

A group of four people (three men and one woman) are seated around a table in a meeting. The image is overlaid with a semi-transparent teal rectangle. The title text is white and centered within the teal area, with a thin orange horizontal line separating the two lines of the title. The authors' names are in a smaller, italicized orange font at the bottom of the teal area.

Donor Classification

Using AWS SageMaker

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INDEX

- ✓ Introduction
- ✓ Data Structure
- ✓ Data Processing
- ✓ Transformation
- ✓ Approaches
- ✓ Challenges & Solutions
- ✓ Analysis results
- ✓ Insights
- ✓ Future Work

Introduction

- To classify if an individual earns more than \$50k accurately
- To request optimum donation amounts from individuals based on their income
- Identify attributes of those who are most likely to donate



Data Structure

Dataset
“Adult” dataset
found on
UCI ML Repo



Columns:

- Age
- Workclass
- Education
- Education-num
- Marital-status
- Occupation
- Relationship
- Race
- Sex
- Capital-gain
- Capital-loss
- Hours-per-week
- Native-country
- Income

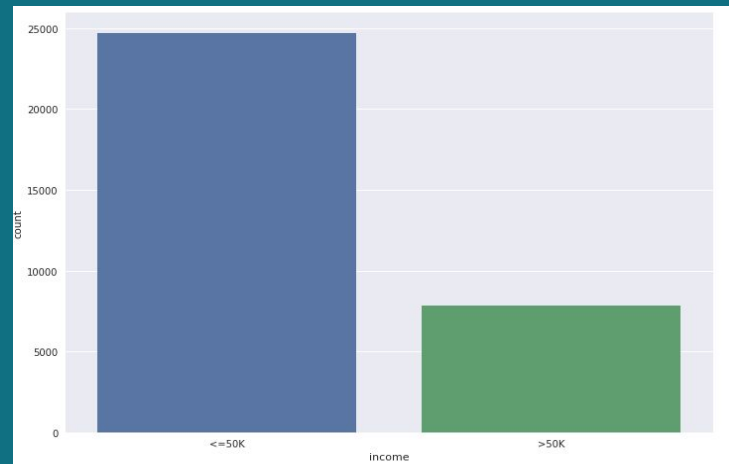
Data Preprocessing :

Dealing with missing
values

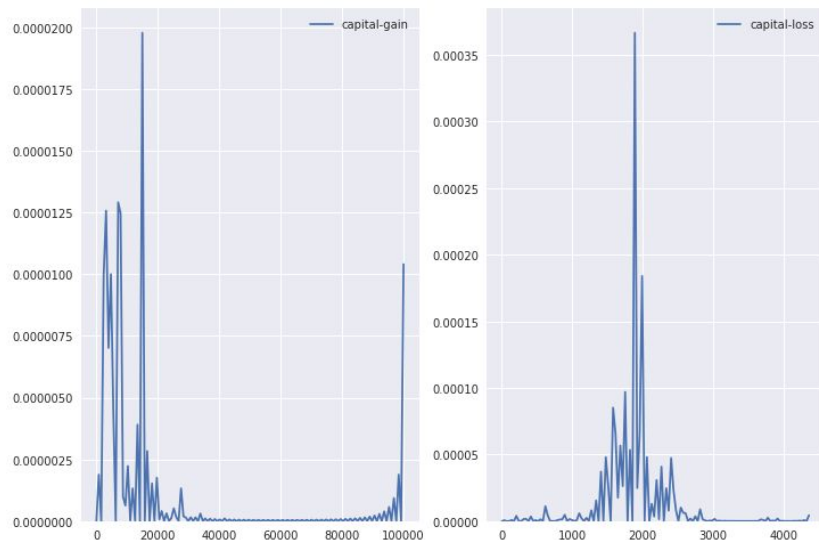
Transformations
on highly skewed
features like
capital
gains/losses

Scaling numeric
features and one-hot
encoding of
categoricals

Income Distribution

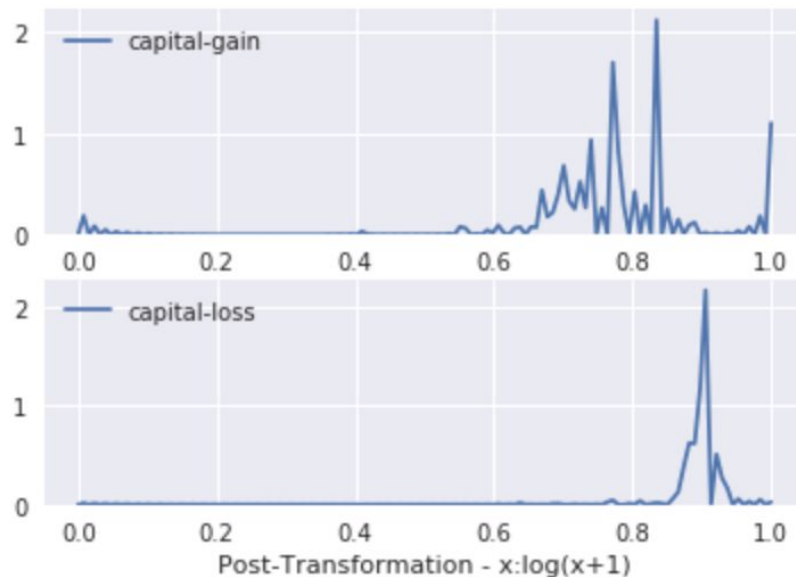


Transformation



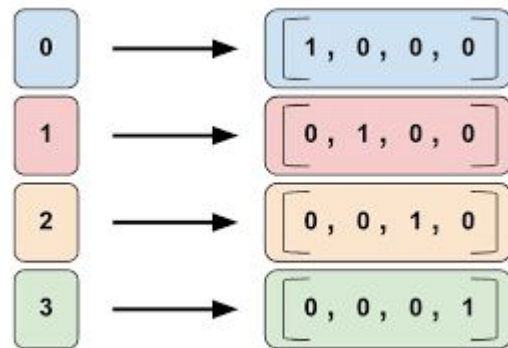
- Skewness in pre-transformed capital gains and loss features

- We slightly increment the value and take a logarithmic transformation to spread the data.
- We constrict the data between (0,1) for improving model performance

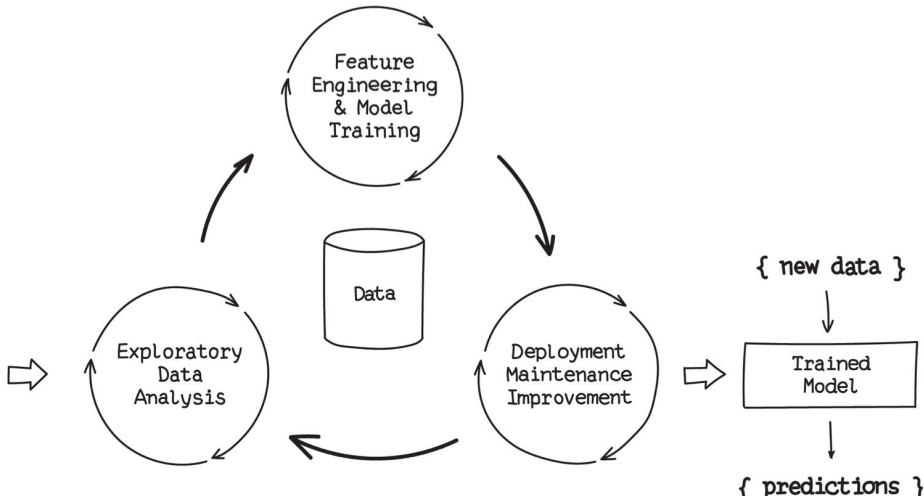


Transformation: OHE

- Before training the model, we have to convert categorical variables to One-Hot Encoded variables
- This is done so the model interprets categorical variables as a vector of numeric values

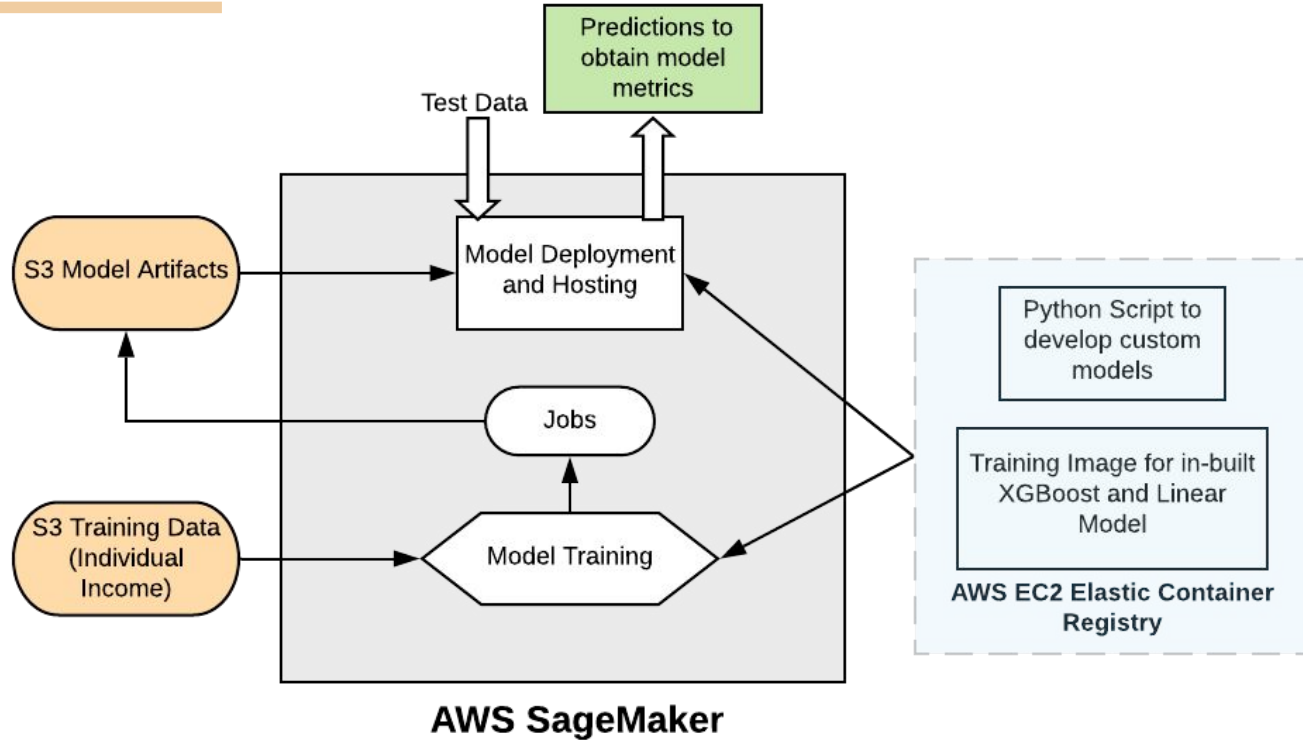


Approaches - General Structure



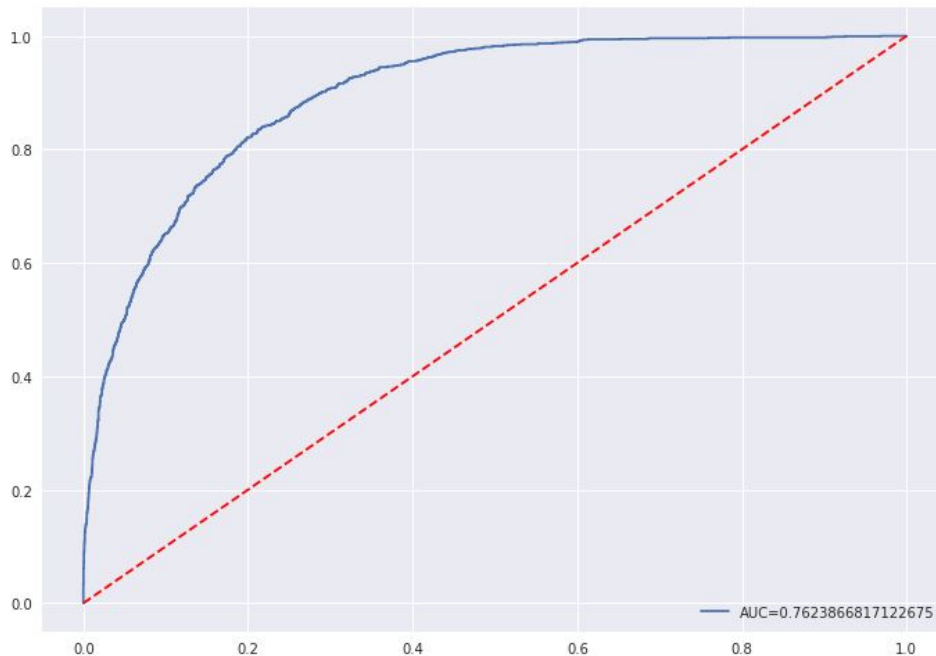
- Models chosen: Logistic Regression, Random Forest, XGBoost
 - Step 1: Generate base model using static hyperparameters
 - Step 2: Use hyperparameter tuning to improve model
 - Step 3: Compare tuned model to base model
 - Step 4: Compare models based on following metrics:
 - Precision, Recall, F1 Score, AUC
 - Step 5: Use best model to generate customer insights

Approaches - Architecture



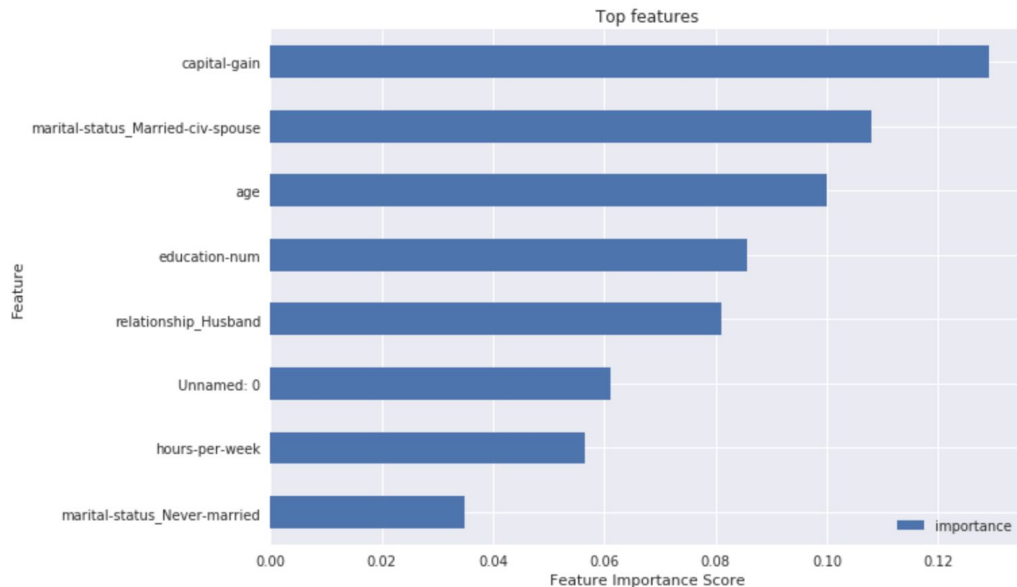
Approaches - Logistic Regression

- Used Sagemaker Linear-Learner and a binary_classifier predictor type
- Challenge: Limited hyperparameters, complicate to extract feature weights
- Best model:
 - L1 = 0.0627
 - Learning_rate = 0.0117
 - Positive Sample Wght = 30.727

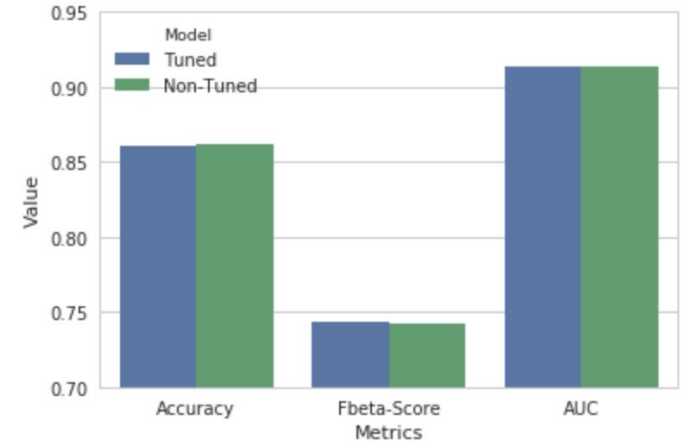
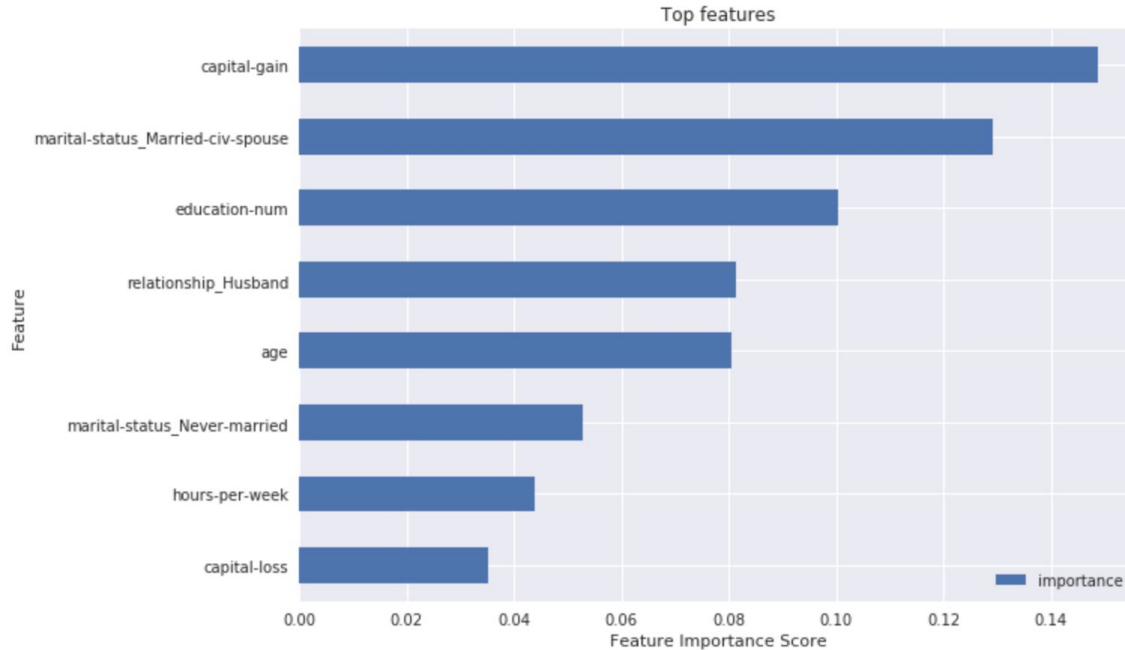


Approaches - RandomForest

- Implemented using Sklearn RandomForestClassifier
- Script fed as entry point to SageMaker
- Training job parameters:
Num_estimators = 100
Min_samples_leaf = 2
- Hyperparameter Tuning:
Num_estimators = 191
Min_samples_leaf = 5

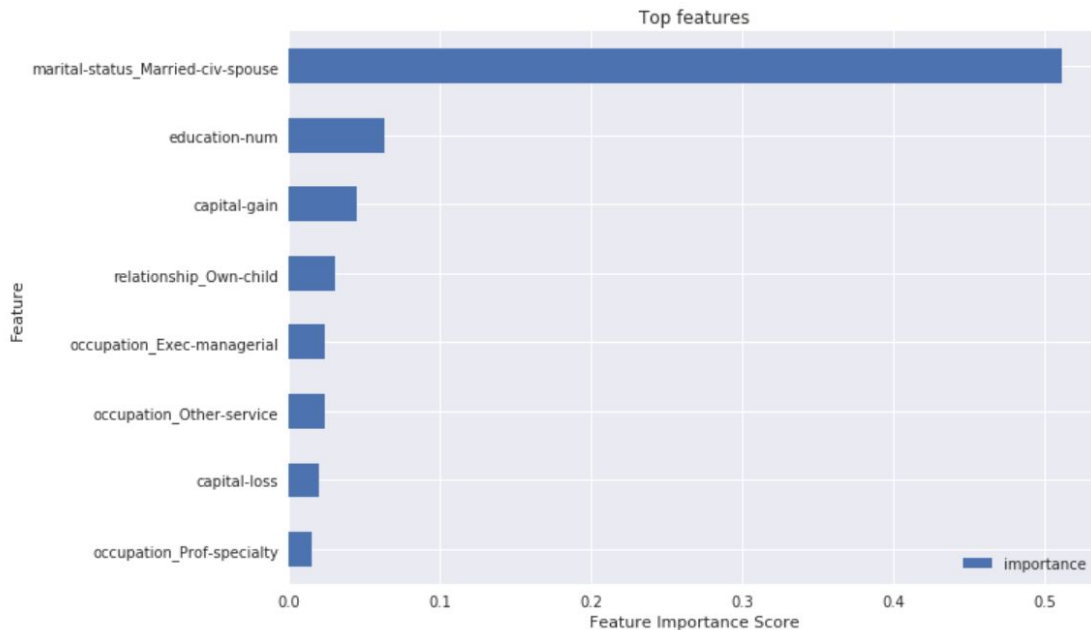


Approaches - Tuned RandomForest



Approaches - XGBoost

- EC2 instance training image is fed into model
- Best model job parameters:
eta= 0.2,
gamma = 3,
max_depth=5,
min_child_weight=6

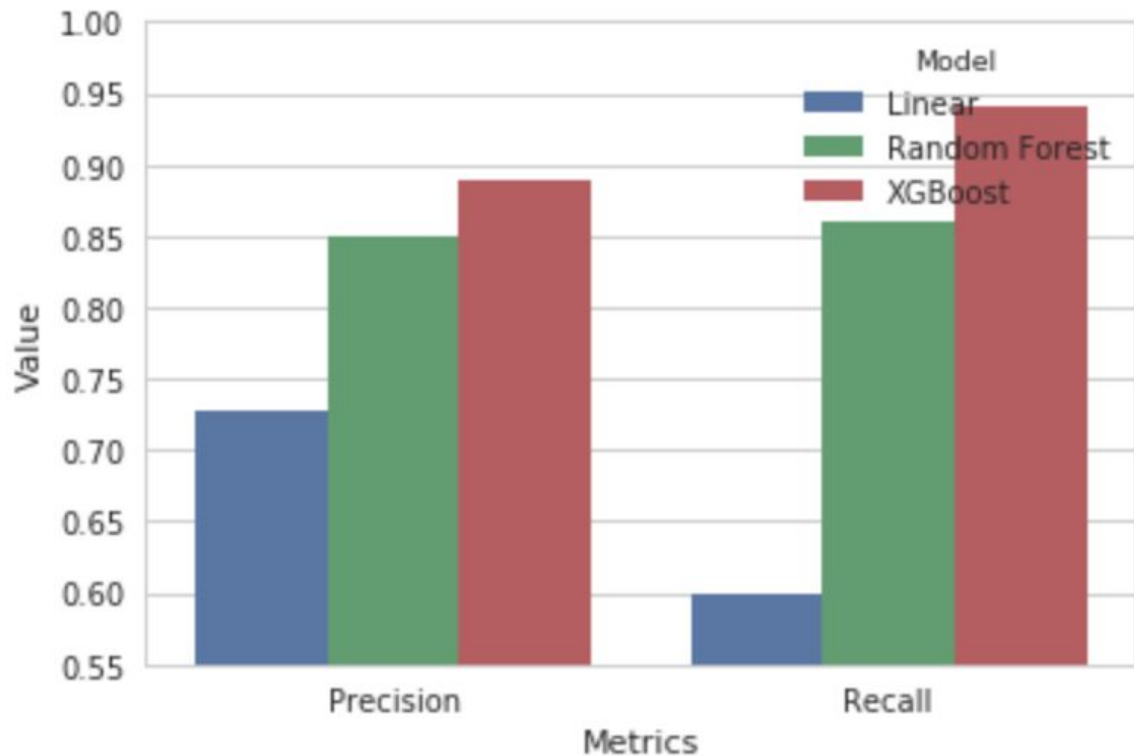


Challenges and Solutions

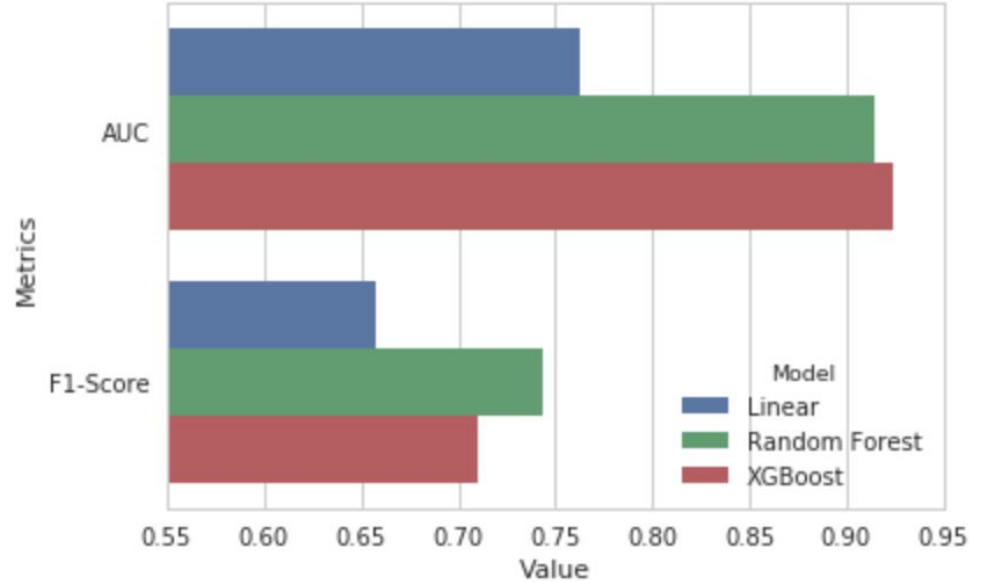
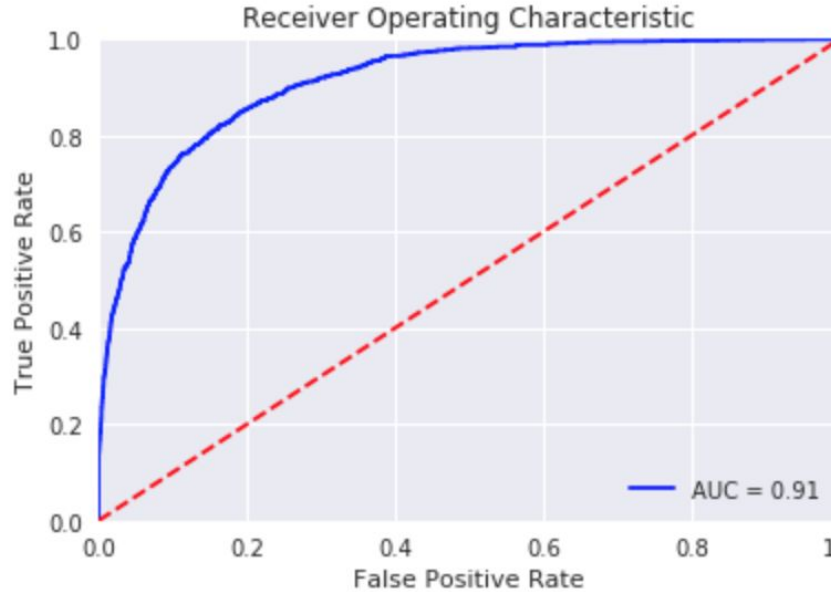


- Random Forest deployed model endpoint does not allow for predicted probabilities.
Solution: Extracted saved model using joblib
- Poor model performance initially
Solution: Used Minmaxscaler to scale numeric features
- Relatively poor logistic regression performance
Solution: Logistic regression was excluded from the final model decision

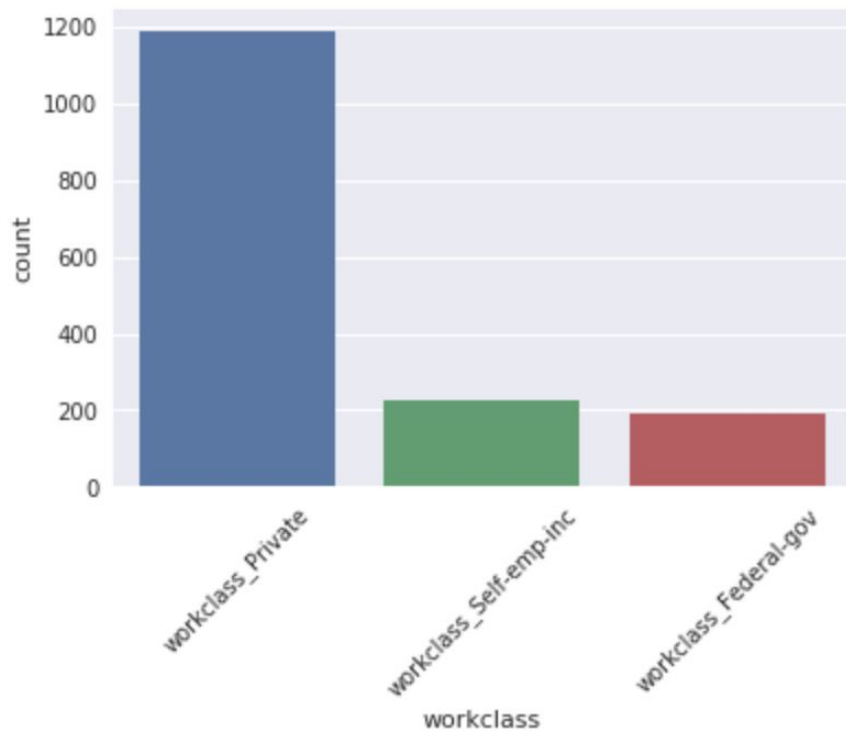
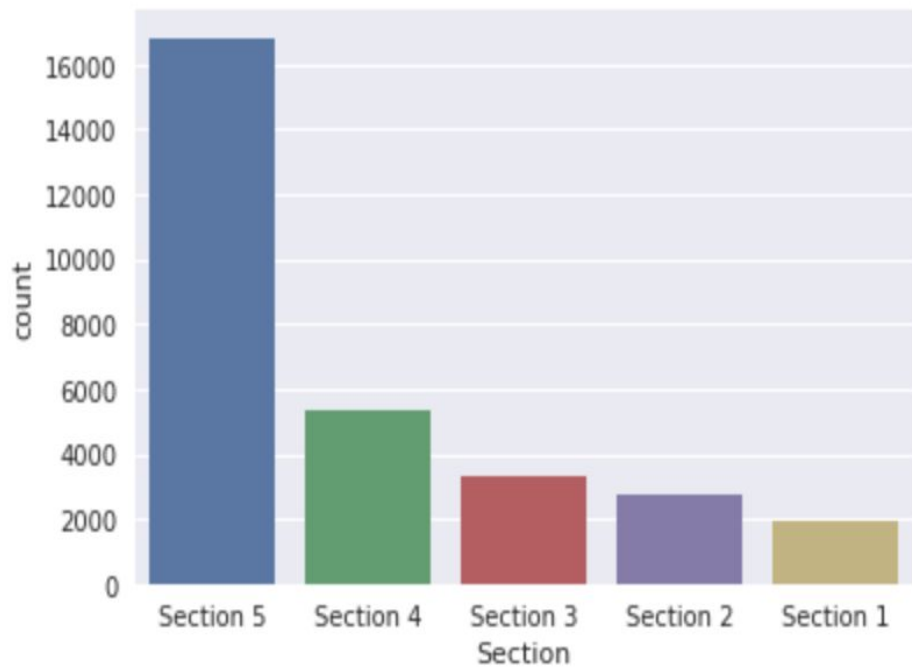
Analysis Results - Model Comparison



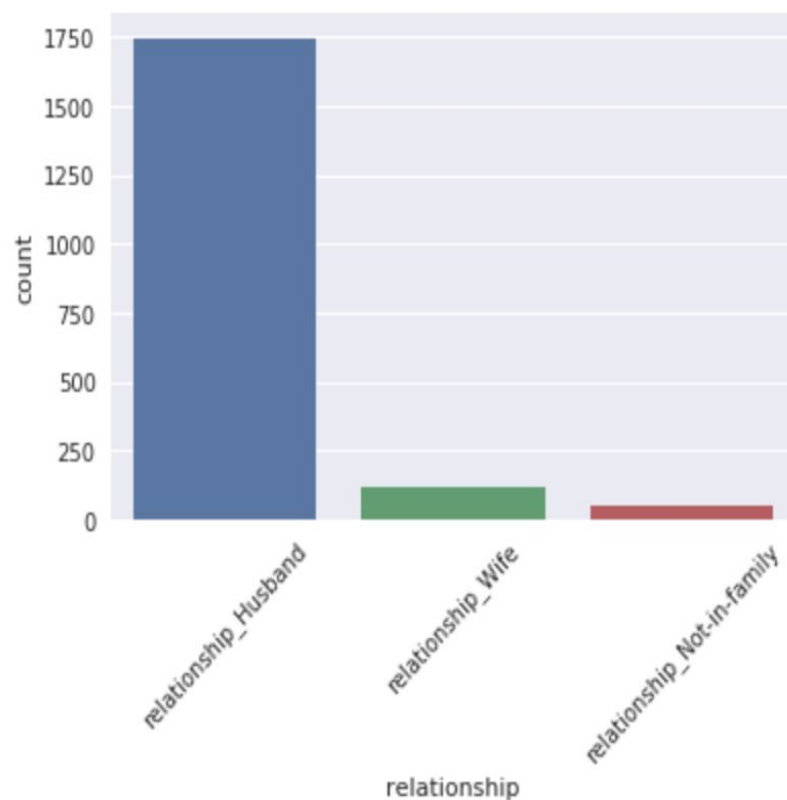
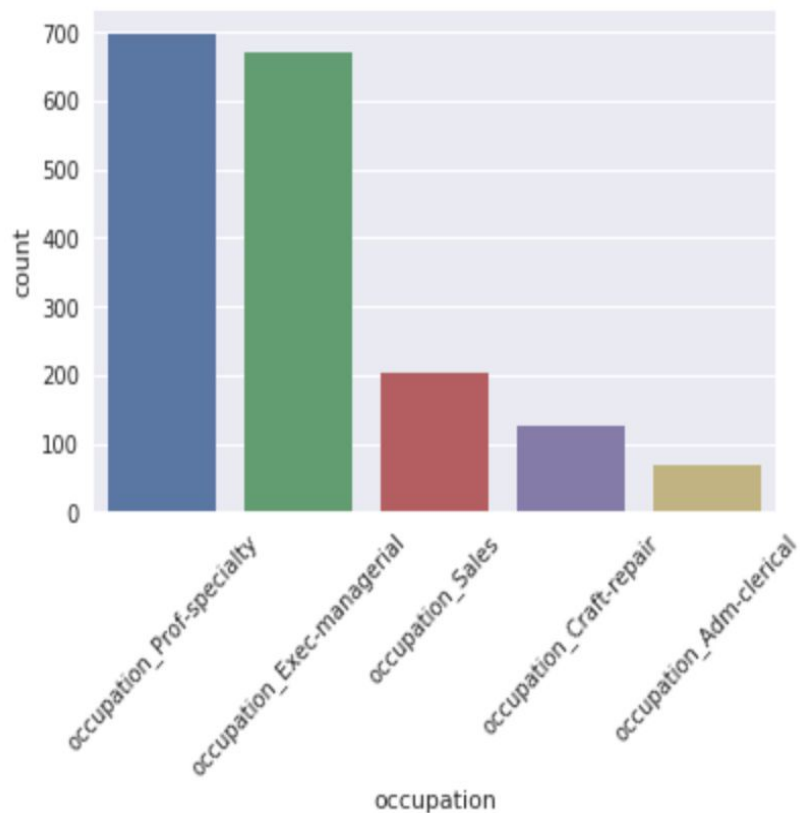
Analysis Results - Model Comparison



Insights



Insights



Future Work



- Implementing a recommender engine to match an individual to a donation request in a more granular fashion
- Appending more data points and features to the existing model
- Donation amounts provided by individuals could be incorporated into the model to optimise donation requests



THANK YOU!

