

FINAL PROJECT

1

Predict the likelihood of working in the nonprofit sector by sex and education

2

Identify how demographic patterns align with nonprofit employment

Project 1

Dataset and Target Variable

- U.S. Census PUMS microdata used for individual-level analysis
 - Restricted to employed adults age 18 and older
 - Target variable: nonprofit_worker (binary classification)
 - Only about 10–11% of workers are nonprofit employees
 - Strong class imbalance reflects real-world labor patterns

Train/Test Split and Class Balance

- Data split into training (75%) and testing (25%) sets
 - Stratified sampling preserves nonprofit proportions
 - Training data contains ~89% non-nonprofit and ~11% nonprofit workers
 - Test set mirrors real-world class distribution

Data Cleaning and Feature Preparation

- Key demographic features selected: age, education, sex, disability, region
 - Missing numeric values replaced using median imputation
 - Missing categorical values replaced using most common category
 - Categorical variables converted using one-hot encoding
 - Numeric variables standardized to comparable scales

Project 2

Supervised Learning Models

- Supervised learning predicts outcomes using labeled data
 - Logistic Regression used as an interpretable linear baseline
 - Random Forest used to capture nonlinear relationships
 - Model evaluation focused on precision, recall, and F1-score
 - Accuracy avoided due to strong class imbalance

Handling Class Imbalance: Balanced Models

- Default models failed to detect nonprofit workers (recall ≈ 0)
 - Class weighting applied to emphasize minority-class errors
 - Balanced Logistic Regression achieved recall ≈ 0.635
 - Balanced Random Forest achieved recall ≈ 0.666
 - Balanced Random Forest produced the strongest overall F1-score

ROC Curves and Model Discrimination

- ROC curves evaluate performance across all thresholds
 - Logistic Regression AUC ≈ 0.673
 - Random Forest AUC ≈ 0.682
 - Both models perform better than random guessing but remain limited

Project 3

Unsupervised Learning and PCA

- Unsupervised learning explores structure without labels
 - Goal: test whether demographics naturally cluster
 - Principal Component Analysis (PCA) reduced dimensionality
 - 95% of variance retained after PCA
 - PCA improved clustering stability but not label alignment

Clustering Methods and Quantitative Results

- Three clustering algorithms tested: k-Means, Agglomerative, DBSCAN
 - k-Means achieved the highest silhouette score (~0.33)
 - Adjusted Rand Index values were near zero across all methods
 - PCA slightly improved DBSCAN ARI but not overall conclusions
 - Clusters did not strongly align with nonprofit employment

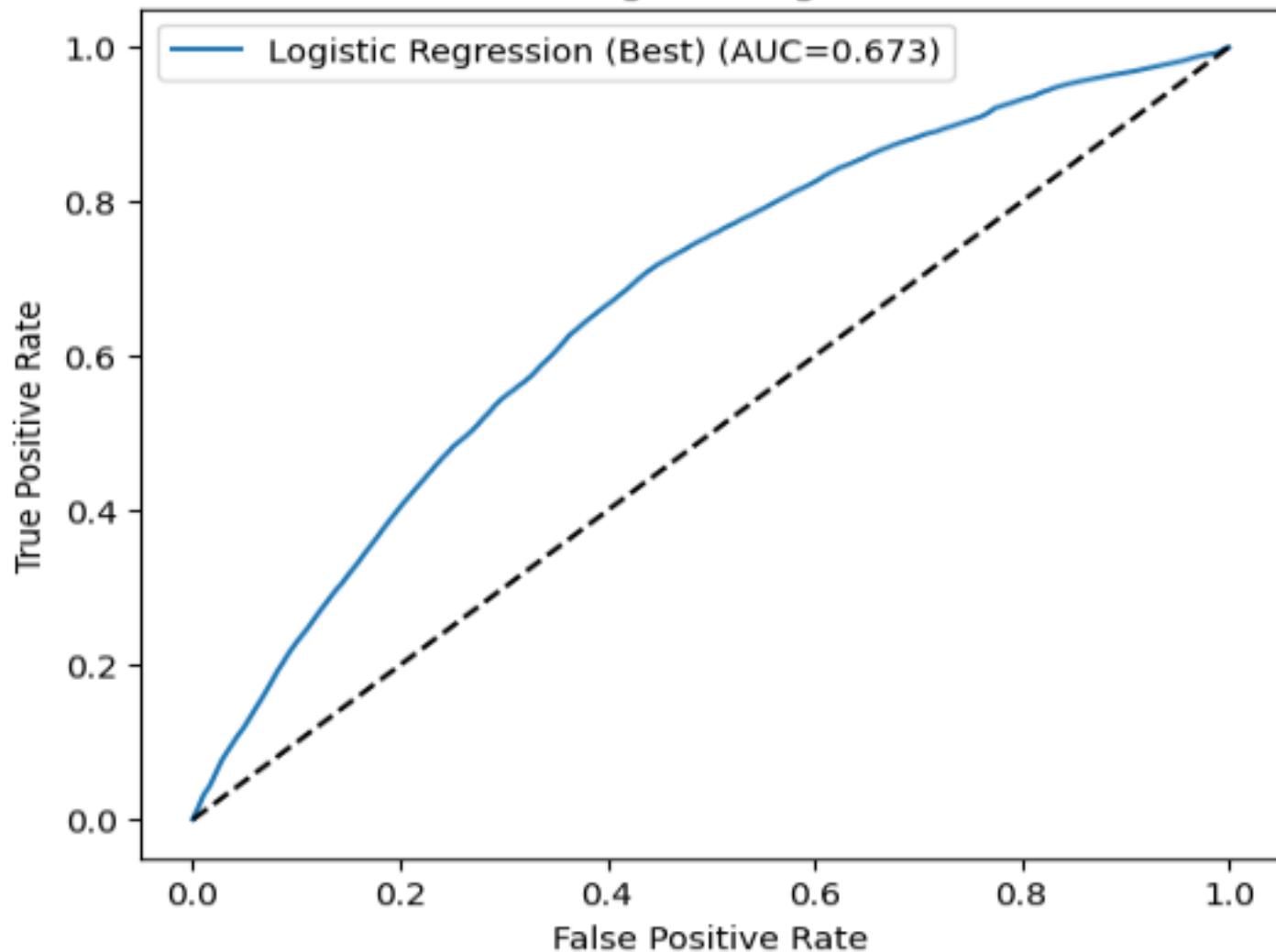
Limitations and Future Work

- Features used alone may be insufficient to predict nonprofit employment
 - Strong class imbalance limits predictive performance
 - Clustering results sensitive to feature choice and distance metrics
 - Future work could include income, occupation, or industry variables
 - Additional methods could include resampling or threshold tuning

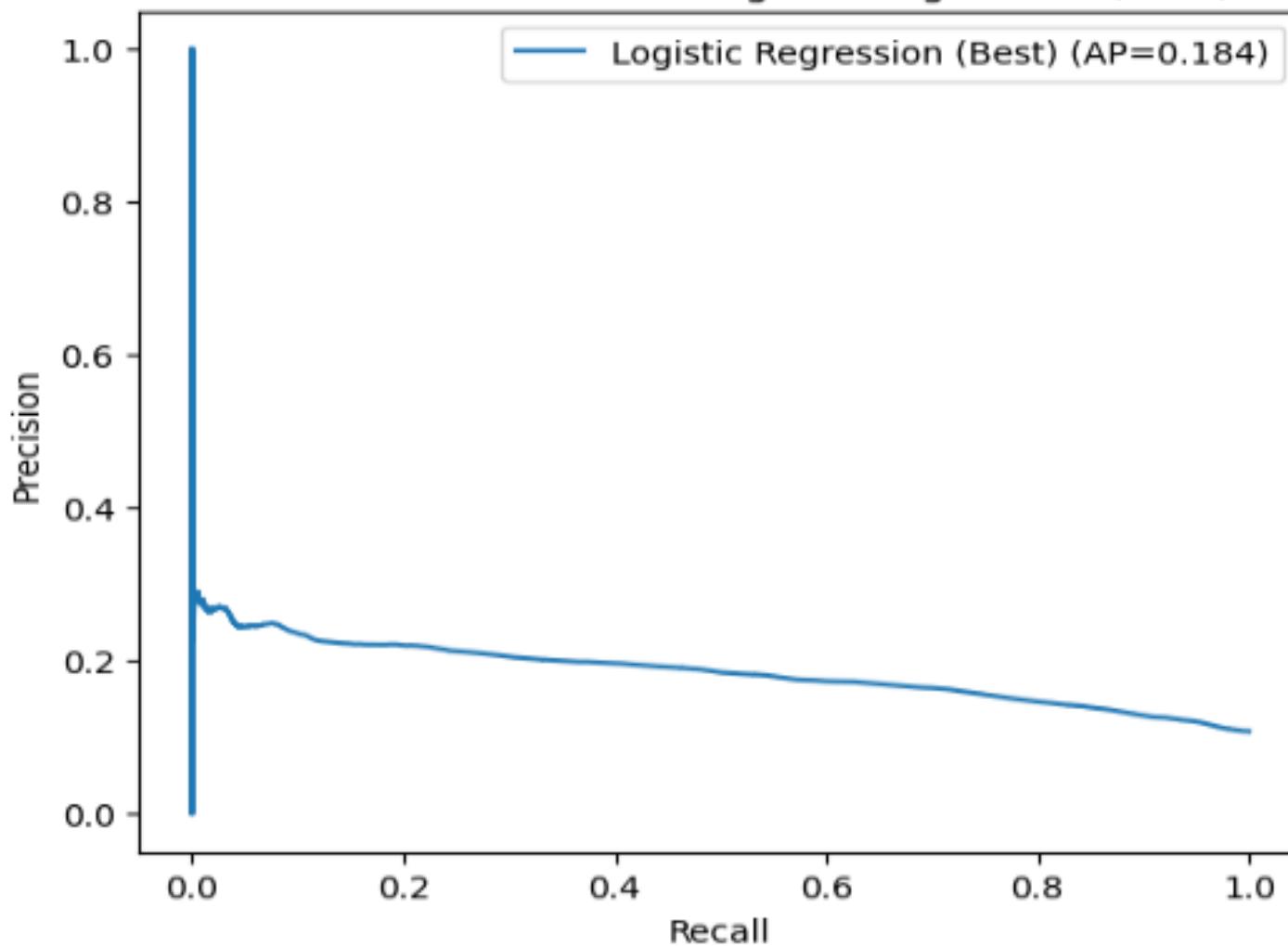
Thank you

Appendix

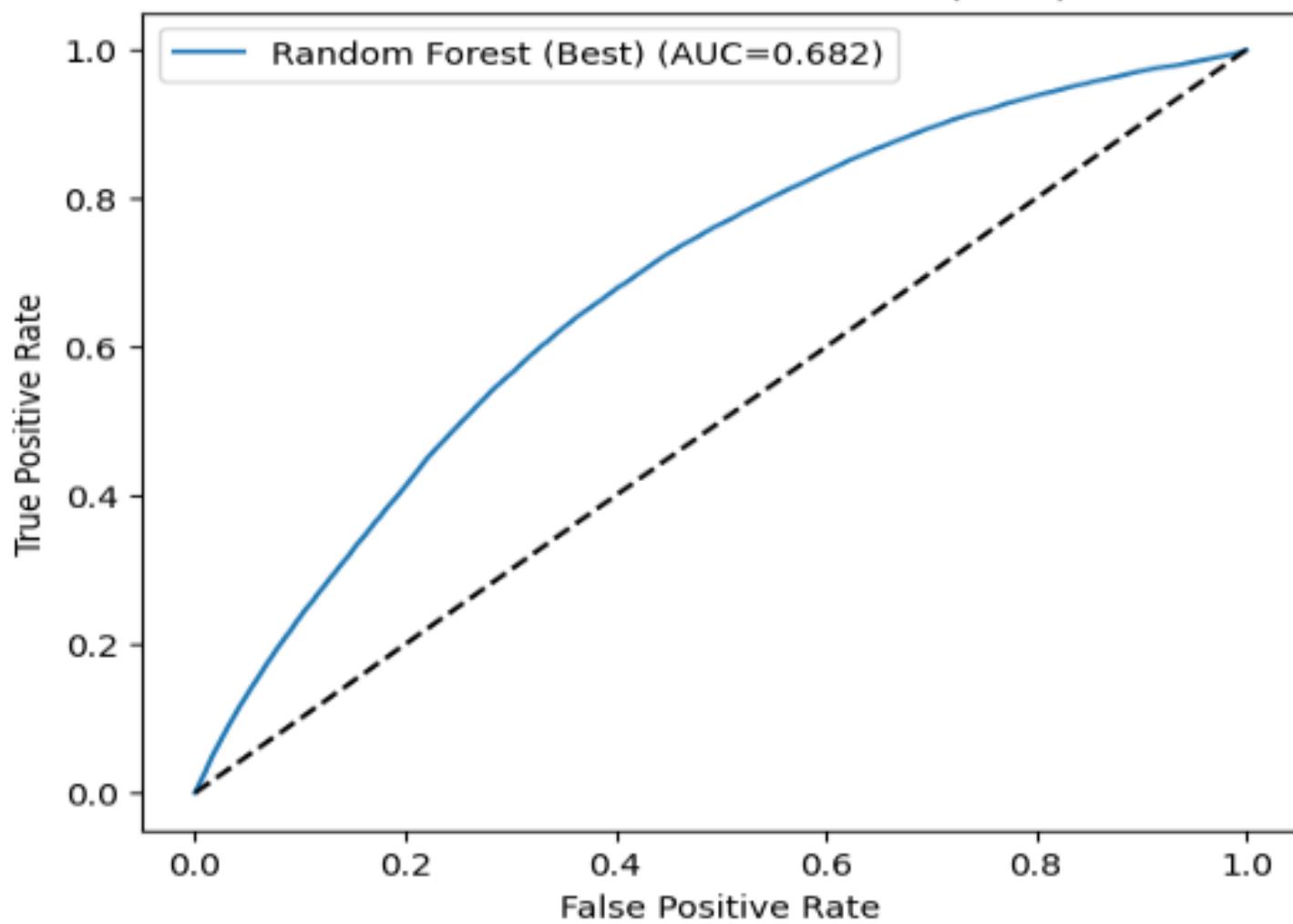
ROC Curve: Logistic Regression (Best)



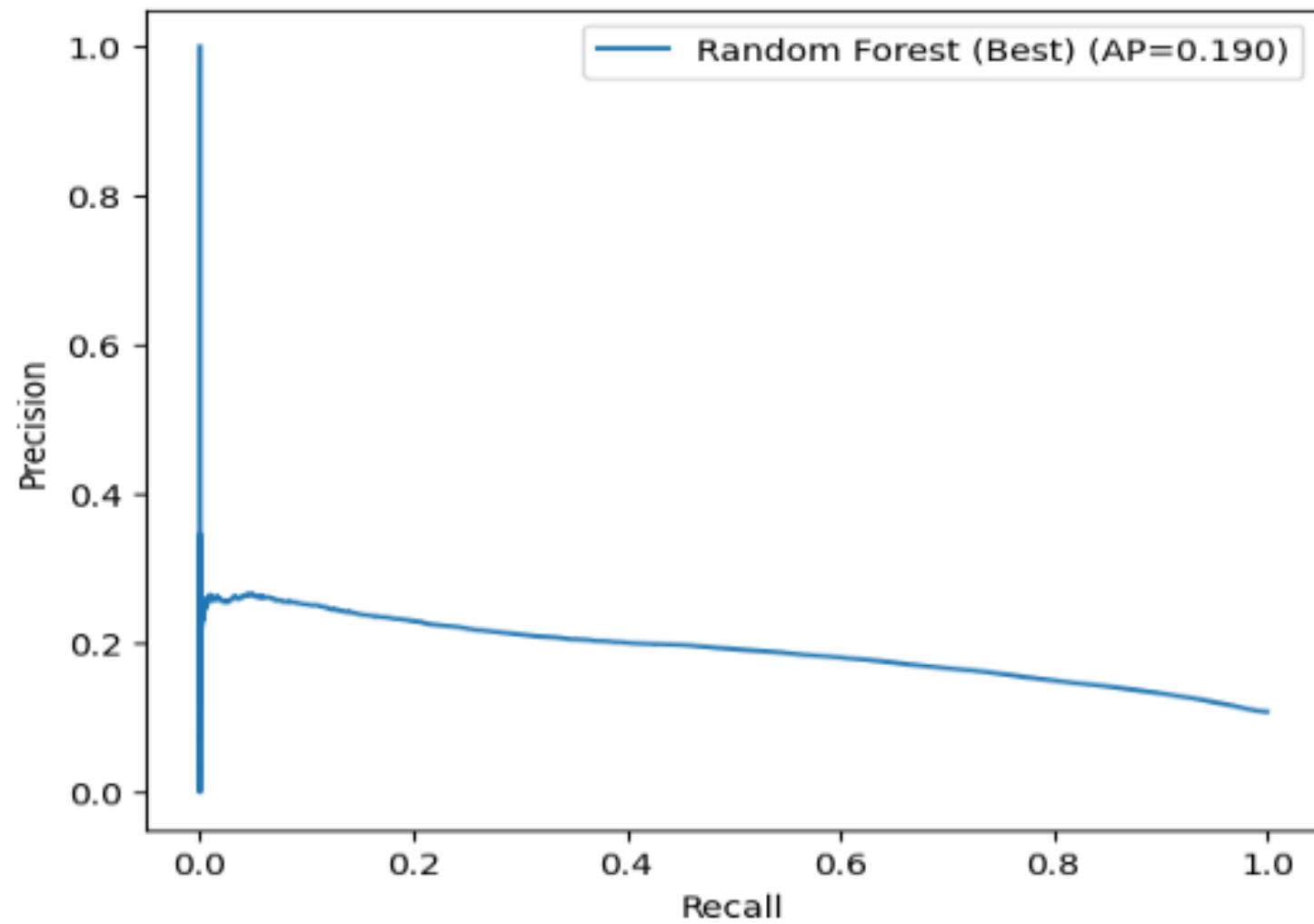
Precision-Recall Curve: Logistic Regression (Best)



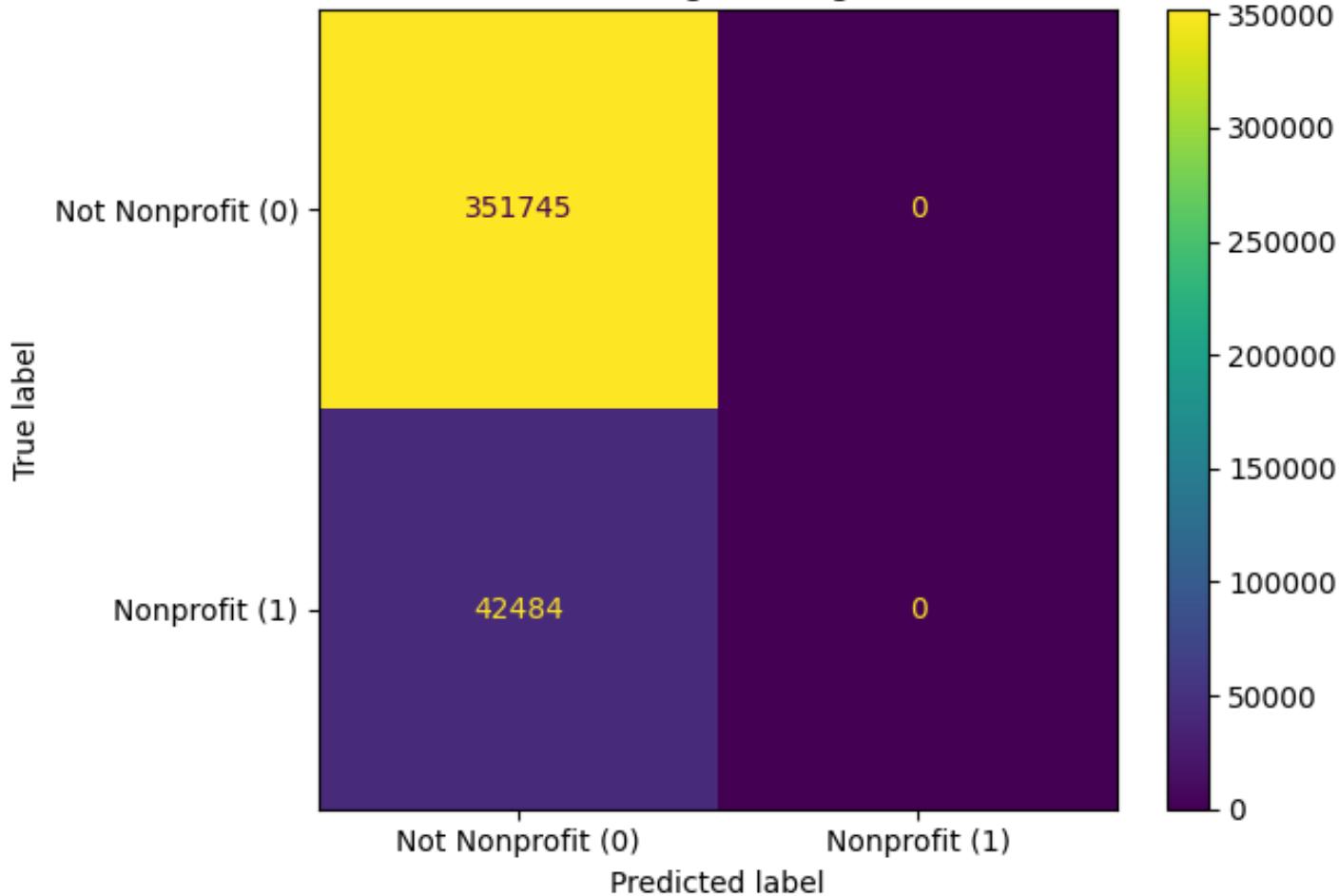
ROC Curve: Random Forest (Best)



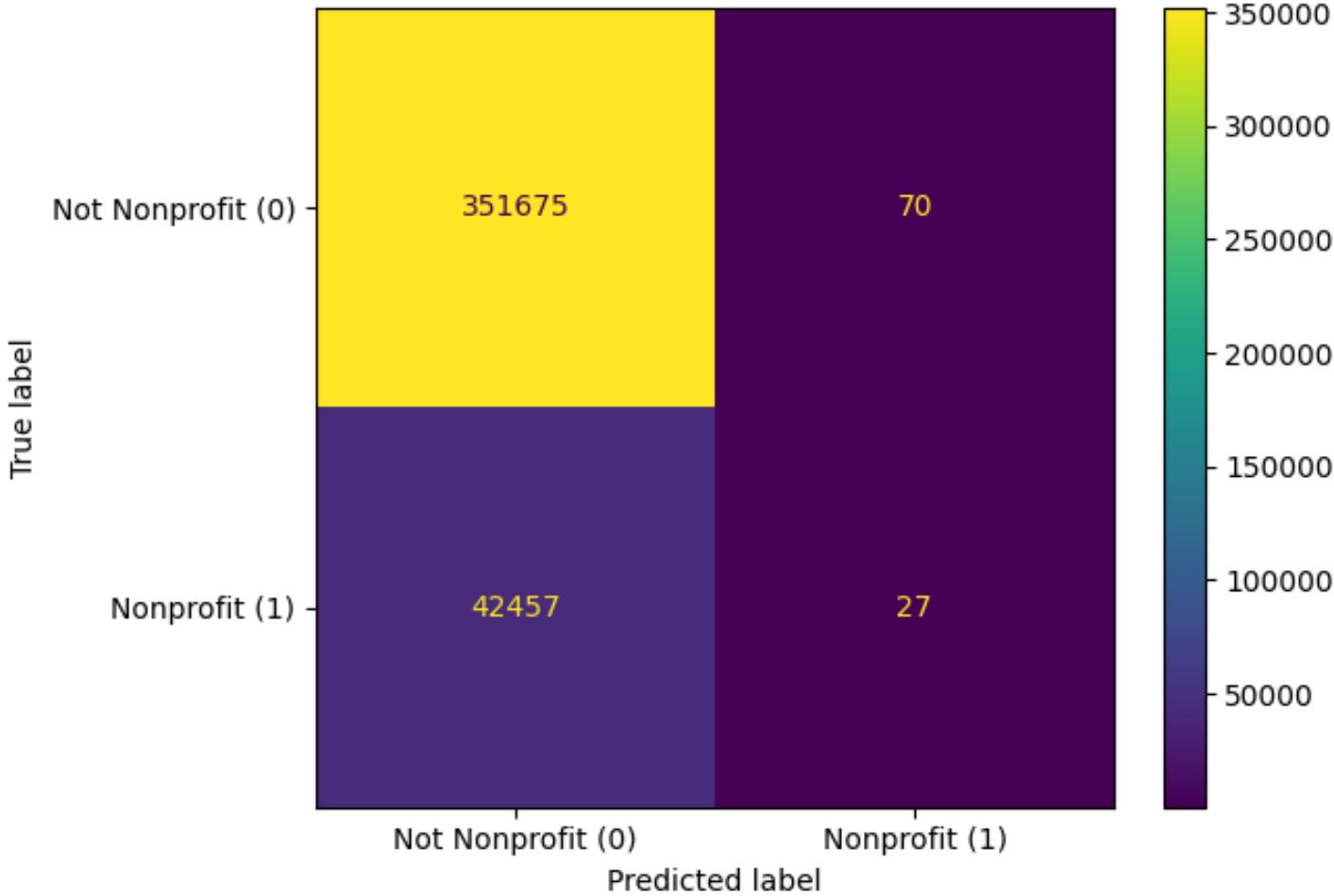
Precision-Recall Curve: Random Forest (Best)



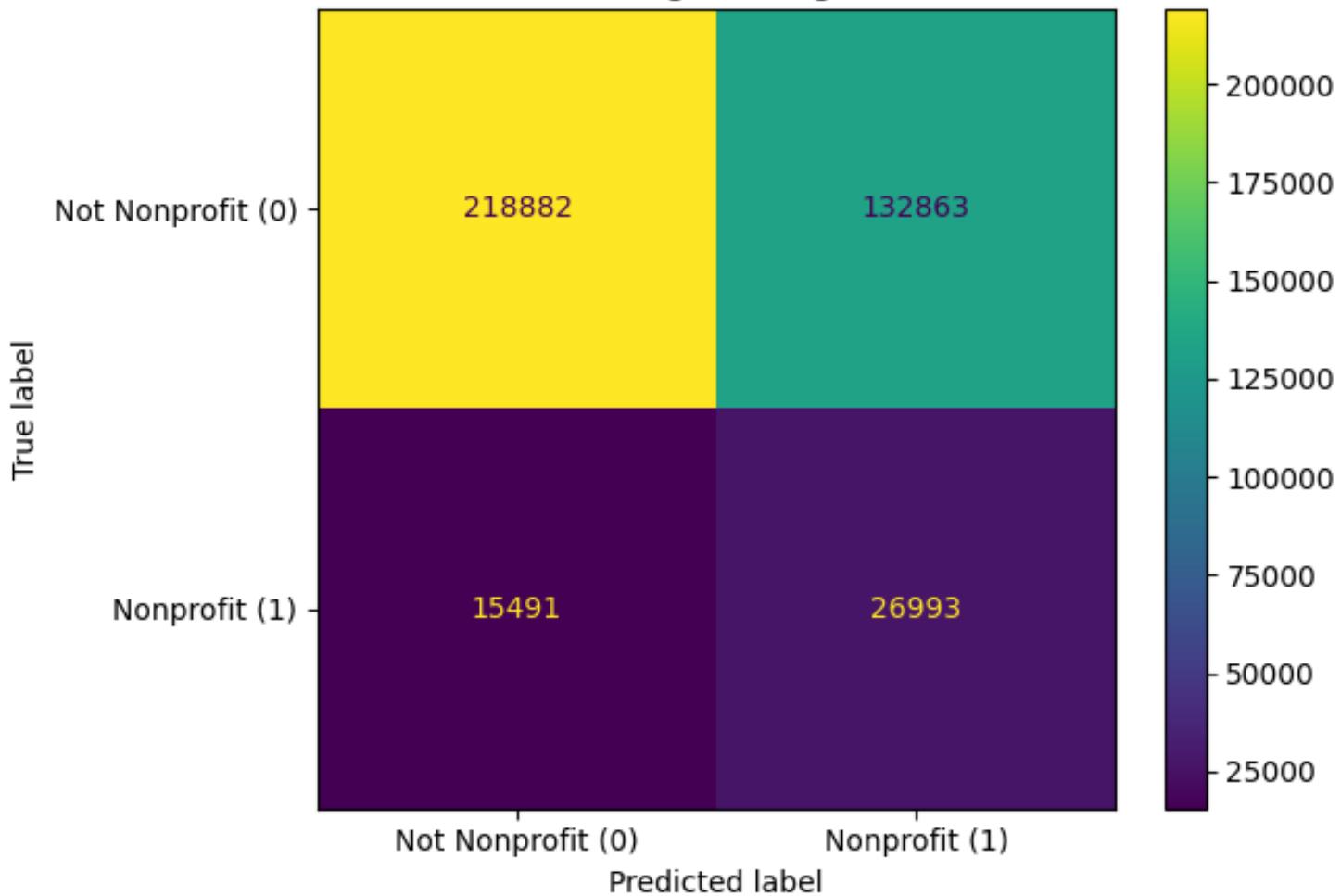
Confusion Matrix — Logistic Regression (Default)



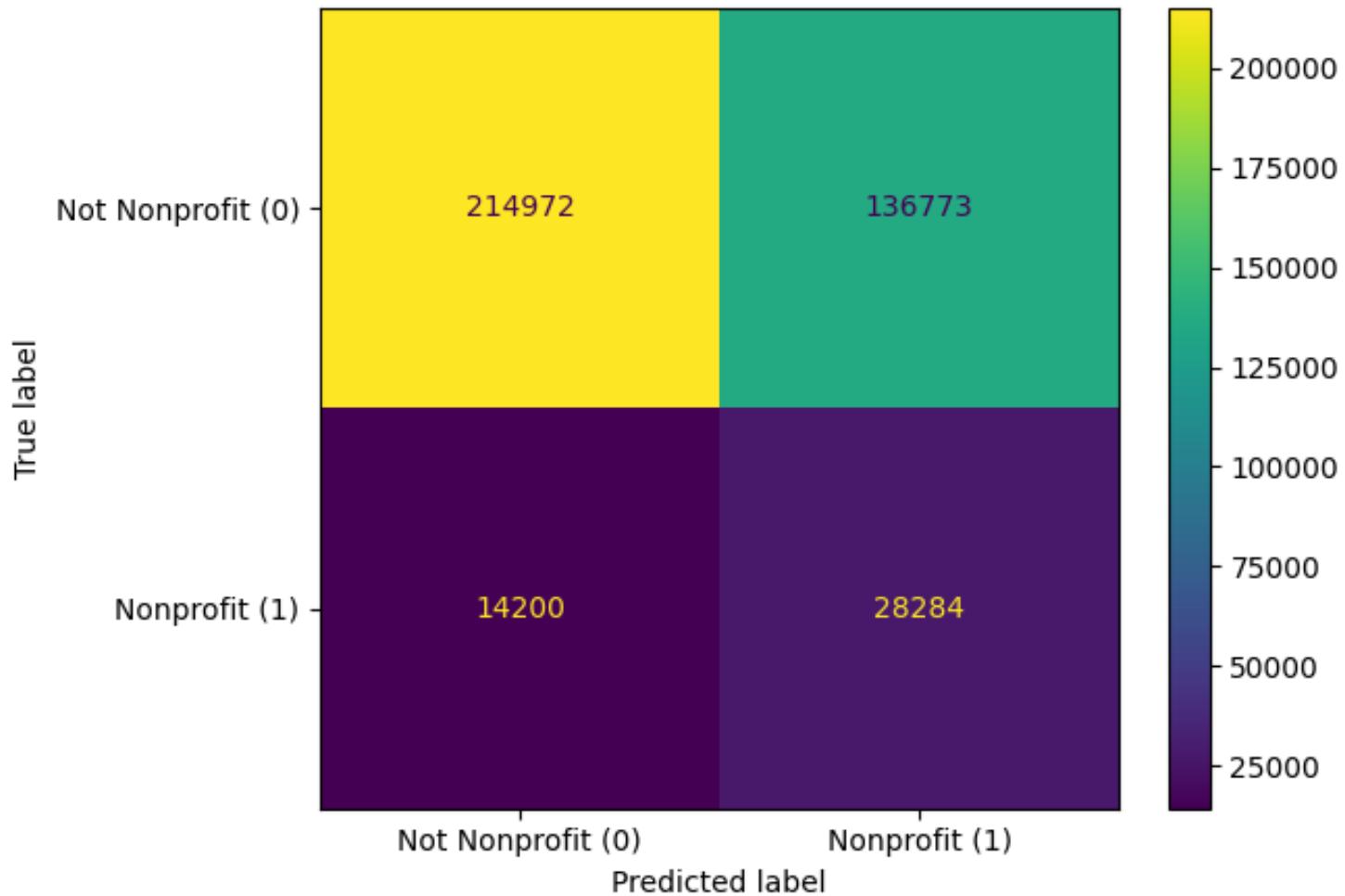
Confusion Matrix — Random Forest (Default)



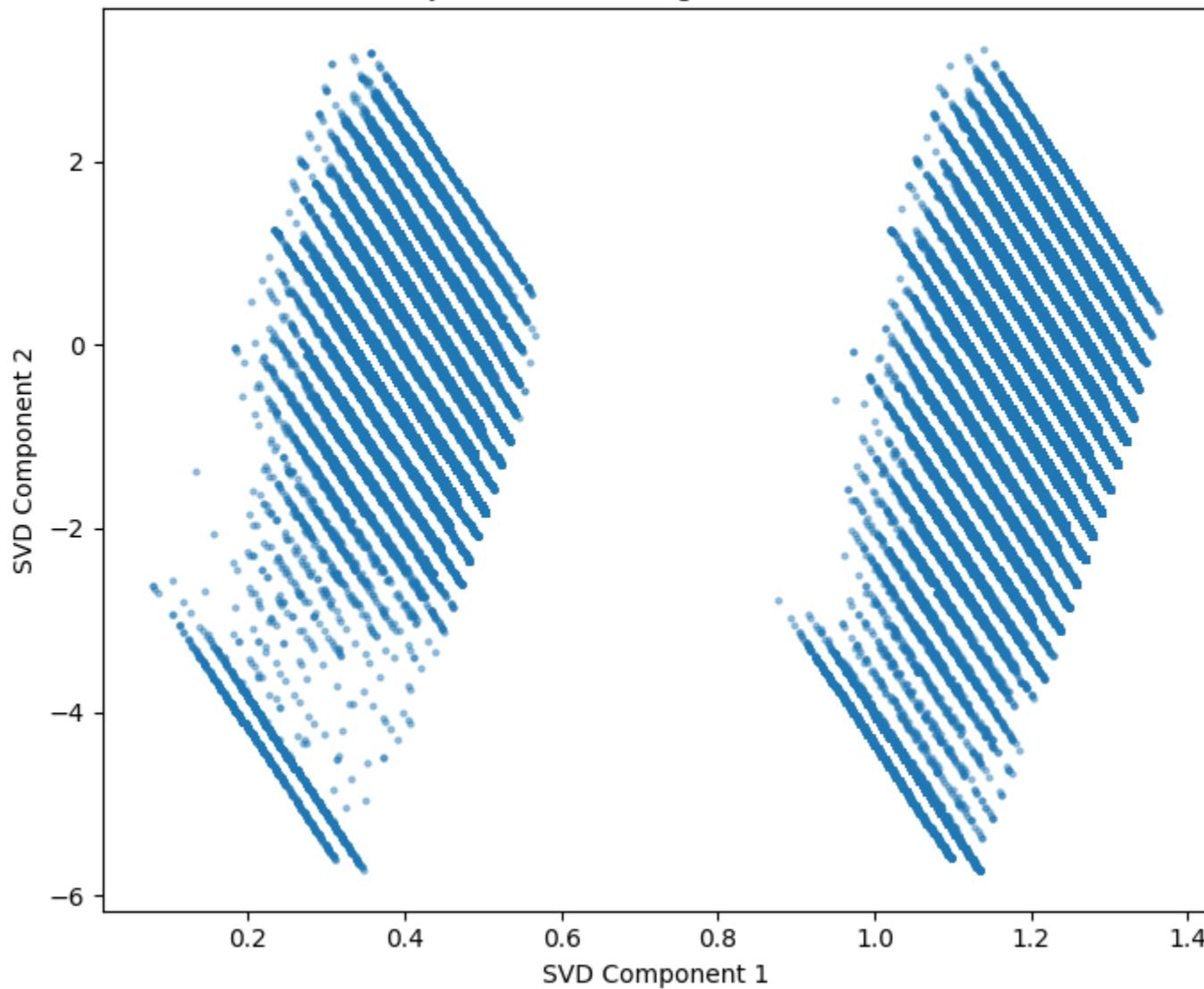
Confusion Matrix — Logistic Regression (Balanced)



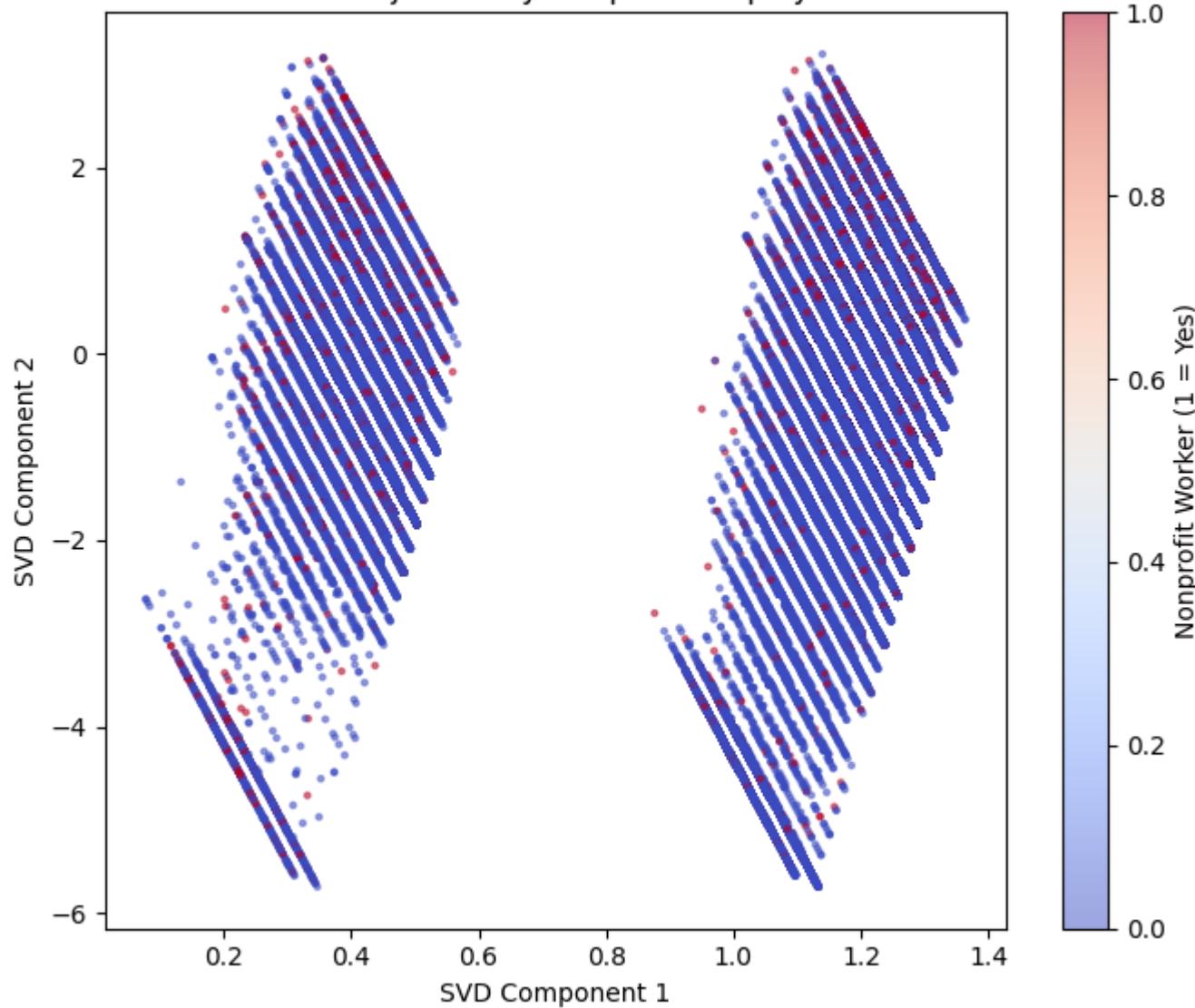
Confusion Matrix — Random Forest (Balanced)



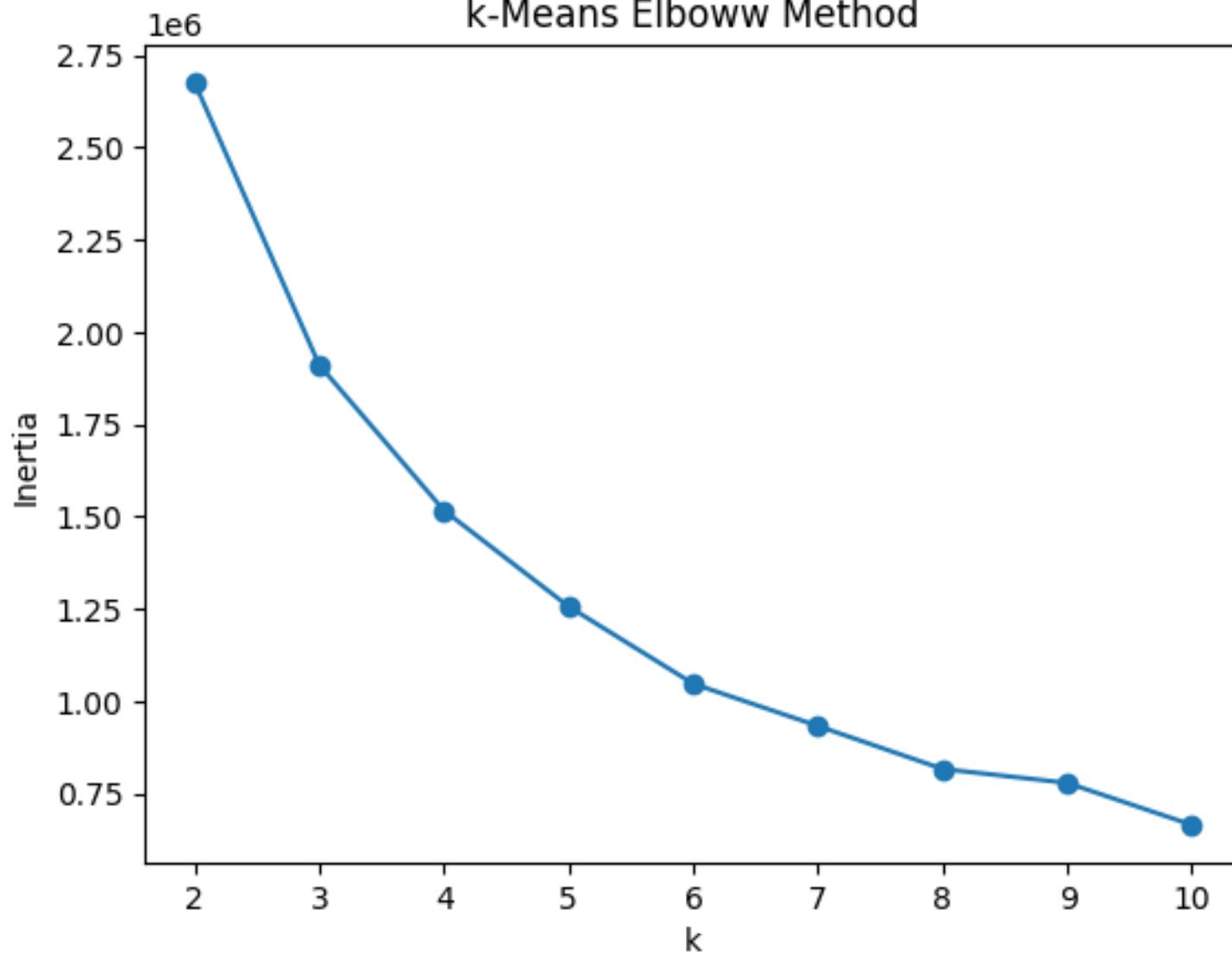
2D PCA Projection of Training Data (All Observations)



2D PCA Projection by Nonprofit Employment



k-Means Elbow Method



Silhouette Scores: Clustering and PCA

