# BANK CHURN ANALYSIS

Data-driven Insights into Customer Churn

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# PROJECT OVERVIEW

This project was initiated to help a European Bank understand and reduce customer churn—a critical issue affecting long-term profitability and customer loyalty.

Using a combination of data mining and clustering techniques, the analysis aimed to uncover churn patterns, identify at-risk customer segments, and propose actionable retention strategies.

# PROJECT GOALS

- Identify customer segments most at risk of churn
- Discover the key drivers behind churn behavior
- Use clustering and correlation to derive actionable patterns
- Recommend strategies to improve retention among high-value customers.

# OBJECTIVES

01 Detect and define customer segments with high churn risk

02 Investigate key drivers contributing to customer attrition

03 Analyse the relationship between Customer Lifetime Value (CLTV) and account activity.

04 Recommend data-informed strategies to enhance customer engagement and retention.

# DATA OVERVIEW

| Feature Name | Data Type | Feature Description |
|---|---|---|
| CCNum | Int | Unique IDs for customer identification |
| Transaction Data and Time | Datetime | Data and time of the customer's last transaction |
| Attrition Flag | Object | Whether the customer is still with the bank or they have attrited |
| Surname | Object | The customers last name |
| Age | Int | The customer's age |
| Gender | Object | Male or Female |
| Credit Score | Int | The customer's credit score |
| Geography | Object | The country the customer is from |
| Tenure | Int | The number of year for which the customer has been with the bank |
| Education Level | Object | The customer's level of education |
| Income Category | Int | The income category customers fall in |
| Credit Limit | Float | The credit limit on the customer's credit card |
| Card Category | Object | The type of card the customer holds |
| Total Transaction Amount | Int | Total amount transacted by the customer |
| Total Transaction Count | Int | Number of transactions conducted by the customer |
| Balance | Float | The customer's account balance |
| Number of Products | Int | The number of product the customer is utilising |
| HasCrCard | Int | Whether or not the customer holds a credit card with the bank |
| isActiveMember | Int | Whether or not the customer is an active member of the bank |
| Estimated Salary | Int | The customer's estimated salary |
| isFraud | Int | Whether or not there is fraudulent activities associated with the customer's account |
| Exited | Int | Whether or not the customer closed their account with the bank |

# PROBLEM-SOLVING PROCESS

1. Defined objectives based on the bank’s concerns
2. Loaded and cleaned the customer dataset (CSV → Pandas)
3. Preprocessed features (handled missing data, encoded categories)
4. Applied data mining techniques – correlation analysis + K-Means clustering
5. Identified significant attributes linked to churn
6. Visualized patterns and built churn-prone profiles
7. Recommended strategies based on customer lifetime value and risk

# WHY THESE TECHNIQUES

Correlation Analysis – helped me to understand the strength of relationships between churn and factors like credit score, product count, or tenure.

K-Means Clustering – uncovered natural groupings in customer behaviour, allowing me to spot risk-prone segments with similar traits.

This combination enabled both interpretability and segmentation, crucial for developing retention strategy

# METHODOLOGY

• Cleaned and preprocessed customer data using Python (Pandas, NumPy)

• Applied correlation analysis to identify important churn indicators.

• Performed K-Means clustering to segment customer groups based on shared attributes

• Visualized results using Matplotlib and Seaborn for clarity and strategic communication

# CHURN-PRONE CUSTOMER PROFILES

## PROFILE 1:

- Low tenure, few products, high credit risk
- Churn Rate: ~27%

## PROFILE 2:

- High balance, but no active product usage
- Churn Rate: ~19%

## PROFILE 3:

- Younger customers with low satisfaction scores
- Churn Rate: ~15%

# SERVICE SCRUTINY – HIGH CLTV CLIENTS

- I analysed balance vs. customer lifetime value
- Found that CLTV is influenced by:
  - Product ownership
  - Customer tenure
  - Engagement frequency
- Monthly balance alone had weak correlation with CLTV.

# MODEL PERFORMANCE SUMMARY

01

## Data Used

10,000+ customer records, cleaned and preprocessed.

02

## Clustering Validation

Elbow Method used to determine optimal clusters.

03

## Churn Risk Indicator

Profiles show clearly varying churn rates, validating segmentation.

# KEY INSIGHTS

01

### LESS PRODUCTS & SHORT RELATIONSHIPS

Customers with fewer products and shorter relationships are more likely to churn.

02

### Lack of Targeted Lead Generation

High-balance customers without engagement also show elevated churn risk.

03

### CHURN DEPENDENCIES

Tenure, product count, credit score, and age emerged as the most predictive features.

04

### CHURN-PRONE PROFILES

Three churn-prone profiles were defined with varying risk levels from 15% to 27%.

# RECOMMENDATIONS

## Onboarding Campaigns for Low-Tenure Customers

Target Profile 1 customers with onboarding support and product suggestions.

Personalised welcome messages.

Guided product walkthroughs within the first 30 days.

## Cross-Selling to Low-Product Customers

Build engagement strategies for Profile 2 (e.g., automated alerts, incentives).

Introduce bundled accounts (e.g. savings + credit).

Use email triggers to recommend products based on balance behavior.

# RECOMMENDATIONS

## Incentivise Inactive High Balance Customers

Offer loyalty rewards to high-value customers based on usage, not just balance.

Offer account upgrades or interest boosts for using more services.

Schedule periodic check-ins via relationship managers.

## Targeted Outreach to At-Risk Youth Segments

Deploy targeted email/SMS outreach to younger at-risk segments.

Mobile-first campaigns and gamified incentives.

Social media engagement and tailored financial education content.

# RECOMMENDATIONS

## Build Predictive Alert System for Relationship Managers

Alert system when a customer hits risk thresholds (e.g. tenure < 6 months, no new products)

Integrate churn risk scores into CRM to improve relationship management.

# NEXT STEPS

- Test real-time churn prediction models using updated customer data.
- Incorporate text analysis from support interactions or feedback forms.
- Develop a dashboard for tracking customer engagement and churn risk.
- Pilot retention campaigns for each of the three risk profiles.

# THANK YOU.