Predictive Model Plan – Student Template

1. Model Logic (Generated with GenAI)

Predictive Modeling Pipeline for Credit Delinquency Forecasting

- **Model Selection**:
  • Logistic Regression as the primary model – interpretable, efficient, and well-suited for binary classification (delinquent vs. non-delinquent)
  • Random Forest as an alternative – captures non-linear relationships and feature interactions while providing feature importance
  • Gradient Boosting (XGBoost) for optimal performance – handles imbalanced data well and achieves high accuracy
- **Key Input Features (Top 5)**:
  • **Missed_Payments** – Strongest predictor; directly reflects payment behavior
  • **Credit_Utilization** – High utilization indicates financial stress
  • **Debt_to_Income_Ratio** – Measures financial leverage and repayment capacity
  • **Credit_Score** – Reflects creditworthiness and financial history
  • **Account_Tenure** – Longer relationships may indicate lower delinquency risk
- **Modeling Workflow**:
  • Data preprocessing: Handle missing values, encode categorical variables, normalize numerical features
  • Feature engineering: Derived features like payment-to-income ratio, utilization trends
  • Train/validation/test split: 70%/15%/15% stratified split to maintain class distribution
  • Model training: Fit models with cross-validation for hyperparameter tuning
  • Model evaluation: Precision, Recall, F1-score, AUC-ROC (focus on recall for delinquent cases)
  • Model interpretation: Feature importance & partial dependence plots
  • Deployment: Save model, create prediction pipeline, establish monitoring procedures
- **Evaluation Metrics**: Precision, Recall, F1-score, AUC-ROC
- **Implementation Considerations**:
  • Handle class imbalance with SMOTE/class weights
  • Regular model retraining with new data
  • Monitor feature drift & performance degradation

2. Justification for Model Choice

Justification for Logistic Regression in Delinquency Prediction

1. **Why Logistic Regression is Appropriate**:
   • Well-suited for binary classification (delinquent vs. non-delinquent)
   • Produces probabilistic outputs for customer risk ranking
   • Financial features (e.g., credit score, debt-to-income) often show linear relationships with delinquency risk
2. **Strengths for Geldium's Needs**:
   • **High interpretability** – coefficients clearly show impact of features
   • **Regulatory compliance** – supports explainable AI requirements (GDPR, CCPA)
   • **Transparency** – easy to document and audit
   • **Efficiency** – fast training/predictions, supports real-time scoring
   • **Stability** – less prone to overfitting with regularization
3. **Trade-offs and Considerations**:
   • Limited ability to model non-linear interactions
   • Requires strong feature engineering to capture complexities
   • Assumes linearity in log-odds, which may not always hold
4. **Business Alignment**:
   • Enables **risk-based pricing** and **credit limit decisions**
   • Interpretability helps customer service explain credit decisions
   • Low complexity reduces IT overhead
   • Coefficients create a clear, auditable trail
5. **Deployment Advantages**:
   • Minimal infrastructure and monitoring needs
   • Quick retraining when new data arrives
   • Easy integration into existing credit systems

3. Evaluation Strategy

Model Evaluation Strategy for Delinquency Prediction

- **Accuracy Metrics**:
  • AUC-ROC (target >0.75)
  • Precision (target >0.60)

  - Recall/Sensitivity (target >0.70)
  - F1-Score (target >0.65)
  - Specificity (target >0.70)
  - Accuracy (target >0.75)
  - Brier Score (target <0.25)
- **Fairness and Bias Metrics**:
  - Equal Opportunity Difference (compare TPR across groups)
  - Demographic Parity Difference (compare PPV across groups)
  - Equalized Odds Difference (FPR & TPR across groups)
  - Calibration Gap (predicted vs. actual rates across groups)
  - Individual fairness – similar customers should receive similar risk scores
- **Group-Based Evaluation**:
  - Assess performance across **Age, Employment_Status, Location**
  - Check for disparate impact in **Credit_Card_Type, Account_Tenure** segments
- **Interpretation Guidelines**:
  - AUC <0.70 = needs improvement
  - Precision <0.50 = too many false alarms
  - Recall <0.60 = missing too many true delinquents
  - Fairness metric disparity >0.10 = possible bias
- **Bias Detection Methods**:
  - Feature importance checks for protected attributes
  - Residual analysis by demographic group
  - Threshold optimization per group
  - Adversarial testing with edge cases
- **Monitoring & Improvement Triggers**:
  - >10% drop in metrics over 3 months
  - >20% change in feature distributions
  - >0.15 rise in fairness disparities
  - Increase in customer complaints or regulator issues
- **Reporting Requirements**:
  - Monthly performance dashboards
  - Quarterly fairness assessments
  - Annual independent validation
  - Ad-hoc reports for business/regulatory changes