Predictive Model Plan – Student Template

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1. Model Logic (Generated with GenAI)

\For predicting customer delinquency, a Gradient Boosting Machine (GBM) will be implemented. This model iteratively builds an ensemble of weak prediction models, typically decision trees, to make accurate predictions. Each new tree corrects the errors made by the previous ones, progressively improving the model's performance.

Function Predict_Delinquency(dataset): // Step 1: Data Preprocessing 1. Handle Missing Values: - Impute 'Income', 'Credit_Score', 'Loan_Balance' using median or more advanced methods (e.g., KNN imputation). 2. Standardize Categorical Data: - Clean 'Employment_Status' (e.g., 'EMP', 'employed' -> 'Employed'). 3. Feature Engineering: - Create 'Missed_Payments_Last_6_Months' by summing 'Late'/'Missed' from Month_1 to Month_6. 4. Encode Categorical Features: - Apply One-Hot Encoding to 'Employment_Status', 'Credit_Card_Type', 'Location'. 5. Scale Numerical Features: - Apply StandardScaler to numerical features ('Age', 'Income', 'Credit_Score', etc.). // Step 2: Split Data 6. Divide the preprocessed dataset into Training (e.g., 80%) and Testing (e.g., 20%) sets. // Step 3: Train the Gradient Boosting Model 7. Initialize a Gradient Boosting Classifier (e.g., XGBoost or LightGBM) - Configure hyperparameters: learning rate, number of estimators, max depth, subsample ratio, etc. - **Crucially, address class imbalance**: Use parameters like `scale_pos_weight` or `is_unbalance` to give more importance to the minority class (delinquent accounts) during training. 8. Train the model on the training data (features predicting 'Delinquent_Account' target). // Step 4: Make Predictions 9. Use the trained model to predict delinquency probabilities on the test set. 10. Convert probabilities to binary predictions (0 or 1) using a chosen threshold (e.g., 0.5, or an adjusted threshold based on desired precision/recall trade-off). // Step 5: Evaluate Performance (Detailed in Section 3) 11. Calculate and report metrics: Precision, Recall, F1-Score, AUC. 12. Assess fairness across demographic subgroups. Return trained_model, performance_metrics End Function

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2. Justification for Model Choice

I selected a Gradient Boosting Machine (GBM) (specifically considering algorithms like XGBoost or LightGBM) as the best choice for identifying high-risk customers.
- Accuracy: GBMs consistently deliver state-of-the-art predictive accuracy on tabular data, which is crucial for a financial prediction task like delinquency where missing high-risk customers can lead to significant losses. While Logistic Regression and Decision Trees are simpler, they often cannot capture the intricate, non-linear relationships present in real-world financial data as effectively as GBMs.
- Transparency (with Tools): While a single GBM is less "transparent" than a single Decision Tree or Logistic Regression, modern interpretability tools like SHAP (SHapley Additive exPlanations) can provide deep insights into how the model makes its decisions. This allows us to understand the contribution of each feature to a customer's delinquency prediction, addressing the need for explainability.
- Ease of Use & Implementation (Libraries): Libraries for XGBoost and LightGBM are highly optimized, well-documented, and relatively straightforward to implement in Python, making them practical for development.
- Relevance for Financial Prediction: GBMs are widely used in financial fraud detection, credit scoring, and risk assessment due to their robust performance and ability to handle diverse feature types (numerical, categorical). They are particularly good at handling class imbalance, which is a common challenge in delinquency datasets where non-delinquent cases far outnumber delinquent ones.
- Suitability for Geldium's Business Needs: Geldium needs to accurately identify high-risk customers to enable proactive interventions. The superior predictive power of GBMs ensures a higher recall of delinquent customers, minimizing missed opportunities to mitigate risk. While some explainability is sacrificed compared to simpler models, the critical need for high accuracy in identifying actual high-risk customers makes GBMs the most suitable compromise.

3. Evaluation Strategy

Evaluating the model's performance rigorously is paramount to ensure it is both effective and fair.
Metrics:

Precision: This will measure how many of the customers flagged as "high-risk" by our model are actually high-risk. A high precision score reduces false positives, meaning fewer low-risk customers are unnecessarily subjected to interventions

Recall: This will measure how many of the actual high-risk customers our model successfully identifies. A high recall score reduces false negatives, ensuring we catch most of the genuinely delinquent accounts.

F1-Score: The harmonic mean of precision and recall. It provides a single score that balances both metrics, especially useful in cases of class imbalance.

ROC-AUC (Receiver Operating Characteristic - Area Under Curve): This will assess the model's ability to distinguish between delinquent and non-delinquent customers across all possible classification thresholds. A higher AUC indicates better discriminatory power.

Confusion Matrix: A visual summary of correct and incorrect predictions, clearly showing true positives, true negatives, false positives, and false negatives.
Interpretation:

For identifying high-risk customers, we would likely prioritize Recall to minimize false negatives (missing actual high-risk customers), even if it means a slightly lower precision (some false positives). The specific business impact of false positives versus false negatives will determine the optimal balance.

The F1-Score will give us a balanced view, and AUC will confirm the model's general capability to separate the classes.

Plans to Detect and Reduce Bias:

Subgroup Analysis: We will systematically evaluate the model's Precision, Recall, and F1-score across different protected demographic attributes (e.g., Age_Group, Credit_Card_Type, Location). This will help identify if the model is performing significantly worse or disproportionately flagging certain groups as high-risk.

Addressing Class Imbalance: As observed, the dataset has a severe class imbalance. We will use techniques such as:

SMOTE (Synthetic Minority Over-sampling Technique) on the training data to create synthetic examples of the minority class (delinquent customers).

Adjusting Class Weights in the GBM algorithm, giving higher penalties for misclassifying the minority class.

· Threshold Adjustment: After initial training, we may adjust the prediction probability threshold to optimize for a specific balance of precision and recall relevant to Geldium's risk tolerance.

Feature Importance and SHAP Values: We will analyze feature importance (from the GBM) and use SHAP values to understand which features drive predictions for specific individuals and groups. This will help us confirm that predictions are based on relevant financial indicators rather than proxies for protected attributes.

Ethical Considerations in Financial Predictions:

Transparency: While GBMs are complex, their interpretability through SHAP is vital. Customers and regulators should understand *why* a decision was made.

Fairness and Non-discrimination: The model should not perpetuate or amplify existing societal biases. Disproportionately flagging certain demographics as high-risk could lead to discriminatory practices, limiting access to financial services or imposing unfair terms. Regular fairness audits are critical.

Privacy: Ensuring customer data used for prediction is handled securely and ethically, adhering to all privacy regulations.

Accountability: Establishing clear accountability for model outcomes and a process for reviewing and challenging predictions. The model should be a tool to assist, not replace, human judgment, especially in edge cases.

Impact on Customers: Understanding the real-world impact of being flagged as "high-risk" (e.g., higher interest rates, reduced credit limits, denial of services) and designing interventions that are supportive rather than punitive.