SQL Bank Customer Churn Analysis

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Introduction

Customer churn is one of the most pressing challenges facing the banking industry today. Even customers who appear to be low-risk, such as those with strong credit scores, high balances, or stable financial histories they still choose to leave their banks. This raises an important question: Why do even wealthy, low-risk customers churn?

The purpose of this project is to investigate the key drivers of customer churn through an SQL-based analysis. By leveraging a structured dataset, the project explores how different customer segments (by age, gender, geography, tenure, balance, and product usage) behave and which groups are most vulnerable to leaving.

The project not only focuses on identifying who is most likely to churn, but also why. Special attention is given to surprising insights, such as the churn of high-value customers, which challenges traditional assumptions about risk.

Through this analysis, the project aims to:

- Highlight patterns and behaviors linked to churn.
- Provide actionable insights that banks can use to improve retention strategies.
- Strengthen the link between raw SQL-driven findings and business decisions.

Ultimately, this introduction sets the stage for a deeper look into the data, the SQL techniques applied, and the strategic recommendations developed from the findings.

Table of Contents

Question 1

Are there any duplicate records

Why i did this

I ran this SQL query to check for duplicate records in the customers table by grouping the data based on customer_id and counting how many times each ID appears. This helps ensure data integrity, since each customer should only appear once in the dataset.

SQL query and answer

```
Query

SELECT customer_id,
       COUNT(*)
FROM customers
GROUP BY customer_id
HAVING COUNT(*) > 1

Output

customer_id COUNT(*)
0           0
```

Results interpretation and reccomandations

- The result showed no duplicate records, meaning the customer_id field contains only unique entries. This confirms that the dataset is clean and ready for accurate analysis without redundancy.

Reccomandations

- Keep Customer IDs Unique
- Make sure each customer has only one ID and no duplicates are added. Use rules in the database to stop duplicates from happening.

- Check for Duplicates Regularly
- Run this kind of check often, especially after adding a lot of new data, to catch any duplicates early.

- Be Careful with Data Sources
- Make sure all places where customer data comes from follow the same rules to avoid entering the same customer more than once.

- Write Down Data Rules
- Create a simple guide that explains customer IDs must be unique so everyone knows and follows the rule.

- Check for Other Data Problems
- Now that IDs are clean, look for other possible issues in the data, like missing details or old information, to make the data even better.

Question 2

Are there missing/null values in the dataset?

Why i did this

I ran this SQL query to check for missing or null values in key columns of the customers dataset. This step is important because missing data can affect the quality of analysis and lead to incorrect insights or broken machine learning models. The query helps ensure data completeness and reliability by identifying any gaps in crucial fields like credit_score, age, and churn.

SQL query and answer

Query

```sql
SELECT SUM(CASE
               WHEN credit_score IS NULL THEN 1
               ELSE 0
           END) AS missing_credit_score,
       SUM(CASE
               WHEN country IS NULL THEN 1
               ELSE 0
           END) AS missing_country,
       SUM(CASE
               WHEN gender IS NULL THEN 1
               ELSE 0
           END) AS missing_gender,
       SUM(CASE
               WHEN age IS NULL THEN 1
               ELSE 0
           END) AS missing_age,
       SUM(CASE
               WHEN tenure IS NULL THEN 1
               ELSE 0
           END) AS missing_tenure,
       SUM(CASE
               WHEN balance IS NULL THEN 1
               ELSE 0
           END) AS missing_balance,
       SUM(CASE
               WHEN products_number IS NULL THEN 1
               ELSE 0
           END) AS missing_products_number,
       SUM(CASE
               WHEN credit_card IS NULL THEN 1
               ELSE 0
           END) AS missing_credit_card,
       SUM(CASE
               WHEN active_member IS NULL THEN 1
               ELSE 0
           END) AS missing_active_number,
       SUM(CASE
               WHEN estimated_salary IS NULL THEN 1
               ELSE 0
           END) AS missing_estimated_salary,
       SUM(CASE
               WHEN churn IS NULL THEN 1
               ELSE 0
           END) AS missing_churn
FROM customers
```

Output

missing_credit_score	missing_country	missing_gender	missing_age	missing_tenure	missing_balance	missing_products_number
0	0	0	0	0	0	0

missing_credit_card	missing_active_number	missing_estimated_salary	missing_churn
0	0	0	0

Results interpretation and reccomandations

- The analysis revealed zero missing values across all examined columns, including critical features like credit_score, age, and churn.

  This confirms that:
- The dataset is complete with no null entries.
- No imputation or data cleaning for missing values is necessary.
- The dataset is suitable for accurate statistical analysis and machine learning without the risk of bias from missing data.

Recommendations

- Maintain Data Completeness that is continue enforcing database constraints (e.g., NOT NULL) for important fields.
- Regularly Monitor Data Quality that is schedule automated checks for missing values after each new data load.
- Validate Input Forms that is ensure data entry interfaces require mandatory fields before submission.
- Document Data Collection Rules that is create and share a clear guide on required fields for all data sources.
- Prepare for Real-Time Data Expansion that is as new columns are added in the future, include them in the missing value check to maintain integrity.

Question 3

What is the schema of the table (columns & data types)?

Why i did this

I used the DESCRIBE customers query to view the schema of the table, including each column’s name, data type, whether it allows NULL values, and whether it’s a primary key or has auto-increment.

Understanding the schema is important because it:

Helps you know what kind of data each column holds (e.g, numbers, text, boolean).

Ensures I use the correct formats in queries.

Guides data validation, cleaning, and modeling decisions.

SQL query and answer

Query

```sql
DESCRIBE customers
```

Output

Field	Type	Null	Key	Default	Extra
customer_id	int unsigned	NO	PRI	NULL	auto_increment
credit_score	int	YES		NULL	
country	varchar(100)	YES		NULL	
gender	enum('Male','Female')	YES		NULL	
age	int	YES		NULL	
tenure	int	YES		NULL	
balance	decimal(12,2)	YES		NULL	
products_number	int	YES		NULL	
credit_card	tinyint(1)	YES		NULL	
active_member	tinyint(1)	YES		NULL	
estimated_salary	decimal(12,2)	YES		NULL	
churn	tinyint(1)	YES		NULL	

Results interpretation and reccomandations

The customers table schema reveals:

- Primary Key: customer_id is the unique identifier, set to auto-increment, ensuring each customer record is distinct.

Data Types:

- Numeric fields such as credit_score, age, balance, and estimated_salary are stored in appropriate integer or decimal formats.
- Categorical data like country and gender use VARCHAR and ENUM respectively, ensuring controlled text inputs.
- Boolean flags (e.g., credit_card, active_member, churn) use TINYINT(1) for efficiency.
- Nullability: Most fields allow NULL values, meaning some data could be missing unless validated at entry.
- The design supports both numerical and categorical analysis while optimizing storage through efficient data types.

Recommendations

- Enforce NOT NULL for Critical Fields, that is columns like credit_score, country, age, and churn are essential for analytics, consider making them NOT NULL to prevent incomplete records.
- Standardize Data Entry Rules, that is for country and gender, ensure consistent values are entered (e.g., avoid typos like "Male" vs "male").
- Document Schema for Analysts, that is maintain a schema reference so that data analysts and developers can write queries without guessing data types.
- Optimize ENUM and Categorical Fields, that is keep ENUM lists updated to include any new gender options or country codes if dataset scope expands.
- Review Decimal Precision, that is ensure decimal(12,2) for balance and estimated_salary matches reporting needs without unnecessary storage size.

Question 4

What is the overall churn rate

Why i did this

This helps us:
Understand how well the company is retaining customers.
Identify if churn is high and may need further analysis or intervention.
Set a benchmark for tracking improvements over time.

SQL query and answer

```
Query

SELECT COUNT(*) AS total_customers,
       SUM(churn) AS churned_customers,
       ROUND(SUM(churn) * 100.0 / COUNT(*), 2) AS churn_rate
FROM customers

Output

total_customers churned_customers   churn_rate
10000           2037                20.37
```

Results interpretation and reccomandations

Metric	Value	Interpretation
Total Customers	10,000	This is the total customer base in the dataset.
Churned Customers	10,000	About **2,037 customers have left** the company.
Churn Rate	20.37%	Roughly **1 in 5 customers is leaving**. This is a moderately high churn rate depending on industry benchmarks.

Recommendations

- Segment Analysis: Break down churn by age, gender, tenure, or region to identify high-risk groups.
- Investigate Churn Drivers: Examine service complaints, usage patterns, and competitor influence to understand why customers leave.
- Retention Strategies: Implement loyalty programs, targeted promotions, and personalized communications.
- Monitor Trends: Track churn over time to evaluate effectiveness of interventions.
- Predictive Analytics: Consider building models to identify customers at high risk of leaving and focus retention efforts on them.

Question 5

What is the churn rate by gender?

Why i did this

This helps us:

- Identify if a specific gender group is leaving more often.
- Tailor retention strategies based on gender-specific needs or behaviors.
- Gain insights for targeted marketing or customer service improvements.

SQL query and answer

```
Query

SELECT gender,
       COUNT(*) AS total_customers,
       SUM(churn) AS churned_customers,
       ROUND(SUM(churn) * 100.0 / COUNT(*), 2) AS churn_rate
FROM customers
GROUP BY gender

Output

gender  total_customers churned_customers   churn_rate
Female  4543            1139                25.07
Male    5457            898                 16.46
```

Results interpretation and reccomandations

- Female Customers: 4,543 total, 1,139 churned → Churn Rate: 25.07%
- Male Customers: 5,457 total, 898 churned → Churn Rate: 16.46%
- Summary: Female customers are leaving at a significantly higher rate than male customers (25.07% vs 16.46%). This indicates a gender-related difference in retention that may require targeted strategies.

Recommendations

- Investigate Female Churn Drivers: Analyze purchasing patterns, complaints, or engagement levels to understand why more female customers are leaving.
- Tailored Retention Programs: Develop gender-specific loyalty initiatives, promotions, or communication strategies aimed at female customers.
- Customer Feedback: Conduct surveys or focus groups with female customers to identify pain points or unmet needs.
- Monitor Trends by Gender: Track churn over time separately for males and females to measure the impact of interventions.
- Targeted Marketing: Customize marketing campaigns and offers based on the preferences and behaviors of each gender group.

Question 6

What is the churn rate by country?

Why i did this

This helps us:

- Identify countries with higher churn risks.
- Understand if location-specific factors are affecting customer retention.
- Tailor marketing, support, or product strategies by region.
- Provide actionable insights to improve services in countries with high churn.

SQL query and answer

Query

```sql
SELECT country,
       COUNT(*) AS total_customers,
       SUM(churn) AS churned_customers,
       ROUND(SUM(churn) * 100.0 / COUNT(*), 2) AS churn_rate
FROM customers
GROUP BY country
```

Output

country	total_customers	churned_customers	churn_rate
Spain	2477	413	16.67
France	5014	810	16.15
Germany	2509	814	32.44

Results interpretation and reccomandations

- Spain: 2,477 total customers, 413 churned → Churn Rate: 16.67%
- France: 5,014 total customers, 810 churned → Churn Rate: 16.15%
- Germany: 2,509 total customers, 814 churned → Churn Rate: 32.44%
- Summary: Germany has a significantly higher churn rate compared to Spain and France, indicating location-specific retention challenges that need urgent attention.

Recommendations

- Investigate Germany's Churn Drivers: Examine factors such as customer service quality, product issues, pricing, or competitive pressures unique to Germany.
- Tailored Retention Strategies: Implement targeted campaigns, loyalty programs, or promotions for Germany customers to reduce churn.
- Customer Feedback: Collect feedback from German customers to understand pain points or unmet needs.
- Regional Marketing & Support: Adjust marketing messaging, support channels, or product offerings to better suit the German market.
- Monitor Country-Level Trends: Track churn trends over time for each country to measure the effectiveness of interventions and adjust strategies accordingly.

Question 7

Does balance level impact churn?

Why i did this

- To understand the range of balances in my dataset and identify the highest balance.
- This helps define appropriate balance groups and understand customer segmentation (e.g, what qualifies as "very high" balance).
- The highest balance is 250,898.09, which justifies my final balance tier being above 250,000.

SQL query and answer

```
## We need to define maximum balance first then run our main query.

Query

SELECT MAX(balance) AS maximum_balance
FROM customers

Output

maximum_balance
250898.09

Query

SELECT COUNT(*) AS total_customers,
       balance_group,
       SUM(churn) AS total_churn,
       ROUND(SUM(churn) * 100.0 / COUNT(*), 2) AS churn_rate
FROM
  (SELECT CASE
              WHEN balance = 0 THEN 'no_balance'
              WHEN balance < 50000 THEN 'low'
              WHEN balance BETWEEN 50000 AND 150000 THEN 'medium'
              WHEN balance BETWEEN 150001 AND 250000 THEN 'high'
              ELSE 'very_high'
          END AS balance_group,
          churn
   FROM customers) AS grouped_data
GROUP BY balance_group;

Output

total_customers balance_group   total_churn churn_rate
968             high            223         23.04
3617            no_balance      500         13.82
5339            medium          1287        24.11
75              low             26          34.67
1               very_high       1           100
```

Results interpretation and reccomandations

- No-Balance Customers (3,617 total): 500 churned → Churn Rate: 13.82%
  Lowest churn among main groups, suggesting relative stability.
- Low-Balance Customers (<50,000, 75 total): 26 churned → Churn Rate: 34.67%
  Highest churn among typical groups, indicating this segment is most at risk.
- Medium-Balance Customers (50,000–150,000, 5,339 total): 1,287 churned → Churn Rate: 24.11%
  Moderate churn rate, still significant and requires attention.
- High-Balance Customers (150,001–250,000, 968 total): 223 churned → Churn Rate: 23.04%
  Similar to medium balance, indicating some retention issues.
- Very High-Balance Customers (>250,000, 1 total): 1 churned → Churn Rate: 100%
  Outlier, but highlights that even high-value customers can churn if dissatisfied.
- **Key Insigh**t: Lower balance levels correlate with higher churn, while very high balances, though rare, can also leave if expectations aren’t met.

Recommendations

- Target Low-Balance Customers: Offer incentives, loyalty rewards, and personalized communication to increase engagement.
- Engage Medium- and High-Balance Customers: Focus on proactive customer support and satisfaction monitoring.
- Monitor Very High-Balance Customers: Provide exceptional service and personalized attention to prevent loss.
- Segmented Retention Strategies: Tailor marketing, offers, and service based on balance tiers.
- Predictive Modeling: Use balance along with other factors to identify high-risk customers and focus retention efforts.

Question 8

Does credit score affect churn?

Why i did this

- I performed this analysis to investigate whether there's a relationship between customers' credit scores and their likelihood to churn.

Understanding this relationship can help the business:

- Identify at-risk customers based on financial profiles.
- Improve retention strategies by focusing more on customer segments with higher churn risk.
- Personalize communication or offers for customers with low credit scores to reduce churn.
- Build predictive models that include credit score as a potential churn predictor.

SQL query and answer

```
Query

SELECT CASE
           WHEN credit_score < 600 THEN 'Very Low'
           WHEN credit_score BETWEEN 600 AND 700 THEN 'Low'
           WHEN credit_score BETWEEN 700 AND 800 THEN 'Average'
           ELSE 'High'
       END AS credit_score_group,
       COUNT(*) AS total,
       SUM(churn) AS churned,
       ROUND(SUM(churn) * 100.0 / COUNT(*), 2) AS churn_rate
FROM customers
GROUP BY credit_score_group;

Output

credit_score_group  total   churned churn_rate
Low                 3850    758     19.69
Average             2471    492     19.91
Very Low            3034    660     21.75
High                645     127     19.69
```

Results interpretation and reccomandations

- Very Low Credit Score (<600): 21.75% churn — highest among all groups, showing slightly higher risk.
- Low Credit Score (600–700): 19.69% churn — similar to high and average scores.
- Average Credit Score (700–800): 19.91% churn — slightly higher than low score, but still in the same range.
- High Credit Score (>800): 19.69% churn — tied with low score for lowest churn rate.
- Overall Insight: Credit score has only a modest effect on churn; customers with very low scores are marginally more likely to leave, but differences between other groups are minimal.

Recommendations

- Focus on Very Low Credit Score Segment:
  Offer financial coaching, flexible repayment plans, and loyalty incentives to reduce churn risk.
- Monitor Credit Score Trends:
  Track customers whose credit score is dropping into the very low range and proactively engage them.
- Integrate with Other Factors:
  Combine credit score with other churn predictors (e.g., account balance, tenure, product usage) for better targeting.
- Personalize Retention Offers:
  Provide tailored offers to financially vulnerable customers to strengthen loyalty.
- Educate Customers:
  Run awareness programs on managing finances and maintaining healthy credit scores.

Question 9

Do customers with more products churn less?

Why i did this

- I ran this analysis to understand how the number of products a customer uses relates to their likelihood of churning. The goal was to:
- Identify whether product engagement (measured by number of products) influences retention.
- Help the business spot risk patterns e.g., if customers with only one product are more likely to leave.
- Support cross-sell or upsell strategies by showing that customers with more products may be more loyal or, conversely, if they’re not.

SQL query and answer

```
Query

SELECT products_number,
       COUNT(*) AS total,
       SUM(churn) AS churned,
       ROUND(SUM(churn) * 100.0 / COUNT(*), 2) AS churn_rate
FROM customers
GROUP BY products_number;

Output

products_number total   churned churn_rate
1               5084    1409    27.71
2               4590    348     7.58
3               266     220     82.71
4               60      60      100
```

Results interpretation and reccomandations

- Customers with 1 product have a relatively high churn rate (27.71%), suggesting lower engagement leads to higher attrition.
- Customers with 2 products show a very low churn rate (7.58%), indicating strong retention when moderate product engagement exists.
- Customers with 3 products have an extremely high churn rate (82.71%), suggesting possible dissatisfaction or overextension.
- Customers with 4 products churn 100% of the time, which may indicate they are closing all accounts or switching providers entirely.
- Overall, retention seems strongest when customers have 2 products, while both very low and very high product counts are linked to higher churn.

Recommendations

- Upsell single-product customers to at least 2 products through targeted offers or bundled benefits.
- Investigate 3+ product customers to identify why churn is so high — this could be due to service dissatisfaction, better competitor offers, or product complexity.
- Review account closure processes for high-product customers to understand whether churn is voluntary or triggered by life events (e.g., relocation, business closure).
- Consider loyalty programs or exclusive perks for multi-product customers to encourage long-term retention.

Question 10

Which combination of features has the highest churn?

Why i did this

- I wanted to dig deeper than just one feature and see which customer groups, based on country, gender, and number of products, are most likely to churn.
- This helps us figure out exactly who to focus on to reduce churn and improve retention strategies.This combination helps uncover patterns across demographic and behavioral segments, so we can:
- Target high-risk customer groups more precisely.
- Understand which profiles are consistently leaving, especially those with extreme churn rates.
- Prioritize retention efforts based on the characteristics of customers most likely to churn.
- Support product or policy review — for example, why are customers with 3 or 4 products churning at such high rates?

SQL query and answer

Query

```sql
SELECT country,
       gender,
       products_number,
       COUNT(*) AS total,
       SUM(churn) AS churned,
       ROUND(SUM(churn) * 100.0 / COUNT(*), 2) AS churn_rate
FROM customers
GROUP BY country,
         gender,
         products_number
ORDER BY churn_rate DESC
LIMIT 10
```

Output

country	gender	products_number	total	churned	churn_rate
Spain	Male	4	2	2	100
France	Male	4	10	10	100
Germany	Male	4	10	10	100
France	Female	4	19	19	100
Germany	Female	4	14	14	100
Spain	Female	4	5	5	100
Germany	Male	3	43	40	93.02
France	Female	3	55	48	87.27
Germany	Female	3	53	46	86.79
Spain	Female	3	41	35	85.37

Results interpretation and reccomandations

- Customers with 4 products in all countries and genders have a 100% churn rate — highly unusual and likely tied to account closure policies or product-related issues.
- Customers with 3 products also have very high churn rates (85–93%), especially in Germany and France.
- High churn in these groups contradicts the assumption that more products = higher loyalty.
- The pattern suggests specific combinations of products and demographics are driving churn rather than the total number of products alone.
- Country and gender appear to be secondary factors — the number of products is the dominant churn driver here, but the issue is amplified in certain markets (Germany, France, Spain).

Recommendations

- Investigate the 4-product group immediately — determine if these accounts are part of a closure process, low-usage group, or impacted by product design flaws.
- Review product bundling strategy — assess whether having multiple products creates complexity, dissatisfaction, or cost concerns for customers.
- Target retention efforts for 3-product customers in Germany and France with tailored incentives, reviews of account usage, and personalised engagement.
- Conduct customer exit interviews or surveys to pinpoint the exact reason for high churn among these high-product-count segments.
- Test alternative product packages to reduce friction — simplify offerings, remove overlapping features, and ensure pricing is competitive.

Question 11

How does tenure (years as a customer) affect churn?

Why i did this

- I conducted this analysis to understand how the length of time a customer has been with the company (tenure) affects their likelihood of churning.
- The goal was to:
- Identify trends over the customer lifecycle that, do new customers churn more? Do long-term customers stay loyal?
- Inform targeted retention strategies based on customer tenure.
- Support lifecycle marketing efforts (e.g., onboarding, mid-term engagement, loyalty programs)

SQL query and answer

Query

```sql
SELECT tenure,
       COUNT(*) AS total,
       SUM(churn) AS churned,
       ROUND(SUM(churn) * 100.0 / COUNT(*), 2) AS churn_rate
FROM customers
GROUP BY tenure
```

Output

tenure	total	churned	churn_rate
0	413	95	23
1	1035	232	22.42
2	1048	201	19.18
3	1009	213	21.11
4	989	203	20.53
5	1012	209	20.65
6	967	196	20.27
7	1028	177	17.22
8	1025	197	19.22
9	984	213	21.65
10	490	101	20.61

Results interpretation and reccomandations

- New customers (0–1 years) have the highest churn rates (23% and 22.42%).
- Indicates a critical onboarding and early engagement gap — customers may not see enough value quickly or face friction using products/services.
- Years 2–7 show a steady churn decline, bottoming at 17.22% in year 7.
- Suggests that customers who stay past the first year are more committed, have integrated services into their routines, and built trust.
- Post–year 7 churn rises slightly (to 19–21%), though still lower than early years.
- Possible signs of relationship fatigue — long-term customers may feel taken for granted or tempted by competitors.
- Overall trend: The first 12 months are the most vulnerable period for customer loss; mid-tenure customers are the most loyal.

Recommendations

- Strengthen onboarding (0–1 year customers)
- Provide proactive welcome calls, tutorials, and follow-ups in the first 90 days.
- Offer incentives for continued engagement (e.g., bonus points, free upgrades).
- Mid-tenure engagement (2–7 years)
- Maintain value delivery through regular product updates, personalised offers, and loyalty rewards to keep satisfaction high.
- Reignite long-term customers (7+ years)
- Launch “VIP re-engagement campaigns” with exclusive perks, anniversary rewards, and personalised check-ins to prevent drift.
- Ongoing churn monitoring
- Set up alerts for activity drop-offs, especially in the 0–1 year and 7+ year segments.
- Leverage tenure-based segmentation in marketing
- Create tailored lifecycle campaigns that address specific needs and risks at each stage.

Question 12

Which customers with a high credit score and high balance still churned?

Why i did this

- To uncover unexpected churn, that is finding those customers who seem happy having high credit scores and lots of money but still left the bank.
- The analysis may signal deeper problems, maybe these good customers left because of their bad experience with the bank such as poor customer service, higher fees and lack of loyalty rewards and this will reveal that churn is not only about money or risk.
- The analysis may also help the bank to take action such as investigating their complaints and creating loyalty programs.

SQL query and answer

Query

```sql
SELECT *
FROM customers
WHERE churn = 1
  AND credit_score > 800
  AND balance > 100000
LIMIT 10
```

Output

customer_id	credit_score	country	gender	age	tenure	balance	products_number	credit_card	active_member	estimated_salary	churn
15571415	805	Germany	Male	56	6	151802.29	1	1	0	46791.09	1
15571778	817	France	Female	55	10	117561.49	1	1	0	95941.55	1
15577999	850	France	Female	62	1	124678.35	1	1	0	70916	1
15584113	823	Germany	Female	53	4	124954.94	1	0	1	131259.6	1
15584620	850	Germany	Female	36	6	143644.16	1	1	0	22102.25	1
15585287	842	Germany	Female	35	9	119948.09	1	1	0	48217.97	1
15587647	850	Germany	Female	66	0	127120.62	1	0	1	118929.64	1
15591698	849	Germany	Female	49	9	132934.89	1	1	0	171056.65	1
15593782	816	Germany	Female	38	5	130878.75	3	1	0	71905.77	1
15602010	850	Germany	Female	45	5	103909.86	1	1	0	60083.11	1

Results interpretation and reccomandations

- Majority of these high-credit, high-balance churners are female.
- Most come from Germany, suggesting a possible country-specific issue.
- Product engagement is low — many hold only one product, indicating weak relationship depth.
- Credit card ownership is common, yet it’s not preventing churn.
- Active membership is low, pointing to low interaction or engagement with the bank.

Recommendations

- Investigate service satisfaction and product offerings in Germany, particularly for female customers.
- Create bundled product incentives to encourage multi-product ownership and deeper engagement.
- Develop exclusive loyalty programs for high-balance customers to increase perceived value.
- Target inactive high-value customers with personalized outreach to re-engage them.
- Monitor and improve customer experience touchpoints beyond financial metrics like credit score and balance.

Thank you very much!