Predict Customer Responses to Marketing Campaigns

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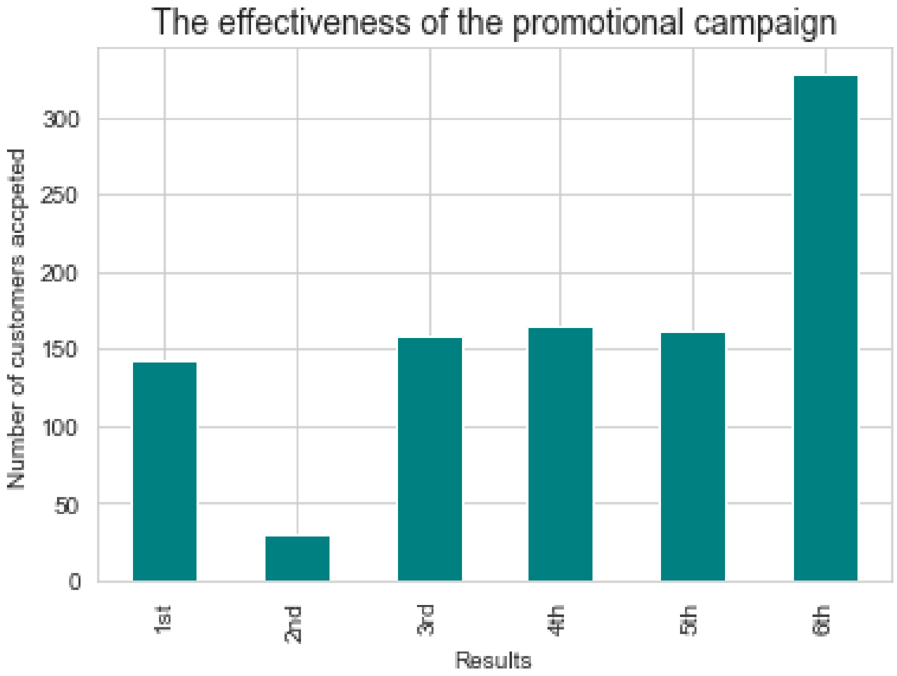
SPRINGBOARD

DATA SCIENCE CAREER TRACK

Problem Statement & Context



The effectiveness of 6 marketing campaigns

- Customer personality analysis is an interesting topic for companies. Marketing campaigns aim to encourage customers to act in some manner. The main interest in this project lies in how customers responded to the last 6th campaign.
- This project trained five different machine learning models to best predict customer responses:
  - What are key factors based on customers' behaviors?
  - Identify what types of customers the business is trying to reach which could help optimize new campaigns by refining audience selection in the future.

Introduction to Data

- The dataset was obtained from Kaggle's competition webpage: (2240 rows and 29 columns)

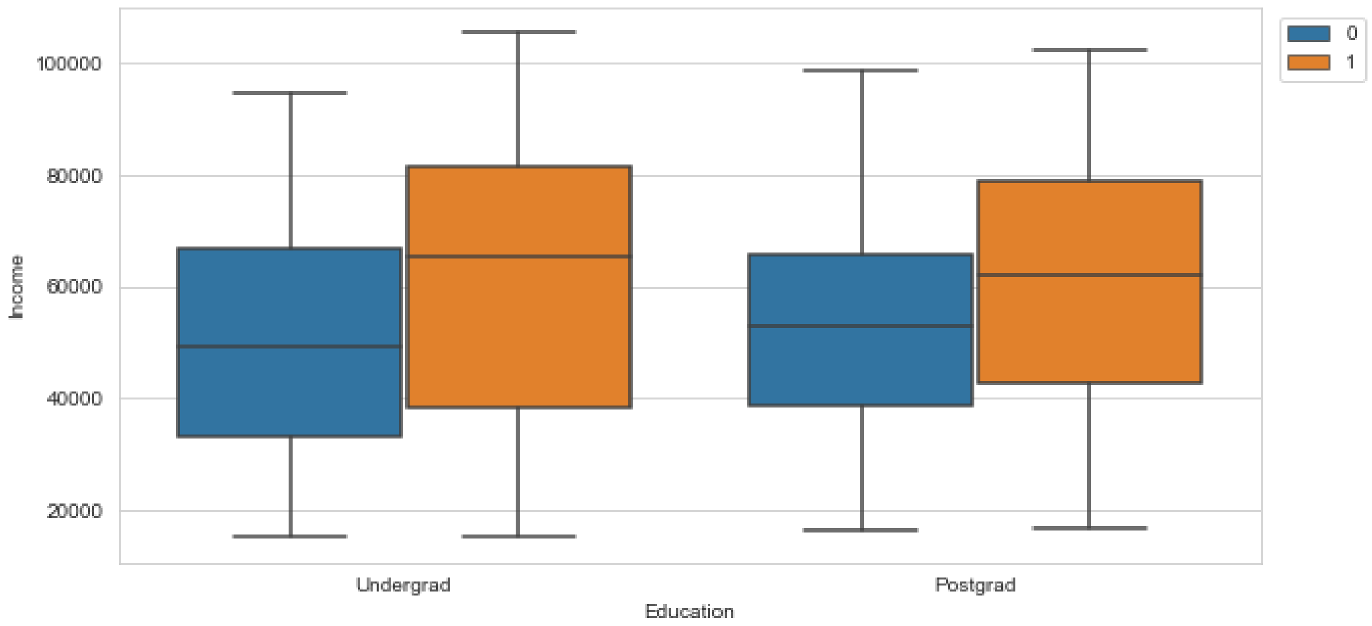
  https://www.kaggle.com/datasets/imakash3011/customer-personality-analysis?select=marketing_campaign.csv

- Data cleaning
  - Missing values are filled in with the statistical value (median)
  - Drop less useful columns
  - Replace the names of the columns
  - Group classes within columns
  - Generate new features

Exploratory Data Analysis (EDA)

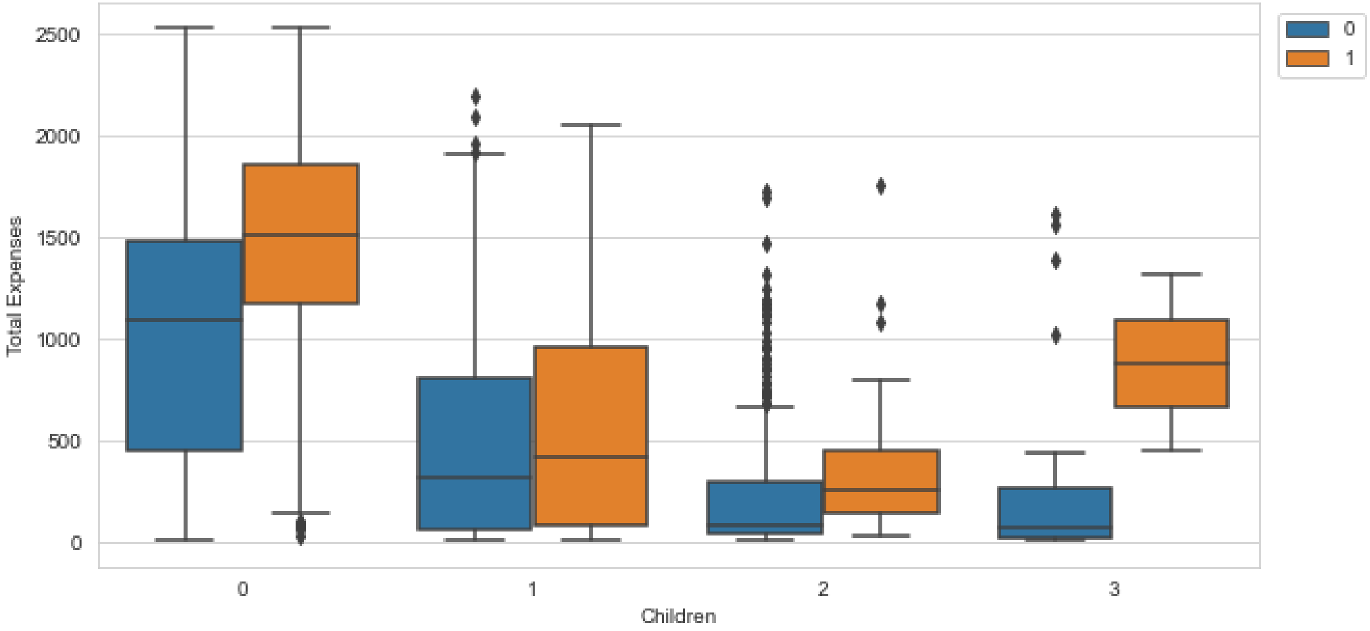
EDA includes:

- Visualization by groups:
  - Income
  - Total expenses
  - Days enrolled
- PCA to look at the data from the most informative viewpoint



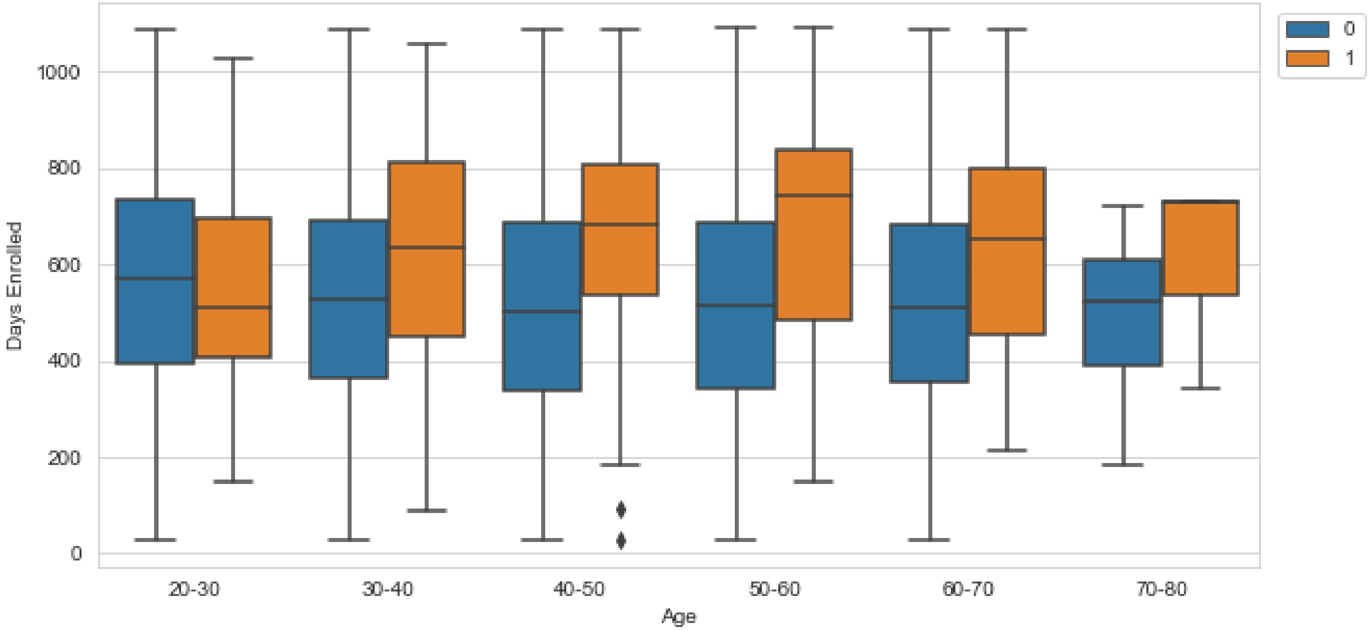
EDA – by Income

- Customers with higher income & undergrad backgrounds are more active with responses to the last campaign.



EDA – by Total Expenses

- Customers with '0' and '1' children are more active in the last campaign than those of '2' and '3'.



EDA – by Days Enrolled

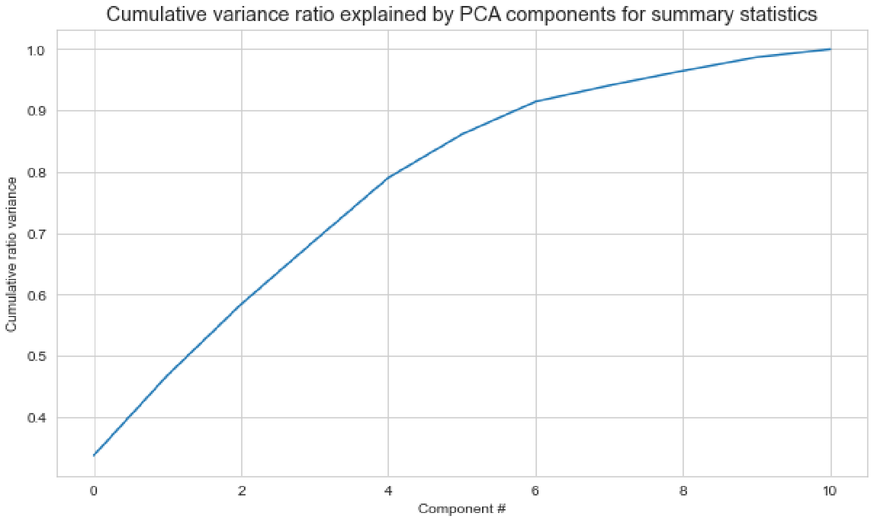
- Customers in different age groups with longer enrolled days are more active in the last campaign. Those of age 20- 30 are slightly different.

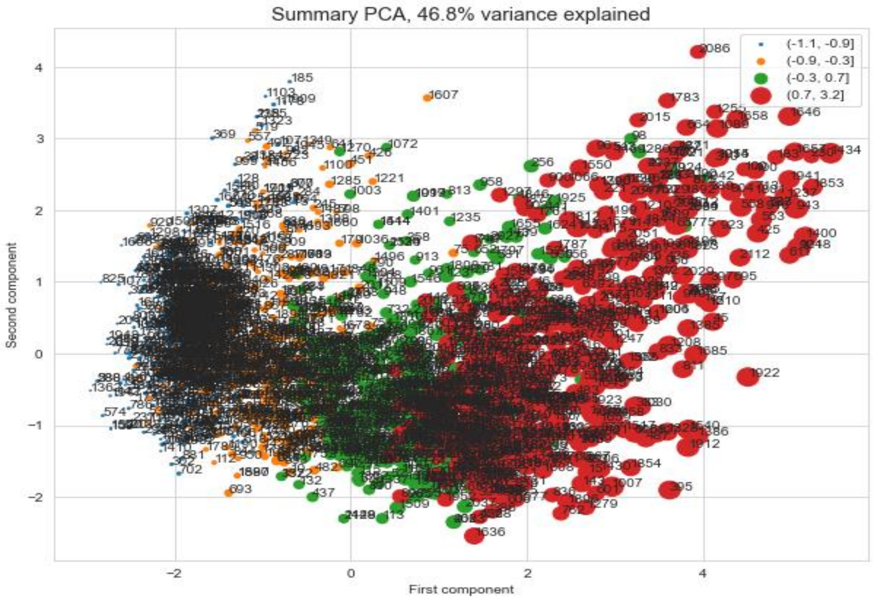
PCA

- Principal Component Analysis (PCA) is a dimensionality reduction technique that allows us to view the data from the most informative viewpoint.

- The first two components of data in the new dimension seem to account for about 50% of the variance, and the first five for over 80%.

- The red points represent the upper quartile of 'TotalExpense' and they spread across the first dimension (>0). There's also a spread of the other quartiles as well.





Data Preprocessing

- Final data includes:
  - Use Sklearn Label Encoder to encode binary categories to numeric values (0/1) for two categorical variables ‘education’ & ‘marital status’.
  - Target variable ‘AcceptedCmp6’: the 0/1 indicators for customers who responded to a given offer or not. It is highly unbalanced between the number of responsive customers and that with have no responses.

Approach

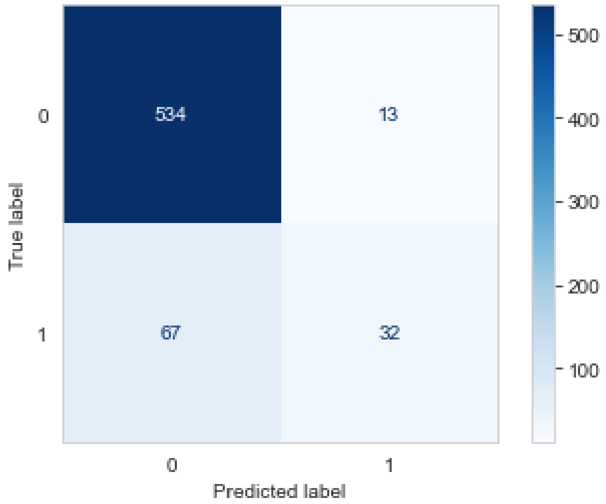
- Five different machine learning algorithms are used to train on the data in order to build an effective classifier that can identify the active customers:
  - Non-ensemble algorithms:
    - Logistic regression
    - KNN
  - Ensemble Algorithms:
    - Random forest
    - Gradient boosting
    - XGBoost
- Each ML model conducted hyperparameter tuning and cross-validation to improve model accuracy
- Evaluation of the model performance

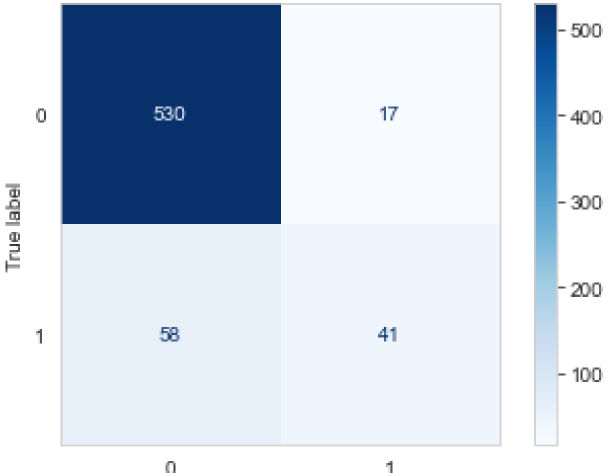
Hyperparameter Tuning

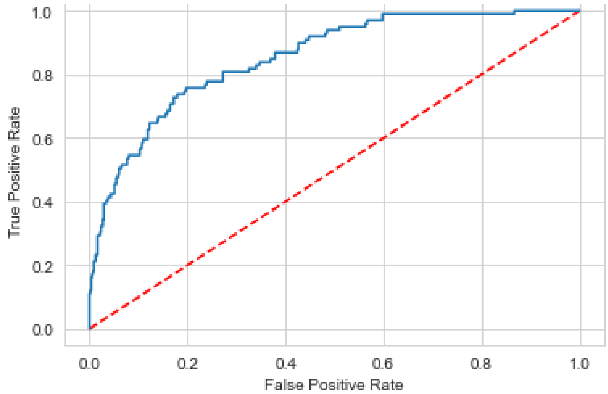
- Logistic Regression
  - Grid search over to find the best regularization parameter C based *only* on the training set; Cs = [0.001, 0.1, 1, 10, 100]
  - C controls the inverse of the regularization strength. A large C can lead to an overfit model, while a small one can lead to an underfit model.
- Random Forest
  - Grid search for the best number of estimators. (n_est=50)
  - Max_depth (10)
- KNN
  - Find the best number of neighbors k=2 using the elbow method
- Gradient Boosting
  - find the best parameters: `{'learning_rate': 0.25, 'max_depth': 2, 'max_features': 2, 'n_estimators': 20}`
- XGBoost
  - "objective":'binary:logistic', "max_depth":3

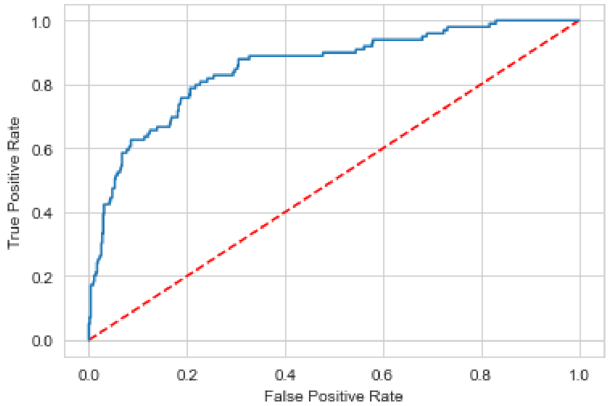
Metrics for Binary Classification

- Confusion matrix
- Roc_auc score
- left: logistic regression
- right: random forest









Model Performance

- The results from implementing each model are as the following:

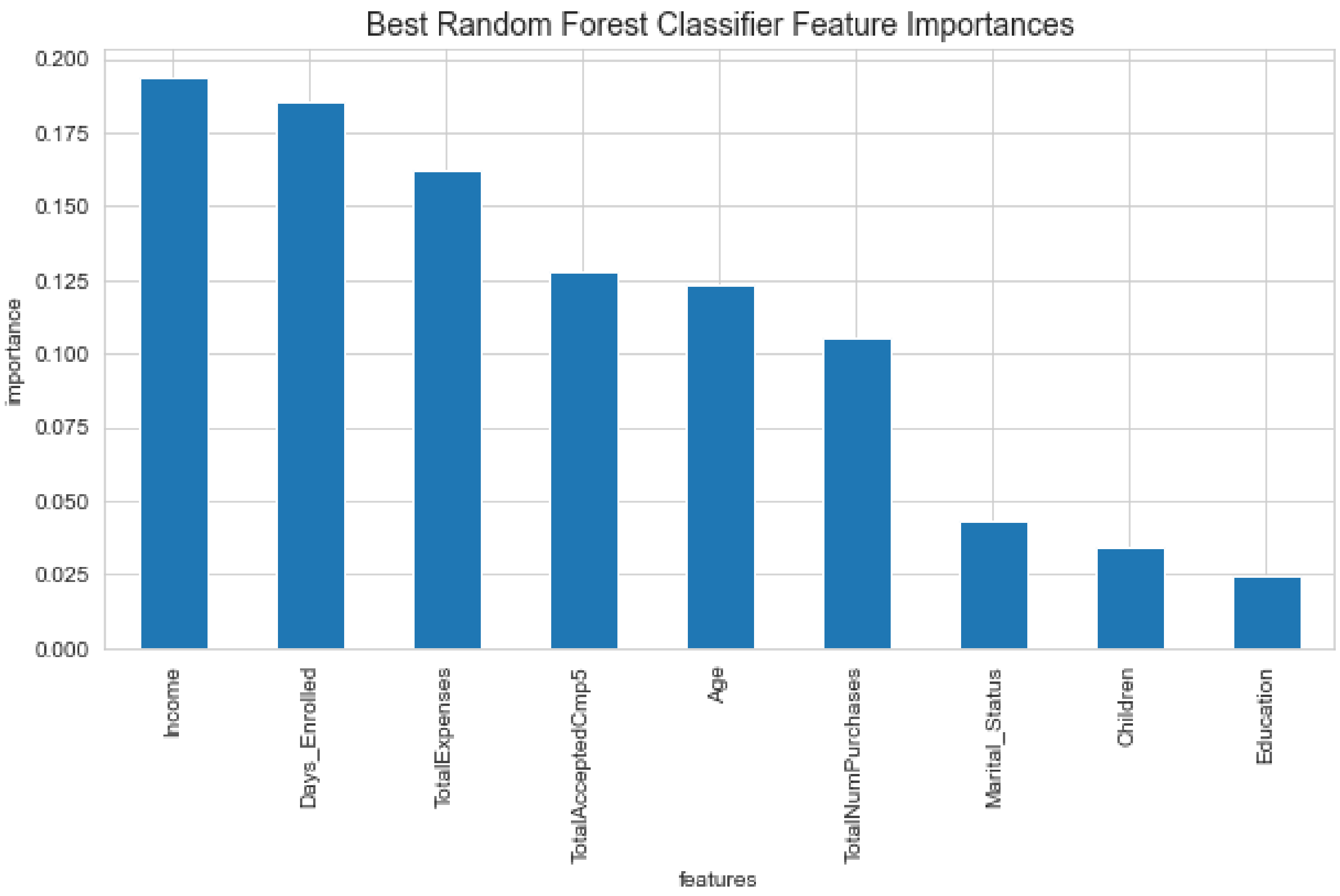
	name	ROC_AUC
0	LogisticRegression	0.853120
1	RandomForestClassifier	0.852898
2	KNeighborsClassifier	0.808976
3	GradientBoostingClassifier	0.821229
4	XGBClassifier	0.827286

Model Selection

- Final optimized models are evaluated based on their predictions, confusion matrix, and roc_auc scores.
- Both Logistic Regression and Random forest classifiers have very strong AUC of 0.85, but the Random forest model has a higher True Positive Rate (TP/P) based on the confusion matrix. The model performance on the test set is consistent with the cross-validation results.
- The best model chosen for this dataset is the random forest classifier, which is typically fast to train, easy to tune, and less likely to overfit.

Important Features

- ‘Income’
- 'Days_Enrolled’
- 'TotalExpenses’
- 'TotalAcceptedCmp5' - total except the last champaign
- 'Age'



Summary

- Final optimized models are evaluated based on their predictions, confusion matrix and roc_auc scores.

- Both Logistic Regression and Random forest classifiers have very strong AUC of 0.85, but the Random forest model has a higher True Positive Rate (TP/P) based on the confusion matrix. The performance on the test set is consistent with the cross-validation results.

- The best model chosen is the random forest classifier, which is fast to train, easy to tune, and with high interpretability of important features.