Final Project (Individual)

Team Primero

Date: 2nd August 2021

LISUM01

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Problem description

ABC is a pharmaceutical company that wants to understand the persistency of a drug as per the physician's prescription for a patient. The company has approached an Analytics company to automate this process of identification. This Analytics company has assigned the task to Team Primero to come up with a solution to automate the persistency of a drug for the client ABC.

Business understanding

The pharma company ABC wants to understand about the persistency of a drug for each patient. There are a bunch of Non-Tuberculous Mycobacterial (NTM) infection data. The company wants to divide each patient as either persistent or not depending on the prescription data. Depending on the persistency count, ABC pharma company would produce medicines in that quantity so that they can run their business strategically.

GitHub Repo Link

https://github.com/ReehaKhan/Project-Healthcare.git

Project lifecycle along with deadline

1. Week 1 (25th July 2021) – Tasks of Week 7, 8 and 9
2. Week 2 (2nd August 2021) – Tasks of Week 10 and 11
3. Week 3 (9th August 2021) – Tasks of Week 12 and 13

Data Intake Report

Name: HealthCare

Report date: 25th July 2021

Internship Batch: LISUM01

Version:<1.0>

Data intake by: Reeha Khan

Data intake reviewer:

Data storage location: https://github.com/ReehaKhan/Project-Healthcare

Tabular data details:

Total number of observations	3424
Total number of files	1
Total number of features	26
Base format of the file	.xlsx
Size of the data	898 KB

Data Set

Bucket	Variable	Variable Description
Unique Row Id	Patient ID	Unique ID of each patient
Target Variable	Persistency_Flag	Flag indicating if a patient was persistent or not
Demographics	Age	Age of the patient during their therapy
	Race	Race of the patient from the patient table
	Region	Region of the patient from the patient table
	Ethnicity	Ethnicity of the patient from the patient table
	Gender	Gender of the patient from the patient table
	IDN Indicator	Flag indicating patients mapped to IDN
Provider Attributes	NTM - Physician Specialty	Specialty of the HCP that prescribed the NTM Rx
Clinical Factors	NTM - T-Score	T Score of the patient at the time of the NTM Rx (within 2 years prior from rxdate)
	Change in T Score	Change in Tscore before starting with any therapy and after receiving therapy (Worsened, Remained Same, Improved, Unknown)
	NTM - Risk Segment	Risk Segment of the patient at the time of the NTM Rx (within 2 years days prior from rxdate)
	Change in Risk Segment	Change in Risk Segment before starting with any therapy and after receiving therapy (Worsened, Remained Same, Improved, Unknown)
	NTM - Multiple Risk Factors	Flag indicating if patient falls under multiple risk category (having more than 1 risk) at the time of the NTM Rx (within 365 days prior from rxdate)
	NTM - Dexa Scan Frequency	Number of DEXA scans taken prior to the first NTM Rx date (within 365 days prior from rxdate)
	NTM - Dexa Scan Recency	Flag indicating the presence of Dexa Scan before the NTM Rx (within 2 years prior from rxdate or between their first Rx and Switched Rx; whichever is smaller and applicable)
Disease/Treatment Factor	Dexa During Therapy	Flag indicating if the patient had a Dexa Scan during their first continuous therapy
	NTM - Fragility Fracture Recency	Flag indicating if the patient had a recent fragility fracture (within 365 days prior from rxdate)
	Fragility Fracture During Therapy	Flag indicating if the patient had fragility fracture during their first continuous therapy
	NTM - Glucocorticoid Recency	Flag indicating usage of Glucocorticoids (>=7.5mg strength) in the one year look-back from the first NTM Rx
	Glucocorticoid Usage During Therapy	Flag indicating if the patient had a Glucocorticoid usage during the first continuous therapy
	NTM - Injectable Experience	Flag indicating any injectable drug usage in the recent 12 months before the NTM OP Rx
	NTM - Risk Factors	Risk Factors that the patient is falling into. For chronic Risk Factors complete lookback to be applied and for non-chronic Risk Factors, one year lookback from the date of first OP Rx
	NTM - Comorbidity	Comorbidities are divided into two main categories - Acute and chronic, based on the ICD codes. For chronic disease we are taking complete look back from the first Rx date of NTM therapy and for acute diseases, time period before the NTM OP Rx with one year lookback has been applied
	NTM - Concomitancy	Concomitant drugs recorded prior to starting with a therapy(within 365 days prior from first rxdate)
	Adherence	Adherence for the therapies

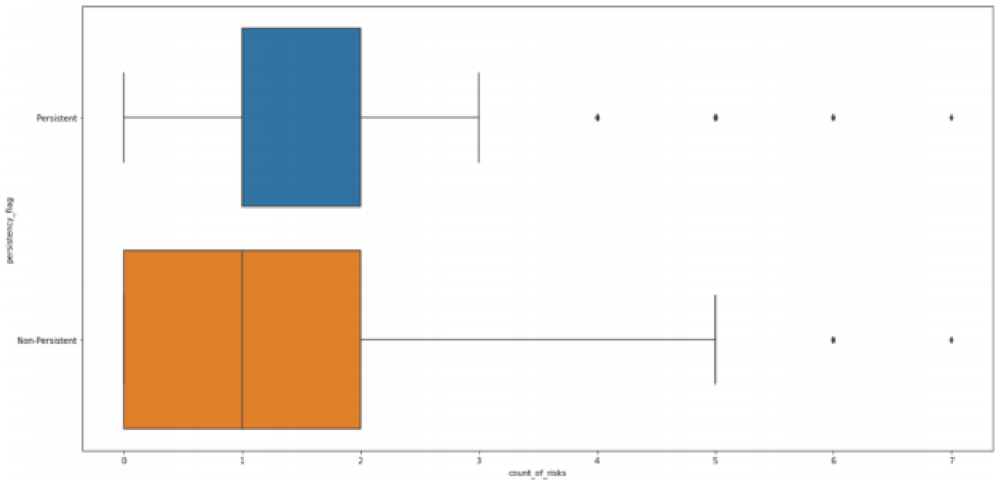
Data Types

The dimension of the dataset is (3424, 69). The features have the following datatypes. ("object" types mean categorical columns):

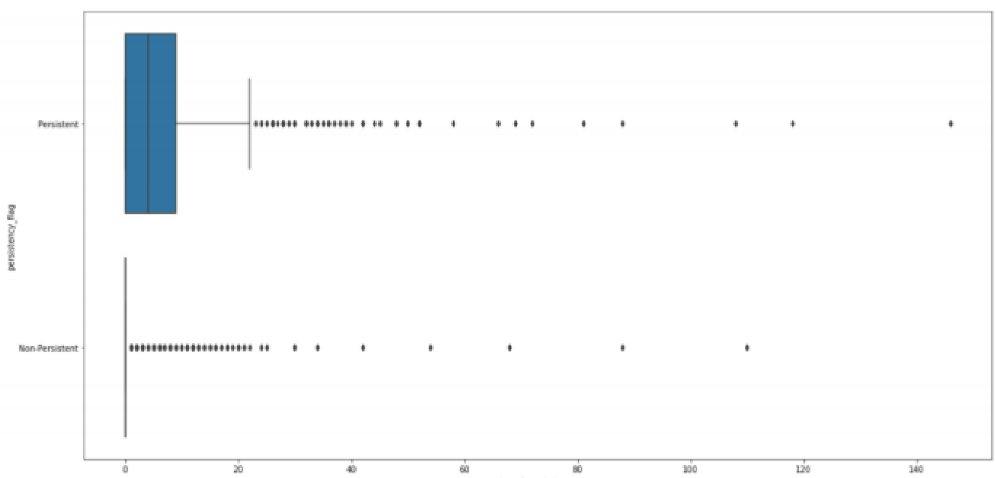
```
Ptid                                                                   object
Persistency_Flag                                                       object
Gender                                                                 object
Race                                                                   object
Ethnicity                                                              object
Region                                                                 object
Age_Bucket                                                             object
Ntm_Speciality                                                         object
Ntm_Specialist_Flag                                                    object
Ntm_Speciality_Bucket                                                  object
Gluco_Record_Prior_Ntm                                                 object
Gluco_Record_During_Rx                                                 object
Dexa_Freq_During_Rx                                                     int64
Dexa_During_Rx                                                         object
Frag_Frac_Prior_Ntm                                                    object
Frag_Frac_During_Rx                                                    object
Risk_Segment_Prior_Ntm                                                 object
Tscore_Bucket_Prior_Ntm                                                object
Risk_Segment_During_Rx                                                 object
Tscore_Bucket_During_Rx                                                object
Change_T_Score                                                         object
Change_Risk_Segment                                                    object
Adherent_Flag                                                          object
Idn_Indicator                                                          object
Injectable_Experience_During_Rx                                        object
Comorb_Encounter_For_Screening_For_Malignant_Neoplasms                 object
Comorb_Encounter_For_Immunization                                      object
Comorb_Encntr_For_General_Exam_W_O_Complaint,_Susp_Or_Reprtd_Dx        object
Comorb_Vitamin_D_Deficiency                                            object
Comorb_Other_Joint_Disorder_Not_Elsewhere_Classified                   object
Comorb_Encntr_For_Oth_Sp_Exam_W_O_Complaint_Suspected_Or_Reprtd_Dx     object
Comorb_Long_Term_Current_Drug_Therapy                                  object
Comorb_Dorsalgia                                                       object
Comorb_Personal_History_Of_Other_Diseases_And_Conditions               object
Comorb_Other_Disorders_Of_Bone_Density_And_Structure                   object
Comorb_Disorders_of_lipoprotein_metabolism_and_other_lipidemias        object
Comorb_Osteoporosis_without_current_pathological_fracture              object
Comorb_Personal_history_of_malignant_neoplasm                          object
Comorb_Gastro_esophageal_reflux_disease                                object
Concom_Cholesterol_And_Triglyceride_Regulating_Preparations            object
Concom_Narcotics                                                       object
Concom_Systemic_Corticosteroids_Plain                                  object
Concom_Anti_Depressants_And_Mood_Stabilisers                           object
Concom_Fluoroquinolones                                                object
Concom_Cephalosporins                                                  object
Concom_Macrolides_And_Similar_Types                                    object
Concom_Broad_Spectrum_Penicillins                                      object
Concom_Anaesthetics_General                                            object
Concom_Viral_Vaccines                                                  object
Risk_Type_1_Insulin_Dependent_Diabetes                                 object
Risk_Osteogenesis_Imperfecta                                           object
Risk_Rheumatoid_Arthritis                                              object
Risk_Untreated_Chronic_Hyperthyroidism                                 object
Risk_Untreated_Chronic_Hypogonadism                                    object
Risk_Untreated_Early_Menopause                                         object
Risk_Patient_Parent_Fractured_Their_Hip                                object
Risk_Smoking_Tobacco                                                   object
Risk_Chronic_Malnutrition_Or_Malabsorption                             object
Risk_Chronic_Liver_Disease                                             object
Risk_Family_History_Of_Osteoporosis                                    object
Risk_Low_Calcium_Intake                                                object
Risk_Vitamin_D_Insufficiency                                           object
Risk_Poor_Health_Frailty                                               object
Risk_Excessive_Thinness                                                object
Risk_Hysterectomy_Oophorectomy                                         object
Risk_Estrogen_Deficiency                                               object
Risk_Immobilization                                                    object
Risk_Recurring_Falls                                                   object
Count_Of_Risks                                                          int64
```

Data Problems

- Null Values: The dataset has no Null values.
- Outliers: There are only two numerical columns, both of which have some outliers.
  1. count_of_risks:



  2. dexa_freq_during_rx:



- Skewness and Kurtosis: There are only two numerical columns, both of which have some outliers.

1. count_of_risks:
   a. Count of risks skewness: 0.8797905232898707
   b. Count of risks Kurtosis: 0.9004859968892842
2. dexa_freq_during_rx:
   a. dexa_freq_during_rx skewness: 6.8087302112992285
   b. dexa_freq_during_rx Kurtosis: 74.75837754795428

Data Cleaning And Transformation

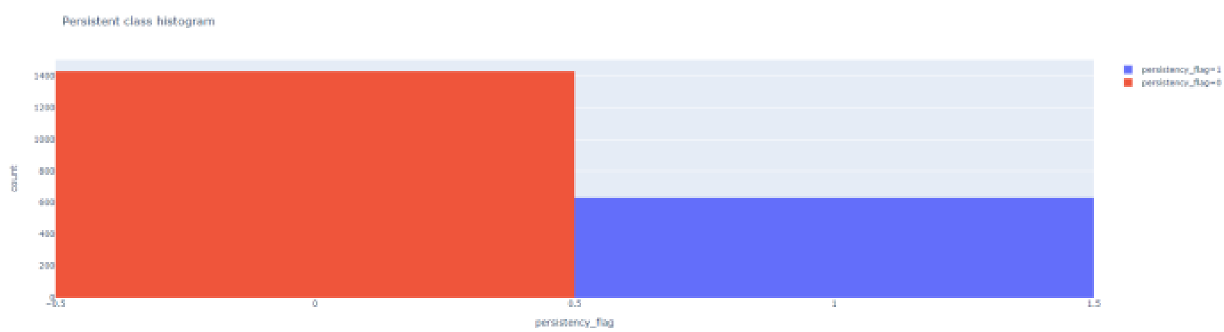
Since there are no Null values, so there is nothing to do in that regard. They are some skewness and Kurtosis in two numerical features, so we scaled their values by RobustScaler() and after that remove their outliers by calculating IQR and remove data smaller/greater than two whiskers. After removing outliers from “dexa_freq_during_rx”, we can now check the decrease in the shape of the data:

Old Shape: (3424, 69)

New Shape: (2964, 69)

All the [‘Y’, ‘N’] values have been changed to [1, 0] to train models on the data, and also we have changed the values of target feature from ['Non-Persistent', 'Persistent'] to [0, 1].

The other problem in the data was the misbalancing of the target feature:



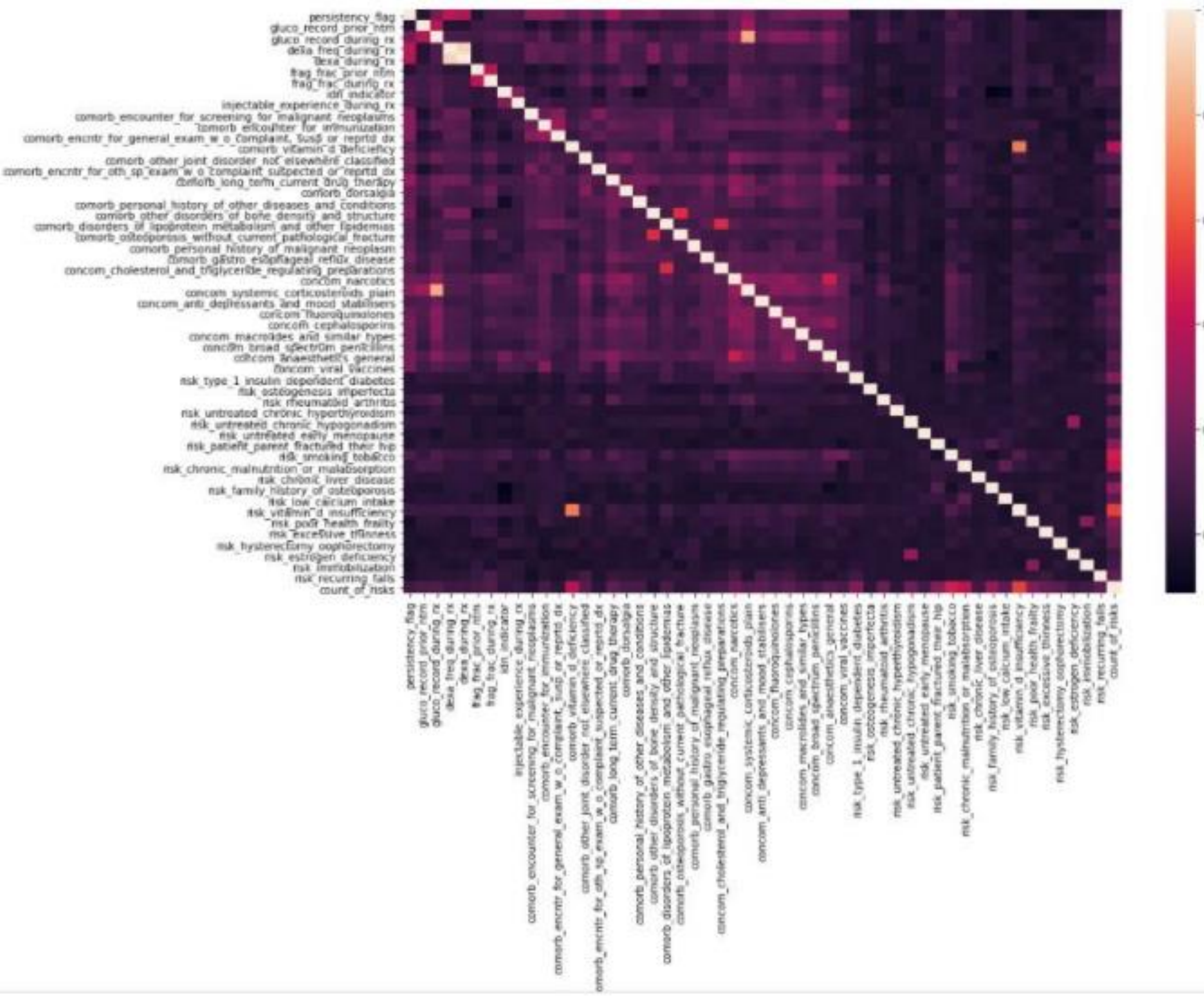
Since misbalanced datasets makes predicting hard and interfere with the models, we can do "Up sampling" on the data. In this method, we increase the records of the minority class such that at the end count of records is same for each class.

Another thing we performed on the dataset is “one hot encoding”. We need numerical values to use classifiers. This is done by using the “get_dummies()” function from Pandas library.

ID	Gender
1	Male
2	Female
3	Not Specified
4	Not Specified
5	Female

ID	Male	Female	Not Specified
1	1	0	0
2	0	1	0
3	0	0	1
4	0	0	1
5	0	1	0

Data Dependency



Final Recommendation

Moving forward, now we can perform classifiers models on the train set. The whole dataset is split into train and test sets (70% for train set and 30% test set).

Model Deployment

Results of different classification models which includes linear models and ensemble and boosting models.

<u>Linear Models</u>

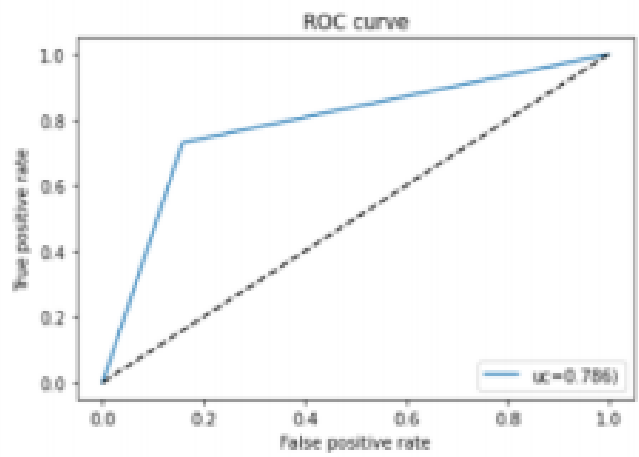
- *Logistic Regression*

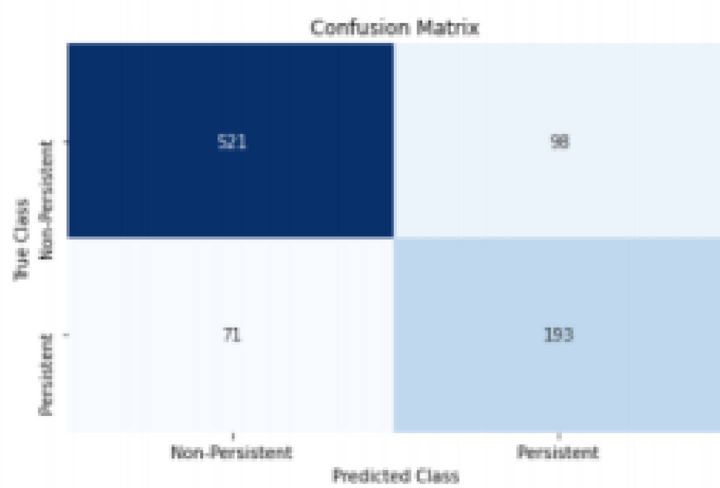
```
Accuracy : 0.8086070215175538
Precision : 0.6632302405498282
Recall : 0.7310606060606061
F1 Score : 0.6954954954954955
                precision    recall  f1-score   support

Non-Persistent       0.88      0.84      0.86       619
    Persistent       0.66      0.73      0.70       264

      accuracy                           0.81       883
     macro avg       0.77      0.79      0.78       883
  weighted avg       0.82      0.81      0.81       883

AUC : 0.7863703676506584
```





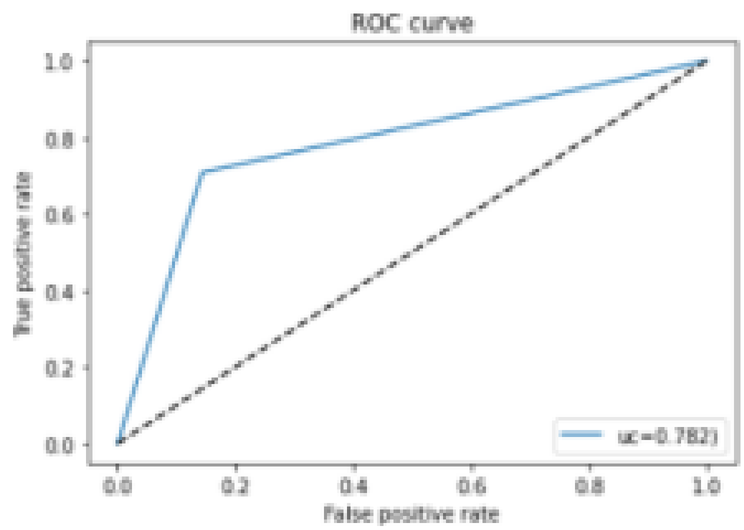
- *Ridge Classifier*

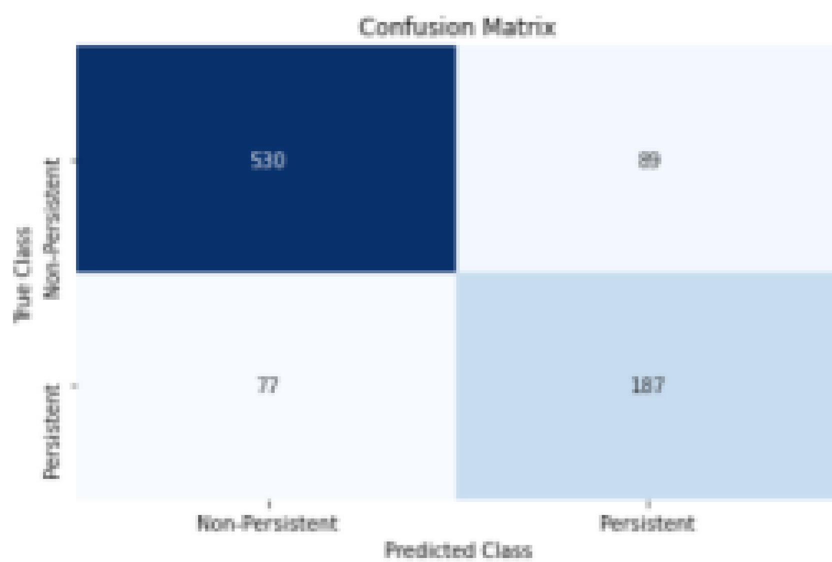
```
Accuracy : 0.812004530011325
Precision : 0.677536231884058
Recall : 0.7083333333333334
F1 Score : 0.6925925925925926
                precision    recall  f1-score   support

Non-Persistent       0.87      0.86      0.86       619
    Persistent       0.68      0.71      0.69       264

      accuracy                           0.81       883
     macro avg       0.78      0.78      0.78       883
  weighted avg       0.81      0.81      0.81       883

AUC : 0.782276521270867
```





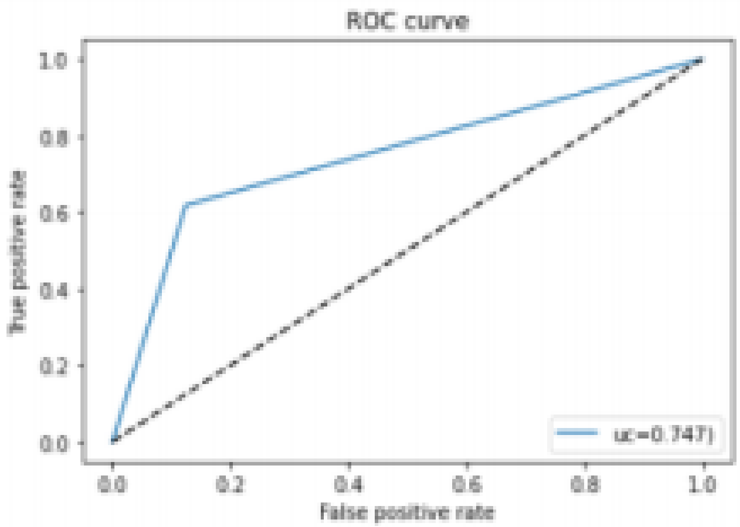
- *SGD Classifier*

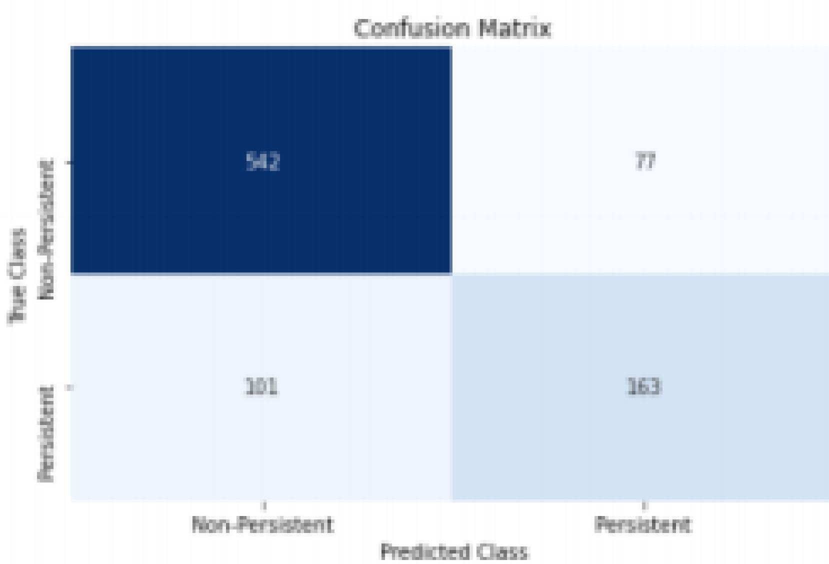
```
Accuracy : 0.7984144960362 4
Precision : 0.6791666666666667
Recall : 0.6174242424242424
F1 Score : 0.6468253968253969
               precision    recall  f1-score   support

Non-Persistent       0.84      0.88      0.86       619
    Persistent       0.68      0.62      0.65       264

      accuracy                           0.80       883
     macro avg       0.76      0.75      0.75       883
  weighted avg       0.79      0.80      0.80       883

AUC : 0.7465150291281147
```





Ensemble and Boosting Models

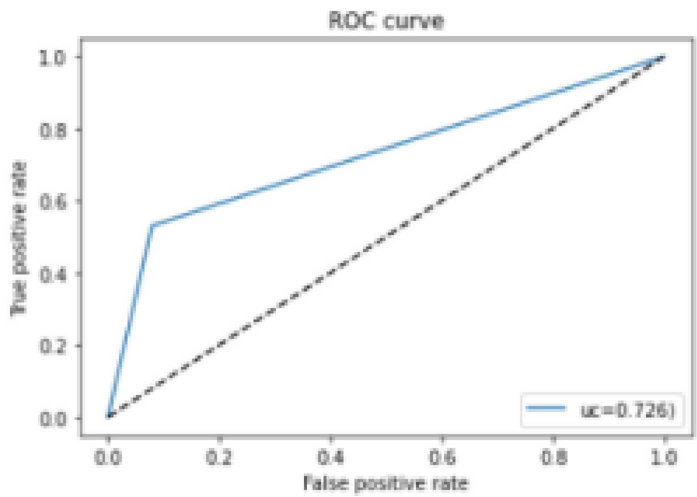
- *Random Forest Classifier*

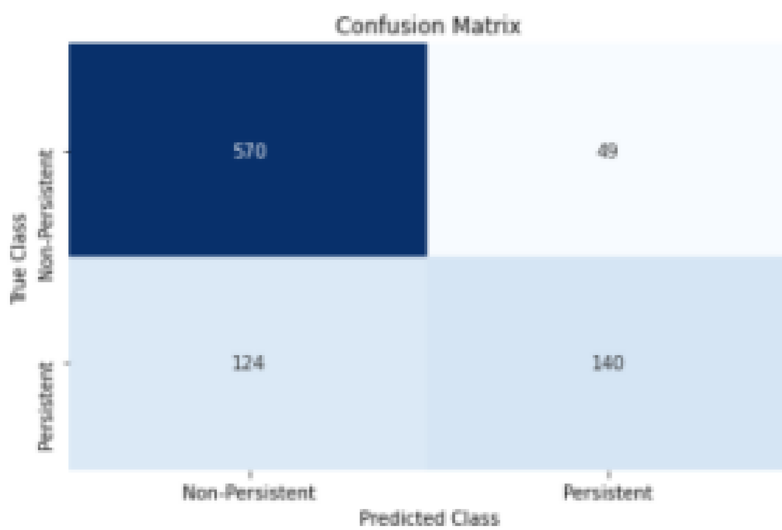
```
Accuracy : 0.8040770101925255
Precision : 0.7407407407407407
Recall : 0.5303030303030303
F1 Score : 0.6181015452538631
               precision    recall  f1-score   support

Non-Persistent       0.82      0.92      0.87       619
    Persistent       0.74      0.53      0.62       264

      accuracy                           0.80       883
     macro avg       0.78      0.73      0.74       883
  weighted avg       0.80      0.80      0.79       883

AUC : 0.7255715474616928
```





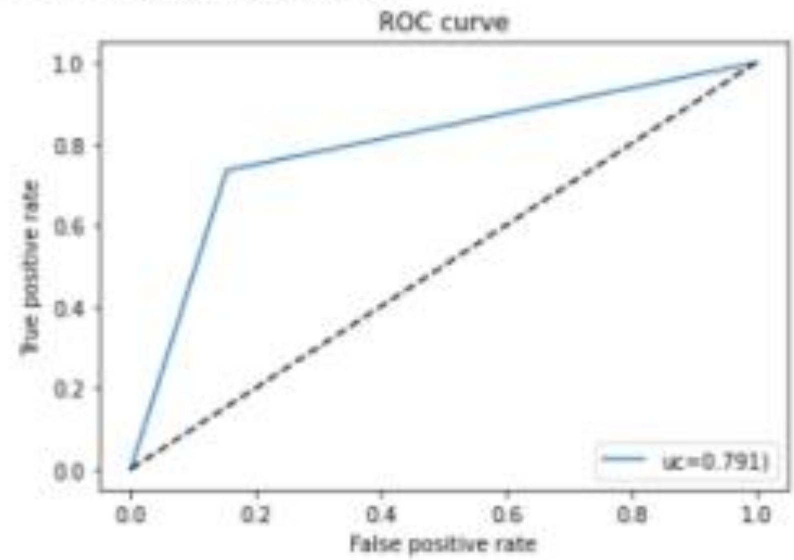
- *Ada Boost Classifier*

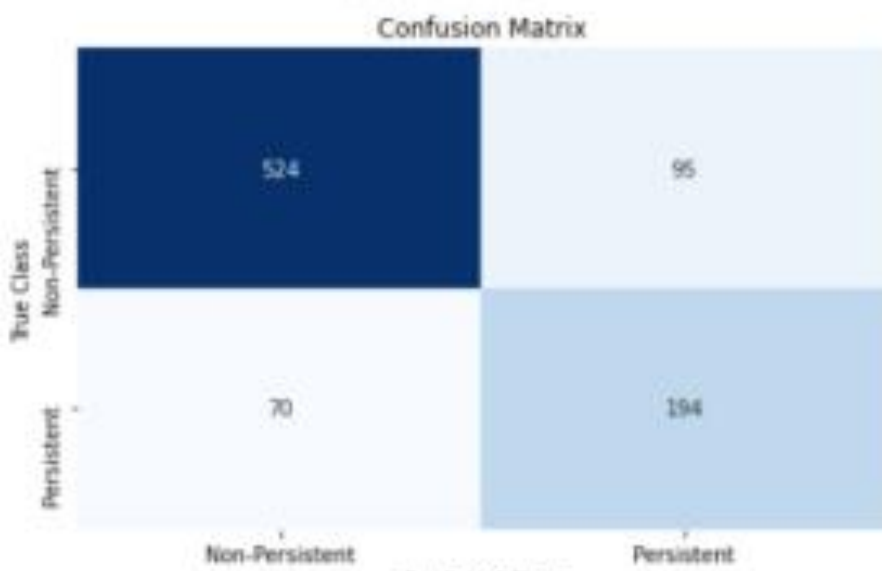
```
Accuracy : 0.8131370328425821
Precision : 0.671280276816609
Recall : 0.7348484848484849
F1 Score : 0.701627486437613
                precision    recall  f1-score   support

Non-Persistent       0.88      0.85      0.86       619
    Persistent       0.67      0.73      0.70       264

      accuracy                           0.81       883
     macro avg       0.78      0.79      0.78       883
  weighted avg       0.82      0.81      0.82       883

AUC : 0.7906875703725462
```





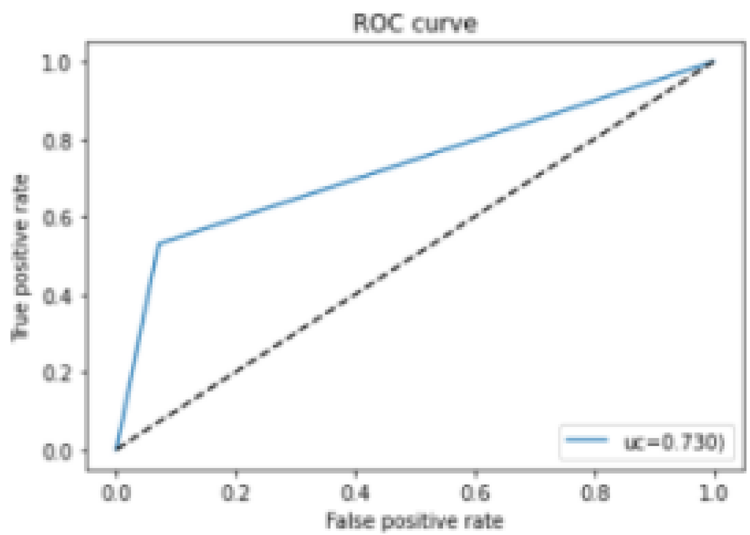
- *Stacking Classifier*

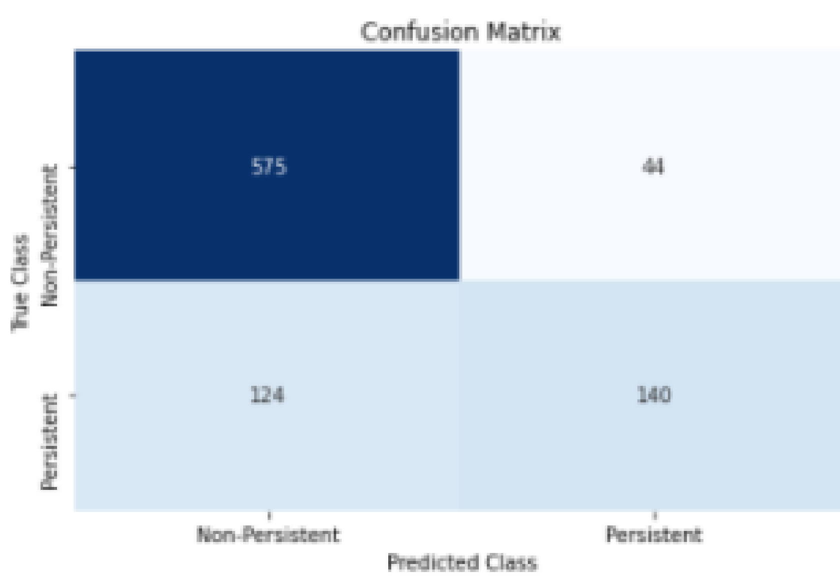
```
Accuracy : 0.8097395243488109
Precision : 0.7608695652173914
Recall : 0.5303030303030303
F1 Score : 0.625
               precision    recall  f1-score   support

Non-Persistent       0.82      0.93      0.87       619
    Persistent       0.76      0.53      0.62       264

      accuracy                           0.81       883
     macro avg       0.79      0.73      0.75       883
  weighted avg       0.80      0.81      0.80       883

AUC : 0.7296103196749399
```





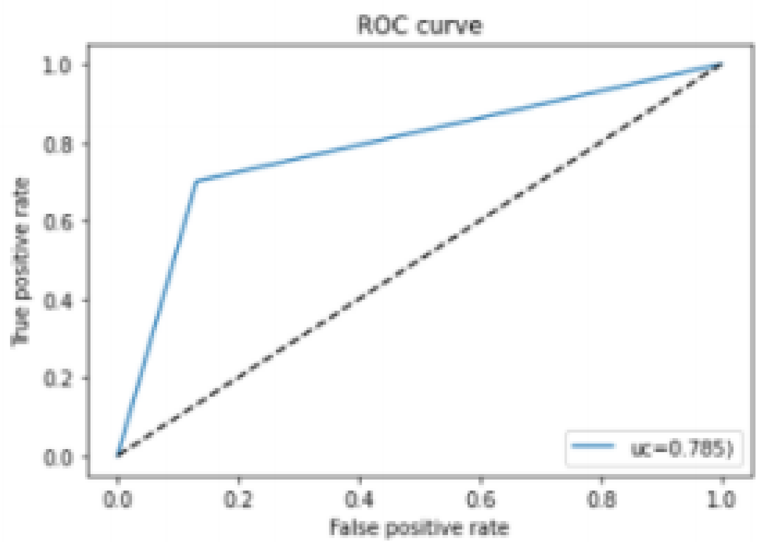
- *XG Boost Classifier*

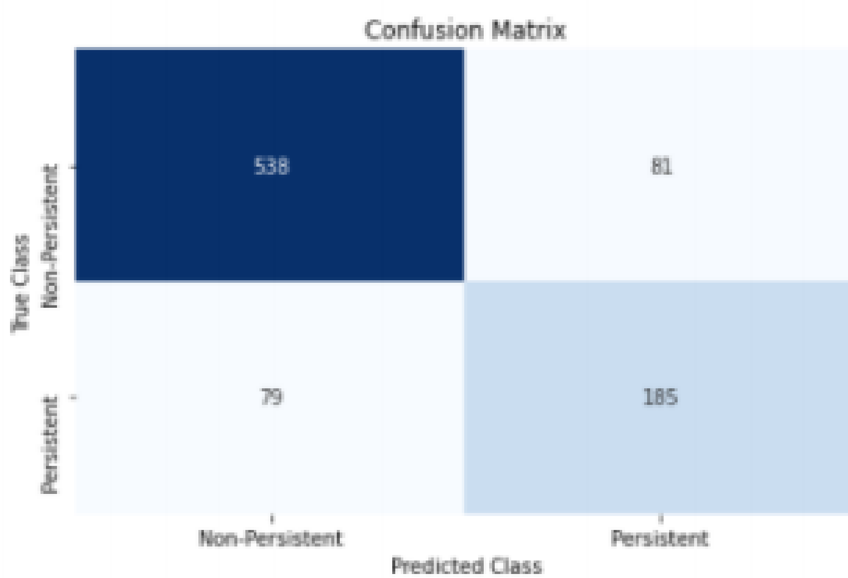
```
Accuracy : 0.8187995469988675
Precision : 0.6954887218045113
Recall : 0.7007575757575758
F1 Score : 0.6981132075471698
                precision    recall  f1-score   support

Non-Persistent       0.87      0.87      0.87       619
    Persistent       0.70      0.70      0.70       264

      accuracy                           0.82       883
     macro avg       0.78      0.78      0.78       883
  weighted avg       0.82      0.82      0.82       883

AUC : 0.7849506780241836
```





Conclusion

- ✓ There is not much of a significant difference between all the classifiers, however, the best can be considered to be:

  1. RidgeClassifier (Linear)
  2. AdaBoostClassifier (Ensemble/Boosting)
  3. XGBoostClassifier (Ensemble/Boosting)

- ✓ All of these classifiers have almost 81% Accuracy, 68% Precision, 71% Recall, 70% F1 Score and 78% AUC.

Training Final Model

As mentioned in the conclusion, all the models approximately have the same results, so we choose one, let’s say “StackingClassifier” and deploy it on whole dataset and save it to “final_model.sav”.