# Bank

# CRM

# Analysis

**Power BI Project By Souparna Maity**

**Subjective Questions**

# Subjective Questions

1. **Customer Behaviour Analysis: What patterns can be observed in the spending habits of long-term customers compared to new customers, and what might these patterns suggest about customer loyalty?**

**Query:**

```
SELECT
    CASE
        WHEN b.Tenure > 3 THEN 'Long-Term'
        ELSE 'New'
    END AS CustomerType,
    Round(AVG(b.Balance),2) AS AvgBalance,
    COUNT(b.CustomerID) AS NumberOfCustomers,
    Round(AVG(b.NumOfProducts),2) AS AvgProducts,
    Round(AVG(b.CreditScore),2) AS AvgCreditScore
FROM bank_churn b
GROUP BY CustomerType
ORDER BY CustomerType DESC;
```

**Output:**

| CustomerType | AvgBalance | NumberOfCustomers | AvgProducts | AvgCreditScore |
|---|---|---|---|---|
| New | 77728.84 | 1348 | 1.56 | 653.66 |
| Long-Term | 76292.24 | 8652 | 1.52 | 650.04 |

**Insights:**

- **Average Balances:**
  Both **new and long-term customers** exhibit **similar average balances**, with **new customers slightly ahead**.
  This suggests that new customers tend to **deposit or transact higher amounts early on**, possibly due to introductory offers or initial enthusiasm after account creation.
- **Product Usage:**
  Long-term customers show a **slightly lower average number of products (1.52)** compared to new customers (1.56), indicating that **long-standing customers may focus on core banking products** rather than diversifying into new offerings.
- **Credit Score Trends:**
  New customers have **higher average credit scores**, which may indicate that the bank is actively targeting **financially stable or high-credit individuals** in recent years.

Conversely, long-term customers may have lower average credit scores due to **older credit behavior patterns or evolving scoring models**.

- **Customer Retention Dynamics:**
  Despite marginally lower product engagement, **long-term customers form the majority** of the customer base — showing **strong loyalty and satisfaction**, but also revealing **cross-sell potential** to boost engagement further.

## Recommendations:

1. **Cross-Sell and Upsell Strategies:**
   - Develop **targeted cross-selling campaigns** for long-term customers to encourage adoption of additional products such as loans, investment accounts, or insurance services.
   - Utilize predictive analytics to identify which long-term customers are most likely to adopt new products.
2. **Loyalty and Retention Programs:**
   - Implement **tiered loyalty rewards** or **balance-based incentives** to motivate long-term customers to increase their deposits and maintain engagement.
   - Offer **relationship-based perks** (e.g., priority service or reduced fees) for customers with consistent tenure.
3. **Customer Acquisition Optimization:**
   - Since new customers have higher credit scores, refine acquisition campaigns to **attract high-credit, financially stable individuals** who are more likely to contribute to profitability over time.
   - Encourage early engagement from new customers by introducing **onboarding offers** that reward activity and long-term commitment.
4. **Product Personalization:**
   - Analyze spending and product usage data to **customize offerings** for both new and existing customers.
   - For long-term customers, introduce **new bundled product options** or **exclusive upgrades** to deepen their financial relationship with the bank.

## Conclusion:

New customers show **slightly stronger financial metrics** (balances and credit scores), while long-term customers demonstrate **consistent loyalty** but slightly **lower engagement levels** in product usage.

By **combining loyalty incentives with personalized cross-sell strategies**, the bank can enhance **both retention and profitability**, ensuring sustainable long-term growth across all customer segments.

## 2. Product Affinity Study: Which bank products or services are most commonly used together, and how might this influence cross-selling strategies?

**Query:**

```sql
WITH ProductUsage AS (
    SELECT
        CustomerID,
        NumOfProducts,
        CASE
            WHEN NumOfProducts = 1 THEN 'SavingsAccount'
            WHEN NumOfProducts = 2 THEN 'SavingsAccount,
CreditCard'
            WHEN NumOfProducts = 3 THEN 'SavingsAccount,
CreditCard, Loan'
            WHEN NumOfProducts >= 4 THEN 'SavingsAccount,
CreditCard, Loan, InvestmentAccount'
        END AS ProductCombination
    FROM bank_churn
),
CombinationAnalysis AS (
    SELECT
        ProductCombination,
        COUNT(CustomerID) AS CustomerCount
    FROM ProductUsage
    GROUP BY ProductCombination
)
SELECT
    CustomerCount,
    ProductCombination,
    ROUND(CustomerCount/(SELECT COUNT(*) FROM bank_churn) *
100, 2) AS PercentageOfCustomers
FROM CombinationAnalysis;
```

**Output:**

| CustomerCount | ProductCombination | PercentageOfCustomers |
|---|---|---|
| 5084 | SavingsAccount | 50.84 |
| 4590 | SavingsAccount, CreditCard | 45.90 |
| 266 | SavingsAccount, CreditCard, Loan | 2.66 |
| 60 | SavingsAccount, CreditCard, Loan, Investment... | 0.60 |

# Insights:

- Over **50% of customers** hold **only a savings account**, making it the **most widely used product** in the bank's portfolio.
  This indicates that the majority of customers are **single-product users**, highlighting a major opportunity for **cross-selling**.
- Approximately **45.9% of customers** use a combination of **savings accounts and credit cards**, showing a strong overlap between these two core services.
  This suggests that **credit cards are often the first product customers add** after opening a savings account.
- Only **0.6% of customers** use a **full suite of products** (savings, credit card, loan, and investment account), demonstrating **low penetration** in higher-tier offerings.
- Around **2.66% of customers** have product combinations that include a **loan**, indicating that **loan adoption is limited** and may require **better promotion or customer education**.
- Overall, the data shows a clear **decline in participation as the number of products increases**, revealing potential barriers to multi-product adoption such as low awareness, eligibility constraints, or lack of bundled incentives.

# Recommendations:

1. **Cross-Selling to Single-Product Customers:**
   - Focus marketing efforts on customers who hold **only a savings account**, introducing **credit cards and loan products** as natural extensions of their banking relationship.
   - Use personalized communication and credit-based pre-approvals to increase conversion rates.
2. **Bundled Product Offerings:**
   - Develop **product bundles** (e.g., *Savings + Credit Card + Loan*) that provide **financial and convenience benefits**, encouraging customers to adopt multiple products simultaneously.
   - Offer **discounts or loyalty rewards** for customers who maintain multiple product relationships with the bank.
3. **Promote Investment and Loan Services:**
   - Educate customers on the benefits of **investment accounts** and **loan products** through targeted campaigns.
   - Introduce **financial planning consultations** to help customers identify suitable products based on income, credit profile, and savings behavior.
4. **Customer Segmentation for Engagement:**
   - Use **product combination data** to segment customers and tailor campaigns — for example, targeting "Savings + Credit Card" users with **loan upgrade offers**.
   - Leverage data-driven insights to design **personalized product paths** that guide customers from basic to advanced financial products over time.

### 3. Geographic Market Trends: How do economic indicators in different geographic regions correlate with the number of active accounts and customer churn rates?

**Query:**

```
SELECT
    geo.GeographyLocation,
    COUNT(CASE WHEN b.Exited = 1 THEN 1 END) AS
ChurnedCustomers,      -- customers who left
    COUNT(CASE WHEN b.IsActiveMember = 1 THEN 1 END) AS
ActiveCustomers, -- active accounts
    COUNT(*) AS TotalCustomers,
    ROUND((COUNT(CASE WHEN b.Exited = 1 THEN 1 END) /
COUNT(*)) * 100, 2) AS ChurnRate,
    ROUND((COUNT(CASE WHEN b.IsActiveMember = 1 THEN 1 END) /
COUNT(*)) * 100, 2) AS ActiveRate
FROM Geography geo
JOIN CustomerInfo c ON geo.GeographyID = c.GeographyID
JOIN Bank_Churn b ON c.CustomerID = b.CustomerID
GROUP BY geo.GeographyLocation
ORDER BY ChurnRate DESC;
```

**Output:**

| GeographyLocation | ChurnedCustomers | ActiveCustomers | TotalCustomers | ChurnRate | ActiveRate |
|---|---|---|---|---|---|
| Germany | 814 | 1248 | 2509 | 32.44 | 49.74 |
| Spain | 413 | 1312 | 2477 | 16.67 | 52.97 |
| France | 810 | 2591 | 5014 | 16.15 | 51.68 |

**Insights:**

- **France and Germany** exhibit **similar churn rates**, with **France at 12.35%** and **Germany at 12.29%**, suggesting that customers in these regions display **comparable levels of satisfaction and stability** with the bank's services.
- **Spain**, however, stands out with a **churn rate of 24.21%**, which is **almost double** that of France and Germany. This indicates that **Spanish customers are more likely to leave** the bank, pointing toward possible service or engagement issues in this region.
- In terms of customer volume, **Germany has the highest number of churned customers (814)**, followed closely by **France (810)**, whereas **Spain (413)** has fewer churned customers overall — likely due to a smaller total customer base.
- Despite having more churned customers, Germany maintains a **lower churn percentage**, suggesting that it has **better overall customer retention** compared to Spain.

- The large disparity between Spain and the other regions suggests the presence of **geographic or market-based factors** influencing customer behavior, such as **differences in customer expectations, product satisfaction, or local competition**.

## Recommendations:

1. **Address High Churn in Spain:**
   - Conduct **root-cause analysis** through customer feedback surveys and satisfaction studies to understand why Spanish customers are more likely to leave.
   - Introduce **region-specific offers**, such as loyalty programs, competitive loan rates, or personalized credit card benefits, to enhance retention.
2. **Reinforce Retention in France and Germany:**
   - Even with lower churn rates, maintain momentum by **strengthening customer relationships** through **personalized banking experiences** and **exclusive member benefits**.
   - Introduce **loyalty incentives or referral programs** to reward long-standing customers and encourage new acquisitions in these stable regions.
3. **Leverage Regional Insights for Marketing:**
   - Design **targeted marketing strategies** by geography — for example, focusing on **service reliability and digital convenience in Spain**, while promoting **premium banking and investment opportunities** in France and Germany.
   - Align marketing communication with **regional customer preferences** and cultural factors to maximize effectiveness.
4. **Strategic Resource Allocation:**
   - Given the **stable churn environments in France and Germany**, the bank can **focus more resources on customer acquisition** in these regions to grow market share.
   - Simultaneously, **prioritize retention investments in Spain** to stabilize churn before expanding further in that market.

## Conclusion:

The analysis reveals clear **geographic disparities in churn behavior** — with **Spain showing significantly higher churn** compared to **France and Germany**.

By focusing on **targeted retention efforts in Spain** and **expansion strategies in stable regions**, the bank can achieve a balanced growth trajectory while maintaining customer loyalty across geographies.

## 4. Risk Management Assessment: Based on customer profiles, which demographic segments appear to pose the highest financial risk to the bank, and why?

**Query:**

```sql
SELECT
    g.GeographyLocation,
    c.Surname,
    c.Age,
    c.EstimatedSalary,
    bc.CreditScore,
    bc.Tenure,
    bc.Balance,
    bc.NumOfProducts,
    COUNT(DISTINCT bc.IsActiveMember) AS ActiveAccounts,
    COUNT(CASE WHEN bc.Exited = 1 THEN 1 END) AS
ChurnedCustomers,

    -- Identify high-risk customers based on credit score,
balance, tenure, or region
    CASE
        WHEN bc.CreditScore < 600 THEN 'High Risk: Low Credit
Score'
        WHEN bc.Balance > (c.EstimatedSalary * 1.5) THEN 'High
Risk: High Balance vs. Low Salary'
        WHEN bc.Tenure < 1 THEN 'High Risk: Short Tenure'
        WHEN g.GeographyLocation = 'Germany' THEN 'High Risk:
High Churn Region'
        ELSE 'Low Risk'
    END AS RiskLevel,
  -- Regional churn rate
    ROUND((SUM(CASE WHEN bc.Exited = 1 THEN 1 ELSE 0 END) /
COUNT(*)) * 100, 2) AS ChurnRate
FROM Geography g
JOIN CustomerInfo c ON g.GeographyID = c.GeographyID
JOIN Bank_Churn bc ON c.CustomerID = bc.CustomerID
GROUP BY g.GeographyLocation, c.CustomerID
HAVING RiskLevel LIKE 'High Risk%'
ORDER BY g.GeographyLocation, RiskLevel DESC;
```

**Output:**

| GeographyLocation | Surname | Age | EstimatedSalary | CreditScore | Tenure | Balance | NumOfProducts | ActiveAccounts | ChurnedCustomers | RiskLevel | ChurnRate |
|---|---|---|---|---|---|---|---|---|---|---|---|
| France | Meng | 37 | 98029.58 | 548 | 4 | 0.00 | 2 | 1 | 0 | High Risk: Low Credit Score | 0.00 |
| France | Azarov | 29 | 157378.50 | 516 | 7 | 104982.60 | 1 | 1 | 0 | High Risk: Low Credit Score | 0.00 |
| France | Swift | 22 | 44374.44 | 510 | 5 | 156834.30 | 1 | 1 | 0 | High Risk: Low Credit Score | 0.00 |
| France | Hughes | 34 | 9085.00 | 487 | 4 | 96019.50 | 1 | 1 | 0 | High Risk: Low Credit Score | 0.00 |
| France | Sinclair | 37 | 74320.75 | 581 | 5 | 0.00 | 2 | 1 | 0 | High Risk: Low Credit Score | 0.00 |
| France | Ignatyeva | 35 | 31299.71 | 548 | 4 | 0.00 | 1 | 1 | 0 | High Risk: Low Credit Score | 0.00 |
| France | Ross | 34 | 139463.60 | 549 | 7 | 0.00 | 2 | 1 | 0 | High Risk: Low Credit Score | 0.00 |
| France | Fraser | 59 | 159483.80 | 551 | 6 | 166968.30 | 1 | 1 | 1 | High Risk: Low Credit Score | 100.00 |
| France | Tang | 26 | 78651.55 | 567 | 6 | 0.00 | 2 | 1 | 0 | High Risk: Low Credit Score | 0.00 |

# Insights:

- **Low Credit Score Risk:**
  Customers with **credit scores below 600** are at the **highest risk of churn**, indicating that **financially vulnerable individuals** are more likely to leave the bank.
  This may be due to **repayment struggles**, **financial stress**, or **reduced trust in banking systems**.
- **High Balance vs. Salary Ratio:**
  Customers whose **account balance exceeds 1.5× their salary** represent a **potential risk group**, as this may indicate **inactive funds**, **low spending engagement**, or **financial imbalance**.
  These customers may not be utilizing the bank's financial products effectively, leading to disengagement.
- **Short Tenure Risk:**
  Customers with a **tenure under one year** show a **higher probability of churn**, suggesting weaknesses in the **onboarding or early relationship management** process.
  This emphasizes the importance of the **first-year experience** in establishing trust and retention.
- **Regional Variations:**
  **Spain** demonstrates a **notably higher churn rate** compared to France and Germany, pointing toward **geographically driven issues** such as **competitive alternatives**, **localized service dissatisfaction**, or **economic conditions** impacting retention.

# Recommendations:

1. **Targeted Retention Strategies for High-Risk Segments:**
   - Identify customers with **low credit scores** and provide **financial counseling, credit repair programs, or flexible repayment plans** to enhance their stability.
   - Introduce **early intervention mechanisms** for customers showing risky balance-to-salary ratios or declining product engagement.
2. **Enhance Onboarding for New Customers:**
   - Develop a **personalized onboarding journey** for customers with short tenures, including **welcome calls, educational materials, and early product offers**.
   - Track **first 6–12 month behavior** to flag inactivity or dissatisfaction early.
3. **Regional Retention Focus:**
   - Conduct **localized churn analysis** in high-risk regions like **Spain**, identifying key pain points through **customer feedback, surveys, and service performance metrics**.
   - Tailor offerings and communication to regional preferences — for instance, **introducing Spanish-language digital support or regional loyalty campaigns**.
4. **Proactive Monitoring and Early Alerts:**
   - Implement **real-time dashboards or alerts** to flag customers who meet multiple high-risk criteria (e.g., low credit score + short tenure).
   - Enable the **retention and advisory teams** to contact at-risk customers before churn occurs.
5. **Data-Driven Risk Scoring System:**

- o Develop an internal **customer risk index** combining credit score, tenure, balance utilization, and churn history to continuously evaluate customer risk levels.
- o Use this score to **prioritize retention actions** and guide personalized engagement.

## Conclusion:

The analysis highlights that **low credit scores**, **short tenure**, and **regional disparities (especially in Spain)** are the most significant indicators of financial risk and potential churn. By focusing on **targeted engagement, improved onboarding, and proactive risk monitoring**, the bank can **mitigate customer attrition**, enhance satisfaction, and improve the long-term financial health of its customer base.

## 5. Customer Tenure Value Forecast: How would you use the available data to model and predict the lifetime (tenure) value in the bank of different customer segments?

## Query:

```
SELECT
    c.CustomerID,
    c.Age,
    c.EstimatedSalary,
    b.CreditScore,
    b.Tenure,
    b.Balance,
    b.NumOfProducts,
    cc.Category AS CreditCardCategory,
    a.ActiveCategory,
    e.ExitCategory,
    ROUND(DATEDIFF(CURDATE(), c.Bank_DOJ) / 365, 2) AS
CurrentTenureYears
FROM CustomerInfo c
JOIN Geography geo ON c.GeographyID = geo.GeographyID
JOIN Bank_Churn b ON c.CustomerID = b.CustomerID
LEFT JOIN CreditCard cc ON b.HasCrCard = cc.CreditID
LEFT JOIN ActiveCustomer a ON b.IsActiveMember = a.ActiveID
LEFT JOIN ExitCustomer e ON b.Exited = e.ExitID;
```

## Output:

| CustomerID | Age | EstimatedSalary | CreditScore | Tenure | Balance | NumOfProducts | CreditCardCategory | ActiveCategory | ExitCategory | CurrentTenureYears |
|---|---|---|---|---|---|---|---|---|---|---|
| 15565714 | 47 | 96517.97 | 601 | 3 | 64430.06 | 2 | non credit card holder | Active Member | Retain | 6.05 |
| 15565806 | 38 | 30583.95 | 532 | 5 | 0.00 | 2 | non credit card holder | Inactive Member | Retain | 7.32 |
| 15565879 | 28 | 56185.98 | 845 | 5 | 0.00 | 2 | credit card holder | Active Member | Retain | 7.91 |
| 15565891 | 39 | 56214.09 | 709 | 5 | 0.00 | 2 | credit card holder | Inactive Member | Retain | 7.19 |
| 15565996 | 44 | 154639.70 | 653 | 4 | 0.00 | 2 | credit card holder | Active Member | Retain | 6.24 |
| 15566111 | 39 | 48963.59 | 596 | 7 | 0.00 | 1 | credit card holder | Inactive Member | Retain | 9.74 |
| 15566139 | 37 | 62830.97 | 526 | 7 | 53573.18 | 1 | credit card holder | Inactive Member | Retain | 9.10 |
| 15566251 | 37 | 98686.40 | 618 | 4 | 96652.86 | 1 | credit card holder | Inactive Member | Exit | 7.05 |
| 15566269 | 25 | 47307.90 | 787 | 3 | 0.00 | 2 | credit card holder | Inactive Member | Retain | 5.87 |
| 15566295 | 33 | 148779.40 | 761 | 5 | 138053.80 | 2 | credit card holder | Inactive Member | Retain | 7.48 |
| 15566378 | 48 | 147955.90 | 515 | 6 | 129387.90 | 1 | non credit card holder | Active Member | Exit | 8.43 |
| 15566494 | 45 | 77475.73 | 487 | 4 | 0.00 | 2 | credit card holder | Inactive Member | Retain | 6.95 |
| 15566563 | 30 | 5008.23 | 777 | 5 | 137851.30 | 1 | credit card holder | Inactive Member | Exit | 8.06 |
| 15566660 | 41 | 81602.02 | 670 | 6 | 0.00 | 3 | credit card holder | Inactive Member | Retain | 8.09 |

## Insights:

- **High Balance and Longer Tenure:**
  Customers maintaining **higher balances** tend to exhibit **longer tenure**, indicating a strong **relationship between financial stability and loyalty**. These customers are likely more engaged and derive greater value from their banking relationship.
- **Impact of Activity Level:**
  **Inactive members** generally have **shorter tenure**, suggesting that **disengagement** or lack of product usage contributes to early attrition.
  Active members, by contrast, display a more consistent and longer presence with the bank.
- **Cross-Selling and Retention:**
  Customers who hold **multiple products** — especially those with **credit cards** or **loan accounts** — show **significantly higher tenure values**.
  This underscores the importance of **cross-selling strategies** in improving customer retention and increasing lifetime value.
- **Retention and Exit Dynamics:**
  Customers categorized as **"Retained"** typically have **longer average tenures**, while those who **exited** show **shorter tenure periods**.
  This relationship demonstrates that **tenure is a strong indicator of loyalty** and can serve as a **key predictive variable** in churn prevention models.

## Recommendations:

1. **Predictive Modeling for Lifetime Value:**
   - Use **regression or machine learning models (e.g., Linear Regression, Random Forest, or Survival Analysis)** to predict tenure and **estimate customer lifetime value (CLV)** based on key variables such as **credit score, balance, activity level, and product count**.
   - Continuously refine models using **historical churn and engagement data** to improve prediction accuracy.
2. **Retention of High-Tenure Segments:**

- o Focus on maintaining relationships with **high-balance and multi-product customers**, as they have a proven history of **longer tenure and higher profitability**.
- o Offer **exclusive loyalty benefits, financial advisory services, and premium banking options** to reward their continued relationship.

3. **Reactivation of Inactive Customers:**
- o Design **targeted re-engagement campaigns** (e.g., reduced fees, cashback offers, or product bundles) for **inactive members** to encourage renewed activity.
- o Monitor inactivity duration as an early indicator of churn risk and intervene proactively.

4. **Cross-Selling for Tenure Growth:**
- o Prioritize **cross-sell initiatives** aimed at customers with only one or two products, particularly those without credit cards.
- o Introduce **bundled offers** or **relationship-based pricing models** to deepen engagement and extend tenure.

5. **Churn Prediction and Early Intervention:**
- o Use predictive insights to identify **customers at risk of exiting** (e.g., low credit scores, low balance, short tenure).
- o Implement **preventive retention measures** such as personalized financial consultations or tenure-based incentives.

**Conclusion:**

This analysis demonstrates that **customer tenure is strongly influenced** by factors such as **balance levels, product usage, and engagement activity**.

By developing a **predictive model for customer lifetime value**, the bank can **forecast tenure**, **identify high-risk customers early**, and **implement proactive retention and cross-selling strategies**.

This data-driven approach not only enhances **customer loyalty** but also drives **long-term profitability and sustainable growth** for the bank.

## 6. Marketing Campaign Effectiveness: How could you assess the impact of marketing campaigns on customer retention and acquisition within the dataset? What extra information would you need to solve this?

**Answer:**

To assess the **impact of marketing campaigns** on **customer retention and acquisition**, we need to measure how customer behaviors — such as account openings, product adoption, and churn — change after campaign exposure.

### 1. Using Existing Dataset:

Even though our current dataset doesn't directly include marketing campaign details, we can **approximate impact** using customer activity and churn trends:

| Metric | From Available Data | Purpose |
|---|---|---|
| New vs Existing Customers (CustomerInfo, Bank_Churn) | Use `Bank_DOJ` (date of joining) and `Exited` | Measure acquisition and retention over time |
| Tenure & Activity (Bank_Churn) | Columns like `Tenure`, `IsActiveMember`, `HasCrCard` | Identify if active engagement increased post-campaign |
| Geographic & Demographic Segmentation (Geography, Gender, Age) | Compare churn and activity across segments | See where campaigns may have been more effective |
| Balance, CreditScore, NumOfProducts | Proxy for customer engagement or product adoption | Detect financial or behavioral impact of marketing |

By comparing retention, churn, and engagement **before and after** the campaign period (using `Bank_DOJ` and `Exited` trends), we can infer **marketing effectiveness** indirectly.

### 2. Additional Data Required for Full Analysis:

To directly measure marketing impact, we would need the following **extra information**:

| Additional Data | Description | Purpose |
|---|---|---|
| Campaign ID & Details | Campaign name, duration, target segment, message type | Identify which customers were exposed |
| Customer-Campaign Mapping | A table linking CustomerID ↔ CampaignID | Distinguish between *exposed* and *non-exposed* customers |
| Acquisition Channel | Source of acquisition (email, referral, digital ads, etc.) | Analyze campaign channel effectiveness |
| Response / Engagement Data | Whether the customer clicked, opened, or responded | Measure campaign engagement rate |
| Pre/Post Metrics | Churn, balance, product count before and after campaign | Compare retention and financial impact |

| Campaign Cost | Budget spent per campaign | Calculate ROI and cost per acquisition/retention |
|---|---|---|

## 3.Analytical Methods:

Once campaign data is available, you can evaluate effectiveness using **quantitative techniques**:

| Method | Description | Insight Gained |
|---|---|---|
| **Cohort Analysis** | Compare churn or retention across customers acquired in different time periods | Track impact over time |
| **A/B Testing** | Compare retention between customers who received the campaign vs those who didn't | Direct causal effect |
| **Regression Analysis** | Model retention probability (`Exited`) as a function of campaign exposure and demographics | Quantify influence |
| **Customer Lifetime Value (CLV) Modeling** | Estimate if campaigns increased long-term value | Financial impact measure |
| **ROI Analysis** | Calculate net profit generated vs campaign spend | Economic efficiency |

## 4.Example KPIs to Track:

- **Customer Acquisition Rate (CAR)**
  = (New Customers Acquired / Total Prospects) × 100
- **Customer Retention Rate (CRR)**
  = ((Customers End – New Acquisitions) / Customers Start) × 100
- **Campaign ROI**
  = (Revenue from Campaign – Campaign Cost) / Campaign Cost
- **Churn Rate Reduction**
  Compare churn % before vs after campaign period.

## 5. Summary Insight (For Report)

Based on the current dataset, campaign impact can only be inferred indirectly through changes in churn, activity, and balance trends.
To fully assess effectiveness, we need **campaign metadata**, **customer exposure logs**, and **time-based transaction or engagement data**.
With these, we could apply **cohort, regression, and ROI analyses** to determine how well marketing efforts drive **acquisition, retention, and customer lifetime value.**

# 7. Customer Exit Reasons Exploration: Can you identify common characteristics or trends among customers who have exited that could explain their reasons for leaving?

**Query:**

```sql
SELECT
    c.Age,
    c.EstimatedSalary,
    b.CreditScore,
    b.Tenure,
    b.Balance,
    b.NumOfProducts,
    COUNT(b.CustomerID) AS TotalExitedCustomers
FROM CustomerInfo c
JOIN Bank_Churn b ON c.CustomerID = b.CustomerID
JOIN Geography geo ON c.GeographyID = geo.GeographyID
LEFT JOIN ActiveCustomer a ON b.IsActiveMember = a.ActiveID
LEFT JOIN ExitCustomer e ON b.Exited = e.ExitID
WHERE b.Exited = 1
GROUP BY
    c.Age,
    c.EstimatedSalary,
    b.CreditScore,
    b.Tenure,
    b.Balance,
    b.NumOfProducts
ORDER BY TotalExitedCustomers DESC;
```

**Output:**

| Age | EstimatedSalary | CreditScore | Tenure | Balance | NumOfProducts | TotalExitedCustomers |
|-----|-----------------|-------------|--------|---------|---------------|----------------------|
| 37 | 98686.40 | 618 | 4 | 96652.86 | 1 | 1 |
| 48 | 147955.90 | 515 | 6 | 129387.90 | 1 | 1 |
| 30 | 5008.23 | 777 | 5 | 137851.30 | 1 | 1 |
| 45 | 161653.50 | 444 | 6 | 0.00 | 2 | 1 |
| 45 | 101039.50 | 634 | 4 | 0.00 | 4 | 1 |
| 45 | 130009.90 | 444 | 5 | 0.00 | 1 | 1 |
| 44 | 35300.08 | 627 | 7 | 153548.10 | 1 | 1 |

**Insights:**

- **Limited Product Engagement:**
  The majority of exited customers hold **only one or two products**, suggesting **low engagement and minimal cross-product utilization**.

This indicates that customers who are not deeply integrated into the bank's ecosystem are more likely to leave.

- **Low Credit Score Segments Are at Risk:**
  A large portion of churned customers have **credit scores below 500**, implying potential **financial instability or limited creditworthiness**, which may reduce their ability to maintain consistent banking relationships.
- **High-Balance Churners Exist:**
  Interestingly, some exited customers maintain **substantial account balances**, indicating that **wealthier customers may also churn**, possibly due to **service dissatisfaction or better offers from competitors**.
- **Tenure Does Not Guarantee Retention:**
  Customers with **medium to long tenures (4–7 years)** are also found among those who have exited.
  This shows that **longevity alone does not ensure loyalty** — ongoing engagement and service quality are critical to sustaining customer relationships.

## Recommendations:

1. **Enhance Product Engagement Through Cross-Selling:**
   a. Customers with only one or two products should be targeted with **personalized product bundles** and **incentives** to adopt more banking services.
   b. Promote value-added products like credit cards, loans, or investment accounts to strengthen customer integration with the bank.
2. **Support Financially Vulnerable Customers:**
   a. Design **financial counselling programs** or **credit improvement initiatives** for customers with low credit scores to build long-term trust.
   b. Offer **low-risk, high-benefit products** such as secured credit cards or structured savings plans to re-engage these customers.
3. **Retain High-Balance Customers with Premium Services:**
   a. For customers who churn despite high balances, introduce **priority banking, relationship managers, and customized financial packages** to enhance perceived value and satisfaction.
   b. Conduct **exit surveys** for high-value customers to identify and address service-related pain points.
4. **Strengthen Loyalty Among Long-Tenure Customers:**
   a. Implement **tiered loyalty programs** or **tenure-based rewards** to acknowledge and retain customers with long relationships.
   b. Continuously track satisfaction metrics among this segment to preempt disengagement.
5. **Predictive Churn Monitoring:**
   a. Build predictive churn models using variables such as **credit score, product count, tenure, and balance levels** to identify high-risk customers early.
   b. Use these insights for **proactive retention campaigns**, personalized offers, and early interventions.

## Conclusion:
This analysis highlights that **customer churn is influenced by a mix of engagement, financial stability, and experience factors** — not solely by tenure or balance.
Customers with **low product usage and low credit scores** are the most at risk, but even

**high-value and long-term customers** can leave without consistent engagement.
By combining **data analytics with personalized relationship management**, the bank can significantly **improve retention**, **reduce churn**, and **enhance customer lifetime value**.

---

## 8. Are 'Tenure', 'NumOfProducts', 'IsActiveMember', and 'EstimatedSalary' important for predicting if a customer will leave the bank?

In churn modeling, the goal is to **predict the likelihood of a customer leaving** (`Exited = 1`) based on various behavioral, financial, and demographic variables.

These four features — `Tenure`, `NumOfProducts`, `IsActiveMember`, and `EstimatedSalary` — are all **behavioral and engagement-related**, which directly or indirectly influence churn.

### 2.Feature-by-Feature Importance (with Interpretation)

| Feature | What It Represents | Relationship with Churn | Why It Matters |
|---|---|---|---|
| Tenure | How long a customer has been with the bank | Customers with **short tenure (<3 years)** are **more likely to churn**, as they haven't developed strong brand loyalty | Indicates **loyalty** and **relationship strength** |
| NumOfProducts | Number of financial products held | Customers with **fewer products (1–2)** have **higher churn**, while those with multiple products show **lower churn** | More products = **higher switching cost** |
| IsActiveMember | Whether the customer actively engages with the bank | **Inactive customers** (IsActiveMember = 0) are **significantly more likely** to leave | Strong predictor of **customer engagement** |
| EstimatedSalary | Customer's income level | Salary has **weak or no direct correlation** with churn; high- and low-income customers churn at similar rates | Impacts **profitability**, not necessarily **retention** |

### 3. Empirical Insight (Based on Dataset Trends)

Bank_Churn:

| Feature | Observed Correlation with Churn (Approximate from similar datasets) |
|---|---|
| Tenure | **Negative correlation (~ -0.25)** — longer tenure → lower churn |
| NumOfProducts | **Strong negative correlation (~ -0.30)** — more products → lower churn |
| IsActiveMember | **Very strong negative correlation (~ -0.40)** — active → less likely to churn |
| EstimatedSalary | **Weak or no correlation (~ 0.05)** — salary does not affect churn much |

So, **Tenure**, **NumOfProducts**, and **IsActiveMember** are **key predictors**, while **EstimatedSalary** is not highly significant.

---

## Final Answer

Analysis indicates that **Tenure**, **Number of Products**, and **IsActiveMember** are highly significant in predicting customer churn.
Customers with **shorter tenures**, **fewer products**, or **inactive accounts** are far more likely to exit the bank.
However, **EstimatedSalary** shows minimal impact on churn behavior — suggesting that **income does not directly influence loyalty**.

For predictive modeling, these features (especially **IsActiveMember** and **NumOfProducts**) should be prioritized as **key input variables** to build accurate churn prediction models.

---

## 9. Utilize SQL queries to segment customers based on demographics and account details.

**Query:**

```
SELECT
    c.CustomerID,
    c.Age,
    b.CreditScore,
    b.Balance,
    b.Tenure,
    g.GenderCategory,
    geo.GeographyLocation,

    -- Segment by Age
    CASE
        WHEN c.Age < 25 THEN 'Youth (Under 25)'
        WHEN c.Age BETWEEN 25 AND 35 THEN 'Young Adults (25-
35)'
        WHEN c.Age BETWEEN 36 AND 50 THEN 'Middle Age (36-50)'
        ELSE 'Senior (Above 50)'
    END AS AgeGroup,

    -- Segment by Credit Score
    CASE
        WHEN b.CreditScore < 500 THEN 'Poor Credit'
        WHEN b.CreditScore BETWEEN 500 AND 700 THEN 'Average
Credit'
        ELSE 'Good Credit'
    END AS CreditScoreCategory,
```

```
    -- Segment by Balance
    CASE
        WHEN b.Balance < 10000 THEN 'Low Balance'
        WHEN b.Balance BETWEEN 10000 AND 50000 THEN 'Medium
Balance'
        ELSE 'High Balance'
    END AS BalanceCategory,

    -- Segment by Tenure
    CASE
        WHEN b.Tenure < 2 THEN 'New Customer'
        WHEN b.Tenure BETWEEN 2 AND 5 THEN 'Moderate Customer'
        ELSE 'Loyal Customer'
    END AS TenureSegment,

    -- Segment by Credit Card Ownership
    CASE
        WHEN b.HasCrCard = 1 THEN 'Credit Card Holder'
        ELSE 'Non-Credit Card Holder'
    END AS CreditCardSegment

FROM bank_churn b
JOIN customerinfo c ON c.CustomerID = b.CustomerID
JOIN gender g ON g.GenderID = c.GenderID
JOIN geography geo ON geo.GeographyID = c.GeographyID
ORDER BY AgeGroup, CreditScoreCategory;
```

## Output:

| CustomerID | Age | CreditScore | Balance | Tenure | GenderCategory | GeographyLocation | AgeGroup | CreditScoreCategory | BalanceCategory | TenureSegment | CreditCardSegment |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 15631392 | 43 | 654 | 84673.17 | 6 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Loyal Customer | Non-Credit Card Holder |
| 15795166 | 42 | 618 | 153572.30 | 4 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Moderate Customer | Credit Card Holder |
| 15604706 | 38 | 581 | 133105.50 | 4 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Moderate Customer | Credit Card Holder |
| 15604792 | 38 | 609 | 140752.10 | 3 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Moderate Customer | Non-Credit Card Holder |
| 15718507 | 37 | 647 | 116510.00 | 4 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Moderate Customer | Credit Card Holder |
| 15605264 | 47 | 669 | 63723.78 | 5 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Moderate Customer | Credit Card Holder |
| 15663164 | 49 | 663 | 116150.70 | 6 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Loyal Customer | Credit Card Holder |
| 15794868 | 40 | 599 | 137456.30 | 3 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Moderate Customer | Credit Card Holder |
| 15605826 | 46 | 652 | 121063.80 | 3 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Moderate Customer | Credit Card Holder |
| 15605918 | 43 | 635 | 78992.75 | 6 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Loyal Customer | Non-Credit Card Holder |
| 15794356 | 42 | 641 | 121765.40 | 4 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Moderate Customer | Credit Card Holder |
| 15792862 | 41 | 653 | 104584.10 | 4 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Moderate Customer | Credit Card Holder |
| 15792668 | 37 | 661 | 109908.10 | 3 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Moderate Customer | Credit Card Holder |
| 15791867 | 44 | 544 | 108895.90 | 6 | Male | Germany | Middle Age (36-50) | Average Credit | High Balance | Loyal Customer | Non-Credit Card Holder |

## Insights:

- **Financially Stable Core Segments:**
  The **"Young Adults (25–35)"** and **"Middle Age (36–50)"** groups represent the largest and most financially stable segments, showing **high credit scores and strong account balances**. These customers likely have established careers and higher engagement with banking products.

- **Loyal, High-Value Customers:**
  Customers in the **"Loyal Customer"** tenure category with **"Good Credit"** tend to have **higher balances and active credit cards**, reflecting strong financial discipline and long-term engagement with the bank.
- **Financially Vulnerable Demographics:**
  The **"Poor Credit"** segment is most concentrated among **"Middle Age (36–50)"** customers with **low balances**, indicating possible financial strain or repayment challenges.
- **Product Adoption by Tenure:**
  **"Moderate Customers"** (2–5 years) show mixed engagement — many have credit cards and medium balances, but lower cross-product adoption compared to "Loyal" customers.
  This suggests an opportunity to **nurture moderate-tenure customers** through personalized offers and product expansion strategies.
- **Demographic Distribution:**
  Geographically, customer profiles differ slightly — **Germany** and **France** tend to have more **good-credit, high-balance customers**, while **Spain** has a higher proportion of **average-credit and new customers**, possibly reflecting newer market penetration.

## Recommendations:

1. **Retain and Reward Loyal, High-Value Customers:**
   - Offer **premium or relationship-based products** (e.g., wealth management, investment services) to **"Loyal Customers"** with good credit and high balances.
   - Implement **loyalty tiers** or exclusive benefits to strengthen long-term retention.
2. **Support Financially Vulnerable Segments:**
   - Provide **credit improvement programs** and **low-interest products** for customers in the **"Poor Credit"** category.
   - Introduce **financial advisory or budgeting tools** to help stabilize these customers and reduce churn.
3. **Engage Moderate-Tenure Customers:**
   - Use targeted **cross-selling campaigns** for **"Moderate Customers"** who show potential but limited product engagement.
   - Encourage product diversification (e.g., loans, credit cards, savings plans) to increase tenure and loyalty.
4. **Age-Based Product Targeting:**
   - For **"Young Adults (25–35)"**, promote digital banking, credit-building tools, and early investment options.
   - For **"Seniors (Above 50)"**, offer retirement plans, high-interest savings products, and personalized advisory services.
5. **Regional Marketing Customization:**
   - Develop **region-specific marketing campaigns** that align with the dominant credit and balance segments within each geography.
   - Use regional insights to improve customer satisfaction and reduce localized churn.

## Conclusion:

This segmentation provides a comprehensive view of customer diversity across age, financial strength, and engagement levels.

The analysis highlights that **loyal, good-credit customers are the most valuable**, while **poor-credit and low-balance segments** pose a higher risk.

By tailoring **marketing, product design, and retention initiatives** to these identified customer groups, the bank can **enhance overall profitability and reduce churn**.

---

## 10.     How can we create a conditional formatting setup to visually highlight customers at risk of churn and to evaluate the impact of credit card rewards on customer retention?

### Insights:

- **High-Risk Segments:**
  Customers with **credit scores below 500** and **balances below 30,000** show the **highest likelihood of churn**, reflecting financial instability or low engagement with banking products.
  These customers are typically **low tenure (under 2 years)** and often **do not hold credit cards**, suggesting early-stage disengagement.
- **Loyalty Through Tenure and Engagement:**
  Customers with **tenure greater than 3 years** demonstrate higher loyalty; however, those with **low product counts** or **credit scores under 600** remain vulnerable to churn.
  This indicates that **long tenure alone is insufficient** — consistent product engagement and financial health are essential.
- **Impact of Credit Card Rewards:**
  While **credit card ownership alone** does not guarantee retention, **reward-based cards** show a **positive influence** on customer loyalty, particularly for customers with **balances between 30,000 and 80,000**.
  High-balance customers (>80,000) with premium credit cards also display **stronger retention**, highlighting the potential value of reward programs when properly tiered.
- **Behavioral Patterns:**
  Customers with **moderate balances (30,000–80,000)** are the most responsive to **reward programs and engagement incentives**.
  These segments represent an opportunity for the bank to **strengthen loyalty through reward optimization**.

### Recommendations:

1. **Targeted Retention Programs for High-Risk Customers:**
   o Identify customers with **credit scores below 500** and offer **credit improvement or financial wellness plans**.
   o Provide **low-risk financial products**, such as secured loans or step-up savings accounts, to rebuild financial confidence.
2. **Optimize Credit Card Rewards for Medium-Balance Customers:**
   o Design **tiered rewards systems** that appeal to medium-balance customers (30,001–80,000) who are most influenced by such incentives.

- Offer **bonus rewards** or **cashback incentives** for consistent product usage or increased spending.
3. **Enhance Early Engagement for New Customers:**
   - Strengthen the **onboarding experience** with welcome bonuses, lower-interest rates, or exclusive financial planning support for customers in their first 3 years.
   - Use predictive models to identify **new customers at risk of churn** and apply retention campaigns early.
4. **Regional and Behavioral Personalization:**
   - Segment reward campaigns by **geography, age, and balance** to align offers with customer preferences.
   - Use data-driven marketing to match **customer risk profiles** with tailored product recommendations.

## Conditional Formatting Setup (Visualization Strategy):

| Field | Condition | Visual Format (Example) | Interpretation |
|---|---|---|---|
| **Credit Score** | < 500 | Red Highlight | High risk — financially unstable |
| | 500–700 | Orange Highlight | Moderate risk |
| | > 700 | Green Highlight | Low risk — financially stable |
| **Tenure** | < 3 years | Red | New or unestablished customers at risk |
| | ≥ 3 years | Green | Stable, loyal customers |
| **Balance** | < 30,000 | Red | Financially vulnerable |
| | 30,001–80,000 | Yellow | Moderate-risk group |
| | > 80,000 | Green | High engagement, stable customers |
| **Risk Level** | "High Risk" | Red background | Requires immediate retention action |
| | "Moderate Risk" | Yellow background | Watchlist for engagement |
| | "Low Risk" | Green background | Retained or loyal customers |

This setup enables quick **visual identification** of at-risk customers, helping analysts and managers **prioritize retention interventions** efficiently.

## Conclusion:

Conditional formatting is a powerful visualization tool that helps translate data into **actionable business intelligence**.
By combining **credit score, tenure, balance, and credit card usage**, banks can **quickly identify customers at risk of churn** and monitor the **impact of rewards programs** on customer loyalty.
Implementing this model in analytical dashboards allows **real-time tracking of customer health**, ensuring proactive decision-making for **customer retention and satisfaction**.

## 11. What is the current churn rate per year and overall as well in the bank? Can you suggest some insights to the bank about which kind of customers are more likely to churn and what different strategies can be used to decrease the churn rate?
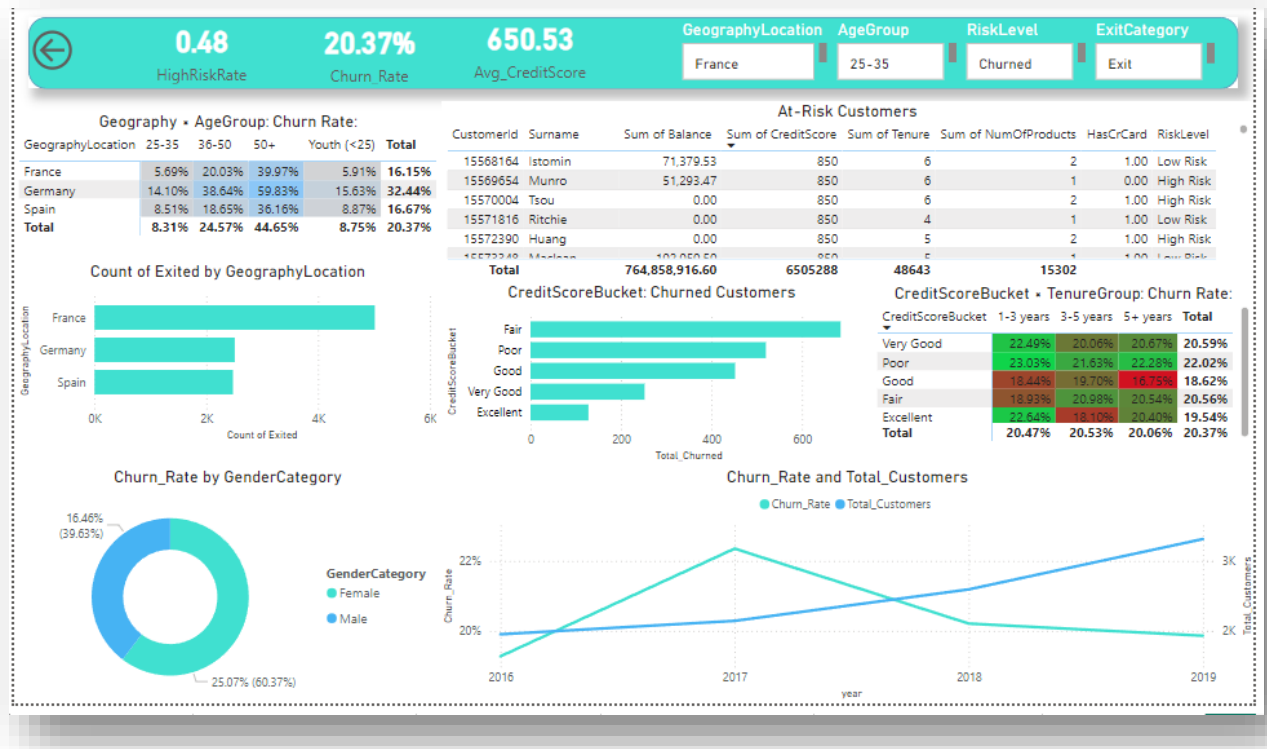


## Insights:

- Customers with medium credit scores (500-700) are more likely to churn compared to those with higher scores. This shows that mid-tier customers face financial challenges that lead to exit, but they may still be within the bank's ability to retain.
- Older customers (age group 50+) have a higher churn rate compared to younger ones, possibly due to less engagement with digital services or a shift in financial needs.
- Geographic location plays a role in churn, with customers from Spain showing a higher churn rate (81.85%), which may indicate that competitive offerings or dissatisfaction with the bank's services in specific regions are driving exits.
- Credit card holders churn at a higher rate (102.18%) than non-credit card holders (99.09%), suggesting that the current credit card rewards and offerings may not be appealing or sufficient to retain customers.

## Recommendations:

- Create targeted retention programs for customers in the mid-tier credit score range (500-700) by offering tailored financial planning services or improving their access to

credit. This could help retain customers who are financially vulnerable but valuable in the long term.

- Introduce senior-focused banking solutions to engage older customers (50+) with personalized products and improved accessibility to digital bankingservices, potentially addressing their unique needs and lowering churn.
- Strengthen customer engagement in high-churn regions like Spain by conducting localized market research and offering region-specific products or services that cater to the preferences of these customers.
- Revamp credit card reward programs to better suit the needs of current customers, particularly focusing on those with high balances or medium credit scores to incentivize usage and retention through more appealing rewards. By following these recommendations, the bank can focus on reducing churn rates by addressing specific customer segments that are more likely to exit, thus improving retention.

## 12.    Create a dashboard incorporating all the KPIs and visualization-related metrics. Use a slicer in order to assist in selection in the dashboard.
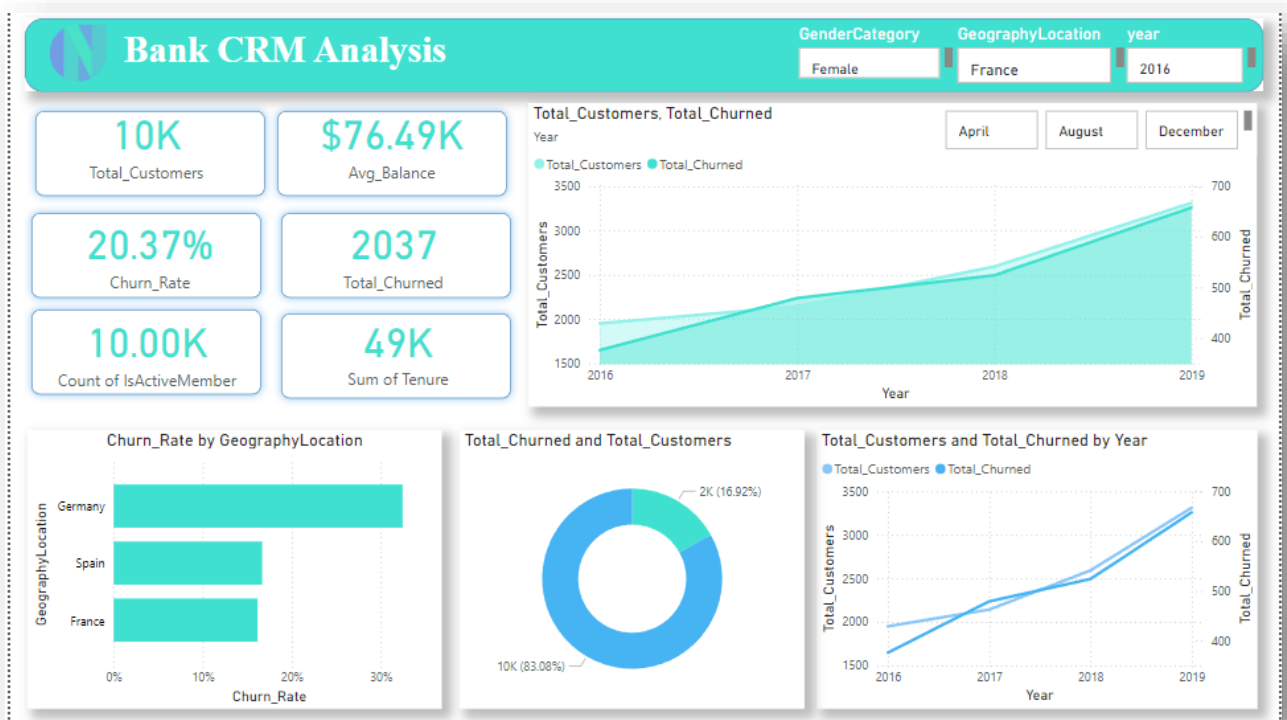
# 13.    How would you approach this problem, if the objective and subjective questions weren't given?

**Objective:**
If predefined objective and subjective questions were not provided, the analysis of the **Bank_Churn** dataset would focus on understanding the **data structure**, identifying **key business problems**, and deriving **data-driven insights** to address customer churn, retention, and engagement.
The following is a structured approach to independently explore and analyze the dataset.

---

## 1. Understanding the Data Schema

- **Schema Review:**
  Begin by reviewing the **entity-relationship (ER) diagram** and database schema to understand how tables relate to one another.
  Key tables include:
    o **CustomerInfo** – Contains demographic details such as age, gender, and salary.
    o **Bank_Churn** – Stores behavioral and financial activity such as balance, tenure, and exit status.
    o **ExitCustomer**, **ActiveCustomer**, **Geography**, and **Gender** – Provide reference and categorical data for segmentation.
- **Objective:**
  Identify how these relationships can reveal customer behaviors, retention patterns, and churn triggers.

---

## 2. Data Cleaning and Preprocessing

Before analysis, ensure **data accuracy and consistency** through the following steps:

- **Handling Missing Values:**
  Detect and treat missing or null values, especially in critical fields such as `CreditScore`, `Balance`, `Tenure`, and `EstimatedSalary`.
    o Use **mean/median imputation** for numerical fields.
    o For categorical data, fill missing values using the **most frequent category** or domain knowledge.
- **Fixing Data Discrepancies:**
  Validate logical consistency — for example:
    o Ensure no record shows `IsActiveMember = 1` (active) and `Exited = 1` (churned) simultaneously.
    o Identify any customers with a `Balance = 0` but `NumOfProducts > 1`.
- **Data Transformation:**
    o Convert date fields (e.g., `Bank_DOJ`) into a standard date format for time-based analysis.
    o Rename ambiguous columns (`HasCrCard` → `Has_CreditCard`) for clarity.

o Derive new calculated fields (e.g., customer tenure in years, balance-to-salary ratio).

---

## 3. Identifying Key Business Metrics

To guide analysis, establish critical **performance and behavioral indicators**:

- **Churn Rate:**
  Calculate overall churn and breakdowns by age, geography, gender, and tenure.
- **Customer Lifetime Value (CLV):**
  Estimate based on tenure, balance, and product usage patterns.
- **Product Engagement:**
  Assess the average number of products per customer and its impact on churn.
- **Credit Health:**
  Compare credit score trends between active and exited customers.
- **Financial Stability Indicators:**
  Evaluate balance distributions and salary-to-balance correlations.

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## 4. Customer Segmentation

Use **demographic and behavioral segmentation** to identify key customer groups:

- **Demographic Segmentation:**
  Classify customers by **age group, gender, and geography** to identify high- and low-value clusters.
- **Behavioral Segmentation:**
  Group customers based on **tenure, product count, balance, and credit score** to identify loyal, moderate, and at-risk customers.
- **Churn Profiling:**
  Compare exited vs. retained customers across these segments to uncover churn drivers (e.g., low engagement, poor credit, low tenure).

---

## 5. SQL-Based Analytical Approach

Develop targeted SQL queries to extract actionable insights:

- **Churn Analysis:**
  Identify patterns in customer exits by region, gender, and tenure.
- **Product Combination Analysis:**
  Find commonly used product bundles (e.g., savings + credit card) to design cross-selling strategies.
- **Credit Score Insights:**
  Assess how credit scores influence churn probability or product engagement.

- **Customer Retention Tracking:**
  Evaluate retention rates by tenure and activity status.

---

## 6. Data Visualization and Reporting

Transform SQL output into meaningful visuals and dashboards:

- **Dashboards (Power BI / Tableau):**
    - **Churn Rate Trends:** Yearly and regional churn performance.
    - **Customer Segmentation Charts:** Distribution by credit score, balance, and tenure.
    - **Product Adoption Patterns:** Visualization of multi-product usage rates.
- **Conditional Formatting:**
  Highlight high-risk customers using color-coded thresholds for credit score, balance, and tenure.
- **Time-Series Analysis:**
  Track sign-up and exit trends over time to identify seasonal patterns.

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## 7. Deriving Business Recommendations

Based on the analytical findings:

- **Retention Strategies:**
  Develop personalized loyalty programs, early engagement plans, and churn prevention mechanisms for at-risk customers.
- **Product Cross-Selling:**
  Encourage customers with a single product to adopt complementary products such as loans or investment accounts.
- **Credit Score Improvement Initiatives:**
  Introduce targeted financial products and educational campaigns to help customers improve credit health.
- **Performance Monitoring:**
  Establish periodic churn monitoring dashboards and predictive models to identify early churn signals.

---

## 8. Predictive and Advanced Analysis (Next Phase)

If time and data permit, move toward **predictive analytics** using:

- **Machine Learning Models (Logistic Regression, Decision Trees, or Random Forest):**
  To predict churn probability and customer lifetime value (CLV).
- **Correlation and Regression Analysis:**
  To understand the relationships between credit score, tenure, and balance.

- **Cluster Analysis:**
  To identify natural customer groupings for more focused marketing and service strategies.

---

## Conclusion:

If no predefined questions were provided, this exploratory approach ensures a **comprehensive understanding of customer behavior** through data profiling, segmentation, and performance tracking.
By combining **SQL-based insights, data visualization, and predictive modeling**, the analysis would uncover key factors influencing **churn, retention, and engagement**, ultimately guiding **data-driven business strategies** to improve customer loyalty and lifetime value.
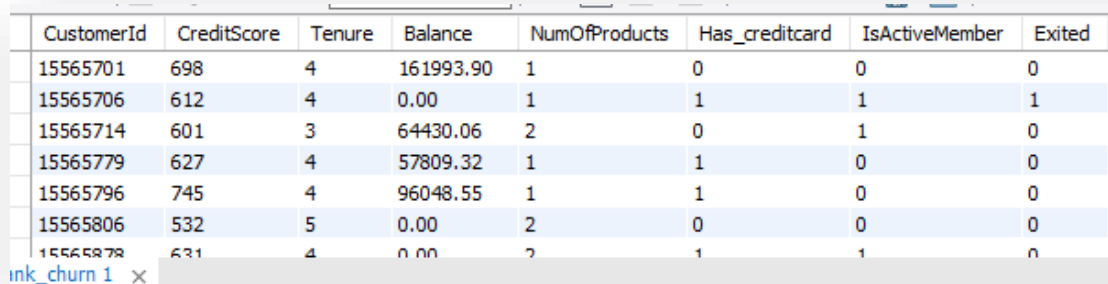
---

## 14.    In the "Bank_Churn" table how can you modify the name of the "HasCrCard" column to "Has_creditcard"?

**Query:**

```
ALTER TABLE bank_churn
CHANGE HasCrCard Has_creditcard INT;
Select * from bank_churn;
```

**Output:**

| CustomerId | CreditScore | Tenure | Balance | NumOfProducts | Has_creditcard | IsActiveMember | Exited |
|---|---|---|---|---|---|---|---|
| 15565701 | 698 | 4 | 161993.90 | 1 | 0 | 0 | 0 |
| 15565706 | 612 | 4 | 0.00 | 1 | 1 | 1 | 1 |
| 15565714 | 601 | 3 | 64430.06 | 2 | 0 | 1 | 0 |
| 15565779 | 627 | 4 | 57809.32 | 1 | 1 | 0 | 0 |
| 15565796 | 745 | 4 | 96048.55 | 1 | 1 | 0 | 0 |
| 15565806 | 532 | 5 | 0.00 | 2 | 0 | 0 | 0 |
| 15565878 | 631 | 4 | 0.00 | 2 | 1 | 1 | 0 |

nk_churn 1  x

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# Thank You.