Multimodal Banking (MDB) Attrition Project

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TD Bank

1. Abstraction and Business Problem

Customer attrition poses a significant financial risk to the banking industry, where even minor decreases in retention can result in millions of dollars in annual lost revenue. U.S **retail-bank retention** fell from **78% to 76%** in 2023, highlighting an urgent need for more effective prediction and intervention strategies.

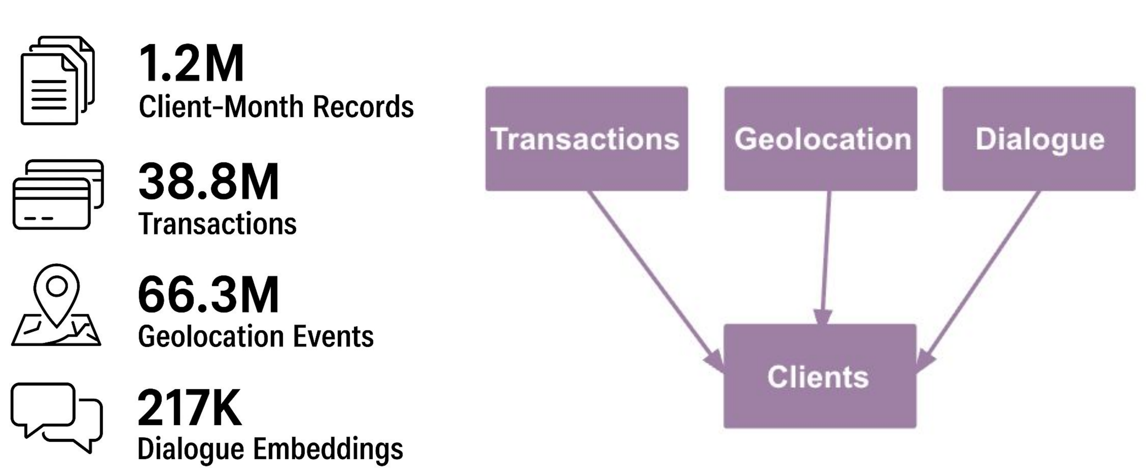
Most existing churn models rely on **single-modal**, structured data, failing to capture the rich, early warning signals hidden within customers' **cross-channel behaviors**. This project addresses this gap by developing a multimodal predictive framework that integrates diverse data streams to identify at-risk clients earlier and more accurately

Project Goal:
To build and validate a machine learning pipeline that fuses transactional, geographic and dialogue data to predict customer churn, enabling proactive and personalized retention efforts.

2. Dataset: MDB-mini

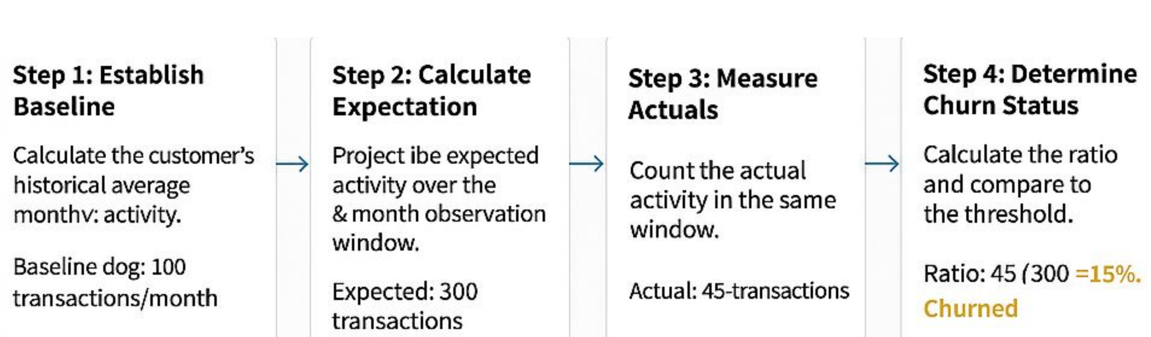
The project uses the Multimodal Banking Dataset (MBD) published by the Sber AI Lab; for our work, we focus on the mini version of this dataset.

Data Scale & Modalities:



3. Target Definition

A customer is defined as **churned** when their activity drops below **20%** below of their expected level. This threshold is the core of our target variable.



4. Methodology: A Multimodal Framework

Our approach follows a structured pipeline from raw data integration to sophisticated modeling, designed to extract deep behavioral patterns.

4.1 Feature Engineering

Our feature engineering framework captures a holistic, multi-faceted view of customer behavior across activity, engagement, and geospatial patterns. All features are derived strictly within the 3-month feature window to prevent data leakage.

Key Feature Groups:

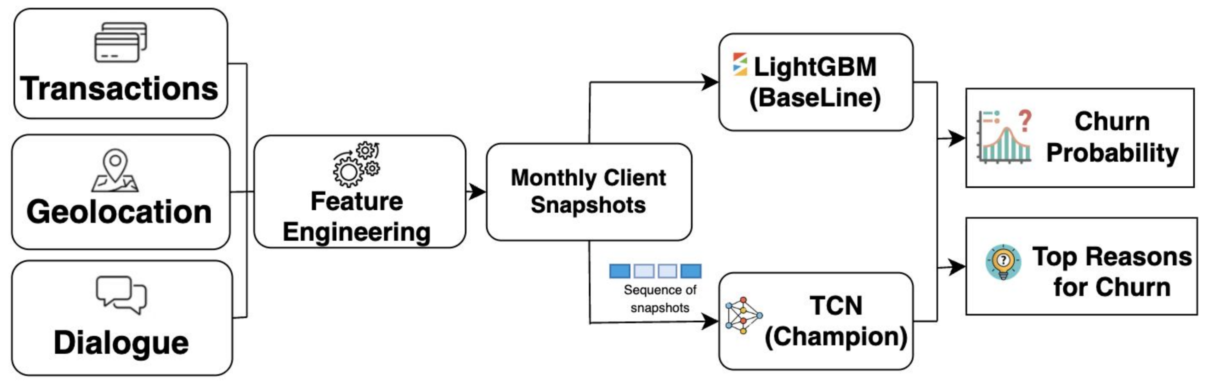
- **Current Month (3 features):** Snapshot of most recent activity (counts, spend, intensity).
- **Recent 3 Months (8 features):** Short-term behavioral patterns through aggregated trends.
- **Time-Series Dynamics (22 features):** Momentum, volatility, stability, and temporal shifts in behavior.
- **Dialog / Customer Service (12 features):** Frequency, recency, and intensity of interaction with support channels.
- **Geospatial Behavior (17 features):** Movement diversity, location dominance, entropy, and stability of top locations.

4.2 Model Architecture

We evaluated two classes of models to establish a robust performance benchmark and capture temporal dynamics.

A. Baseline Model: LightGBM: A powerful gradient-boosted model chosen for its high performance on heterogeneous tabular data, speed, and inherent handling of class imbalance. This established a strong, fair baseline.

B. Champion Model: Temporal Convolutional Network (TCN): A sequential deep learning model selected to analyze client behavior over time. By processing sequences of monthly features, the TCN can identify subtle, time-dependent patterns and deteriorating engagement trends that static models often miss.



5. Results & Key Findings

LightGBM
Train: 202,357 samples (9.25% churn) | Test: 34,160 samples (9.84% churn)
Features: 71 | Positive Class Weight: 9.81 | Optimal Threshold: 0.337

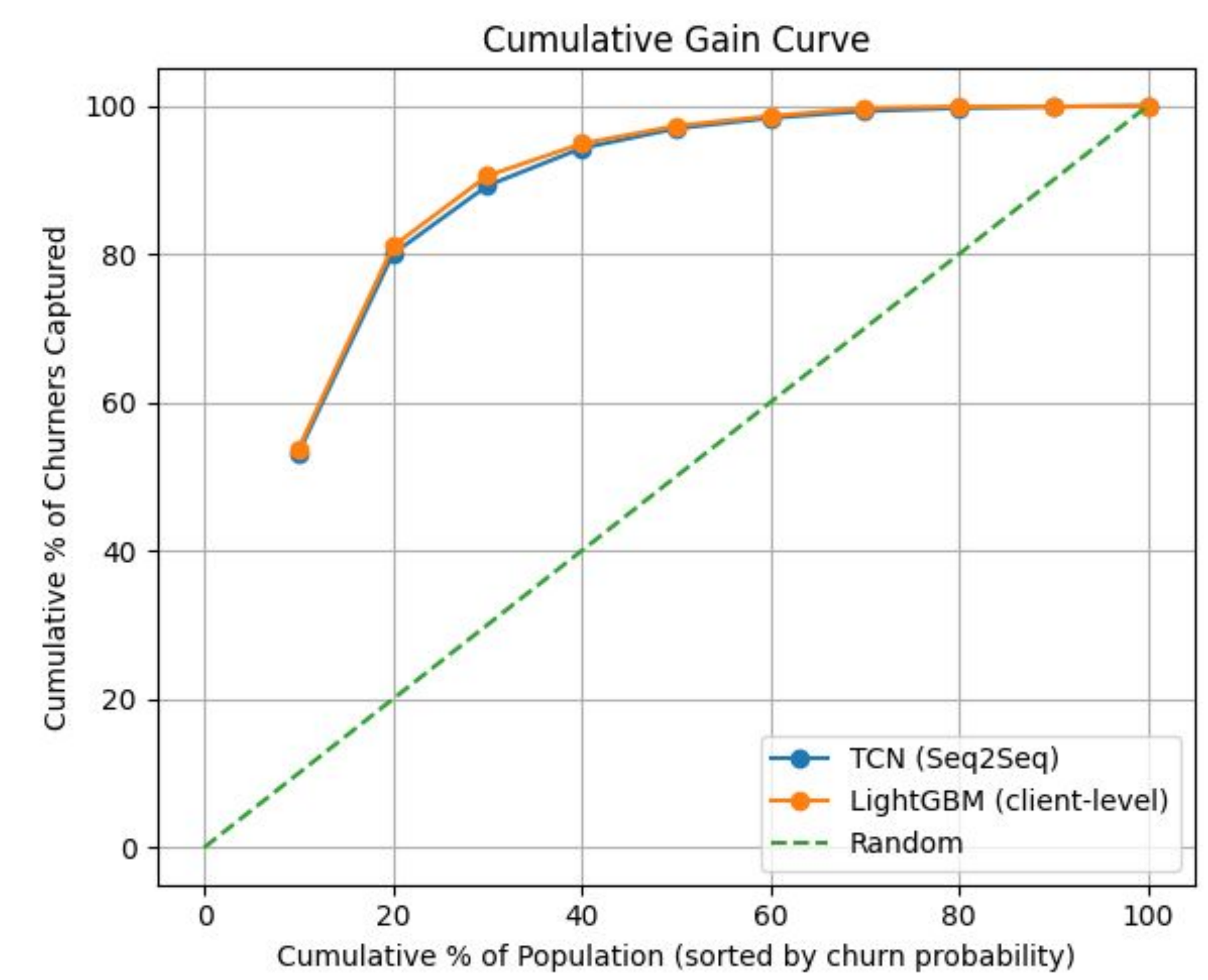
TCN
Train: 202,357 samples (9.25% churn) | Test: 34,160 samples (9.84% churn)
Features: 71 | Optimal Threshold: 0.497

Metric	LightGBM	TCN	Difference	Winner
AUC-ROC	0.9138	0.9109	-0.0029	LightGBM
Precision	0.5025	0.5619	+0.0594	TCN (+11.8%)
Recall	0.6830	0.6776	-0.0054	LightGBM
F1 Score	0.5790	0.6143	+0.0353	TCN (+6.1%)

When comparing, TCN (Seq2Seq) performs comparably to LightGBM in ROC-AUC, but delivers stronger precision, F1-score, and PR-AUC which are metrics that matter most in churn prediction. This indicates that **TCN is better at predicting the true churners while reducing false positives**. It is more effective on decision making focusing on retention.

Evaluation: Cumulative Gain curve

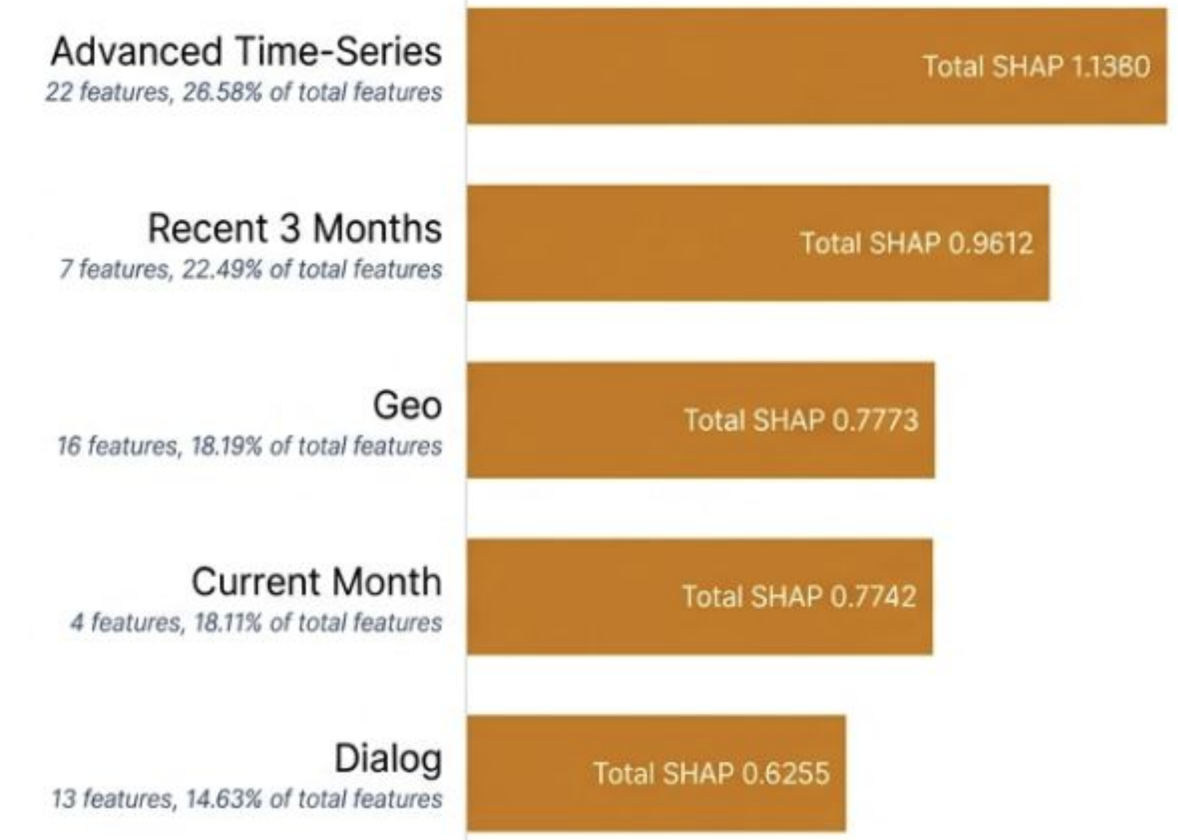
The Cumulative Gain Curve demonstrates the real business impact of our models by showing how many actual churners we can capture when we target a given percentage of the highest-risk clients.



Key Finding: The sequence-based TCN model consistently outperforms client-level LightGBM by a small margin, capturing **~80% of churners** by targeting only the **top 20% at-risk clients.**

6. SHAP Analysis

The Four Dimensions of Churn Risk



- **Advanced Time-Series** features contribute the most, indicating that patterns such as volatility, trend changes, and temporal irregularities are the strongest signals of churn.
- **Patterns over time** matter more than single events, and TCN can capture when habits break.
- **Geo + dialogue signals** refine predictions but play secondary roles.

7. Conclusion & Business Impact

In General, **the TCN model delivers high accuracy and clear explanations**, capturing behavioral shifts over time that static models miss. In enabled early detection of disengagement by identifying the drops in clident's interaction behaviors. The model transforms churn prediction from a black-box score into transparent, actionable insights.

Business Impact

- **Proactive intervention:** Shifts from reactive win-backs to proactive retention, giving a 1–2 month action window to prevent revenue loss.
- **Targeted ROI:** Focusing on the top 20% highest-risk clients captures 80%+ of likely churners, boosting marketing efficiency.
- **Personalized Offers:** Feature importance allows for hyper-personalized interventions for each specific user.

Future Scope

Expand Data Coverage	Real Time Deployment	A/B Test Interventions
Add newest monthly data & signals	Build live scoring pipeline	Measure lift vs. current strategy

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