In [1]:
```
# Step 1: Load & Inspect Dataset

import pandas as pd

# Load the dataset
df = pd.read_csv('/Users/maazhussain/Desktop/Projects/Banking Churn Risk & F

# Show structure and first rows
print("Shape:", df.shape)
df.info()
df.head()
```

```
Shape: (10000, 14)
<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
```

Out[1]:

	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 [3]:
```
# Step 2: Clean & Prepare

# Drop non-essential columns
df_clean = df.drop(columns=["RowNumber", "CustomerId", "Surname"])

# Check the cleaned dataset
print("Cleaned shape:", df_clean.shape)
df_clean.head()
```

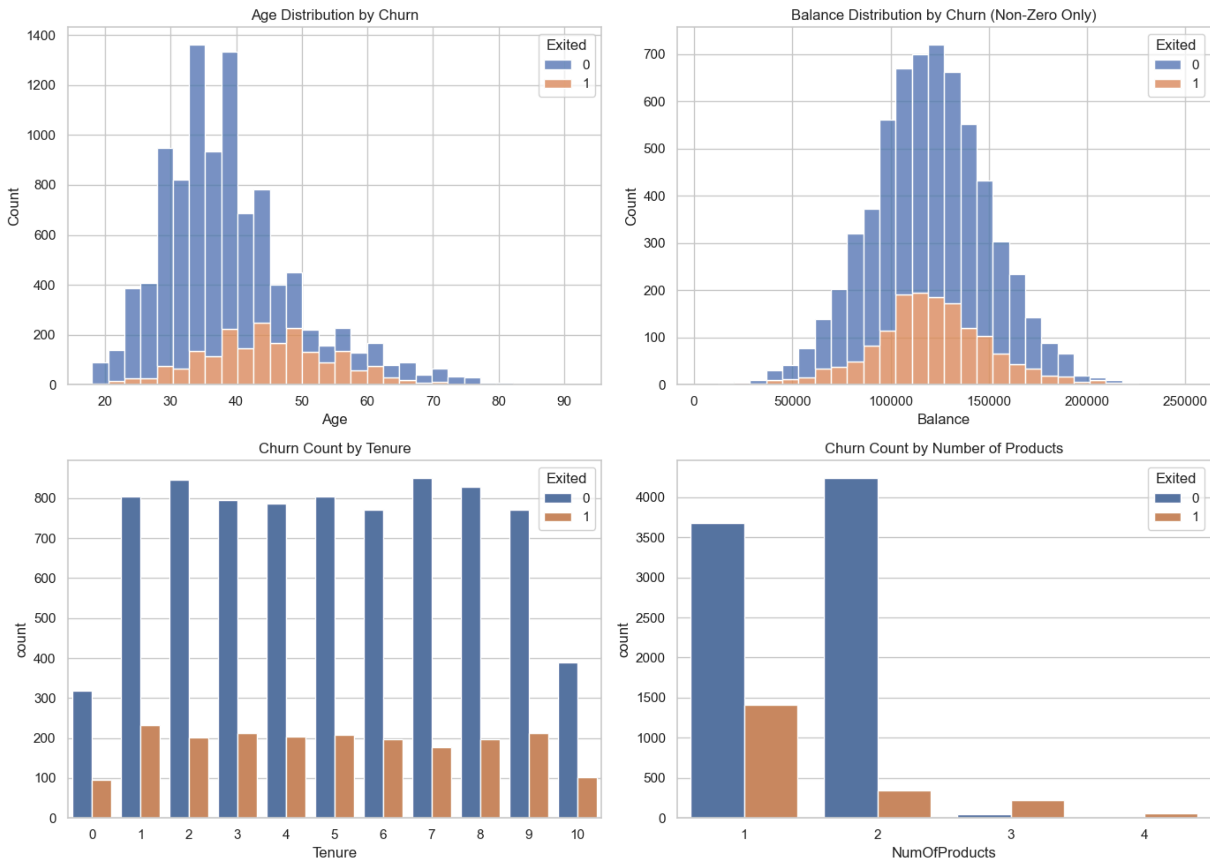
```
Cleaned shape: (10000, 11)
```

Out[3]:

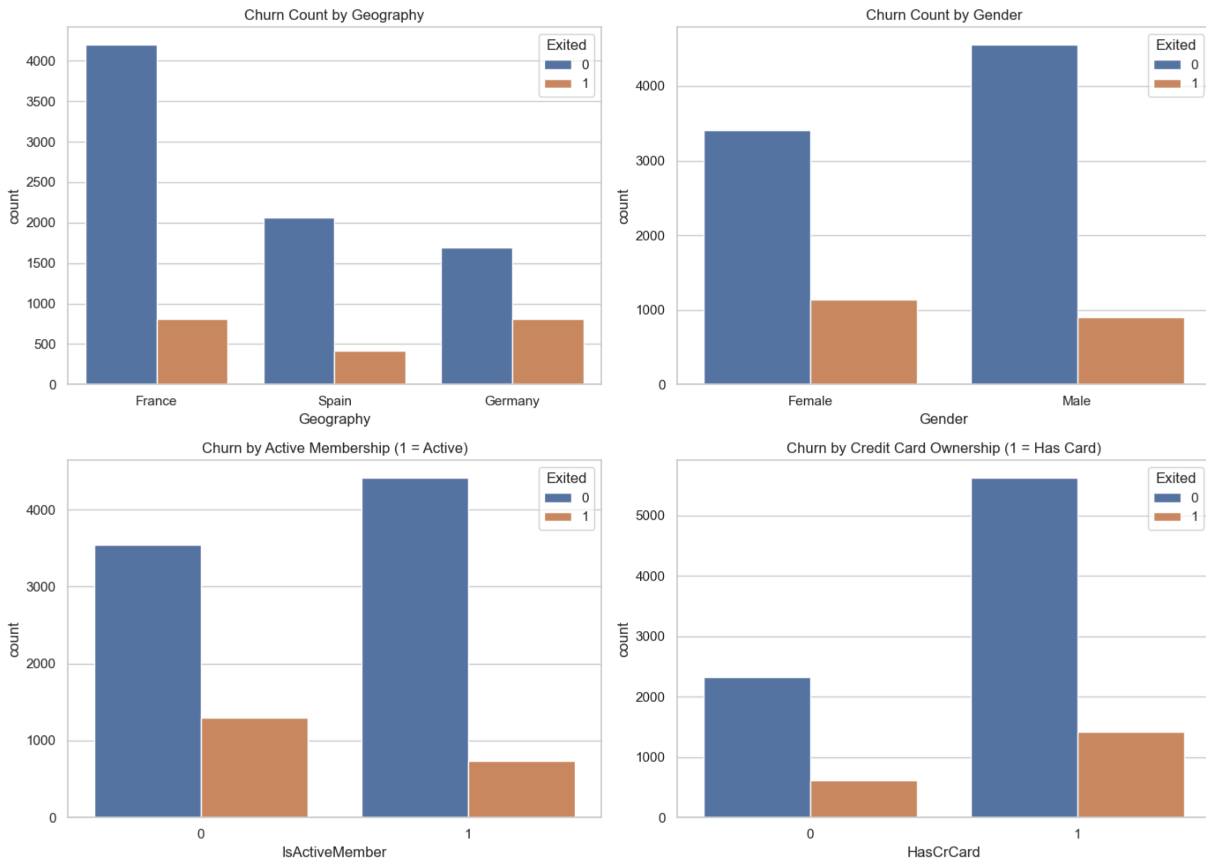
	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCr(
0	619	France	Female	42	2	0.00	1	
1	608	Spain	Female	41	1	83807.86	1	
2	502	France	Female	42	8	159660.80	3	
3	699	France	Female	39	1	0.00	2	
4	850	Spain	Female	43	2	125510.82	1	

In [5]:

```
# Step 3: EDA – Visualize churn vs key features

import seaborn as sns
import matplotlib.pyplot as plt

sns.set(style="whitegrid")
fig, axes = plt.subplots(2, 2, figsize=(14, 10))

# 1. Age vs Churn
sns.histplot(data=df_clean, x="Age", hue="Exited", multiple="stack", bins=30
axes[0, 0].set_title("Age Distribution by Churn")

# 2. Balance vs Churn (exclude zero balances)
sns.histplot(data=df_clean[df_clean["Balance"] > 0], x="Balance", hue="Exite
axes[0, 1].set_title("Balance Distribution by Churn (Non-Zero Only)")

# 3. Tenure vs Churn
sns.countplot(data=df_clean, x="Tenure", hue="Exited", ax=axes[1, 0])
axes[1, 0].set_title("Churn Count by Tenure")

# 4. Num of Products vs Churn
sns.countplot(data=df_clean, x="NumOfProducts", hue="Exited", ax=axes[1, 1])
axes[1, 1].set_title("Churn Count by Number of Products")

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



In [7]:
```
# Step 4: Churn Breakdown by Categorical Features

import seaborn as sns
import matplotlib.pyplot as plt

sns.set(style="whitegrid")
fig, axes = plt.subplots(2, 2, figsize=(14, 10))

# 1. Geography vs Churn
sns.countplot(data=df_clean, x="Geography", hue="Exited", ax=axes[0, 0])
axes[0, 0].set_title("Churn Count by Geography")

# 2. Gender vs Churn
sns.countplot(data=df_clean, x="Gender", hue="Exited", ax=axes[0, 1])
axes[0, 1].set_title("Churn Count by Gender")

# 3. IsActiveMember vs Churn
sns.countplot(data=df_clean, x="IsActiveMember", hue="Exited", ax=axes[1, 0]
axes[1, 0].set_title("Churn by Active Membership (1 = Active)")

# 4. HasCrCard vs Churn
sns.countplot(data=df_clean, x="HasCrCard", hue="Exited", ax=axes[1, 1])
axes[1, 1].set_title("Churn by Credit Card Ownership (1 = Has Card)")

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



In [9]:
```
# Step 5.1: Prepare data for modeling

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# Copy the clean dataframe
model_df = df_clean.copy()

# Encode categorical columns: Geography and Gender
model_df["Geography"] = LabelEncoder().fit_transform(model_df["Geography"])
model_df["Gender"] = LabelEncoder().fit_transform(model_df["Gender"])

# Define features and target
X = model_df.drop("Exited", axis=1)
y = model_df["Exited"]

# Split into training and testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

X_train.shape, X_test.shape
```

Out[9]: ((8000, 10), (2000, 10))

In [11]:
```
# Step 5.2: Train & Evaluate Logistic Regression

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusior

# Initialize and train model
```

```python
lr = LogisticRegression(max_iter=1000)
lr.fit(X_train, y_train)

# Predict on test set
y_pred = lr.predict(X_test)

# Evaluation
print(" Accuracy:", accuracy_score(y_test, y_pred))
print("\n Classification Report:\n", classification_report(y_test, y_pred))
print("\n Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
 Accuracy: 0.8165

 Classification Report:
               precision    recall  f1-score   support

           0       0.83      0.97      0.89      1607
           1       0.61      0.18      0.28       393

    accuracy                           0.82      2000
   macro avg       0.72      0.58      0.59      2000
weighted avg       0.79      0.82      0.77      2000


 Confusion Matrix:
 [[1561   46]
 [ 321   72]]
```

```
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_logistic.p
y:469: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion
  n_iter_i = _check_optimize_result(
```

In [13]:

```python
# Step 5.3: Random Forest Classifier

from sklearn.ensemble import RandomForestClassifier

# Initialize and train
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

# Predict
rf_pred = rf.predict(X_test)

# Evaluation
from sklearn.metrics import classification_report, accuracy_score, confusion

print(" Random Forest Accuracy:", accuracy_score(y_test, rf_pred))
print("\n Classification Report:\n", classification_report(y_test, rf_pred))
print("\n Confusion Matrix:\n", confusion_matrix(y_test, rf_pred))
```

```
Random Forest Accuracy: 0.8645

Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.96      0.92      1607
           1       0.75      0.47      0.58       393

    accuracy                           0.86      2000
   macro avg       0.81      0.71      0.75      2000
weighted avg       0.85      0.86      0.85      2000


Confusion Matrix:
[[1545   62]
 [ 209  184]]
```

Capstone Report – Banking Churn Risk Analysis

__Objective__

To analyze customer churn in a European bank and identify key drivers using exploratory data analysis and predictive modeling. The goal is to support data-driven retention strategies.

__Dataset Summary__

Source: Kaggle – Churn for Bank Customers Rows: 10,000 customers Target Variable: Exited (1 = churned, 0 = retained) Key Features: Age, Geography, Tenure, Balance, Products, Credit Card Ownership, Activity

__Key Insights from EDA__

Feature Churn Trend Age Older customers (40+) churn more frequently Balance High churn even among high-balance customers Products Single-product customers are most likely to churn Geography Germany has the highest churn ratio among regions Activity Inactive users show significantly higher churn Credit Card Non-card holders churn slightly more often

__Model Results__

Model | Accuracy | Churn Recall | Churn Precision | F1 (Churn) Logistic Regression | 81.7% | 18% | 61% | 28% Random Forest | 86.5% | 47% | 75% | 58%

__Conclusion:__ Random Forest significantly outperforms logistic regression, capturing more than double the churners. It's recommended for deployment.

__Recommendations__

Focus retention efforts on older, inactive customers with only one product Target Germany with tailored campaigns Promote cross-selling to increase product ownership

Build automated churn risk dashboards for real-time decision-making

```
In [ ]:
```