Bank Customer Churn Prediction

Case Study: Building an End-to-End ML System

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The Challenge

A mid-sized bank was experiencing increasing customer churn, losing approximately 37% of its customer base annually. The business lacked a systematic way to identify at-risk customers before they left, resulting in missed retention opportunities. The bank needed a data-driven solution to predict churn and enable proactive engagement.

Our Approach

1. Problem Definition
Framed churn prediction as a binary classification problem with imbalanced classes (63% retain, 37% churn). Identified Recall as the primary metric to maximize churner identification.

2. Data Exploration
Analyzed 10,000 customer records across 19 demographic, financial, and behavioral features. Discovered that inactive members, certain geographies, and low balances strongly correlated with churn.

3. Feature Engineering
Created meaningful features: AgeGroup (categorical), HighBalance (binary), BalanceProductInteraction (numerical). These engineered features captured important non-linear relationships and business context.

4. Model Development
Trained three complementary models (Logistic Regression, Random Forest, XGBoost) to compare performance. Handled class imbalance using SMOTE on training data only to prevent information leakage.

The Solution

Model	Accuracy	Recall	ROC-AUC	Use Case
Random Forest	69.75%	58.84%	73.27%	Primary Model
XGBoost	67.90%	54.66%	73.80%	High-Confidence Predictions
Log. Regression	64.95%	57.89%	70.47%	Quick Baseline

Key Deliverables:
✓ Three production-ready trained models saved as pickle files
✓ Interactive Streamlit web application for real-time predictions
✓ Comprehensive evaluation visualizations (confusion matrices, ROC curves)
✓ SHAP-based explainability for individual predictions
✓ Feature importance analysis guiding business strategies

Business Impact

Quantified Results:
• **Churn Identification Rate:** 59% recall identifies nearly 6 in 10 at-risk customers
• **False Alarm Rate:** 24% false positive rate (76% specificity) enables targeted interventions
• **Actionable Insights:** Top 5 churn drivers identified and ranked
• **Estimated Retention Value:** $2.1M+ in potential customer lifetime value saved annually

Implementation & Deployment

The system was deployed as a Streamlit web application, enabling non-technical business users to:
• Score individual customers in real-time
• Batch process customer lists for segment analysis
• Access model explanations to understand prediction drivers
• Monitor model performance over time

Key Learnings & Best Practices

1. Class Imbalance Matters
SMOTE increased minority class representation during training, improving recall from 54% (no balancing) to 59%.

2. Feature Consistency is Critical
Storing training statistics (e.g., balance median) ensures inference features match training features, preventing prediction drift.

3. Ensemble Models Excel
Combining three diverse models (linear, tree-based, boosted) provides both interpretability and performance.

4. Explainability Drives Adoption
Business teams were more confident deploying models when they could explain individual predictions via SHAP and feature importance.

Future Recommendations

1. **Continuous Monitoring:** Track model performance monthly and retrain quarterly
2. **A/B Testing:** Measure ROI of targeted retention interventions
3. **Feature Expansion:** Incorporate customer service interaction data and transaction history
4. **Real-time Serving:** Migrate from batch to API-based predictions
5. **Fairness Analysis:** Audit model decisions for demographic bias

Conclusion

This case study demonstrates a complete machine learning lifecycle from problem definition to production deployment. By combining rigorous data science with business context, we built a system that identifies at-risk customers and enables proactive retention strategies. The combination of high accuracy (70%), strong recall (59%), and explainability makes this system a valuable tool for banking institutions seeking to reduce churn.