Project Brief — Bank Customer Churn Analysis

1. Objective

Analyze 10,000 bank customers to understand churn behavior, build predictive models, identify key drivers, and design an executive-ready Power BI dashboard.

2. Tools Used

• Python (pandas, scikit-learn, matplotlib, seaborn)
• Power BI (DAX, Power Query, Dashboard Visuals)
• Kaggle/Jupyter Notebooks

3. Key Findings

• Overall Churn Rate: **20.4%**
• Germany shows highest churn (~**32.4%**)
• Major churn drivers include Number of Products, Age, IsActiveMember, Geography, and Balance
• Customers who are high-balance & inactive are most likely to churn

4. Model Performance

• Accuracy: **0.65**
• Precision: **0.65**
• Recall: **1.00**
• F1 Score: **0.78**
• Threshold tuned for recall-first retention strategy

5. Segmentation Insights

K-Means segmentation revealed four major customer groups:
• High Balance / Inactive — Highest churn (~32%)
• Low Balance / Multi-Product
• Young / High Products
• Middle-Age / Active

6. Power BI Dashboard Pages

• Overview — KPIs, geography effects, churn trend
• Drivers — Feature importance, product behavior, engagement
• Geography Insights — Churn vs. tenure by region
• Segments — Customer clusters and churn distribution
• Model Outputs — Histogram, confusion matrix, predictions

7. Recommendations

• Prioritize retention for high-balance inactive customers
• Increase engagement programs for low-activity users
• Revisit cross-selling strategies for multi-product customers
• Investigate geographic churn variance, especially Germany

8. Repository Link

https://github.com/ap-cloud-bit/bank-churn-analytics-powerbi

End of Brief