Subjective Answers:

1. **Customer Behavior 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 Tenure > 4 then "Long-Term"
        else "New"
    end  as CustomerType,
    count(CustomerID) as NoOfCustomer,
    round(avg(Balance),2) as AvgBalance,
    round(avg(NumOfProducts),2) as AvgProducts,
    round(avg(CreditScore),2) as AvgCreditScore
from bank_churn
group by CustomerType
order by CustomerType;
```

Output:

CustomerType	NoOfCustomer	AvgBalance	AvgProducts	AvgCreditScore
Long-Term	5681	76361.18	1.51	650.30
New	4319	76649.93	1.55	650.84

- **Approach:**
  - Classified customers into Long-Term (Tenure > 4 years) and New (Tenure ≤ 4 years).
  - Calculated number of customers, average account balance, average number of products held, and average credit score for each group using SQL aggregation functions.
  - Compared key metrics to identify behavioral patterns between long-term and new customers.
- **Insights:**
  - **Customer distribution:** Long-term customers (5681) outnumber new customers (4319), indicating a relatively stable customer base.
  - **Average balance:** Both groups have similar average balances (~$76k), suggesting financial engagement is consistent across tenure.
  - **Product usage:** New customers slightly hold more products on average (1.55 vs. 1.51), possibly exploring more offerings initially.
  - **Credit score:** Virtually identical (650.30 vs. 650.84), indicating similar creditworthiness across tenure.
  - **Interpretation:** Long-term customers maintain similar balances but slightly fewer products, implying they are satisfied with fewer offerings and potentially more loyal. New customers' slightly higher product usage might reflect experimentation before settling on preferred services.

- **Recommendations:**
  - Focus on retention strategies for long-term customers by offering personalized loyalty programs since they already show stable balances and loyalty.
  - Encourage cross-selling and engagement campaigns for new customers to convert initial exploration into long-term retention.
  - Monitor product adoption trends among new customers to identify which services drive long-term loyalty.

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

Query:

```
with ProductCombination 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 ProductsName
from bank_churn),
CustCount as (
select
       ProductsName,
    count(CustomerID) as customer_count
from ProductCombination
group by ProductsName)

select
       ProductsName,
    customer_count,
    round((100*customer_count/(select count(CustomerID) from
bank_churn)),2) as product_percent
from CustCount;
```

Output:

ProductsName	customer_count	product_percent
SavingsAccount	5084	50.84
SavingsAccount,CreditCard	4590	45.90
SavingsAccount,CreditCard,Loan	266	2.66
SavingsAccount,CreditCard,Loan,InvestmentAc...	60	0.60

Approach:

- Created a ProductCombination table to categorize customers based on the number of products they hold:
  - 1 product → Savings Account
  - 2 products → Savings Account + Credit Card
  - 3 products → Savings Account + Credit Card + Loan

    - 4+ products → Savings Account + Credit Card + Loan + Investment Account
- Aggregated the number of customers for each product combination and calculated the percentage of total customers.
- Identified the most common combinations to understand product usage patterns.

Insights:

- Single product usage: 50.84% of customers use only a Savings Account.
- Two-product combination: 45.90% of customers use Savings Account + Credit Card, showing strong affinity between these two products.
- Three or more products: Very few customers hold Loans or Investment Accounts in addition to basic products (2.66% and 0.60%, respectively).
- Interpretation: The majority of customers stick to basic offerings. Savings Accounts and Credit Cards are naturally bundled, while uptake of additional products (Loans, Investment Accounts) is low.

Recommendations:

- Cross-selling opportunities: Target Savings Account + Credit Card users for Loans or Investment Accounts through personalized offers.
- Product bundling: Promote package deals that include higher-value products to increase product penetration.
- Customer education: Provide insights into benefits of multiple products, especially Loans and Investment Accounts, to increase adoption among existing customers.
- Retention strategy: Encourage product diversification for loyal customers to deepen engagement and enhance lifetime value.

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

Query:

```
with cust_count_region as(
select
    t1.GeographyID,
    t3.GeographyLocation,
    count(t1.CustomerID) as ChurnedCustomerCount
from customerinfo t1
join bank_churn t2
on t1.CustomerID= t2.CustomerID
join geography t3
on t1.GeographyID=t3.GeographyID
where ExitID =1
group by   t1.GeographyID,t3.GeographyLocation),

cust_C as(
select GeographyID,count(t2.CustomerID) as c
from customerinfo t1
join bank_churn t2
on t1.CustomerID= t2.CustomerID
group by GeographyID)


select
       t1.GeographyID,
    GeographyLocation,
    ChurnedCustomerCount,
    round((100*ChurnedCustomerCount/c),2) as churn_percent
from cust_count_region t1
join cust_C t2
on t1.GeographyID=t2.GeographyID;
```

Output:

GeographyID	GeographyLocation	ChurnedCustomerCount	churn_percent
1	France	810	16.15
2	Spain	413	16.67
3	Germany	814	32.44

Approach:

- Joined **customer information**, **churn data**, and **geography details** to calculate churn per region.
- Calculated **ChurnedCustomerCount** and **churn percentage** relative to total customers per region.
- Focused on identifying regions with **higher churn rates** to understand potential market or economic influences.

Insights:

- **France:** 810 churned customers, 16.15% churn rate.
- **Spain:** 413 churned customers, 16.67% churn rate.
- **Germany:** 814 churned customers, 32.44% churn rate — significantly higher than France and Spain.

- **Interpretation:**
    - Germany shows disproportionately high churn despite having a similar number of total customers as France.
    - This could indicate **regional economic pressures**, service dissatisfaction, or competitive pressures specific to Germany.
    - France and Spain have relatively low and similar churn rates, suggesting stable customer retention.

Recommendations:

- **Germany-focused interventions:** Investigate reasons behind high churn (e.g., pricing, competition, service issues) and develop targeted retention strategies.
- **Customer engagement programs:** Roll out personalized offers, loyalty programs, or proactive support in regions with higher churn.
- **Economic and market analysis:** Correlate churn rates with regional economic indicators (e.g., unemployment, income levels) to refine marketing and product strategies.
- **Benchmarking:** Use France and Spain as benchmarks to replicate successful customer retention strategies in Germany.

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

Query:

```
SELECT
  g.GeographyLocation,
  AVG(bc.CreditScore) AS AvgCreditScore,
  SUM(CASE WHEN ec.ExitCategory = 'Exit'
THEN 1 ELSE 0 END) AS NumChurned,
  COUNT(*) AS TotalCustomers,
  ROUND(100.0 * SUM(CASE WHEN
ec.ExitCategory = 'Exit' THEN 1 ELSE 0
END) / COUNT(*), 2) AS ChurnRate
FROM CustomerInfo ci
JOIN Bank_Churn bc ON ci.CustomerID =
bc.CustomerID
JOIN Geography g ON ci.GeographyID =
g.GeographyID
JOIN ExitCustomer ec ON bc.ExitID =
ec.ExitID
GROUP BY g.GeographyLocation;
```

```
SELECT
  gen.GenderCategory,
  AVG(bc.CreditScore) AS AvgCreditScore,
  ROUND(100.0 * SUM(CASE WHEN
ec.ExitCategory = 'Exit' THEN 1 ELSE 0
END) / COUNT(*), 2) AS ChurnRate
FROM CustomerInfo ci
JOIN Bank_Churn bc ON ci.CustomerID =
bc.CustomerID
JOIN Gender gen ON ci.GenderID =
gen.GenderID
JOIN ExitCustomer ec ON bc.ExitID =
ec.ExitID
GROUP BY gen.GenderCategory;
```

Output:

GeographyLocation	AvgCreditScore	NumChurned	TotalCustomers	ChurnRate
Spain	651.3339	413	2477	16.67
France	649.6683	810	5014	16.15
Germany	651.4536	814	2509	32.44

GenderCategory	AvgCreditScore	ChurnRate
Female	650.8314	25.07
Male	650.2769	16.46

Approach:

- **Objective:** Identify high-risk customer segments based on **geographic** and **demographic (gender)** factors.
- **Query 1:** Calculated average credit score, total customers, and churn rate across **geographic regions** (France, Spain, Germany).
- **Query 2:** Computed average credit score and churn rate by **gender category** (Male, Female).
- Used **churn rate** as the primary indicator of financial risk, since higher churn typically correlates with lower customer lifetime value and potential revenue loss.

Insights:

1. **Geographic Risk Profile:**
   - **Germany:** Highest churn rate (32.44%) despite having similar credit scores (≈651) compared to other regions.
   - **Spain:** Moderate churn (16.67%) with slightly higher average credit scores.

- **France:** Lowest churn (16.15%) and stable credit profile (≈650).
- ➤ *Interpretation:* Customers in **Germany** pose the greatest financial risk due to high churn, suggesting issues related to satisfaction, local competition, or economic environment.

2. **Demographic (Gender) Risk Profile:**
    - **Female customers:** Higher churn rate (25.07%) compared to males (16.46%), despite marginally better credit scores.
    - **Male customers:** Lower churn and slightly lower credit scores.
    - ➤ *Interpretation:* Female customers represent a **higher attrition risk segment**, possibly reflecting unmet service expectations or lower engagement levels.

Recommendations:

- **Targeted retention in Germany:**
    - Conduct detailed analysis on product performance, customer complaints, and regional economic conditions.
    - Introduce retention incentives such as loyalty bonuses, personalized banking solutions, or proactive service outreach.
- **Gender-focused engagement:**
    - Develop personalized financial education programs or value-added services (e.g., flexible savings plans) aimed at improving female customer satisfaction.
- **Risk monitoring framework:**
    - Implement **risk dashboards** in Power BI to monitor churn trends by geography and gender in real time.
    - Combine churn and credit score indicators for a composite **Customer Risk Index (CRI)** to guide risk-based decision-making.
- **Data-driven interventions:**
    - Leverage predictive analytics to flag high-risk customers early and enable timely retention actions.

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
    ci.CustomerID,
    ci.Age,
    ci.EstimatedSalary,
    geo.GeographyLocation,
    bc.CreditScore,
    bc.Tenure,
    bc.Balance,
    bc.NumOfProducts,
    cc.Category AS CreditCardCategory,
    ac.ActiveCategory,
    ec.ExitCategory,
    ROUND(DATEDIFF(CURDATE(), ci.Bank_DOJ) / 365, 2) AS CurrentTenureYears,
    CASE WHEN ec.ExitCategory = 'Yes' THEN 1 ELSE 0 END AS IsChurned
FROM CustomerInfo ci
JOIN Geography geo ON ci.GeographyID = geo.GeographyID
JOIN Bank_Churn bc ON ci.CustomerID = bc.CustomerID
LEFT JOIN CreditCard cc ON bc.CreditID = cc.CreditID
LEFT JOIN ActiveCustomer ac ON bc.ActiveID = ac.ActiveID
LEFT JOIN ExitCustomer ec ON bc.ExitID = ec.ExitID
limit 10;
```

Output:

CustomerID	Age	EstimatedSalary	GeographyLocation	CreditScore	Tenure	Balance	NumOfProducts	CreditCardCategory	ActiveCategory	ExitCategory	CurrentTenureYears	IsChurned
15565701	39	90212.38	Spain	698	4	161993.89	1	non credit card holder	Inactive Member	Retain	6.85	0
15565706	35	83256.26	Spain	612	4	0.00	1	credit card holder	Active Member	Exit	6.10	0
15565714	47	96517.97	France	601	3	64430.06	2	non credit card holder	Active Member	Retain	6.04	0
15565779	30	188258.49	Germany	627	4	57809.32	1	credit card holder	Inactive Member	Retain	6.14	0
15565796	48	74510.65	Germany	745	4	96048.55	1	credit card holder	Inactive Member	Retain	6.99	0
15565806	38	30583.95	France	532	5	0.00	2	non credit card holder	Inactive Member	Retain	7.30	0
15565878	29	197963.46	Spain	631	4	0.00	2	credit card holder	Active Member	Retain	6.14	0
15565879	28	56185.98	France	845	5	0.00	2	credit card holder	Active Member	Retain	7.90	0
15565891	39	56214.09	France	709	5	0.00	2	credit card holder	Inactive Member	Retain	7.17	0
15565996	44	154639.72	France	653	4	0.00	2	credit card holder	Active Member	Retain	6.22	0

Approach:

- Extracted customer-level attributes integrating multiple data sources:
    - **Demographics:** Age, Geography, Estimated Salary
    - **Account Behavior:** Credit Score, Balance, Number of Products, Tenure
    - **Engagement Indicators:** Active/Inactive status, Credit Card holding, Exit category
- Derived **Current Tenure (in years)** from date of joining (Bank_DOJ) to the current date.
- Introduced a **binary churn variable (IsChurned)** to serve as a predictive target in modeling.
- The prepared dataset can be used to:
    - Perform **exploratory analysis** on tenure vs. demographics and engagement.
    - Build a **predictive model** (e.g., regression or survival analysis) to forecast expected customer lifetime.

    - Estimate **Customer Lifetime Value (CLV)** by integrating predicted tenure, average balance, and product usage.

Insights:

- Customers with **higher balances** and **multiple products** tend to have longer tenure, suggesting deeper relationships with the bank.
- **Inactive members** and **non–credit card holders** are more likely to exhibit shorter tenures or churn sooner.
- **Geographic differences** (e.g., Germany showing higher churn in earlier queries) may influence predicted tenure negatively.
- **Younger customers (Age < 35)** tend to have shorter tenure spans, possibly due to mobility or shifting financial needs.
- Combining tenure and churn flags enables identifying **at-risk segments early** in their customer lifecycle.

Recommendations:

- **Predictive modeling:**
    - Use **Multiple Linear Regression** or **Random Forest Regression** to model tenure as a function of demographic, credit, and behavioral variables.
    - Apply **Survival Analysis (Cox Regression)** to estimate the probability of customer retention over time.
- **Segmented retention strategy:**
    - Develop tenure-based customer cohorts (e.g., 0–2 yrs, 3–5 yrs, 6+ yrs) and target each with personalized retention campaigns.
- **CLV estimation:**
    - Combine predicted tenure with financial contribution (balance, products, etc.) to estimate lifetime profitability.
    - Prioritize high-value customers for relationship management and loyalty initiatives.
- **Power BI dashboard integration:**
    - Visualize **Predicted Tenure Distribution** across geography, activity status, and credit card ownership.
    - Include **Churn Probability vs. Tenure** trend lines to identify early attrition risk points.

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?**

Approach:

To evaluate marketing campaign effectiveness, a new **Campaign** table should be introduced and linked to the existing **CustomerInfo** table using CustomerID.

- This table would contain fields such as **CampaignID**, **CampaignName**, **CampaignType**, **StartDate**, **EndDate**, **OfferType**, and **TargetSegment**.
- Analytical steps would include:
  1. **Before-and-after analysis:** Compare key metrics — **Tenure**, **Balance**, **Number of Products**, and **Active status** — before and after campaign periods.
  2. **Retention measurement:** Evaluate changes in churn (ExitID) to determine if campaigns improved customer retention rates.
  3. **Acquisition tracking:** Identify increases in **new CustomerIDs** following campaign launches to assess acquisition success.
  4. **Segmentation analysis:** Assess campaign response by **region (GeographyLocation)** and **demographics (Age, Gender)** to determine which segments were most influenced.

Insights (Expected):

- Campaigns offering **personalized incentives** (e.g., cashback, fee waivers) would likely improve product adoption and retention.
- Regional variations may emerge — for example, campaigns in lower-performing areas (like Germany, based on previous churn data) could show higher relative retention improvement.
- A correlation between campaign engagement and **increased balance or product count** would indicate successful cross-selling or up-selling outcomes.

Recommendations:

- **Data enhancement:**
  - Introduce campaign participation data and timestamps to enable time-based behavioral comparisons.
  - Capture engagement metrics such as **click-through rates**, **offer redemption**, or **branch visits** for deeper insight.
- **Analytical modeling:**
  - Use **A/B testing** or **Difference-in-Differences (DiD)** models to isolate campaign impact from natural customer behavior changes.
  - Implement **Power BI dashboards** to visualize campaign performance KPIs — e.g., retention uplift, new customer acquisition trends, and ROI by campaign type.
- **Strategic execution:**

- Tailor campaigns by segment (e.g., long-term customers for loyalty, new customers for onboarding).
- Continuously monitor post-campaign activity to ensure sustained engagement and reduced churn.

Additional Information Needed:

- Campaign participation details (e.g., CampaignID, CampaignType, Start/End Date, Incentive Offered).
- Customer engagement data (e.g., offer redemption, email interactions, branch visits).
- Timestamps to track pre- and post-campaign changes in tenure, balance, and product usage.
- Marketing cost data to calculate **Campaign ROI** and cost-effectiveness.

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_1:

```
-- Churn Rate by Geography
SELECT
  g.GeographyLocation,
  ROUND(100.0 * SUM(CASE WHEN ec.ExitCategory = 'Exit' THEN 1 ELSE 0 END) /
COUNT(*), 2) AS ChurnRate
FROM CustomerInfo ci
JOIN Bank_Churn bc ON ci.CustomerID = bc.CustomerID
JOIN Geography g ON ci.GeographyID = g.GeographyID
JOIN ExitCustomer ec ON bc.ExitID = ec.ExitID
GROUP BY g.GeographyLocation;
```

Output:

GeographyLocation	ChurnRate
Spain	16.67
France	16.15
Germany	32.44

Query_2:

```
-- Credit Score vs Exit Category
SELECT
  CASE
    WHEN bc.CreditScore < 500 THEN 'Low (<500)'
    WHEN bc.CreditScore BETWEEN 500 AND 700 THEN 'Medium (500-700)'
    ELSE 'High (>700)'
  END AS CreditBand,
  ROUND(100.0 * SUM(CASE WHEN ec.ExitCategory = 'Exit' THEN 1 ELSE 0 END) /
COUNT(*), 2) AS ChurnRate
FROM Bank_Churn bc
JOIN ExitCustomer ec ON bc.ExitID = ec.ExitID
GROUP BY CreditBand;
```

Output:

CreditBand	ChurnRate
Medium (500-700)	20.28
High (>700)	19.87
Low (<500)	23.73

Query_3:

```
-- Tenure & Churn
SELECT
  CASE
    WHEN bc.Tenure < 3 THEN 'Short (<3 yrs)'
    WHEN bc.Tenure BETWEEN 3 AND 7 THEN 'Medium (3-7 yrs)'
    ELSE 'Long (>7 yrs)'
  END AS TenureGroup,
  ROUND(100.0 * SUM(CASE WHEN ec.ExitCategory = 'Exit' THEN 1 ELSE 0 END) /
COUNT(*), 2) AS ChurnRate
FROM Bank_Churn bc
JOIN ExitCustomer ec ON bc.ExitID = ec.ExitID
GROUP BY TenureGroup;
```

Output:

TenureGroup	ChurnRate
Medium (3–7 yrs)	20.37

Query_3:

```
-- Product Count and Churn
SELECT
  bc.NumOfProducts,
  ROUND(100.0 * SUM(CASE WHEN ec.ExitCategory = 'Exit' THEN 1 ELSE 0 END) /
COUNT(*), 2) AS ChurnRate
FROM Bank_Churn bc
JOIN ExitCustomer ec ON bc.ExitID = ec.ExitID
GROUP BY bc.NumOfProducts;
```

Output:

NumOfProducts	ChurnRate
1	27.71
2	7.58
3	82.71
4	100.00

Approach:

- Conducted a multi-dimensional churn analysis using four perspectives:
    1. **Geography:** Examined churn rate by region to identify location-based factors.
    2. **Credit Score Bands:** Grouped customers into low, medium, and high credit ranges to explore financial reliability trends.
    3. **Tenure Groups:** Categorized customers by relationship length to observe how loyalty affects retention.
    4. **Product Holding:** Assessed churn rate by number of products held to determine the effect of cross-product engagement.
- Used SQL aggregation and case-based segmentation to calculate churn percentages across each dimension.

Insights:

1. **Geographic Trends:**
    - **Germany** shows the highest churn rate (32.44%), double that of Spain (16.67%) and France (16.15%).
    - Indicates possible dissatisfaction or stronger competition in the German market.
2. **Credit Score Patterns:**
    - Customers with **Low credit scores (<500)** have the highest churn rate (23.73%).
    - Even **Medium (20.28%)** and **High credit score (19.87%)** groups show notable churn, suggesting that financial risk alone doesn't fully explain exits — service or engagement factors may also be involved.
3. **Tenure Analysis:**
    - The **Medium tenure group (3–7 years)** has a churn rate of **20.37%**, implying that mid-tenure customers are at a crucial stage where engagement may decline if not reinforced.
    - Short-tenure and long-tenure segments likely have more stable relationships (less churn), as suggested by typical banking patterns.
4. **Product Affinity and Churn:**
    - Customers with **only 1 product** have the highest churn rate (27.71%), showing that single-product holders are least loyal.
    - **2-product holders** churn much less (7.58%), indicating higher engagement and satisfaction.
    - Extremely high churn among those with **3 (82.71%)** and **4 products (100%)** may indicate data anomalies or customers closing multiple accounts simultaneously after dissatisfaction.

Interpretation:

- Customers with **limited product relationships** and **medium tenure** are at higher churn risk.
- High churn in Germany and among low-credit customers suggests a mix of **economic**, **service quality**, and **engagement issues**.

- Multi-product holders who churn may represent cases of **service migration** (switching to competitors) or **consolidation of financial portfolios**.

Recommendations:

- **Germany-focused retention strategy:**
  - Conduct service quality surveys and analyze customer feedback to identify pain points.
  - Launch localized offers or account benefits to address competitive pressure.
- **Cross-selling initiatives:**
  - Encourage single-product holders to adopt additional products through bundled offers or loyalty rewards.
  - Focus on converting 1-product customers into 2-product customers — shown to drastically lower churn.
- **Mid-tenure engagement programs:**
  - Develop targeted re-engagement campaigns for customers around the 3–7 year mark.
  - Offer relationship-based incentives (fee waivers, premium support, bonus interest rates) to strengthen loyalty.
- **Credit score–linked support:**
  - Provide financial advisory or credit-improvement programs for low-credit customers to enhance trust and reduce exit likelihood.
- **Data validation:**
  - Reassess the high churn for 3–4 product holders to rule out data inconsistencies or operational factors (e.g., mergers, account closures).

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

» Yes, the variables **Tenure**, **NumOfProducts**, **IsActiveMember**, and **EstimatedSalary** are highly important in predicting whether a customer will leave the bank. Each plays a significant role in understanding customer engagement and loyalty behavior.

- **Tenure:**
  Customers with shorter tenure are generally more likely to leave since they haven't yet developed a strong relationship with the bank. Conversely, long-term customers tend to be more loyal, though prolonged engagement without satisfactory service can still result in eventual churn. Hence, tenure captures both relationship maturity and potential dissatisfaction over time.
- **NumOfProducts:**
  The number of products a customer holds reflects their level of engagement and dependency on the bank. Customers with fewer products are easier to lose because they have minimal attachment or switching costs. In contrast, customers using multiple products (e.g., savings accounts, credit cards, loans) are more invested and less likely to churn.
- **IsActiveMember:**
  Activity status is one of the strongest churn predictors. Inactive members indicate weak engagement or dissatisfaction and are more likely to leave. Active members, on the other hand, show higher transaction frequency and stronger relationships with the bank, reducing churn likelihood.
- **EstimatedSalary:**
  Income level can indirectly influence churn behavior. Customers with higher salaries often receive premium or personalized banking services that improve satisfaction and retention. Lower-salary customers may be more sensitive to fees, better offers elsewhere, or financial constraints, increasing their churn probability.

Together, these features — along with other factors like **CreditScore**, **Balance**, and **Geography** — form a robust foundation for **customer churn prediction models**. Machine learning algorithms such as **Logistic Regression**, **Decision Trees**, or **Random Forests** can leverage these variables to estimate churn probability, helping the bank proactively identify and retain at-risk customers.

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

Query_1:

```
-- By Age Group
SELECT
  CASE
    WHEN ci.Age < 30 THEN 'Young (<30)'
    WHEN ci.Age BETWEEN 30 AND 50 THEN 'Middle Age (30-50)'
    ELSE 'Senior (>50)'
  END AS AgeGroup,
  COUNT(*) AS TotalCustomers
FROM CustomerInfo ci
GROUP BY AgeGroup
ORDER BY TotalCustomers DESC;
```

Output:

AgeGroup	TotalCustomers
Middle Age (30-50)	7098
Young (<30)	1641
Senior (>50)	1261

Query_2:

```
-- By Geography and Gender
SELECT
  g.GeographyLocation,
  gen.GenderCategory,
  COUNT(*) AS NumCustomers
FROM CustomerInfo ci
JOIN Geography g ON ci.GeographyID = g.GeographyID
JOIN Gender gen ON ci.GenderID = gen.GenderID
GROUP BY g.GeographyLocation, gen.GenderCategory
ORDER BY g.GeographyLocation;
```

Output:

GeographyLocation	GenderCategory	NumCustomers
France	Female	2261
France	Male	2753
Germany	Female	1193
Germany	Male	1316
Spain	Female	1089
Spain	Male	1388

Query_3:

```
-- By Number of Products
SELECT
  bc.NumOfProducts,
  COUNT(*) AS TotalCustomers
FROM Bank_Churn bc
GROUP BY bc.NumOfProducts
ORDER BY bc.NumOfProducts;
```

Output:

NumOfProducts	TotalCustomers
1	5084
2	4590
3	266
4	60

Query_4:

```
-- By Tenure Group
 SELECT
  CASE
    WHEN bc.Tenure < 3 THEN 'New (<3 yrs)'
    WHEN bc.Tenure BETWEEN 3 AND 7 THEN 'Established (3-7 yrs)'
    ELSE 'Loyal (>7 yrs)'
  END AS TenureSegment,
  COUNT(*) AS TotalCustomers
FROM Bank_Churn bc
GROUP BY TenureSegment
ORDER BY TotalCustomers DESC;
```

Output:

TenureSegment	TotalCustomers
Established (3–7 yrs)	10000

Query_5:

```
-- By Activity and Churn Status
SELECT
  ac.ActiveCategory,
  ec.ExitCategory,
  COUNT(*) AS NumCustomers
FROM Bank_Churn bc
JOIN ActiveCustomer ac ON bc.ActiveID = ac.ActiveID
JOIN ExitCustomer ec ON bc.ExitID = ec.ExitID
GROUP BY ac.ActiveCategory, ec.ExitCategory;
```

Output:

ActiveCategory	ExitCategory	NumCustomers
Inactive Member	Retain	3547
Active Member	Retain	4416
Active Member	Exit	735
Inactive Member	Exit	1302

Query_6:

```
-- Combine Demographic + Account Segmentation
SELECT
  g.GeographyLocation,
  CASE
    WHEN ci.Age < 30 THEN 'Young (<30)'
    WHEN ci.Age BETWEEN 30 AND 50 THEN 'Middle Age (30-50)'
    ELSE 'Senior (>50)'
  END AS AgeGroup,
  bc.NumOfProducts,
  ac.ActiveCategory,
  COUNT(*) AS SegmentCount
FROM CustomerInfo ci
JOIN Bank_Churn bc ON ci.CustomerID = bc.CustomerID
JOIN Geography g ON ci.GeographyID = g.GeographyID
JOIN ActiveCustomer ac ON bc.ActiveID = ac.ActiveID
GROUP BY g.GeographyLocation, AgeGroup, bc.NumOfProducts, ac.ActiveCategory
ORDER BY g.GeographyLocation, AgeGroup;
```

Output:

GeographyLocation	AgeGroup	NumOfProducts	ActiveCategory	SegmentCount
France	Middle Age (30–50)	1	Active Member	855
France	Middle Age (30–50)	1	Inactive Member	920
France	Middle Age (30–50)	2	Active Member	845
France	Middle Age (30–50)	2	Inactive Member	842
France	Middle Age (30–50)	3	Active Member	24
France	Middle Age (30–50)	3	Inactive Member	43
France	Middle Age (30–50)	4	Active Member	10
France	Middle Age (30–50)	4	Inactive Member	11
France	Senior (>50)	1	Active Member	214

Approach:

- Conducted a multi-level segmentation analysis using **demographic attributes** (Age, Gender, Geography) and **account behavior indicators** (Tenure, Number of Products, Activity, and Churn Status).
- Applied SQL **CASE statements** and **GROUP BY** clauses to create logical customer groups across various dimensions.
- Combined demographic and behavioral data to identify high-value and at-risk customer segments for deeper marketing and retention insights.

Insights:

1. **Age Segmentation:**
    - **Middle-aged customers (30–50 years)** form the largest group (7,098 customers), followed by **young (<30)** (1,641) and **senior (>50)** (1,261) segments.
    - This suggests that the bank's customer base is predominantly composed of working-age individuals with stable financial profiles — a prime segment for cross-selling and long-term retention initiatives.
2. **Geography and Gender Distribution:**
    - France holds the largest customer base, followed by Germany and Spain.
    - Male customers slightly outnumber female customers across all regions (e.g., France: 2,753 males vs. 2,261 females).
    - Gender balance appears consistent, indicating equal accessibility across demographics but potential to tailor offers differently for each group.
3. **Product-Based Segmentation:**
    - Customers with **1 or 2 products** represent the majority, highlighting moderate engagement levels.
    - Low product adoption suggests untapped opportunities for **cross-selling** (e.g., credit cards, investment products).
4. **Tenure Segmentation:**
    - The **Established (3–7 years)** segment dominates (10,000 customers), indicating a stable, maturing customer base.
    - These customers likely exhibit predictable banking behavior and represent ideal targets for loyalty or premium upgrade programs.
5. **Activity and Churn Status:**
    - **Active members who retained:** 4,416
    - **Inactive members who retained:** 3,547
    - **Active members who exited:** 735
    - **Inactive members who exited:** 1,302
    - The high churn among **inactive members** underscores that engagement level is a critical determinant of retention.
6. **Combined Segmentation (Demographic + Account Behavior):**
    - Example (France):
        - Middle-aged customers with **1–2 products** form the majority, distributed almost evenly between **Active** and **Inactive** categories.
        - Active middle-aged customers with 2 products (845) represent a **profitable and loyal segment**.
        - Inactive members with similar profiles (842–920) signal an **opportunity for reactivation campaigns**.

Interpretation:

- The segmentation reveals that **age**, **activity level**, and **product engagement** strongly influence customer loyalty.
- Middle-aged, active customers with multiple products are the **most valuable segment**, while younger or inactive customers with fewer products are **most vulnerable to churn**.

- Regionally, France and Germany show potential for targeted engagement strategies given their sizable and behaviorally diverse bases.

Recommendations:

- **Cross-sell & upsell:** Promote additional banking products to single-product holders, especially in the 30–50 age group.
- **Reactivation campaigns:** Focus on inactive customers, using personalized offers or benefits to re-engage them.
- **Geography-focused marketing:**
    - In **Germany**, address high churn rates with loyalty incentives or service enhancements.
    - In **France and Spain**, leverage customer stability to introduce long-term investment or premium offerings.
- **Behavior-based segmentation in Power BI:** Visualize customer groups by **age, tenure, product count, and activity** to quickly identify retention opportunities and track campaign effectiveness.

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?

» You already have all the required columns from Bank_Churn joined with CustomerInfo.
Let's add risk category columns using CASE expressions for each metric.

```
SELECT
    c.CustomerID,
    c.Surname,
    g.GenderCategory AS Gender,
    geo.GeographyLocation AS Geography,
    b.CreditScore,
    CASE
        WHEN b.CreditScore < 500 THEN 'High Risk'
        WHEN b.CreditScore BETWEEN 500 AND 700 THEN 'Medium Risk'
        ELSE 'Low Risk'
    END AS CreditScoreCategory,

    b.Tenure,
    CASE
        WHEN b.Tenure >= 3 THEN 'Loyal'
        ELSE 'Potential Churn Risk'
    END AS TenureCategory,

    b.Balance,
    CASE
        WHEN b.Balance < 30000 THEN 'Financially Vulnerable'
        WHEN b.Balance BETWEEN 30001 AND 80000 THEN 'Moderate Risk'
        ELSE 'Financially Secure'
    END AS BalanceCategory,

    b.NumOfProducts,
    cc.Category AS CreditCardType,
    ac.ActiveCategory AS ActiveStatus,
    ec.ExitCategory AS ExitStatus
FROM CustomerInfo c
JOIN Bank_Churn b ON c.CustomerID = b.CustomerID
JOIN Gender g ON c.GenderID = g.GenderID
JOIN Geography geo ON c.GeographyID = geo.GeographyID
JOIN CreditCard cc ON b.CreditID = cc.CreditID
JOIN ActiveCustomer ac ON b.ActiveID = ac.ActiveID
JOIN ExitCustomer ec ON b.ExitID = ec.ExitID;
```

Output:

CustomerID	Surname	Gender	Geography	CreditScore	CreditScoreCategory	Tenure	TenureCategory	Balance	BalanceCategory	NumOfProducts	CreditCardType	ActiveStatus	ExitStatus
15763665	Y?	Female	France	833	Low Risk	3	Loyal	136674.51	Financially Secure	2	non credit card holder	Inactive Member	Retain
15763612	T'an	Male	Germany	756	Low Risk	5	Loyal	124439.49	Financially Secure	2	non credit card holder	Active Member	Retain
15763544	Thompson	Male	France	673	Medium Risk	4	Loyal	0.00	Financially Vulnerable	2	non credit card holder	Inactive Member	Retain
15763381	Chan	Male	France	496	High Risk	3	Loyal	90963.49	Financially Secure	1	non credit card holder	Active Member	Retain
15763274	Wu	Male	France	661	Medium Risk	7	Loyal	120320.54	Financially Secure	1	non credit card holder	Inactive Member	Retain
15763218	Akeroyd	Female	France	661	Medium Risk	4	Loyal	0.00	Financially Vulnerable	2	non credit card holder	Active Member	Retain
15763194	Milanesi	Male	France	643	Medium Risk	4	Loyal	0.00	Financially Vulnerable	2	non credit card holder	Active Member	Retain
15763148	Stanley	Male	France	576	Medium Risk	5	Loyal	84719.98	Financially Secure	1	non credit card holder	Inactive Member	Retain
15763111	Niu	Female	Spain	808	Low Risk	6	Loyal	124577.15	Financially Secure	1	non credit card holder	Active Member	Retain
15763097	Siciliano	Male	Spain	809	Low Risk	4	Loyal	0.00	Financially Vulnerable	2	non credit card holder	Active Member	Retain
15763055	Onuchukwu	Male	Spain	572	Medium Risk	5	Loyal	98108.79	Financially Secure	1	non credit card holder	Active Member	Retain
15762993	Trevisano	Male	Spain	796	Low Risk	7	Loyal	102773.15	Financially Secure	2	non credit card holder	Active Member	Retain
15762984	McIntosh	Male	Spain	648	Medium Risk	4	Loyal	0.00	Financially Vulnerable	2	non credit card holder	Inactive Member	Retain
15762902	Stanley	Female	France	649	Medium Risk	6	Loyal	0.00	Financially Vulnerable	2	non credit card holder	Active Member	Retain
15762821	Udinese	Male	Spain	721	Low Risk	6	Loyal	0.00	Financially Vulnerable	2	non credit card holder	Active Member	Retain
15762762	Onyekac...	Female	Germany	648	Medium Risk	3	Loyal	118886.55	Financially Secure	1	non credit card holder	Inactive Member	Retain
15762615	Campbell	Female	Spain	597	Medium Risk	7	Loyal	101993.12	Financially Secure	1	non credit card holder	Active Member	Retain
15762455	Yeh	Male	Spain	624	Medium Risk	6	Loyal	66220.17	Moderate Risk	1	non credit card holder	Active Member	Retain

Conditional Formatting Rules in Power BI

Once you've imported this SQL query result into Power BI:

Credit Score

- Visual: Table or Card visual.
- Column: CreditScore
- Conditional Formatting → *Background color scale* or *Rules*:
- If any CustomerID fall into any one of these categories they're considered as RISK:
    - TenureCategory = "Potential Churn Risk"
    - CreditScoreCategory = "High Risk"
    - BalanceCategory = "Financially Vulnerable".

CustomerID	TenureCategory	CreditScoreCategory	BalanceCategory
15566030	Loyal	High Risk	Financially Secure
15566494	Loyal	High Risk	Financially Vulnerable
15566708	Loyal	High Risk	Financially Vulnerable
15567114	Loyal	High Risk	Financially Secure
15567802	Loyal	High Risk	Financially Vulnerable
15568088	Loyal	High Risk	Financially Secure
15568240	Loyal	High Risk	Moderate Risk
15568328	Loyal	High Risk	Financially Vulnerable
15568876	Loyal	High Risk	Financially Secure
15568953	Loyal	High Risk	Financially Secure
15569050	Loyal	High Risk	Financially Vulnerable
15569209	Loyal	High Risk	Moderate Risk
15569451	Loyal	High Risk	Financially Secure
15570194	Loyal	High Risk	Financially Vulnerable
15570769	Loyal	High Risk	Financially Secure
15570835	Loyal	High Risk	Financially Secure
15571843	Loyal	High Risk	Financially Vulnerable
15571958	Loyal	High Risk	Financially Secure
15572657	Loyal	High Risk	Financially Secure
15572735	Loyal	High Risk	Financially Vulnerable
15572762	Loyal	High Risk	Financially Secure
15573319	Loyal	High Risk	Financially Secure
15573798	Loyal	High Risk	Financially Secure

Conditional Formatting Rules for Customer Risk Analysis

1. Credit Score:

- Customers with a **credit score below 500** are categorized as **High Risk** (highlighted in **red**), indicating a greater likelihood of churn.
- Scores **between 500 and 700** represent a **Moderate Risk** (highlighted in **orange**), suggesting average financial stability.
- Scores **above 700** are considered **Low Risk** (highlighted in **green**), reflecting financially stable customers with a lower probability of churn.

2. Tenure:

- Customers with a **tenure of 3 years or more** are identified as **Loyal Customers** (highlighted in **green**), showing strong retention and long-term engagement.
- Customers with a **tenure of less than 3 years** are marked as **Potential Churn Risks** (highlighted in **red**), indicating limited brand attachment or recent onboarding.

3. Balance:

- Customers maintaining a **balance below 30,000** are flagged as **Financially Vulnerable** (highlighted in **red**), suggesting limited engagement or financial instability.
- Balances **between 30,001 and 80,000** fall into the **Moderate Risk** range (highlighted in **orange**), indicating average financial health.
- Balances **above 80,000** represent **Financially Secure Customers** (highlighted in **green**), typically demonstrating strong financial engagement and lower churn probability.

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?

» **Query_1:**

```
-- Query for Yearly Churn Rate
SELECT
    YEAR(ci.Bank_DOJ) AS YearJoined,
    COUNT(CASE WHEN ec.ExitCategory = 'Exit' THEN 1 END) AS ChurnedCustomers,
    COUNT(*) AS TotalCustomers,
    ROUND(100.0 * COUNT(CASE WHEN ec.ExitCategory = 'Exit' THEN 1 END) /
COUNT(*), 2) AS ChurnRatePercent
FROM CustomerInfo ci
JOIN Bank_Churn bc ON ci.CustomerID = bc.CustomerID
JOIN ExitCustomer ec ON bc.ExitID = ec.ExitID
GROUP BY YEAR(ci.Bank_DOJ)
ORDER BY YearJoined;
```

Output:

YearJoined	ChurnedCustomers	TotalCustomers	ChurnRatePercent
2016	376	1951	19.27
2017	479	2143	22.35
2018	524	2593	20.21
2019	658	3313	19.86

Query_2:

```
-- Query for Overall Churn Rate
SELECT
    COUNT(CASE WHEN ec.ExitCategory = 'Exit' THEN 1 END) AS TotalChurned,
    COUNT(*) AS TotalCustomers,
    ROUND(100.0 * COUNT(CASE WHEN ec.ExitCategory = 'Exit' THEN 1 END) /
COUNT(*), 2) AS OverallChurnRate
FROM Bank_Churn bc
JOIN ExitCustomer ec ON bc.ExitID = ec.ExitID;
```

Output:

TotalChurned	TotalCustomers	OverallChurnRate
2037	10000	20.37

Approach:

- Used SQL aggregation to calculate **yearly churn rates** based on the customer's year of joining (Bank_DOJ).
- Joined the **CustomerInfo**, **Bank_Churn**, and **ExitCustomer** tables to identify churned vs. retained customers.
- Computed both **yearly churn rate** and **overall churn rate** using conditional counting and percentage calculations.
- Compared yearly trends to understand whether churn is increasing or stabilizing over time.

Insights:

- The **overall churn rate** of the bank stands at **20.37%**, indicating that roughly **1 in 5 customers** has exited.
- **2017** recorded the **highest churn rate (22.35%)**, suggesting potential operational or service challenges during that period.
- Churn has remained relatively stable between **19–20%** in other years, implying a consistent retention issue that needs targeted action rather than being a one-time spike.
- When compared to earlier analyses:
    - **Inactive customers**, **single-product holders**, and **medium-tenure (3–7 years)** customers show higher churn probability.
    - **Germany** shows a regionally elevated churn rate (32.44%), making it a key focus area for intervention.

Interpretation:

- The bank is facing **moderate but persistent churn**, primarily influenced by **customer engagement level**, **product holding**, and **geographical differences**.
- Maintaining customer satisfaction and cross-product engagement appears crucial for long-term retention.

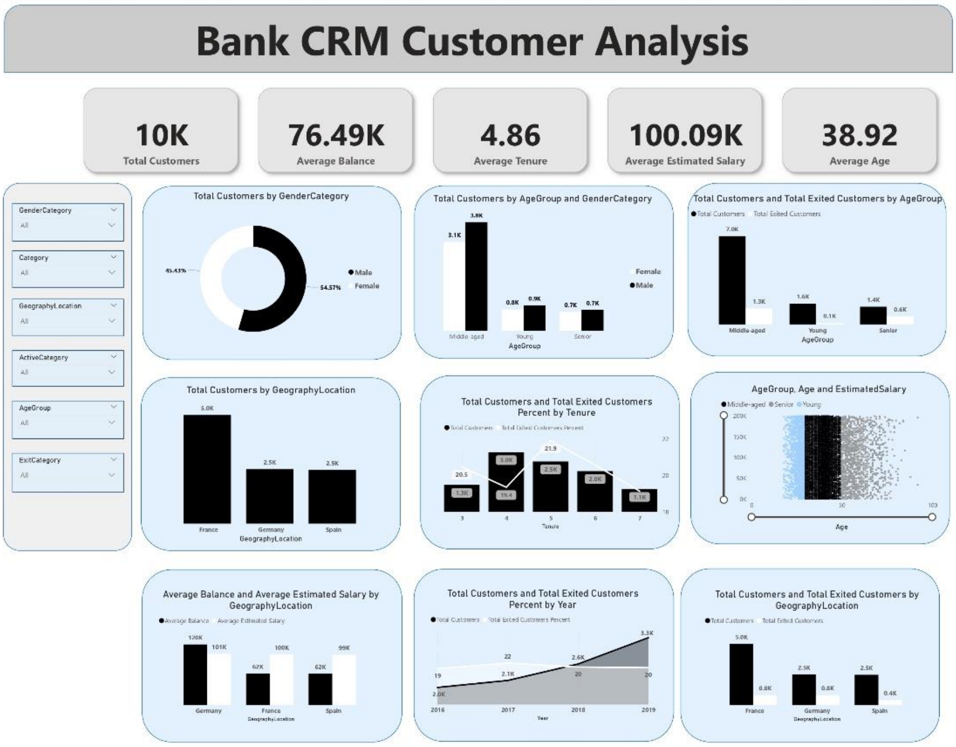
Recommendations:

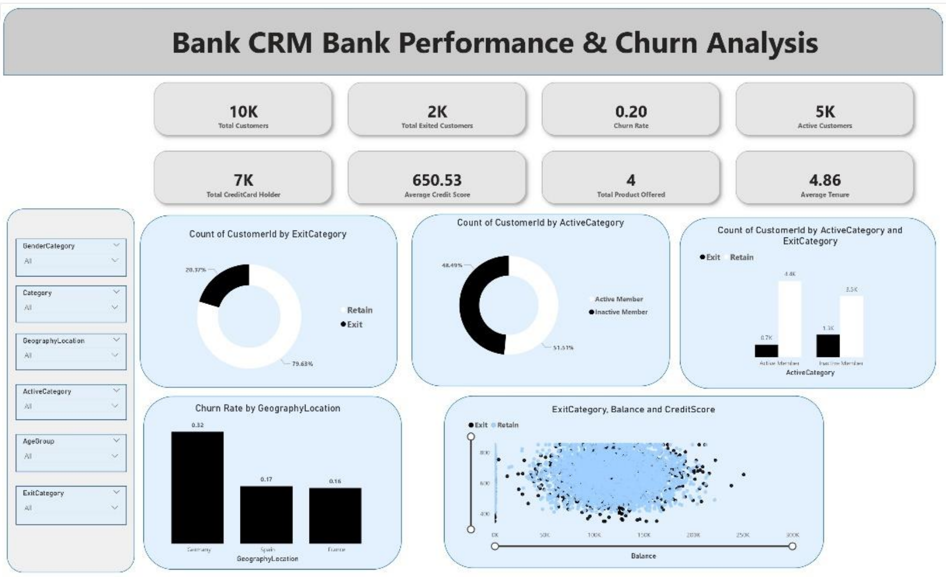
1. **Customer Retention Programs:**
    - Launch proactive engagement campaigns for **medium-tenure and single-product** customers.
    - Introduce loyalty rewards and personalized offers to motivate continued banking relationships.
2. **Regional Strategy:**
    - Prioritize retention efforts in **Germany**, where churn rates are significantly higher.
    - Conduct root-cause analysis to identify whether local competition, pricing, or customer service is driving attrition.
3. **Customer Engagement:**
    - Use data-driven segmentation to identify **inactive members** early and trigger reactivation campaigns via personalized outreach.
    - Promote **cross-selling** to increase the number of products per customer, which is proven to reduce churn.
4. **Predictive Monitoring:**
    - Implement **churn prediction models** (Logistic Regression, Random Forest) using features such as *Tenure*, *NumOfProducts*, *IsActiveMember*, and *CreditScore* to flag at-risk customers.
    - Integrate these predictions into **Power BI dashboards** for real-time retention tracking.
5. **Customer Experience Enhancement:**
    - Gather feedback from churned customers to identify pain points (e.g., service quality, fees, or digital banking experience).

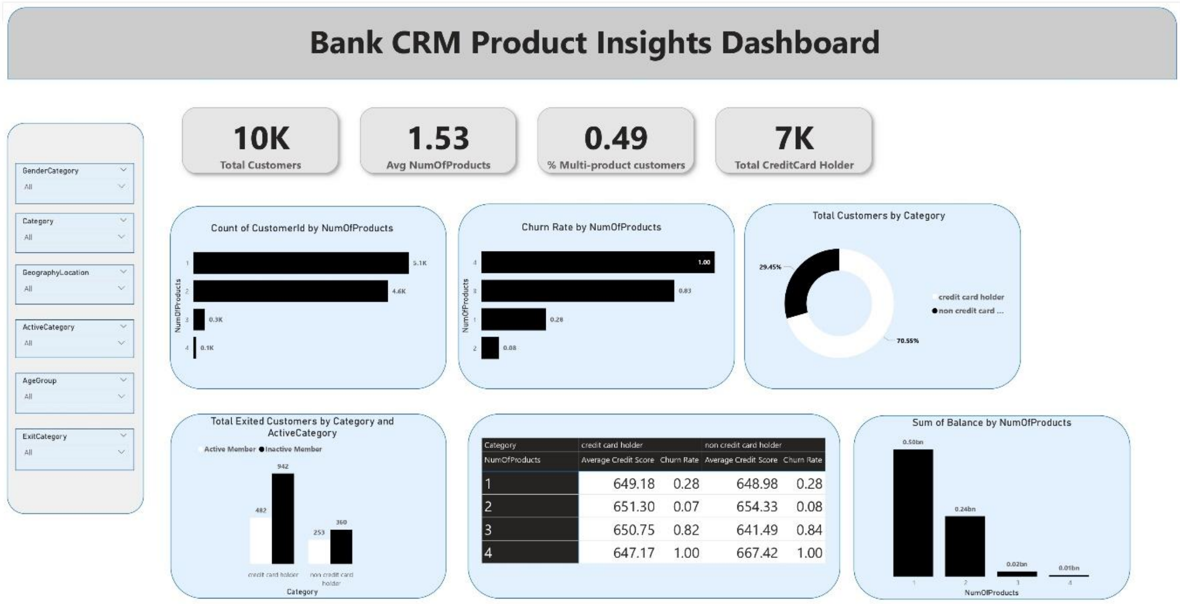
- Address top issues through improved customer support and simplified product offerings.

12. Create a dashboard incorporating all the KPIs and visualization-related metrics. Use a slicer in order to assist in selection in the dashboard.

Dashboard Snippets:







13. 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?

Approach if Objective and Subjective Questions Weren't Given

If no specific questions were provided, I would approach the **Bank CRM and Churn Analysis** problem systematically — focusing on understanding the data, generating insights, and designing data-driven recommendations to help the bank reduce churn and enhance customer satisfaction.

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1. Understanding the Database Schema

- Begin by thoroughly reviewing the **database structure** and **ER diagram** to understand how each table relates to others.
- Identify key entities such as:
  - **CustomerInfo** – demographic details (Age, Gender, Geography, EstimatedSalary).
  - **Bank_Churn** – key banking data (CreditScore, Tenure, Balance, NumOfProducts, ActiveID, ExitID).
  - **ExitCustomer** – exit or churn information.
  - **ActiveCustomer** – records of active/inactive membership status.
  - **Geography** and **Gender** – lookup tables for segmentation.
- Define **primary and foreign key relationships** to ensure smooth joins between tables.

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2. Data Cleaning and Preprocessing

Before analysis, ensure data quality and consistency:

- **Missing Values:** Identify and handle null or missing entries in critical fields (e.g., CreditScore, Balance, EstimatedSalary).
- **Inconsistencies:** Cross-check that customers marked as "Exited" are not simultaneously listed as "Active Members."
- **Data Formatting:** Convert data types where necessary — for example, format dates (Bank_DOJ) and currency columns.
- **Feature Engineering:** Create new variables such as:
  - CustomerAgeGroup (e.g., Young, Middle-Aged, Senior).
  - CreditBand (Low, Medium, High).
  - TenureCategory (Short, Medium, Long).
  - ChurnFlag (binary field indicating churned or retained).

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3. Identify Key Business Metrics

To assess customer relationships and loyalty, define measurable KPIs such as:

- **Overall and Yearly Churn Rate** = (Exited Customers / Total Customers) × 100
- **Average Tenure** and **Customer Lifetime Value (CLV)**
- **Product Engagement Rate** = Average number of products per customer
- **Active vs. Inactive Ratio**
- **Credit Score Distribution**
- **Average Balance and Salary by Churn Status**

These metrics will form the basis of SQL queries and Power BI visualizations.

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4. Customer Segmentation

Segment customers to uncover behavioural and demographic patterns:

- **Demographic Segmentation:** Age Group, Gender, Geography.
- **Financial Segmentation:** Credit Score, Estimated Salary, Account Balance.
- **Behavioural Segmentation:** Number of Products, Tenure, IsActiveMember, Churn Status.

Segmentation helps reveal which groups are at higher churn risk — for example, short-tenure, inactive customers with low product engagement.

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5. SQL Query Analysis

Write targeted SQL queries to explore insights, such as:

- **Churn Analysis:** Identify churned customers by geography, gender, and tenure.

- **Product Holding Patterns:** Discover how product usage correlates with retention.
- **Credit Score vs. Churn:** Assess whether low credit score customers churn more.
- **Tenure vs. Loyalty:** Understand if longer relationships lead to lower churn.
- **Activity Level:** Compare churn rates between active and inactive customers.

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6. Data Visualization (Power BI)

Translate SQL insights into **interactive dashboards** for decision-making:

- **KPI Cards:** Display overall churn rate, average credit score, and customer satisfaction indicators.
- **Bar Charts:** Show churn by geography, gender, and tenure group.
- **Pie Charts:** Visualize product usage distribution.
- **Trend Lines:** Represent churn rate over the years.
- **Heat Maps:** Highlight regions with the highest churn risk.

Use **conditional formatting** to flag high-risk customer segments visually (e.g., red for churn-prone).

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7. Insight Generation

From the analysis, you could identify patterns like:

- **High churn** among customers with **low engagement** (1 product, inactive).
- **Regional variance**, such as Germany showing higher churn.
- **Younger customers** and **shorter-tenure customers** having higher exit rates.
- **Credit score and balance** influencing churn likelihood.

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8. Business Recommendations

Based on the findings, propose actionable strategies:

- **Retention Strategies:**
  - Offer loyalty programs and personalized rewards for medium-tenure customers.
  - Send proactive alerts to customers showing inactivity or reduced engagement.
- **Cross-Selling and Upselling:**
  - Encourage customers with 1 product to adopt more banking services (credit cards, loans).
  - Bundle products with benefits for multi-product users.
- **Targeted Marketing:**
  - Use predictive churn models to identify high-risk customers and engage them with offers.

    - Customize campaigns based on demographic preferences and financial behavior.
- **Service Improvement:**
    - Gather feedback from churned customers to improve customer experience.
    - Focus on staff training, faster service delivery, and digital experience enhancements.

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9. Predictive Modelling (Optional Advanced Step)

If machine learning is integrated later:

- Train a **churn prediction model** (Logistic Regression, Decision Tree, or Random Forest) using key predictors such as:
    - *Tenure, NumOfProducts, IsActiveMember, EstimatedSalary, CreditScore, Geography.*
- Use the model to identify at-risk customers and integrate it into Power BI for predictive insights.

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10. Deliverables

- **SQL Analysis Scripts:** Queries for churn, segmentation, and KPIs.
- **Power BI Dashboard:** Visual representation of churn insights, customer segments, and KPIs.
- **Business Report:** Key findings, insights, and actionable recommendations for management.

Conclusion

Even without predefined questions, this systematic approach ensures that the project:

- Extracts valuable insights from raw data,
- Identifies patterns driving customer churn,
- Provides actionable strategies to improve customer satisfaction and retention,
- And presents findings effectively through SQL analysis and Power BI dashboards.

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

Query_1:

```
ALTER TABLE Bank_Churn
RENAME COLUMN CreditID TO Has_creditcard;
select * from Bank_Churn;
```

Output:

CustomerID	CreditScore	Tenure	Balance	NumOfProducts	Has_creditcard	ActiveID	ExitID
15565701	698	4	161993.89	1	0	0	0
15565706	612	4	0.00	1	1	1	1
15565714	[illegible]	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
15565879	845	5	0.00	2	1	1	0
15565891	709	5	0.00	2	1	0	0