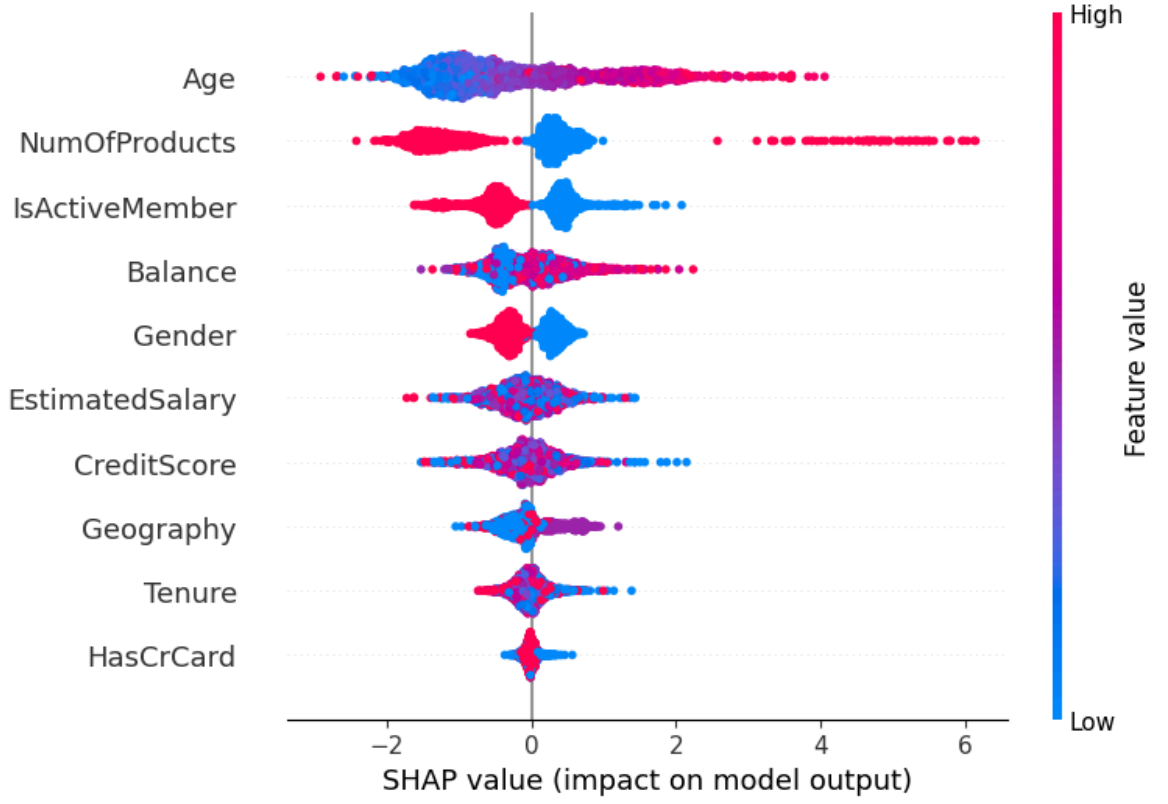


In [37]:
```
# Compare model performances
results = pd.DataFrame({
    'Model': ['XGBoost', 'TabPFN'],
    'Accuracy': [accuracy_score(y_test, y_pred), accuracy_score(y_test, tabpfn_p
    'ROC AUC': [roc_auc_score(y_test, model.predict_proba(X_test)[:,1]), roc_auc
})

print("\nModel Comparison:")
print(results)

# Top 3 impactful features from XGBoost
top_features = pd.Series(model.feature_importances_, index=X.columns).sort_value
print("\nTop 5 Most Important Features:")
print(top_features)
```

```
Model Comparison:
     Model  Accuracy   ROC AUC
0  XGBoost     0.861  0.846747
1   TabPFN     0.863  0.865208

Top 5 Most Important Features:
NumOfProducts      0.324759
IsActiveMember     0.213897
Age                0.127817
Geography          0.080982
Balance            0.055760
dtype: float32

Top 5 Most Important Features:
NumOfProducts      0.324759
IsActiveMember     0.213897
Age                0.127817
Geography          0.080982
Balance            0.055760
dtype: float32
```

In [38]:
```python
# SHAP values for detailed feature effects
import shap
explainer = shap.TreeExplainer(model)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```

```
c:\Users\CORE\AppData\Local\Programs\Python\Python39\lib\site-packages\tqdm\auto.
py:21: TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. Se
e https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```



As seen before:

- Older people are leaving

- Churn is concentrated for 1, 3, or 4 products
- Inactive members tend to leave more
- People with higher balance are leaving more
- The churn is higher within females
- Estimated Salary alone would not be very useful, but it helps when combined with Geography, for example
- Looking at Geography, Germans are leaving more
- Lower Credit Score show slightly higher churn, but it is not a very useful feature
- Tenure and Has Credit Card alone are not very useful features as well