

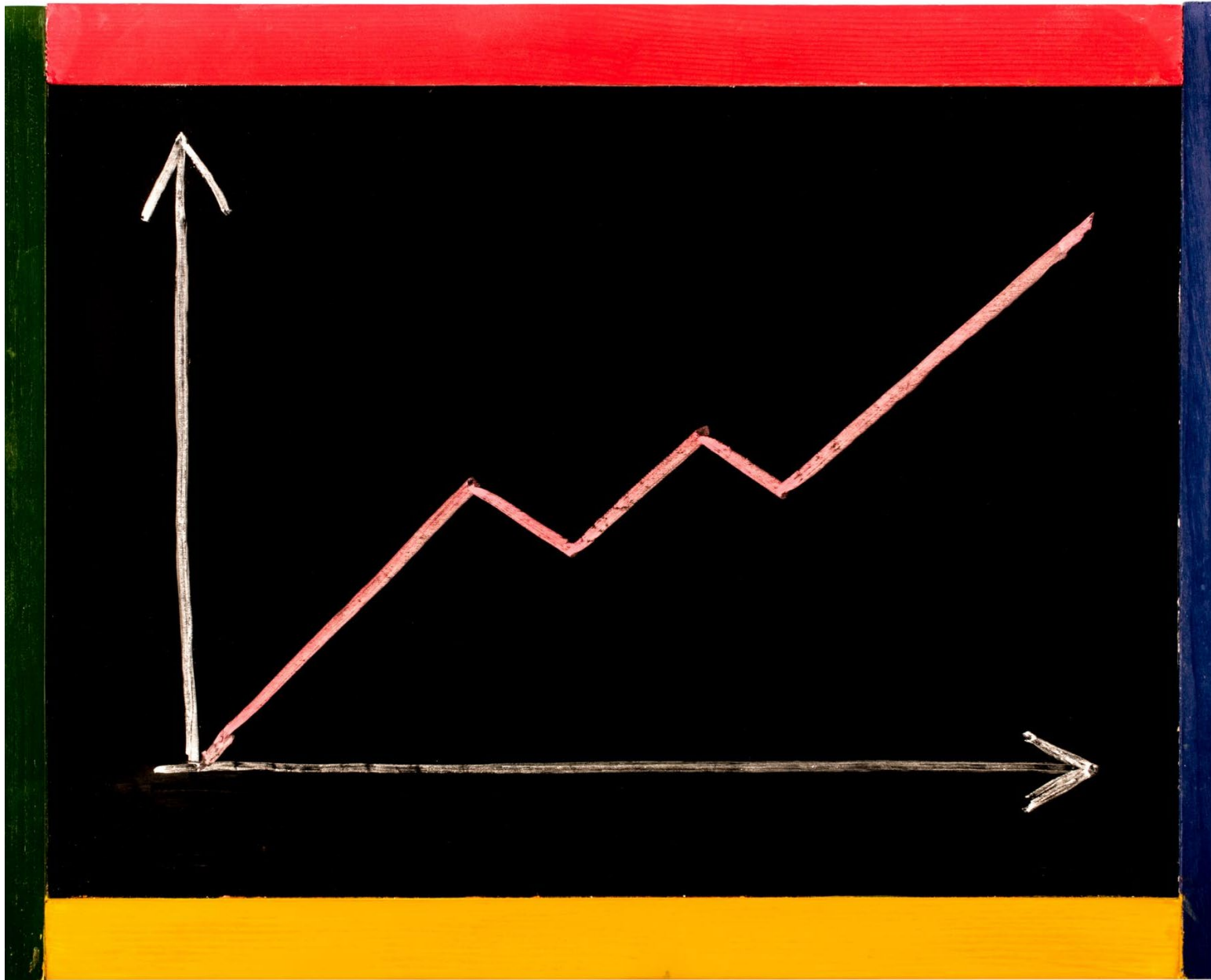
# Exploratory Data Analysis of Customer Churn: Uncovering Key Insights for Retention

Analyzing patterns to enhance customer loyalty  
and retention

# Meeting Program

- Project Overview and Dataset Description
- Data Cleaning and Preparation
- Exploring Churn Distribution and Categorical Drivers
- Numerical Feature Analysis to Identify Churn Patterns
- Key Drivers of Churn and Actionable Recommendations

# Project Overview and Dataset Description



# Defining the Objective and Target Variable

## Objective Identification

- The main goal is to identify key factors that lead to customer churn for better retention strategies.

## Target Variable:

- Exited (1 = churned, 0 = retained).

## Target Variable Explanation

- The target variable indicates whether a customer has churned or remained loyal, directing the analysis approach.

# Outlining Steps Taken in the Analysis

## Dataset Exploration

Initial step involves examining the dataset to understand its structure and content.

## Data Cleaning

Removing errors and inconsistencies from the data to ensure high quality for analysis.

## Feature Analysis

Analyzing key features to identify patterns relevant to retention and churn.

## Deriving Insights

Extracting meaningful conclusions to inform strategies reducing churn rates.





# Initial Exploration of the Dataset

## **Examine Data Types**

Understanding data types helps identify appropriate analysis techniques and potential preprocessing steps.

## **Summary Statistics**

Calculating mean, median, mode, and range provides insight into data distribution and central tendencies.

## **Distribution Analysis**

Visualizing distributions helps detect patterns, outliers, and potential data quality issues early in analysis.

# Data Cleaning and Preparation



# Dropping Non-Informative Identifiers

## Purpose of Dropping Identifiers

- Removing unique identifiers helps eliminate irrelevant data that does not aid churn prediction.
- No Missing values found.
- Dataset Ready with 10,000 rows x 11 features.

## Focus on Meaningful Features

- Streamlining the dataset allows models to concentrate on features that improve prediction accuracy.

|       | RowNumber   | CustomerId   | CreditScore  | Age          | Tenure       | Balance      | NumOfProducts | HasCrCard   | IsActiveMember | EstimatedSalary | Exited       |
|-------|-------------|--------------|--------------|--------------|--------------|--------------|---------------|-------------|----------------|-----------------|--------------|
| count | 10000.00000 | 1.000000e+04 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000  | 10000.00000 | 10000.000000   | 10000.000000    | 10000.000000 |
| mean  | 5000.50000  | 1.569094e+07 | 650.528800   | 38.921800    | 5.012800     | 76485.889288 | 1.530200      | 0.70550     | 0.515100       | 100090.239881   | 0.203700     |
| std   | 2886.89568  | 7.193619e+04 | 96.653299    | 10.487806    | 2.892174     | 62397.405202 | 0.581654      | 0.45584     | 0.499797       | 57510.492818    | 0.402769     |
| min   | 1.00000     | 1.556570e+07 | 350.000000   | 18.000000    | 0.000000     | 0.000000     | 1.000000      | 0.00000     | 0.000000       | 11.580000       | 0.000000     |
| 25%   | 2500.75000  | 1.562853e+07 | 584.000000   | 32.000000    | 3.000000     | 0.000000     | 1.000000      | 0.00000     | 0.000000       | 51002.110000    | 0.000000     |
| 50%   | 5000.50000  | 1.569094e+07 | 650.528800   | 38.921800    | 5.012800     | 76485.889288 | 1.530200      | 0.70550     | 0.515100       | 100090.239881   | 0.203700     |
| 75%   | 7500.75000  | 1.562853e+07 | 584.000000   | 32.000000    | 3.000000     | 0.000000     | 1.000000      | 0.00000     | 0.000000       | 51002.110000    | 0.000000     |
| max   | 10000.00000 | 1.598501e+07 | 900.000000   | 45.000000    | 10.000000    | 9849.534000  | 1.000000      | 1.00000     | 1.000000       | 100103.015000   | 0.000000     |





# Assessing Missing Values and Data Integrity

## Identifying Missing Data

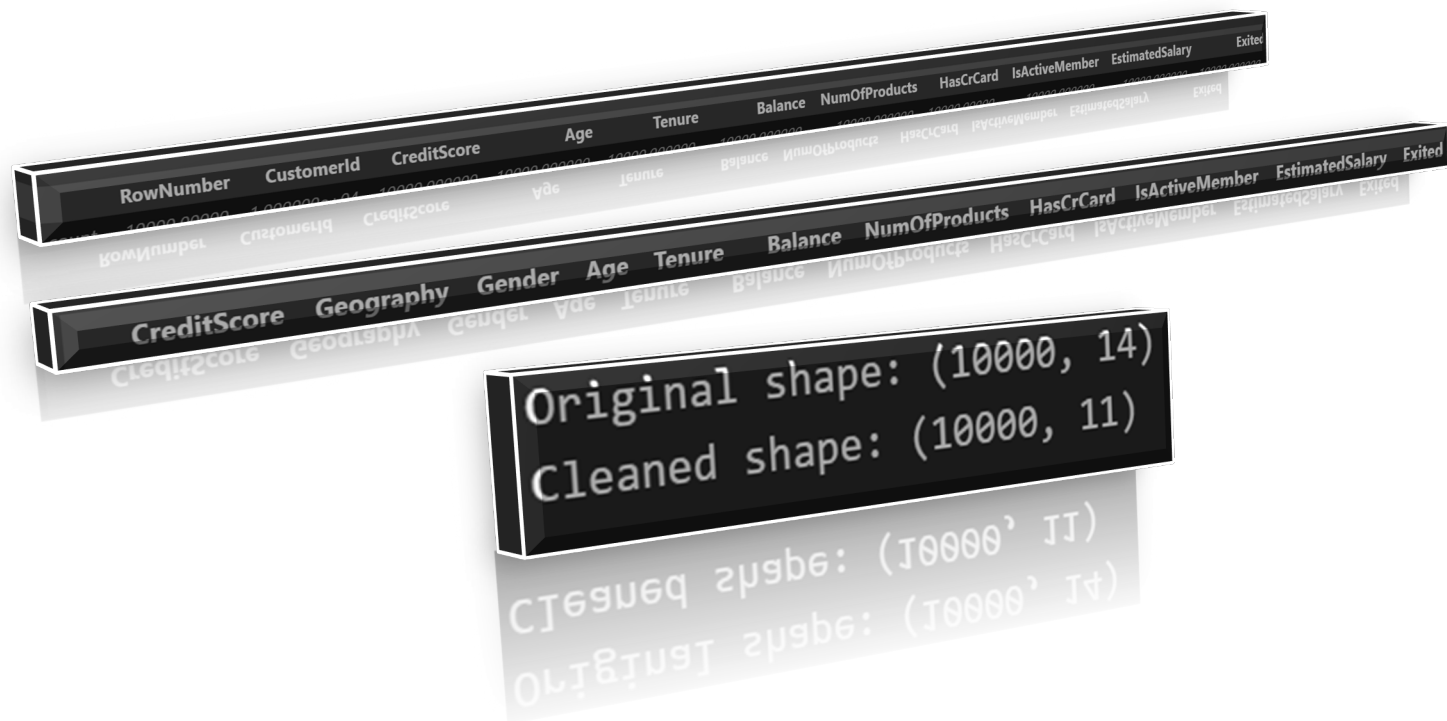
Detect and locate missing or incomplete data points in datasets to prevent analysis errors.

## Ensuring Data Consistency

Check for inconsistencies or anomalies to maintain dataset integrity and increase reliability.

## Improving Analysis Accuracy

Address data quality issues to ensure accurate and dependable analytical results.



# Final Dataset Shape and Readiness for Analysis

## Dataset Dimensions Confirmed

The dataset's rows and columns are verified to ensure accurate data structure after cleaning.

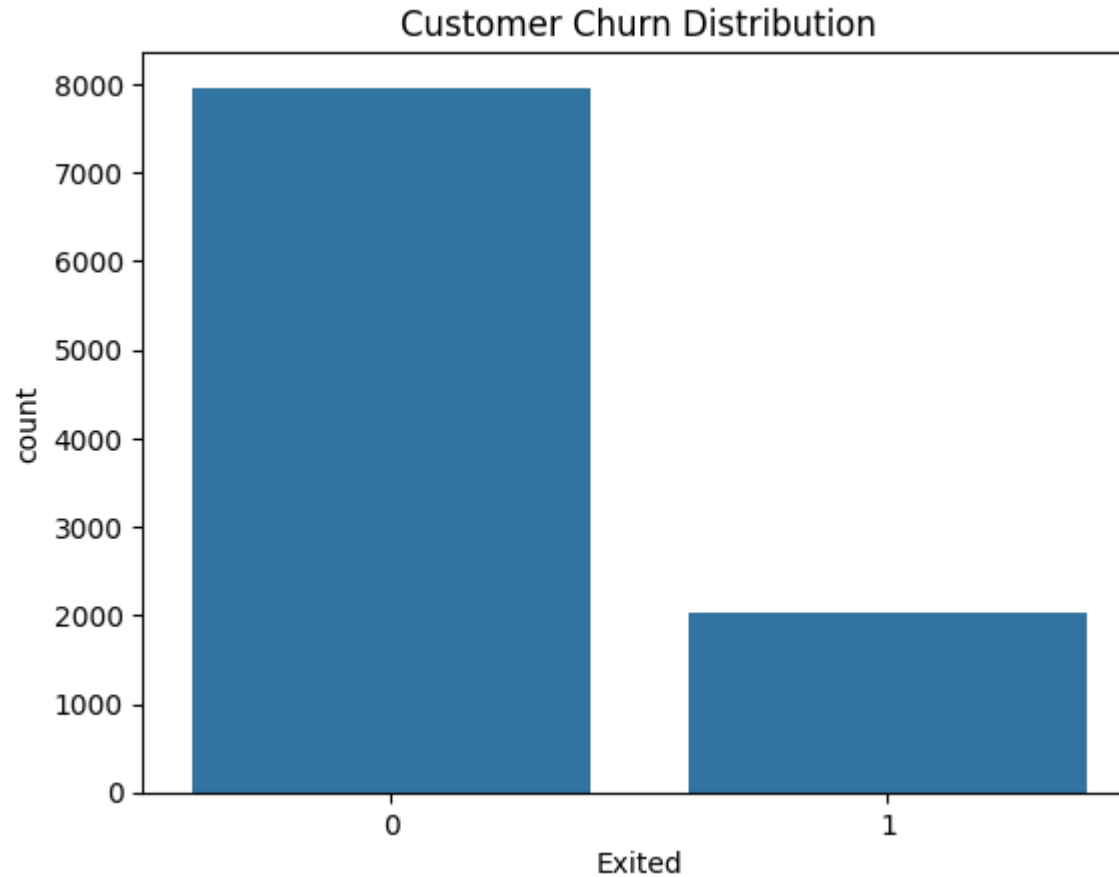
## Data Cleaning Completed

Cleaning processes have refined the data, removing errors and inconsistencies for analysis readiness.

## Ready for Exploratory Analysis

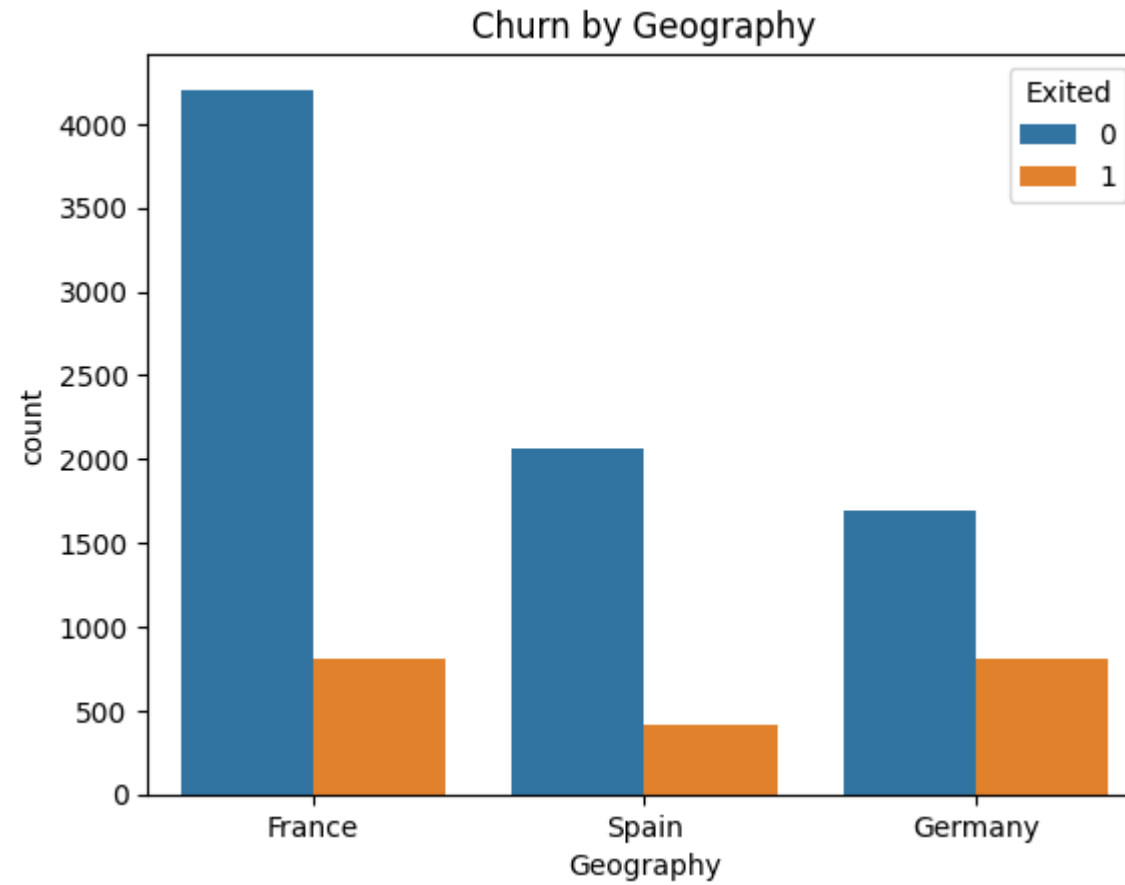
The prepared dataset is now suitable for performing exploratory data analysis effectively.

# Exploring Churn Distribution and Categorical Drivers



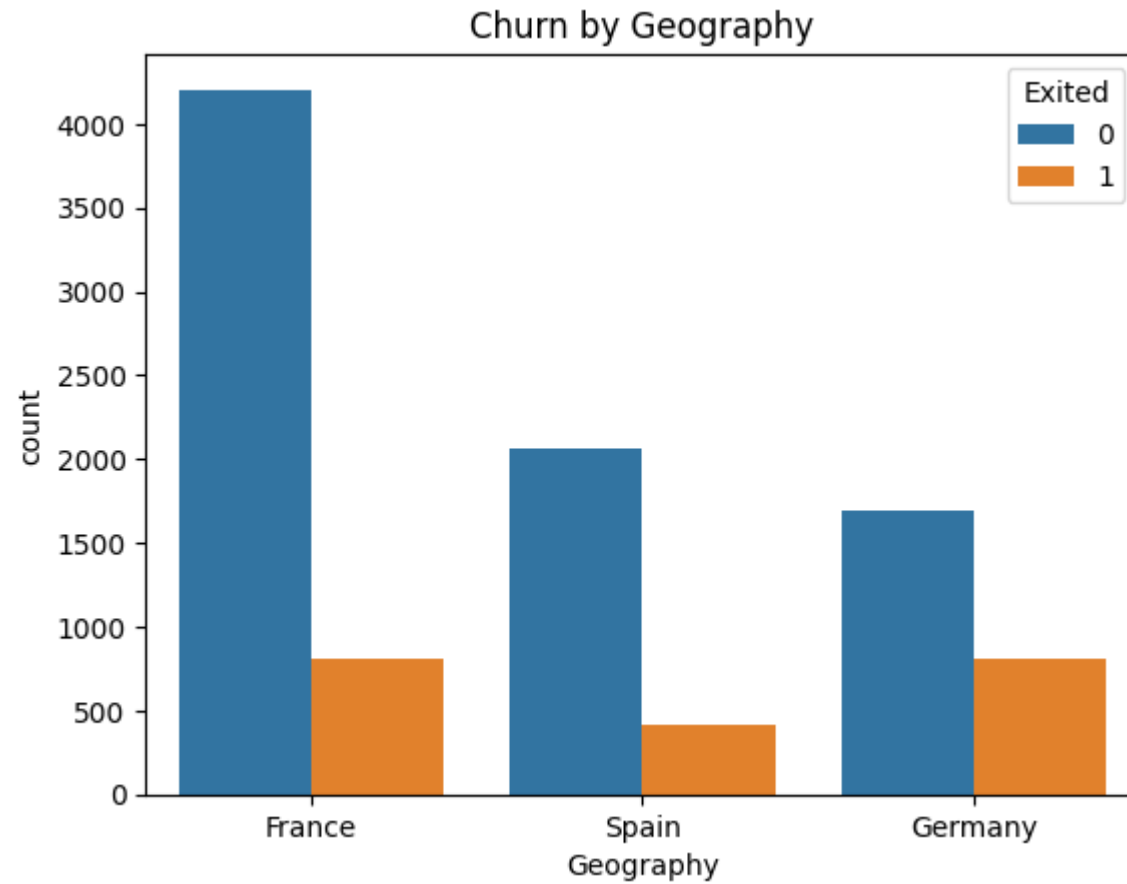
## Churn Distribution

- Insight: ~20% of customers churn, ~80% retained.
- Sets up the challenge → churn is a minority class.



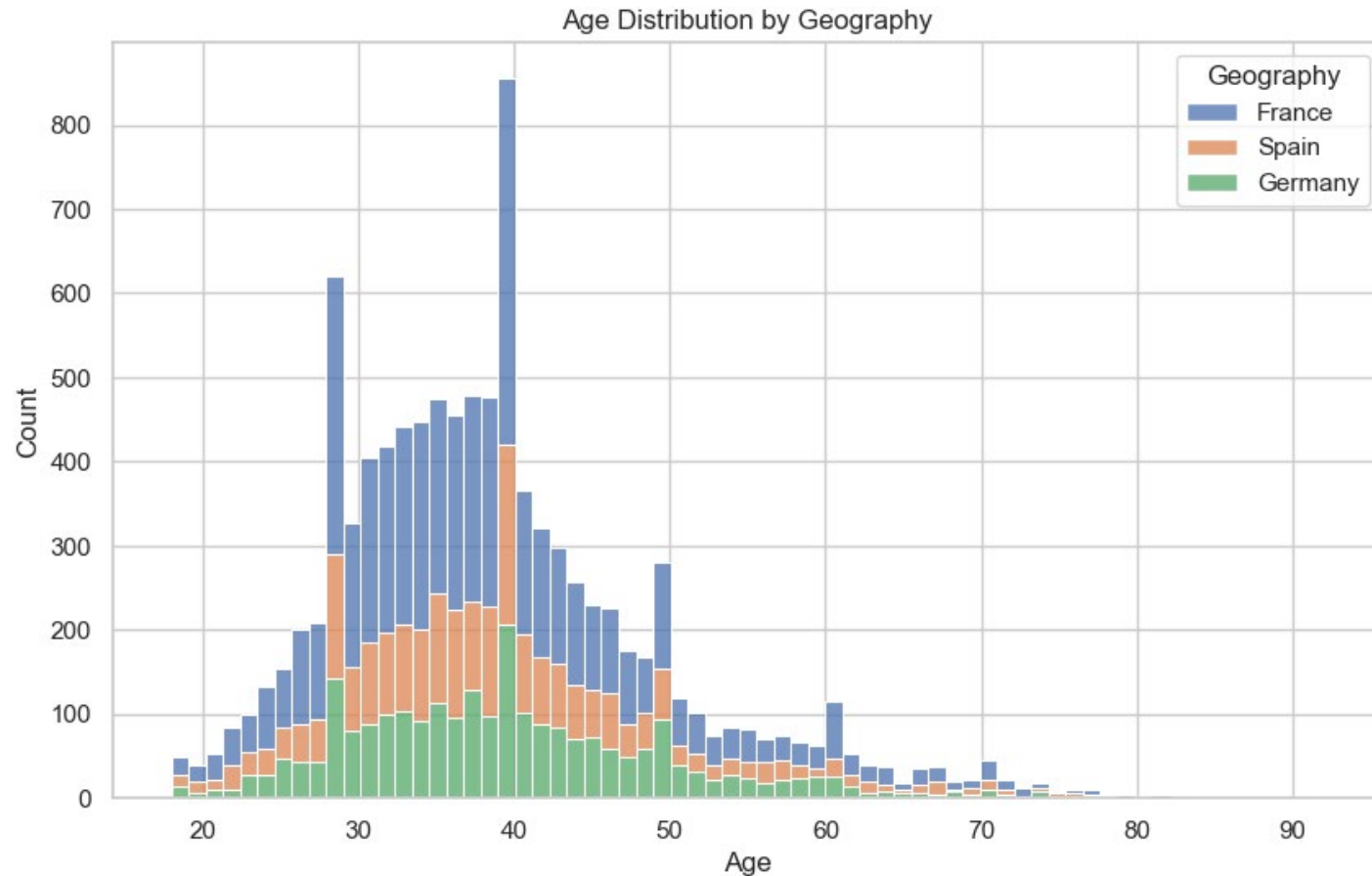
Insight: Germany has the highest churn, France the lowest.

## Analyzing Churn by Geography



## Investigating Churn by Geography

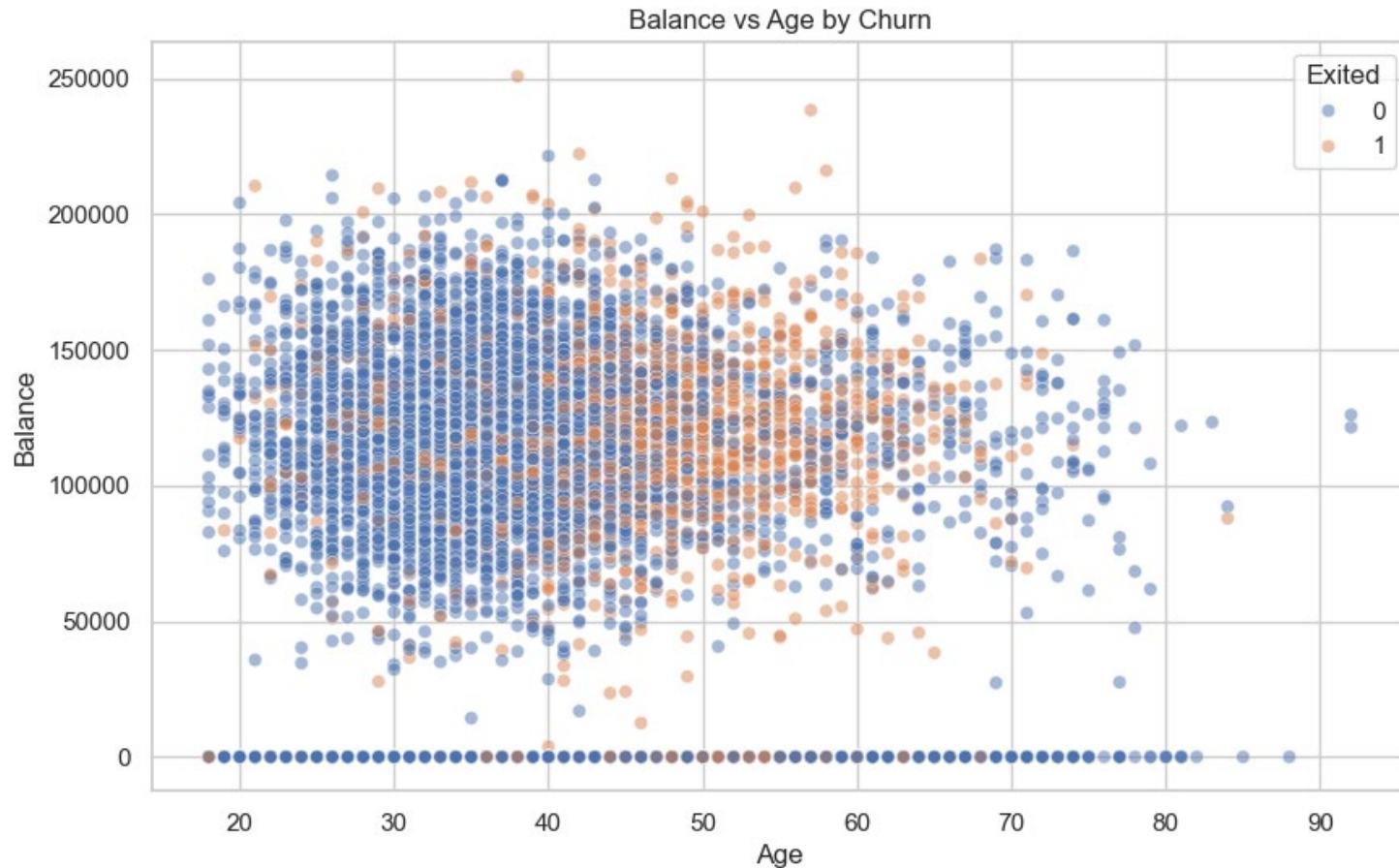
Insight: Germany has the highest churn, France the lowest.



## Age Distribution by Geography – Key Takeaways

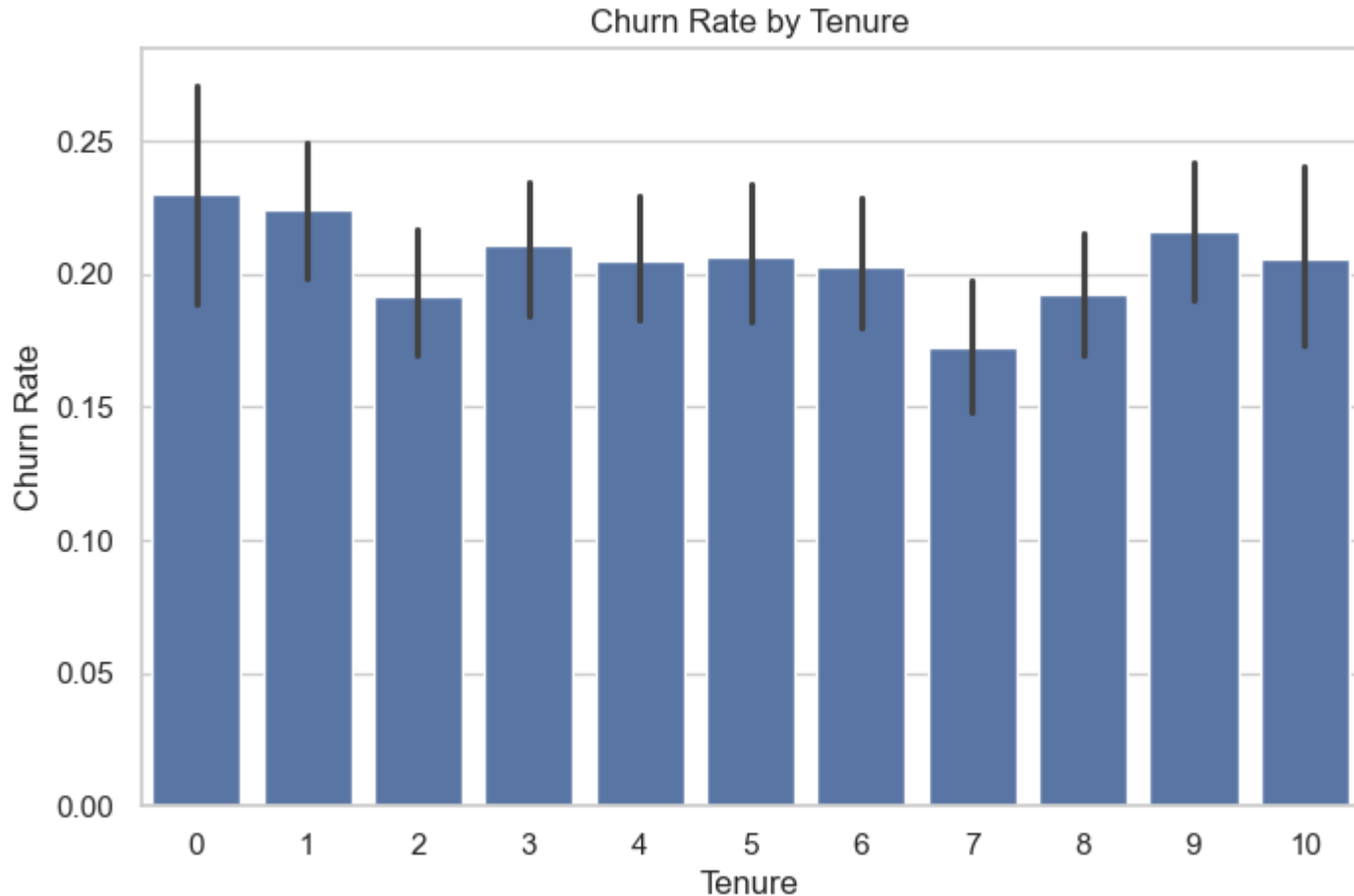
- The **age profile of customers differs significantly by geography.**
- France has the largest base of customers across most age groups, concentrated around **30–40 years old.**
- Germany shows a **heavier concentration of older customers**, which aligns with our earlier finding that **older age correlates with higher churn.**
- Spain's distribution is more balanced, sitting between the other two markets.
- This suggests that **Germany's higher churn rate is partly explained by its older customer base**, while France's younger profile may contribute to its lower churn.





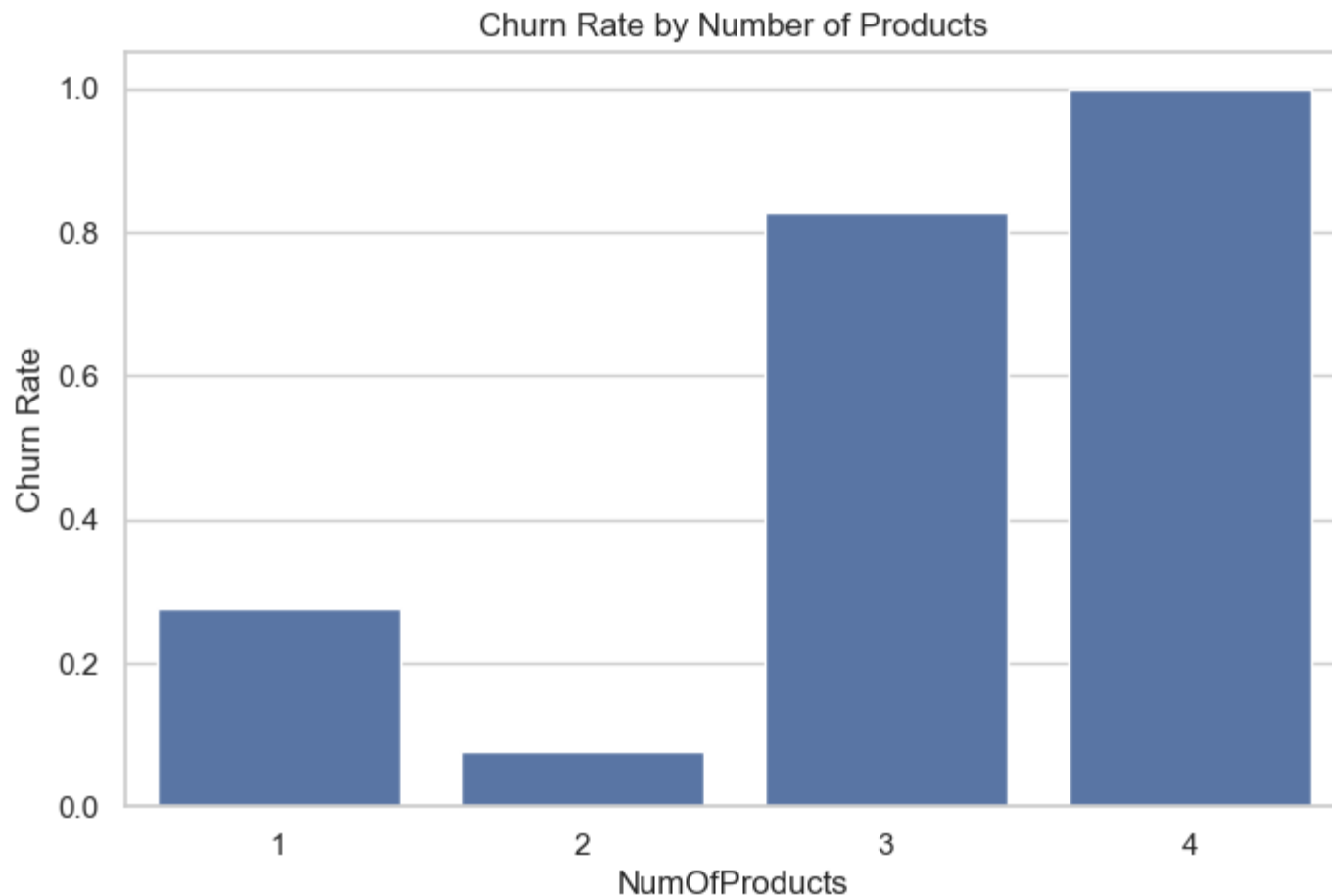
# Balance vs Age by Churn - Takeaways

- **Balance vs Age by Churn – Key Takeaways**
- Churn (orange points) is **more concentrated among older customers with higher balances**.
- Younger customers with similar balances tend to remain loyal (blue points).
- A significant number of **zero-balance customers did not churn**, suggesting that inactivity doesn't always translate to leaving – possibly due to other products or stickiness factors.
- This confirms that **age and balance together explain a portion of churn risk**: older, high-value customers are more likely to exit.
- **Overall Insight:**
- Customer churn isn't explained by age or balance alone – it's their **interaction** that reveals high-risk segments, especially older customers holding larger balances.



## Churn by Tenure – Key Takeaways

- Churn is relatively **consistent across tenure levels**, with rates fluctuating between ~17% and ~23%.
- Customers with **very short tenure (0–1 years)** churn more, suggesting onboarding and early experience matter.
- Churn dips slightly at **7–8 years**, indicating long-term loyalty effects, but rises again at 9–10 years.
- **Overall:** tenure alone is not a strong predictor of churn, but **new customers** represent a higher risk segment that could benefit from early retention strategies.



# Churn by Number of Products – Key Takeaways

- Clear non-linear relationship between product ownership and churn:
  - Customers with **1 product churn moderately** (~25%).
  - Customers with **2 products churn the least** (~8%).
  - Churn **spikes dramatically** for customers with **3 (~82%) and 4 (~100%) products**.
- This suggests that **holding 2 products creates loyalty**, but customers with **too many products may feel overextended or dissatisfied**.
- **Business Implication:** Encourage **cross-sell to 2 products** for stability, while reviewing pain points for customers with 3 or more products.
- **Overall Insight:**
- Product ownership is one of the strongest churn predictors. **Two products = retention sweet spot**, while **three or more products signal high churn risk**.

# Investigating Churn by Active Membership Status

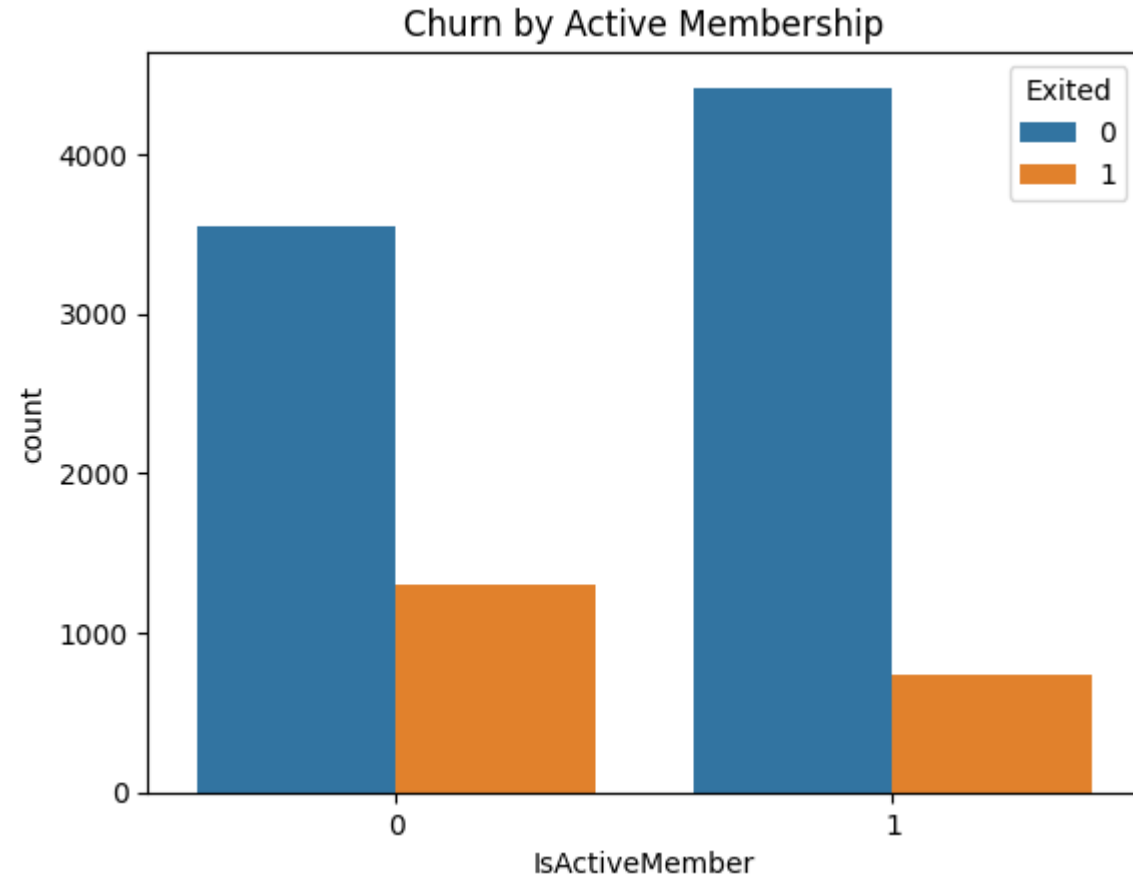
## Churn Rate Analysis

Comparing churn rates reveals how member activity impacts retention rates significantly.

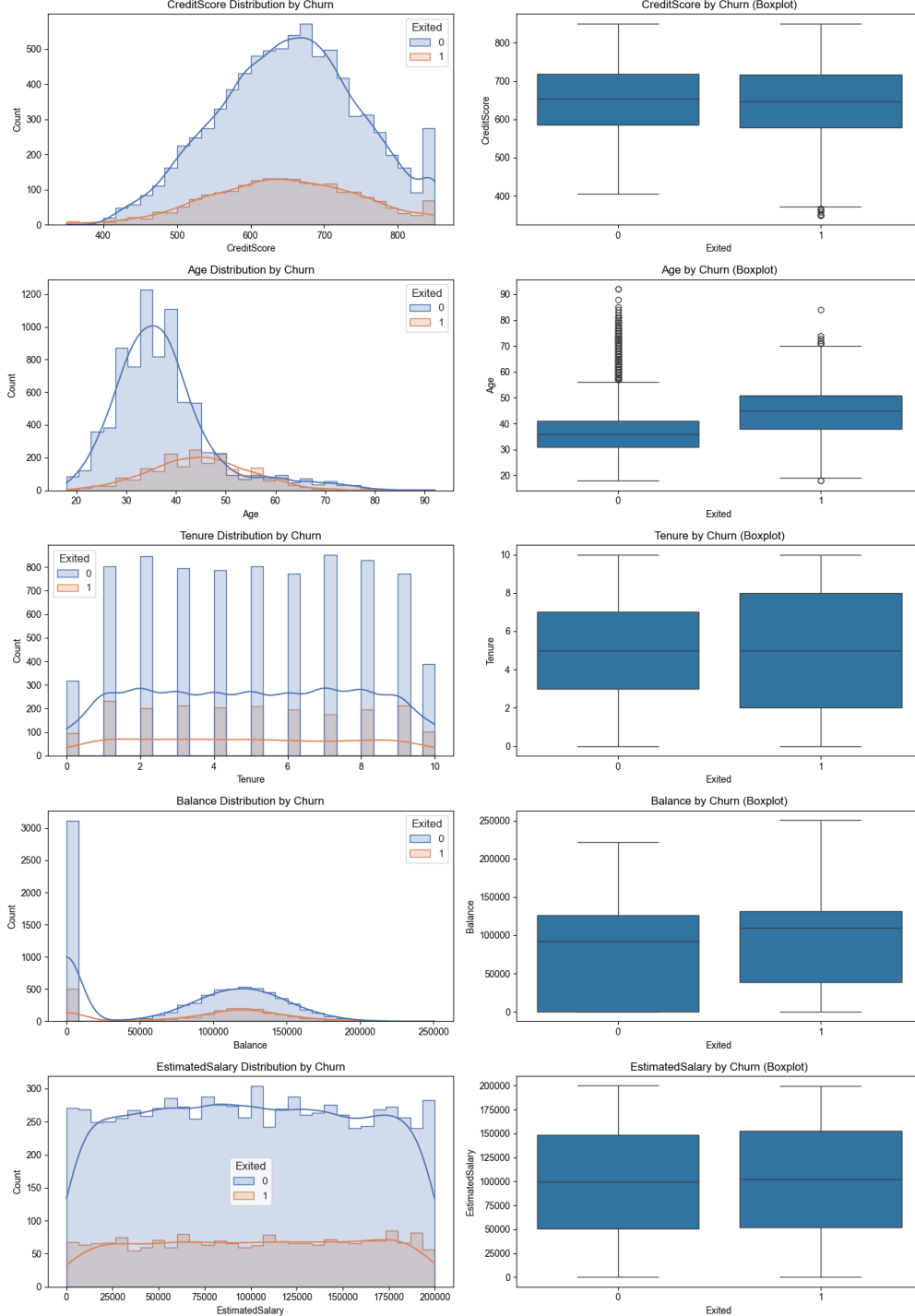
## Engagement and Retention

Higher engagement levels among active members strongly correlate with improved retention.

Insight: Inactive members churn at much higher rates.



# Numerical Feature Analysis to Identify Churn Patterns



# Age and Balance Correlations with Churn

## Age Impact on Churn

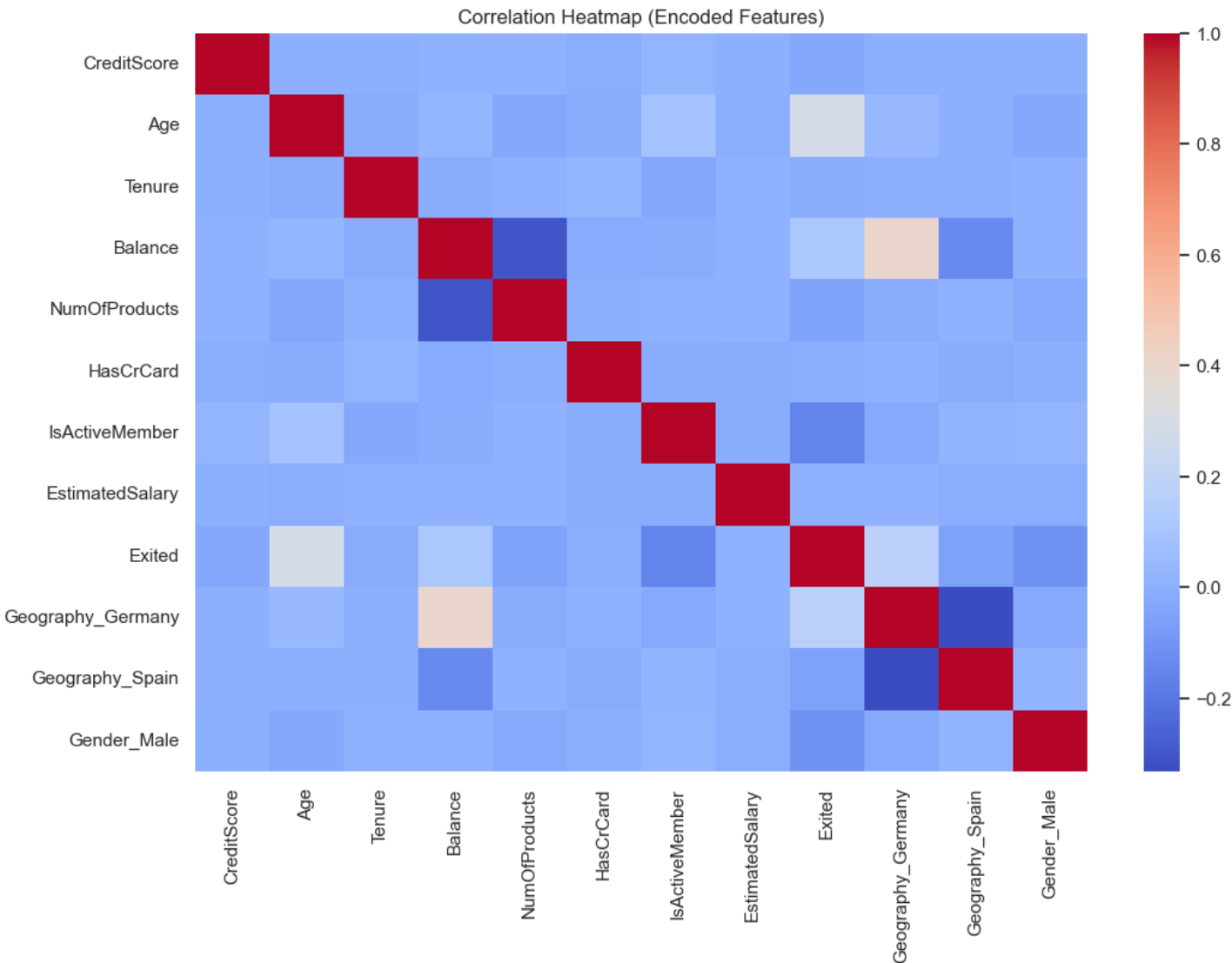
**Age** is a strong churn driver – older customers are more likely to leave.

## Account Balance Influence

**Balance** shows extremes: customers with very high balances churn more, but zero-balance customers are often retained.

## Combined Factors Analysis

**Credit score, tenure, and salary** have limited impact on churn.



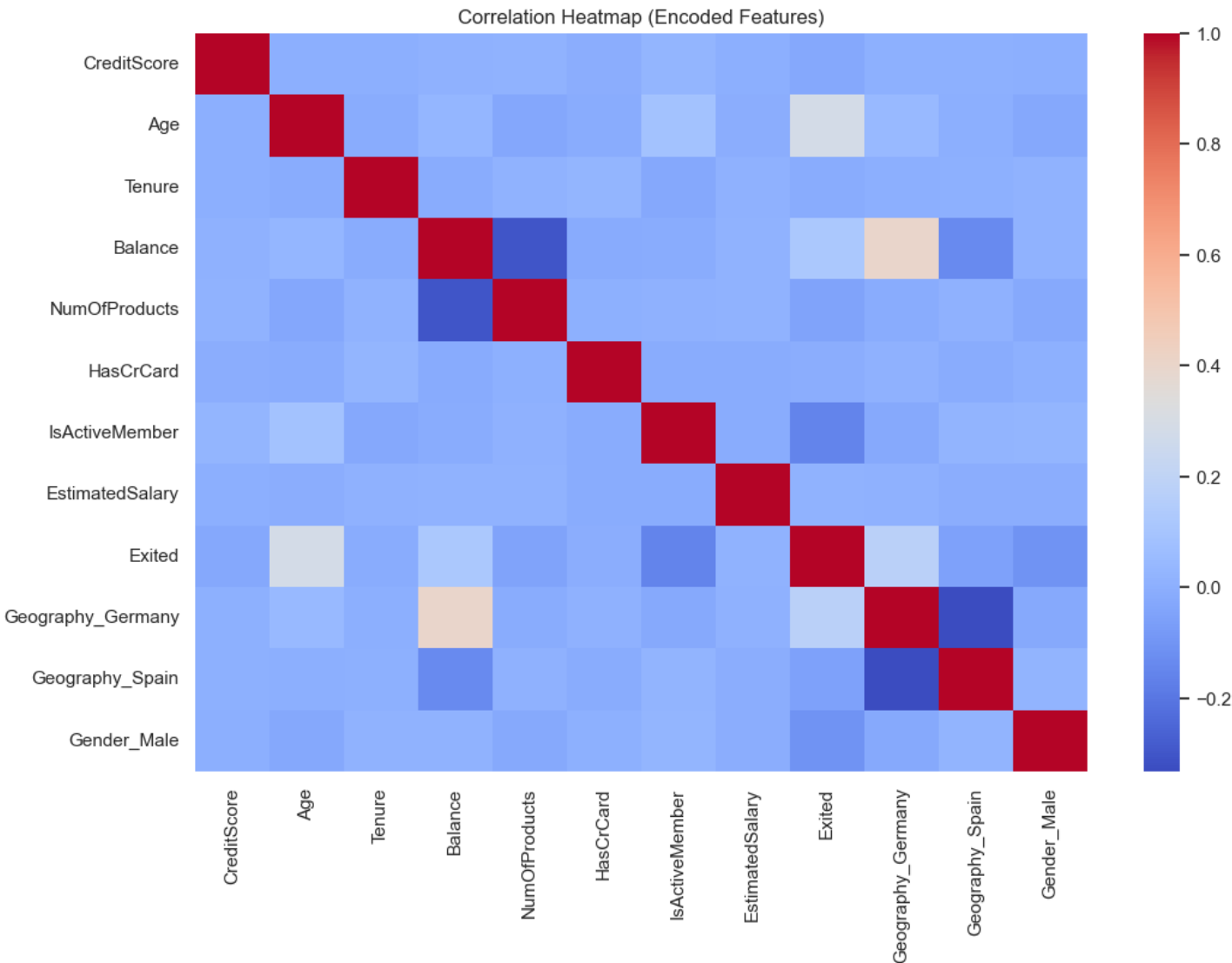
# Feature Relationships with Churn.

## Correlation Heatmap – Key Takeaways

- The heatmap highlights relationships between **customer attributes** and the **churn outcome (Exited)**.
- Age** shows a positive correlation with churn, confirming that **older customers are more likely to leave**.
- Balance** has a modest positive correlation with churn, suggesting that customers with higher account balances are more prone to exit.
- IsActiveMember** is negatively correlated with churn, meaning **active members are less likely to churn**, supporting earlier categorical insights.
- Number of Products** shows a negative correlation, but recall our earlier finding that churn rises again at 3–4 products, showing a **non-linear effect** not fully captured by correlation alone.
- Features like **CreditScore**, **Tenure**, and **EstimatedSalary** show very weak correlations with churn, indicating limited predictive value.
- Geography dummies (Germany, Spain) show clear relationships: **German customers are more likely to churn**, while French customers (the reference group) are least likely.
- Overall Insight:**  
The correlation heatmap reinforces that **age, activity status, geography, balance, and product ownership** are the most influential features, while others like credit score and salary contribute very little. This helps prioritize which factors to focus on in predictive modeling and business strategies.



# Key Drivers of Churn and Actionable Recommendations



## Top Predictive Features: Geography, Membership, Products, Age, Balance

### Key Drivers Identified in EDA

- **Geography** → German customers churn at much higher rates; French customers are least likely to churn.
- **Membership** → Inactive members are nearly twice as likely to leave compared to active members.
- **Number of Products** → Customers with **2 products churn the least**; churn spikes dramatically for those with **3+ products**.
- **Age** → Older customers show a clear trend toward higher churn.
- **Balance** → Higher account balances are modestly linked with churn; customers with **zero balances often remain loyal**.

### Overall Insight:

- Churn is most influenced by **customer demographics (age, geography)** and **behavioral factors (products, membership activity)**, while variables like credit score, tenure, and salary play a minimal role.



# Retention Strategies to Reduce Churn

## **Personalized Offers**

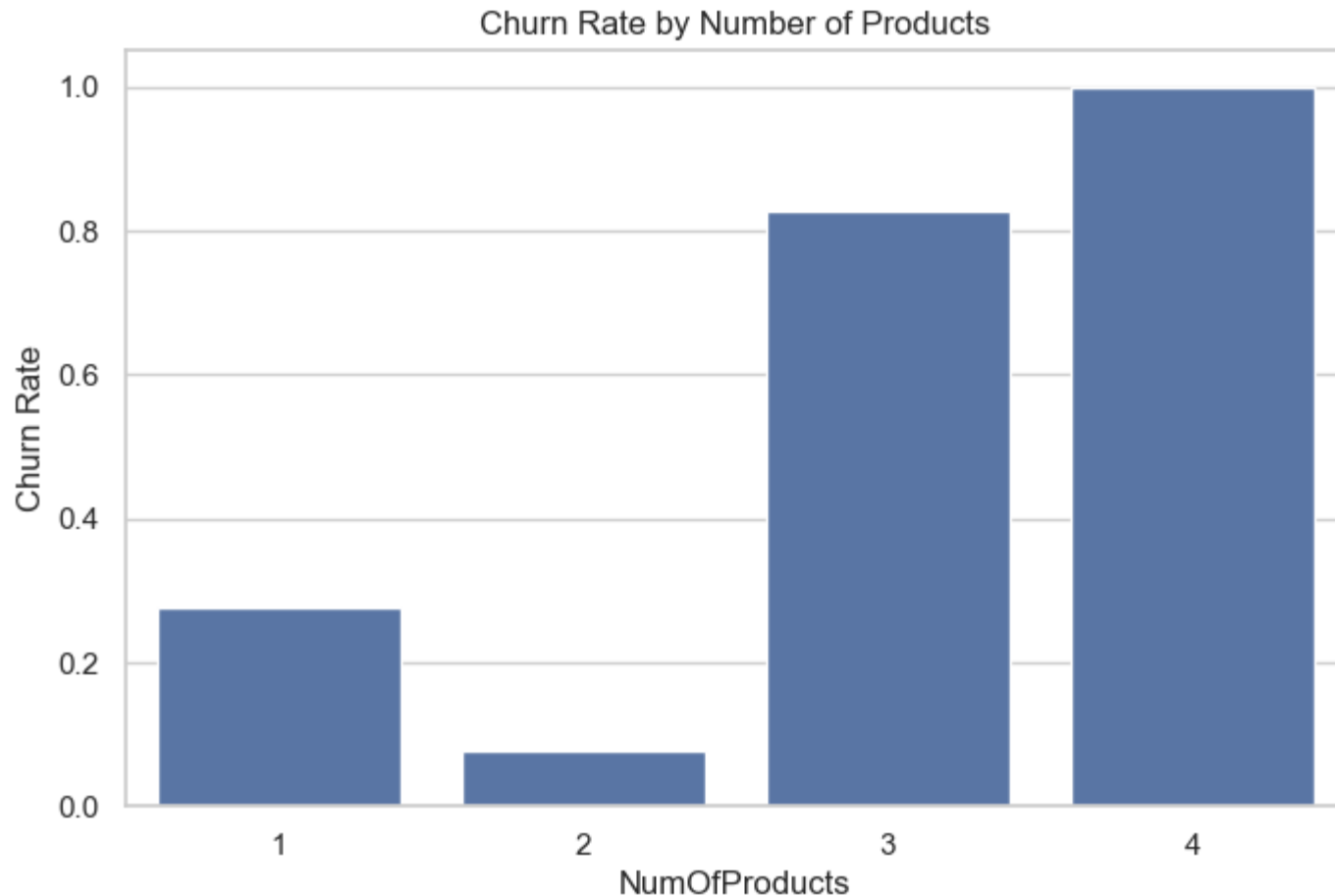
Tailoring offers to individual customer preferences increases satisfaction and reduces churn effectively.

## **Improved Customer Service**

High-quality and responsive customer support fosters loyalty and decreases customer attrition.

## **Enhanced Engagement**

Engaging customers through interactive communication channels strengthens relationships and lowers churn rates.



# Targeted Engagement for High-Risk Segments

## High-Risk Profiles to Address

- **Single-product customers:** More likely to churn; should be encouraged to adopt a second product through cross-sell offers.
- **3+ product customers:** Show extremely high churn; investigate dissatisfaction or product complexity driving exits.
- **Inactive members:** Engagement campaigns (loyalty rewards, reminders) can reduce churn.
- **Older, high-balance customers:** Proactive relationship management needed, as they represent valuable but vulnerable clients.

## Proactive Retention Strategy:

- By focusing on these **specific high-risk segments**, organizations can reduce churn more effectively than with one-size-fits-all strategies.

# Conclusion

## **Value of Data Insights**

Exploratory data analysis revealed clear churn drivers: geography, membership activity, product ownership, age, and balance. These insights provide a fact-based understanding of why customers leave.

## **Reducing Customer Churn**

By targeting inactive members, German customers, single-product holders, and older high-balance clients, organizations can design retention programs that directly address high-risk segments.

## **Driving Business Growth**

Focusing on churn reduction not only improves retention but also creates opportunities for cross-selling, stronger customer relationships, and long-term profitability. Data-driven decisions ensure strategies are both effective and scalable.