Project Report

Definition

Project Overview

This project aims to enhance a German mail-order company's customer acquisition strategy. Key points:

1. Data Analysis and Machine Learning
2. Using Demographic Data from Arvato Financial Solutions
3. Comparing the General Population to Current Customers
4. Objective: Identifying Patterns That Distinguish Customers from Non-Customers
5. Applying Machine Learning to Predict Customers
6. Expected Outcome: Saving Resources with Targeted Advertising

Problem Statement

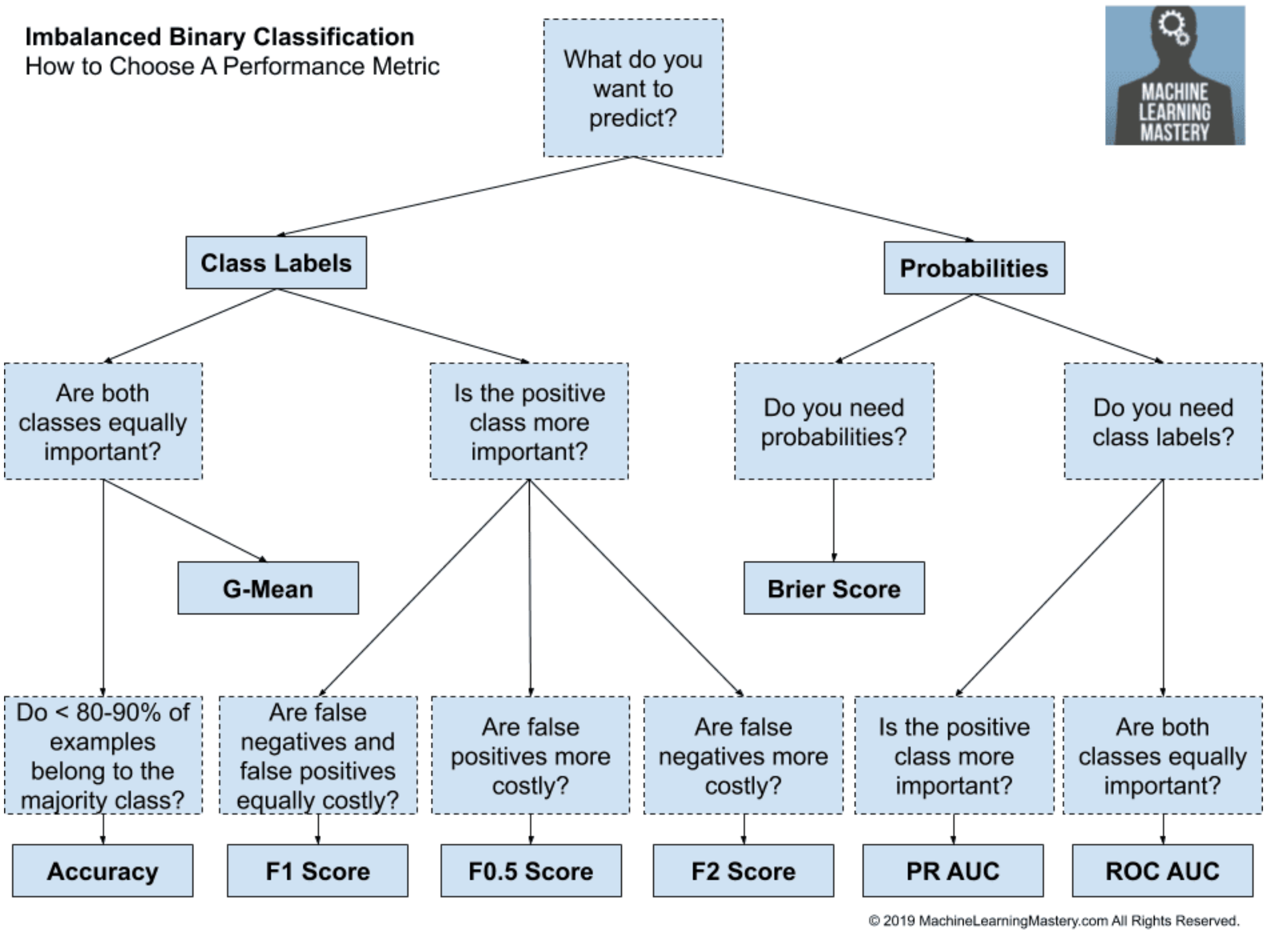
Problem: Dataset with response variable that represents whether an individual became a customer of the mail-order company after the campaign

Strategy: The data serves as a training set that will be used to build an optimal predictive algorithm for a separate data set for testing. Maybe need:

- Algorithms and model: Classification
- Data Preparation: Add/Remove/Transform Attributes
- Feature Engineering

Metrics

Source: https://machinelearningmastery.com/tour-of-evaluation-metrics-for-imbalanced-classification/



This choice is justified by several factors:

1. **Binary Classification**: Our problem involves predicting whether an individual is likely to become a customer or not, which is a binary classification task

2. **Predicting Class Labels**: The final decision is necessary; it is not about understanding the risks and making an informed decision(`Predicting Probabilities`).

3. **The positive class is more important**: Identifying potential customers holds greater value than focusing on excluding non-potential ones.

4. **Imbalanced Dataset**: The customer base is likely smaller than the general population, resulting in an imbalanced dataset.

=> Recall is an important metric when the focus is on capturing as many positive instances as possible, especially in cases of class imbalance or when the cost of false negatives is high

Additionally, we will use ROC AUC, precision, and F1-score to provide a more nuanced understanding of the model's performance, especially in terms of balancing false positives and false negatives in our customer predictions.

Analysis

Data Exploration

Key points from our data exploration phase:

1. Dataset Contents:
    - Dataset feature : 367 features (includes `RESPONSE`)
    - Explained feature in DIAS Attributes - Values 2017.xlsx
        - 'AGER_TYP', 'ALTERSKATEGORIE_GROB', 'ALTER_HH', 'ANREDE_KZ', ...
        - Total: 310
    - Unexplained features in DIAS Attributes - Values 2017.xlsx
        - 'CJT_TYP_4', 'CJT_TYP_6', 'KOMBIALTER', 'D19_VERSI_ONLINE_QUOTE_12', ...
        - Total: 57
2. Statistical Analysis:
    - RangeIndex: 42962 entries, 0 to 42961
    - Columns: 367 entries, LNR to ALTERSKATEGORIE_GROB
    - dtypes: float64(267), int64(94), object(6)
    - memory usage: 120.3+ MB
3. Data Sampling Insights:

- Number features

LNR	AGER_TYP	AKT_DAT_KL	ALTER_HH	ALTER_KIND1	ALTER_KIND2	ALTER_KIND3	ALTER_KIND4	ALTERSKATEGORIE_FEIN	ANZ_HAU
1763	2	1.0	8.0	NaN	NaN	NaN	NaN	8.0	15.0
1771	1	4.0	13.0	NaN	NaN	NaN	NaN	13.0	1.0
1776	1	1.0	9.0	NaN	NaN	NaN	NaN	7.0	0.0
1460	2	1.0	6.0	NaN	NaN	NaN	NaN	6.0	4.0
1783	2	1.0	9.0	NaN	NaN	NaN	NaN	9.0	53.0

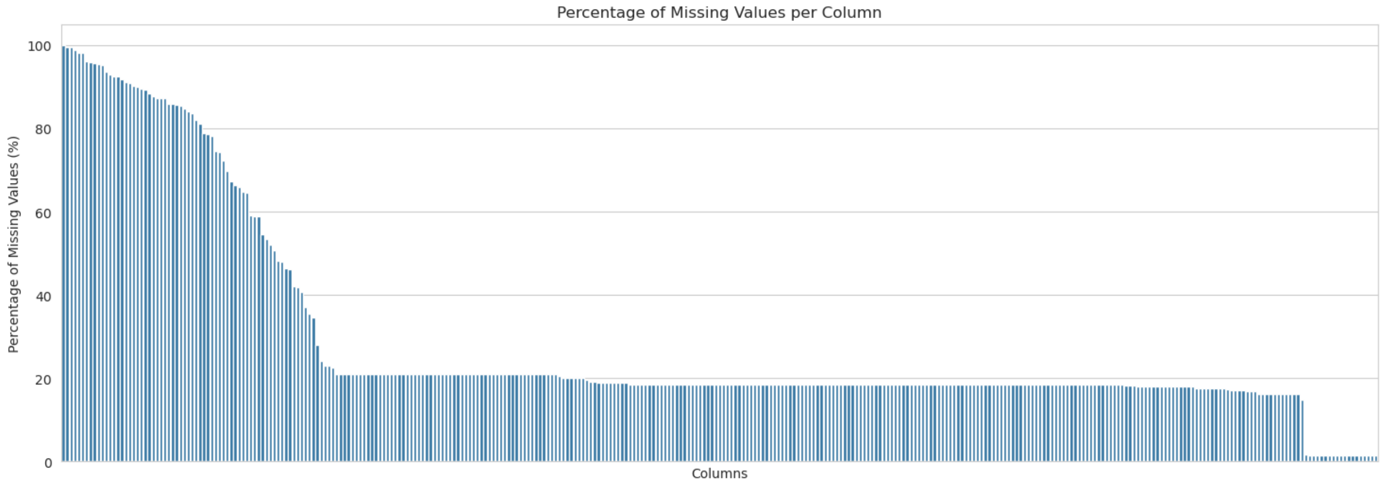
- Object features

CAMEO_DEU_2015	CAMEO_DEUG_2015	CAMEO_INTL_2015	D19_LETZTER_KAUF_BRANCHE	EINGEFUEGT_AM	OST_WEST_KZ
5D	5.0	34.0	D19_UNBEKANNT	1992-02-10 00:00:00	W
5B	5.0	32.0	D19_TELKO_MOBILE	1997-05-14 00:00:00	W
2D	2.0	14.0	D19_LEBENSMITTEL	1995-05-24 00:00:00	O
2D	2.0	14.0	D19_UNBEKANNT	1992-02-10 00:00:00	W
7B	7.0	41.0	D19_BEKLEIDUNG_GEH	1992-02-10 00:00:00	W

```
mailout_train['CAMEO_INTL_2015'].unique()
```

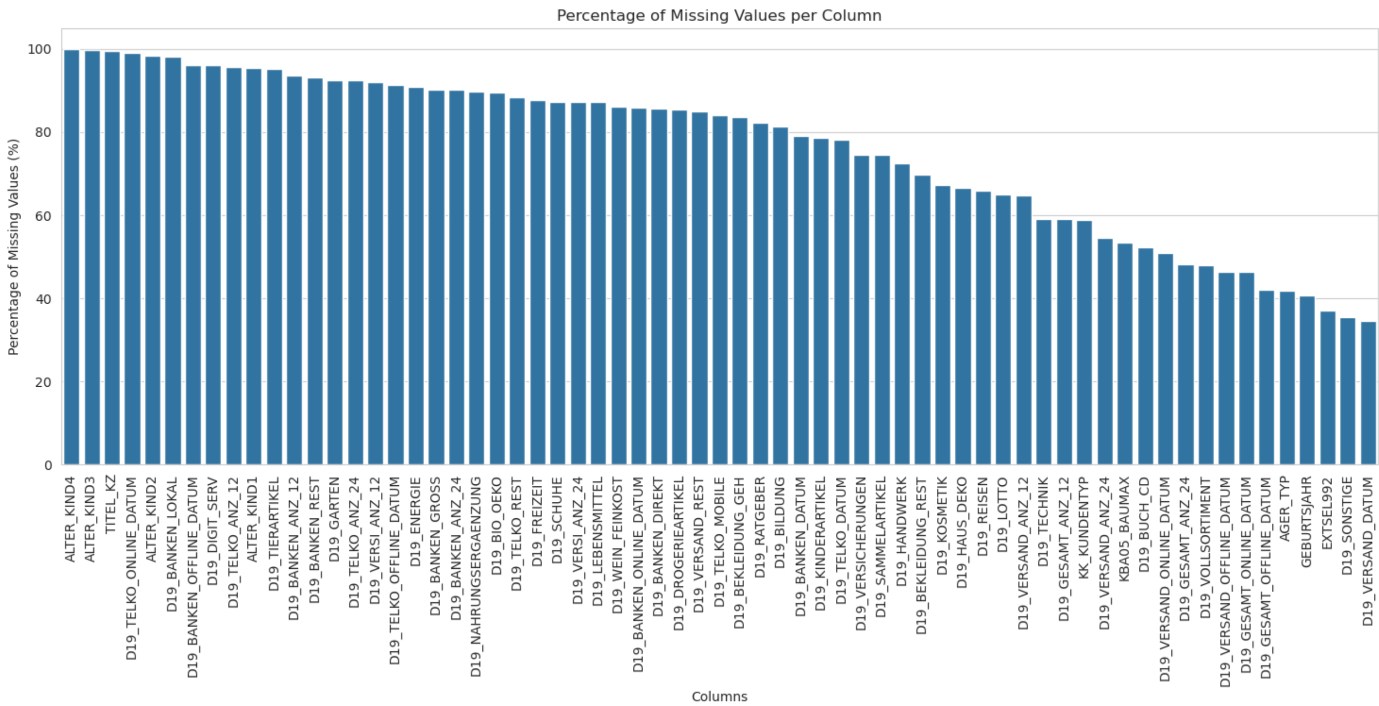
```
array([34.0, 32.0, 14.0, 41.0, 24.0, 33.0, nan, 25.0, 31.0, 22.0, 43.0,
       13.0, 55.0, 23.0, 54.0, 51.0, 45.0, 12.0, 44.0, 35.0, 15.0, 52.0,
       '23', '44', '14', '55', '51', '45', '43', '22', '54', '24', '25',
       '13', '12', '35', '33', '41', '15', '52', '31', '32', '34', 'XX'],
      dtype=object)
```

1. Identified Data Abnormalities:



Columns with more than 30% missing values:

['AGER_TYP', 'ALTER_KIND1', 'ALTER_KIND2', 'ALTER_KIND3', 'ALTER_KIND4', 'D19_BANKEN_ANZ_12', 'D19_BANKEN_ANZ_24', 'D19_BANKEN_DATUM', 'D19_BANKEN_DIREKT', 'D19_BANKEN_GROSS', 'D19_BANKEN_LOKAL', 'D19_BANKEN_OFFLINE_DATUM', 'D19_BANKEN_ONLINE_DATUM', 'D19_BANKEN_REST', 'D19_BEKLEIDUNG_GEH', 'D19_BEKLEIDUNG_REST', 'D19_BILDUNG', 'D19_BIO_OEKO', 'D19_BUCH_CD', 'D19_DIGIT_SERV', 'D19_DROGERIEARTIKEL', 'D19_ENERGIE', 'D19_FREIZEIT', 'D19_GARTEN', 'D19_GESAMT_ANZ_12', 'D19_GESAMT_ANZ_24', 'D19_GESAMT_OFFLINE_DATUM', 'D19_GESAMT_ONLINE_DATUM', 'D19_HANDWERK', 'D19_HAUS_DEKO', 'D19_KINDERARTIKEL', 'D19_KOSMETIK', 'D19_LEBENSMITTEL', 'D19_LOTTO', 'D19_NAHRUNGSERGAENZUNG', 'D19_RATGEBER', 'D19_REISEN', 'D19_SAMMELARTIKEL', 'D19_SCHUHE', 'D19_SONSTIGE', 'D19_TECHNIK', 'D19_TELKO_ANZ_12', 'D19_TELKO_ANZ_24', 'D19_TELKO_DATUM', 'D19_TELKO_MOBILE', 'D19_TELKO_OFFLINE_DATUM', 'D19_TELKO_ONLINE_DATUM', 'D19_TELKO_REST', 'D19_TIERARTIKEL', 'D19_VERSAND_ANZ_12', 'D19_VERSAND_ANZ_24', 'D19_VERSAND_DATUM', 'D19_VERSAND_OFFLINE_DATUM', 'D19_VERSAND_ONLINE_DATUM', 'D19_VERSAND_REST', 'D19_VERSI_ANZ_12', 'D19_VERSI_ANZ_24', 'D19_VERSICHERUNGEN', 'D19_VOLLSORTIMENT', 'D19_WEIN_FEINKOST', 'EXTSEL992', 'GEBURTSJAHR', 'KBA05_BAUMAX', 'KK_KUNDENTYP', 'TITEL_KZ']

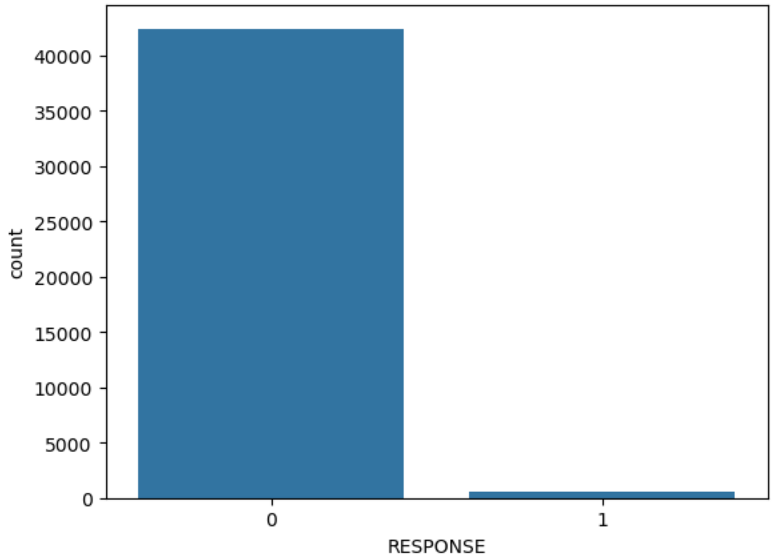


1. Preprocessing Needs:
    - Data Cleaning:
        - Address missing values through imputation or removal
        - Correcting Errors such as typos or incorrect formats.
    - Feature Engineering: `describe as below`
    - Data Reduction
        - Sampling: using techniques like random sampling or stratified sampling to create a manageable subset
2. Feature Engineering Opportunities:
    - Creating New Features from `EINGEFUEGT_AM`
    - Encoding Categorical Variables for `D19_LETZTER_KAUF_BRANCHE`, `CAMEO_DEU_2015`, `OST_WEST_KZ`
    - Handling Missing Values include as Imputation
3. Conclusion:

- Thorough data preprocessing required for reliable subsequent analysis and modeling
- Rich dataset with potential for insightful customer segmentation and prediction

Exploratory Visualization

```
Number of negative responses (RESPONSE = 0) in clean_mailout_train: 42430 (98.76%)
Number of positive responses (RESPONSE = 1) in clean_mailout_train: 532 (1.24%)
```



The problem with the dataset is imbalance

Algorithms and Techniques

We will consider the following approaches to handle it:

1. Oversampling the minority class.
2. Undersampling the majority class.
3. Rely on cost-sensitive learning- parameters like `is_unbalanced`, `class_weight`, `scale_pos_weight`
4. Implement Self-Training and Semi-Supervised Learning

Benchmark

Model Name	Technique	ROC_AUC	Recall	Precision	F1 Score	Accuracy
XX	XX	0	0	0	0	0

The table above is the benchmark result for comparing solutions. ROC AUC, recall, and F1 are the main scores that we need to focus on. Other scores are considered as costs that need to be improved if possible.

Methodology

Data Preprocessing

1. Exact data `from DIAS Attributes - Values 2017.xlsx`, detect unknow data in each feature

   ```
   Total number of rows with unknown values: 288
   ```

2. Detect stranger character in feature has `object` datatype like `XX` and `X`

   ```
   for column in azdias.select_dtypes(include=['object']):
      print(f'Feature: {column}')
      print(azdias[column].unique())
   ```

   ```
   Feature:
   ['9' 4.0 '4' 3.0 nan 9.0 '2' '8' 2.0 '1' '7' '5' 8.0 7.0 '3' '6' 6.0 5.0 1.0 'X']
   ```

3. Replace `XX` and `X` Values with `NaN`
   1. Columns `CAMEO_INTL_2015` and `CAMEO_DEU_2015` have **XX** values replaced with NaN.

    2. Column `CAMEO_DEUG_2015` has **X** values replaced with NaN.
4. Convert String Values to Float
    1. Convert `CAMEO_DEUG_2015` and `CAMEO_INTL_2015` columns from `string` to `float32`.
5. Convert to Category Codes
    1. Convert categorical columns to their respective category codes. (`D19_LETZTER_KAUF_BRANCHE`, `CAMEO_DEU_2015`, `OST_WEST_KZ`)
6. Feature Engineering on Datetime Feature
    1. Convert `EINGEFUEGT_AM` to datetime and extract `hour`, `day_of_week`, and `month`.
    2. Drop the original `EINGEFUEGT_AM` column.
7. Replace `unknown` value with `NaN` - feature take from step **(1)**
    1. Replace special values (-1, 0, 9, 10) with `NaN` for specific feature groups.
8. Remove Features
    1. Drop columns with more than 30% `NaN` values.
9. Ensure Consistency in Data Formats
10. Convert `int64` columns to `int32` and `float64` columns to `float32`.
11. Drop the useless columns
    1. Drop the `LNR` column if it exists.

Implementation

The process for which metrics, algorithms, and techniques were implemented with the given datasets or input data has been thoroughly documented. Complications that occurred during the coding process are discussed.

1. Metrics
    1. `cal_metrics`: This function evaluates the overall performance of the model by `calculating AUC`, generating a `classification report`, and `visualizing the confusion matrix`.
2. Algorithms
    1. Random Forest Classifier model
        1. a robust
        2. easy-to-interpret model
        3. performs well on small datasets
    2. Xboost model
        1. Dealing with complex datasets - Can handle `NaN` data
        2. High performance
        3. Can invest time in hyperparameter tuning.
3. Technique
    1. Data Preprocessing
        1. Handling missing values (2 options)
            1. Replace `NaN` by mean / median /...
            2. Keep it as is and choose a model that can handle `NaN` data such as `Xboost`, `CatBoost`
        2. Feature Engineering
        3. Encoding categorical variables
        4. Remove features with more than 40% missing (`NaN`) values
    2. Handling Class Imbalance
        1. Resampling Techniques
        2. Algorithmic Approaches - class weighting
    3. Model Evaluation
        1. splitting the data into training and validation sets
        2. identify and calculate metrics

Refinement

The process of improving upon the algorithms and techniques used is clearly documented. Both the initial and final solutions are reported, along with intermediate solutions, if necessary.

1. Find the best hyperparameters using `GridSearchCV`

    1.1. Implement

```
smote_tom_rf = GridSearchCV(random_smotetom_pipeline, param_grid=new_params, cv=kf, scoring='recall',
return_train_score=True, verbose=1, n_jobs=-1)
```

2. Resampling Techniques

    2.1. Implement

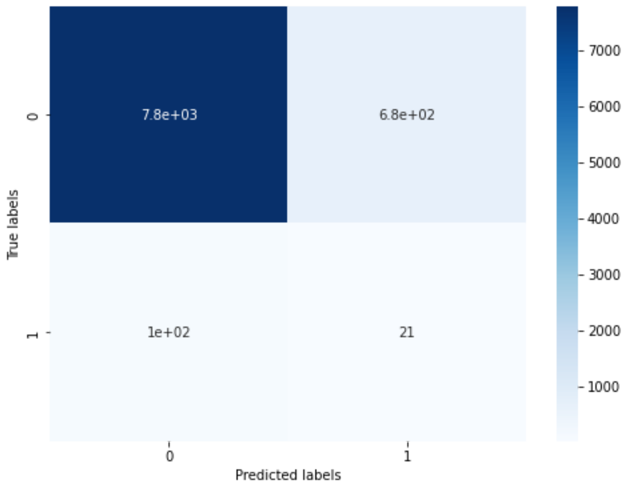
```
random_smotetom_pipeline = ImbPipeline([
    ('smote', SMOTETomek(random_state=42)),
    ('classifier', RandomForestClassifier(random_state=13))
])
```

2.2. Result

```
Random Forest - Validation AUC: 0.6577
Model Performance Results:
              precision    recall  f1-score   support

         0.0       0.99      0.92      0.95      8472
         1.0       0.03      0.17      0.05       121

    accuracy                           0.91      8593
   macro avg       0.51      0.55      0.50      8593
weighted avg       0.97      0.91      0.94      8593
```



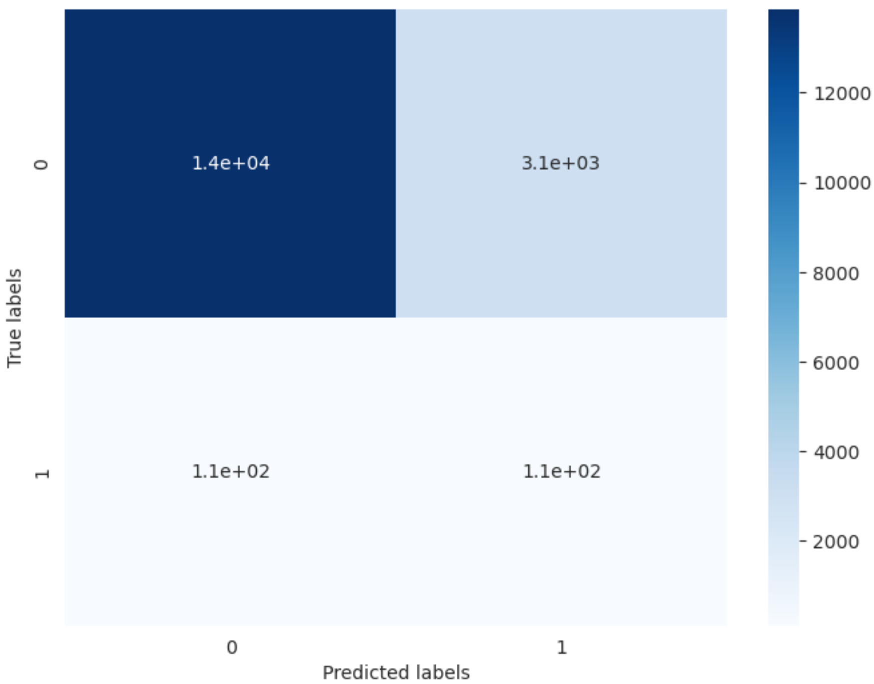
3. Algorithmic Approaches - Class Weighting

3.1. Implement

```
# Fixed class_weight
rfb = RandomForestClassifier(n_estimators=100, random_state=13, class_weight=class_weights)
```

3.2. Result

Model Name	Technique	ROC_AUC	Recall	Precision	F1 Score	Accuracy
Random Forest	class_weight	0.736374	0.495413	0.033687	0.063084	0.813326



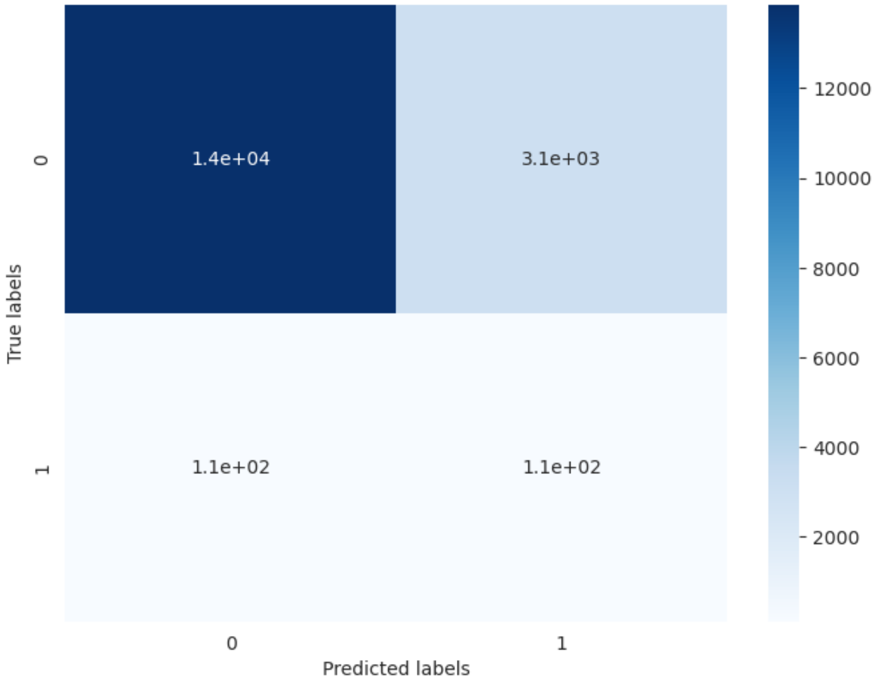
4. Class Weighting and Self Training 4.1. Implement

```
rf_classifier = RandomForestClassifier(**hyperparameters, class_weight=class_weights)

classifier, iterations, test_recalls, pseudo_labels = self_train(rf_classifier, X_train_impute, y_train, X_val_impute,
y_val, test_data.copy())
```

4.2. Result

Model Name	Technique	ROC_AUC	Recall	Precision	F1 Score	Accuracy
Random Forest	class_weight & self_training	0.736648	0.495413	0.033750	0.063195	0.813675



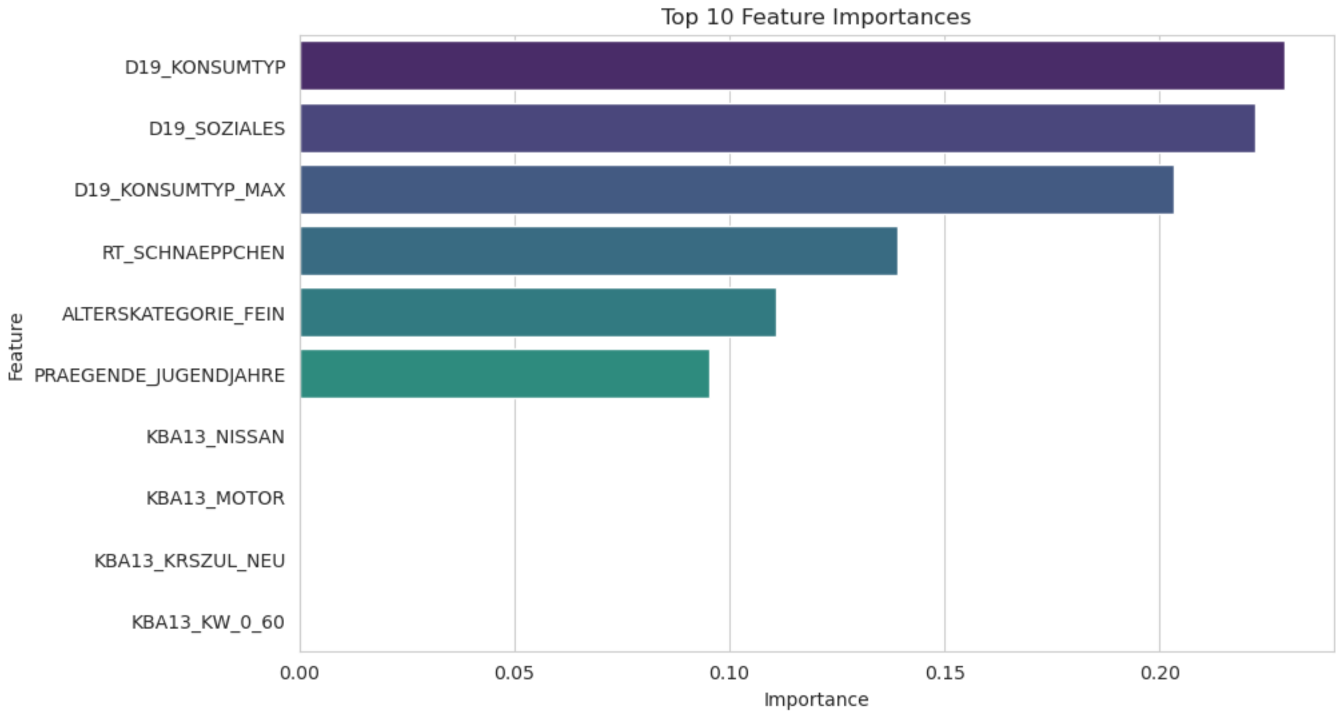
Results

Model Evaluation and Validation

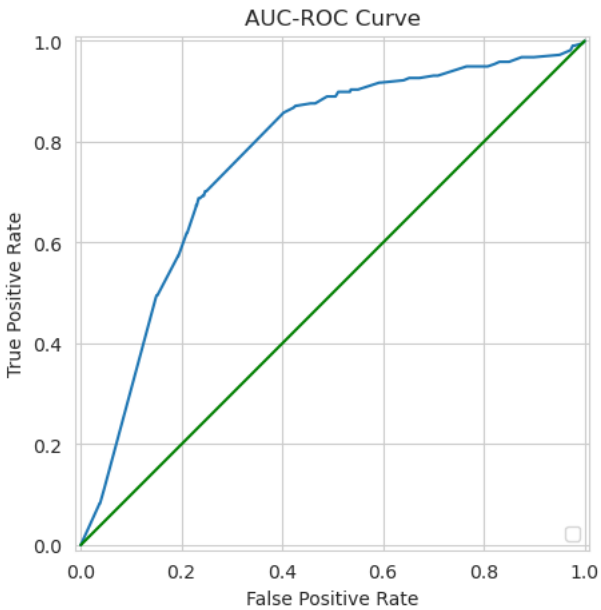
The best model is:

Model Name	Technique	ROC_AUC	Recall	Precision	F1 Score	Accuracy
`XGBoost`	`scale_pos_weight & self_training`	**0.768915**	**0.701835**	**0.035027**	**0.066725**	0.750946

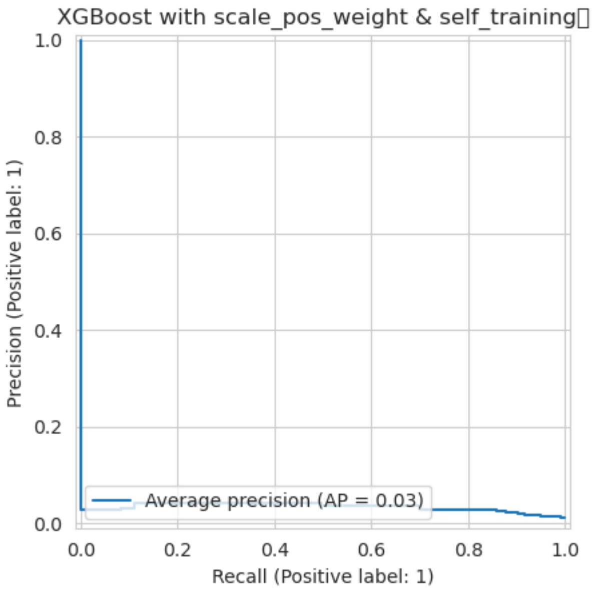
- Important features



- AUC-ROC Curve



- Precision-Recall Curve (PR curve)



Justification

Model Name	Technique	ROC_AUC	Recall	Precision	F1 Score	Accuracy
Random Forest	RandomOverSampler	0.729993	0.541284	0.027936	0.053129	0.755252
Random Forest	SMOTE	0.636855	0.133028	0.028856	0.047424	**0.932208**
Random Forest	SMOTE Tomek	0.636855	0.133028	0.028856	0.047424	**0.932208**
Random Forest	SMOTE ENN	0.652443	0.321101	0.029724	0.054411	0.858423
Random Forest	class_weight	0.736374	0.495413	0.033687	0.063084	0.813326
Random Forest	class_weight & self_training	0.736648	0.495413	0.033750	0.063195	0.813675
XGBoost	scale_pos_weight	0.768904	**0.701835**	0.035003	0.066681	0.750771
`XGBoost`	`scale_pos_weight & self_training`	**0.768915**	**0.701835**	**0.035027**	**0.066725**	0.750946

- Since the project dataset is imbalanced, so higher ROC_AUC and recall scores are positive signs.

References

- https://www.kaggle.com/code/marcinrutecki/best-techniques-and-metrics-for-imbalanced-dataset
- https://www.analyticsvidhya.com/blog/2020/10/improve-class-imbalance-class-weights/
- https://towardsdatascience.com/a-gentle-introduction-to-self-training-and-semi-supervised-learning-ceee73178b38