Data Glacier

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# Data Science: Healthcare Persistency of a drug (Group Project)

**Dec 2021**

Prepared by Bao Nguyen

# Team Members

| Team | | | | |
|---|---|---|---|---|
| Name | Email | Country | College/Company | Specialization |
| Bao Khanh Nguyen | nguyenkhanhbao8695@gmail.com | USA | American Energy Project | Data Science |
| Seyedeh Marzieh Hosseini | shosseini@uni-potsdam.de | Germany | University of Potsdam | Data Science |
| Guillermo Leija | leija.guillermo@gmail.com | Mexico | IEBS Business School | Data Science |
| Zain Ul Haq | zainulhaq904@gmail.com | Germany | University of Rostock | Data Science |

# Agenda

- Executive Summary
- Problem Statement
- Approach
- EDA
- Model Development
- Model Selection
- Model Evaluation
- Conclusion

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# Executive Summary

ABC company also one of pharmaceutical companies, wants to know how long a medicine will last in a patient's system (persistency of a drug). Based on prescription data, the ABC corporation needs to determine whether a patient is persistent or not. ABC pharma would manufacture medicines in that number based on the persistency count so that they could operate their firm effectively and avoid the risks of NTM infections.

**ML Problem:**

With an objective to gather insights on the factors that are impacting the persistency, build a classification for the given dataset

**Target Variable:** Persistency_Flag

# Problem Description

ABC is a pharmaceutical business that wants to know the persistency of a drug after a physician has prescribed it for a patient. This company has approached an analytics firm to automate the identifying procedure. This analytics firm has entrusted our team with the task of developing a solution to automate the persistence of a medicine for the client ABC.

# Business Understanding

One of the long-lasting business issues in the world of pharmaceutical companies is the persistency of drugs which can significantly affect the outcome of medical treatments. One of the important factors that is related to persistency is the adherence of the patient to the prescribed regimens, meaning if the patient is committed to the prescribed regimens or not. There is a lot of information about Non-Tuberculous Mycobacterial (NTM) infections. In fact, related studies show that around 50%-60% of the patients with different illnesses in US miss doses, take the wrong doses, or drop off treatment in the first year. Additionally, the illness, either chronic or acute can be related to the adherence and persistency of drugs.

# Project’s Steps

- Problem understanding
- Data Understanding
- Data Cleaning and Feature engineering
- Model Development
- Model Selection
- Model Evaluation
- Report the accuracy, precision and recall of both the class of target variable
- Report ROC-AUC as well
- Deploy the model
- Explain the challenges and model selection

# Methodologies

- Data was taken from github and analysed
- Problem understanding
- Data Understanding
- Data Cleaning and Feature engineering
- Model Development
- Model Selection
- Model Evaluation

# Data Intake Report

- Name: Healthcare – Data Science Report date: 25th April 2021
- Data storage location: https://github.com/Khanhbao8695/HealthCar_DS2021
- Total number of files 1
- Total number of features 26
- Base format of the file .xlsx
- Size of the data 898 KB

# Data Cleaning

- Checking Missing Value/ NAN / Null Data
- Checking Outliers
- Data Wrangling , Transformation and Standardization

# Analyzing dependency of variable (Before Transformation)

```
Non-Persistent : 62.35 %
Persistent : 37.65 %
```

The analysis showed more non persistence of drugs than persistence

# Missing Values

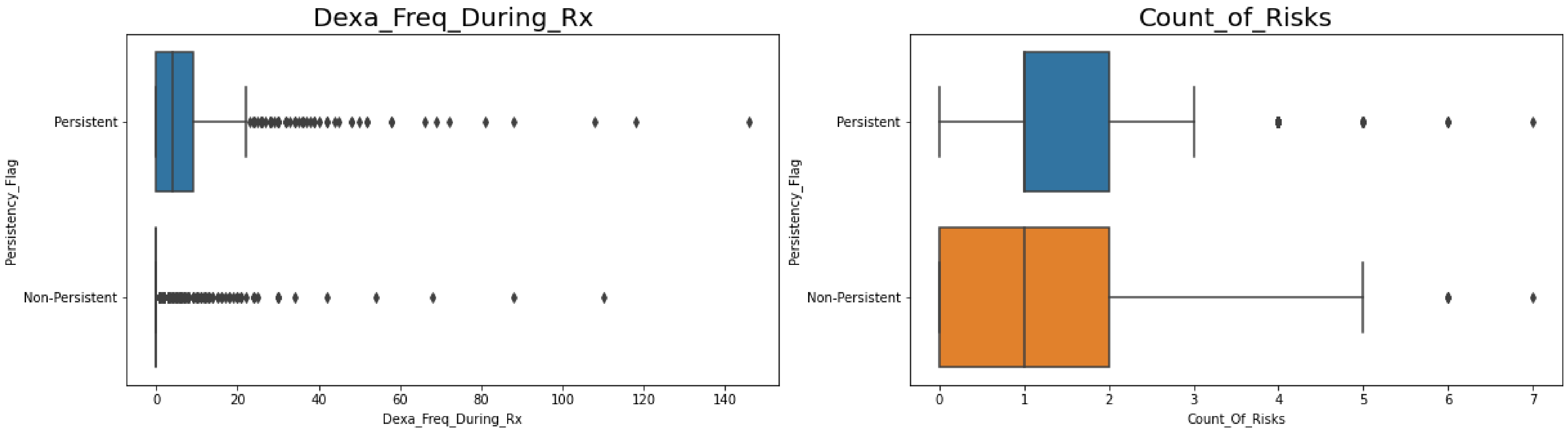
```
df.isnull().sum()
```

**No missing values were found**

```
for col in df.columns:
    pct_missing = np.mean(df[col].isnull())
    print('{} - {}'.format(col,pct_missing))
```

```
Ptid - 0.0
Persistency_Flag - 0.0
Gender - 0.0
Race - 0.0
Ethnicity - 0.0
Region - 0.0
Age_Bucket - 0.0
Ntm_Speciality - 0.0
Ntm_Specialist_Flag - 0.0
Ntm_Speciality_Bucket - 0.0
Gluco_Record_Prior_Ntm - 0.0
Gluco_Record_During_Rx - 0.0
Dexa_Freq_During_Rx - 0.0
Dexa_During_Rx - 0.0
Frag_Frac_Prior_Ntm - 0.0
Frag_Frac_During_Rx - 0.0
Risk_Segment_Prior_Ntm - 0.0
Tscore_Bucket_Prior_Ntm - 0.0
Risk_Segment_During_Rx - 0.0
Tscore_Bucket_During_Rx - 0.0
Change_T_Score - 0.0
Change_Risk_Segment - 0.0
Adherent_Flag - 0.0
Idn_Indicator - 0.0
Injectable_Experience_During_Rx - 0.0
```

# Checking Outliers




As we can see on these graphs, it is clearly to conclude that both Dexa_Freq_During_Rx and Count_of_Risks variables have outliers. Therefore, we will implement solutions to deal with this issue

# Data Transformation to resolve outliers

- Our approach to deal with the skewness and outliers for these variables is using IQR Score. To remove outliers, this approach uses the IQR values calculated before. Anything outside of the range of (Q1 - 1.5 IQR) and (Q3 + 1.5 IQR) is considered an outlier and should be eliminated.
- In this project, for Dexa_Freq_During_Rx and Count_of_Risks, we will remove any data outside of the range of (Q1 - 1.5 IQR) and (Q3 + 1.5 IQR) or two whiskers.

- For the Old Shape (3424,69) for both of Count of Risk" and “Dexa Freq During Rx" variable but after removed the outliers with this method, the new shape only (2964,69), which remove 460 data outside of the range of (Q1 - 1.5 IQR) and (Q3 + 1.5 IQR).

# LABEL Encoding for categorical variables

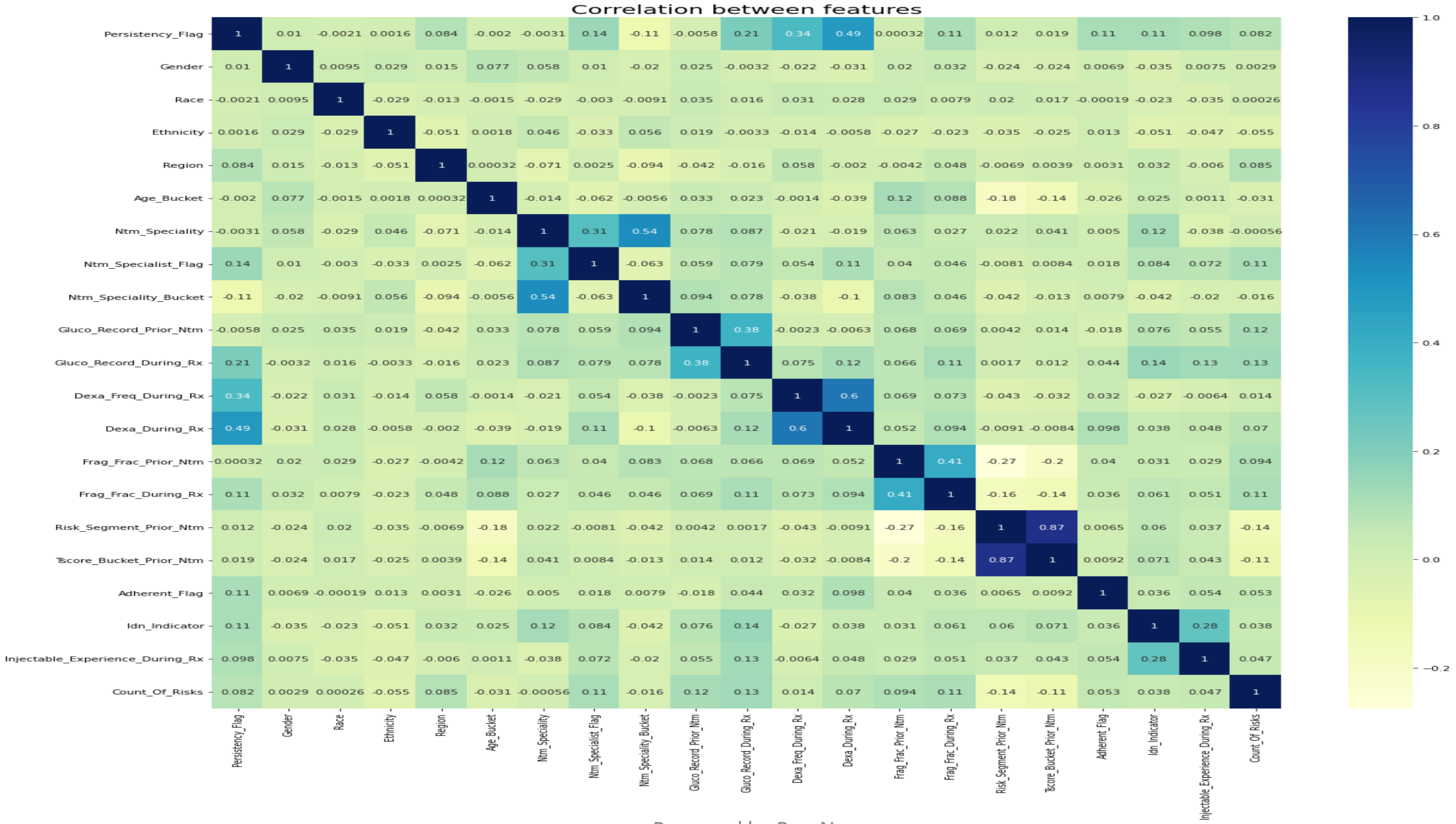
- We  need to pre-process our categorical data from words to number to make it easier for the computer to understands. To do this we will use LabelEncoder() provided by sklearn. Basically, it will transform a categorical column from this (example to describe this approach):

| Gender | Race |
|---|---|
| Male | Asian |
| Female | Other/Unknown |
| Male | Caucasian |

...into something like this... For example, Male will be 1 and Female will be 0

| Gender | Race |
|---|---|
| 1 | 1 |
| 0 | 3 |
| 1 | 2 |

# EDA (1): Correlation after transformation

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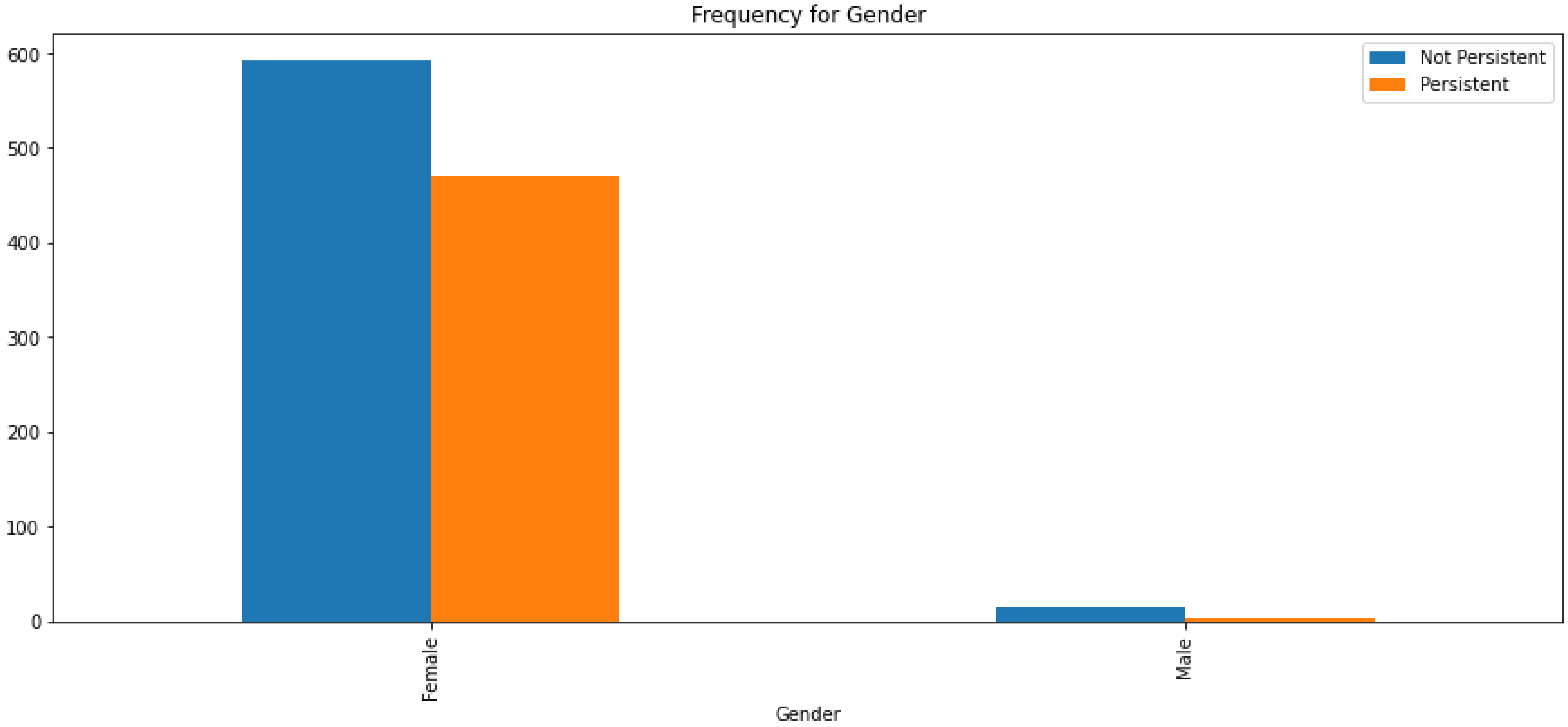
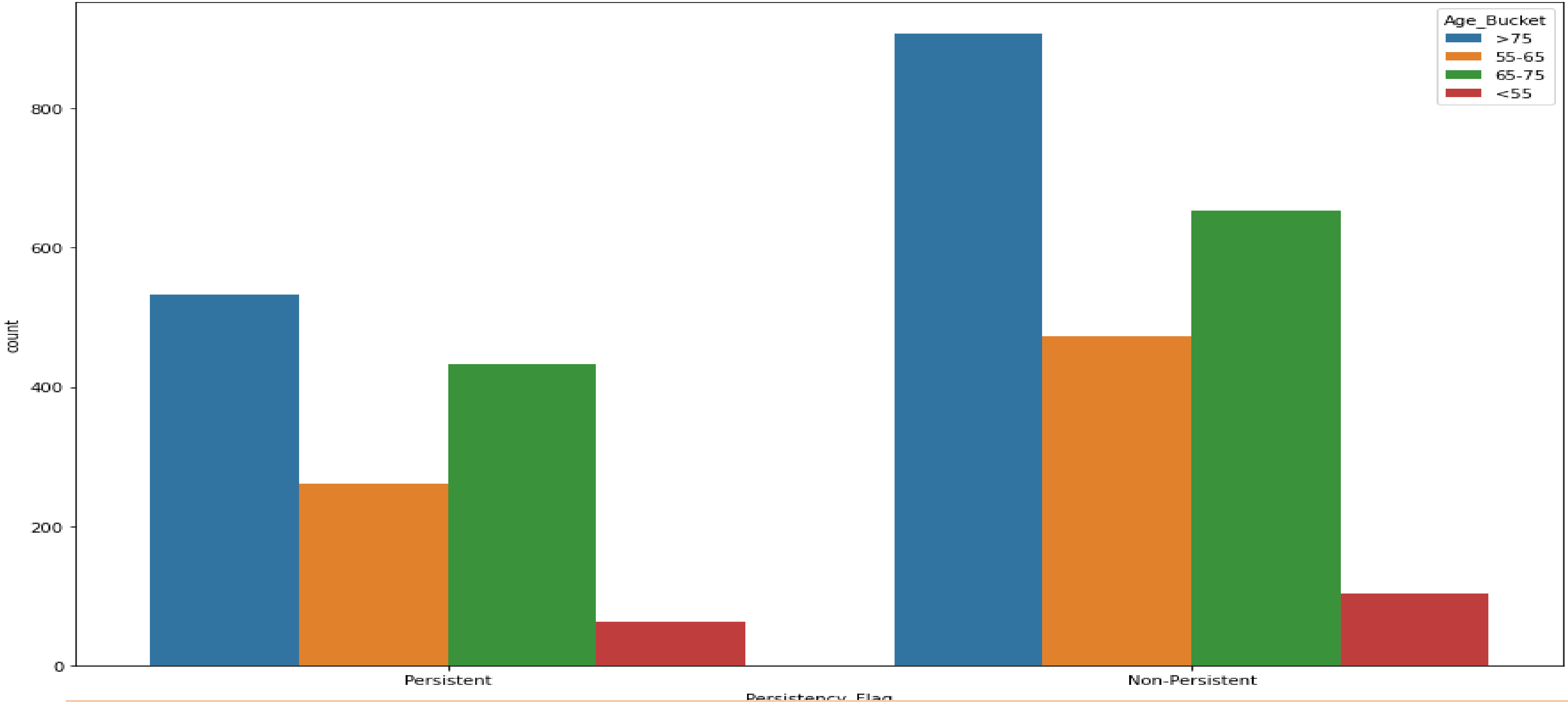
# EDA (2): Gender



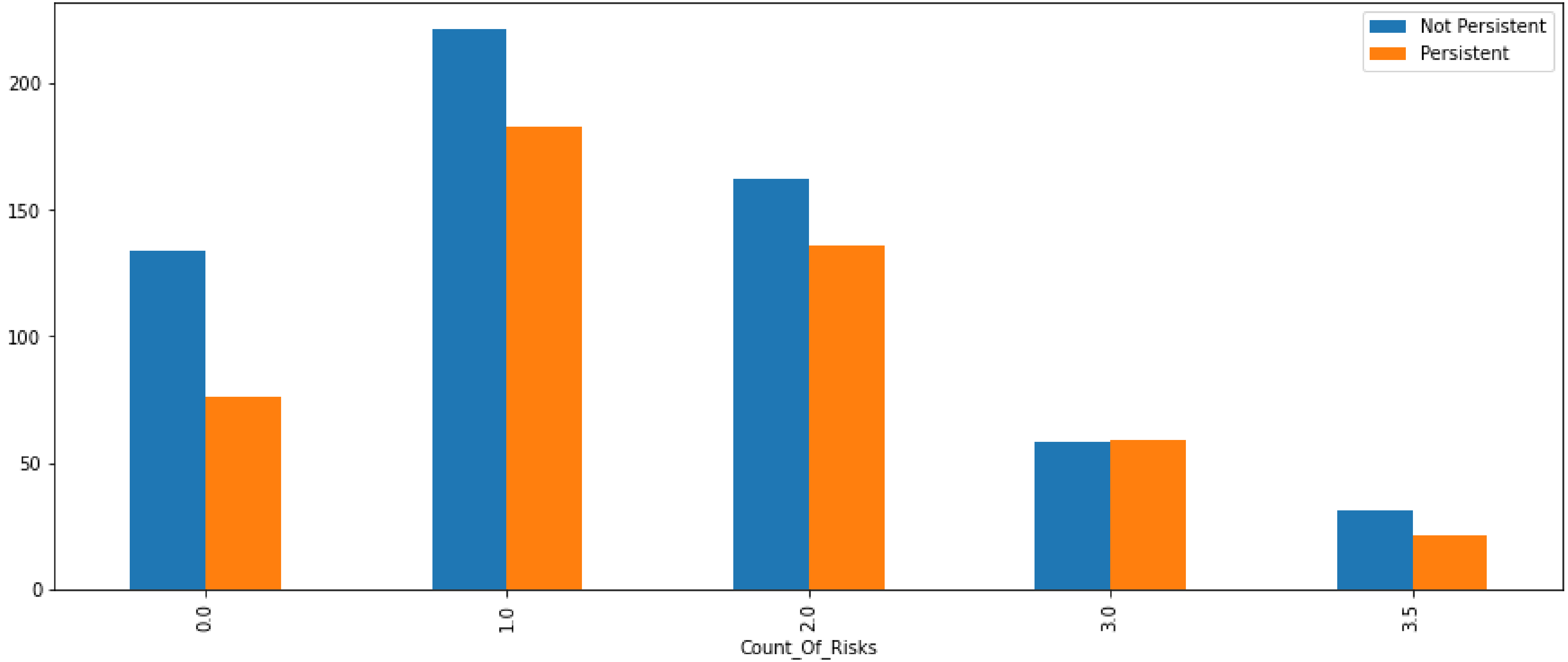

**It shows that females are most persistent with drug compliance**

# EDA (3): Age



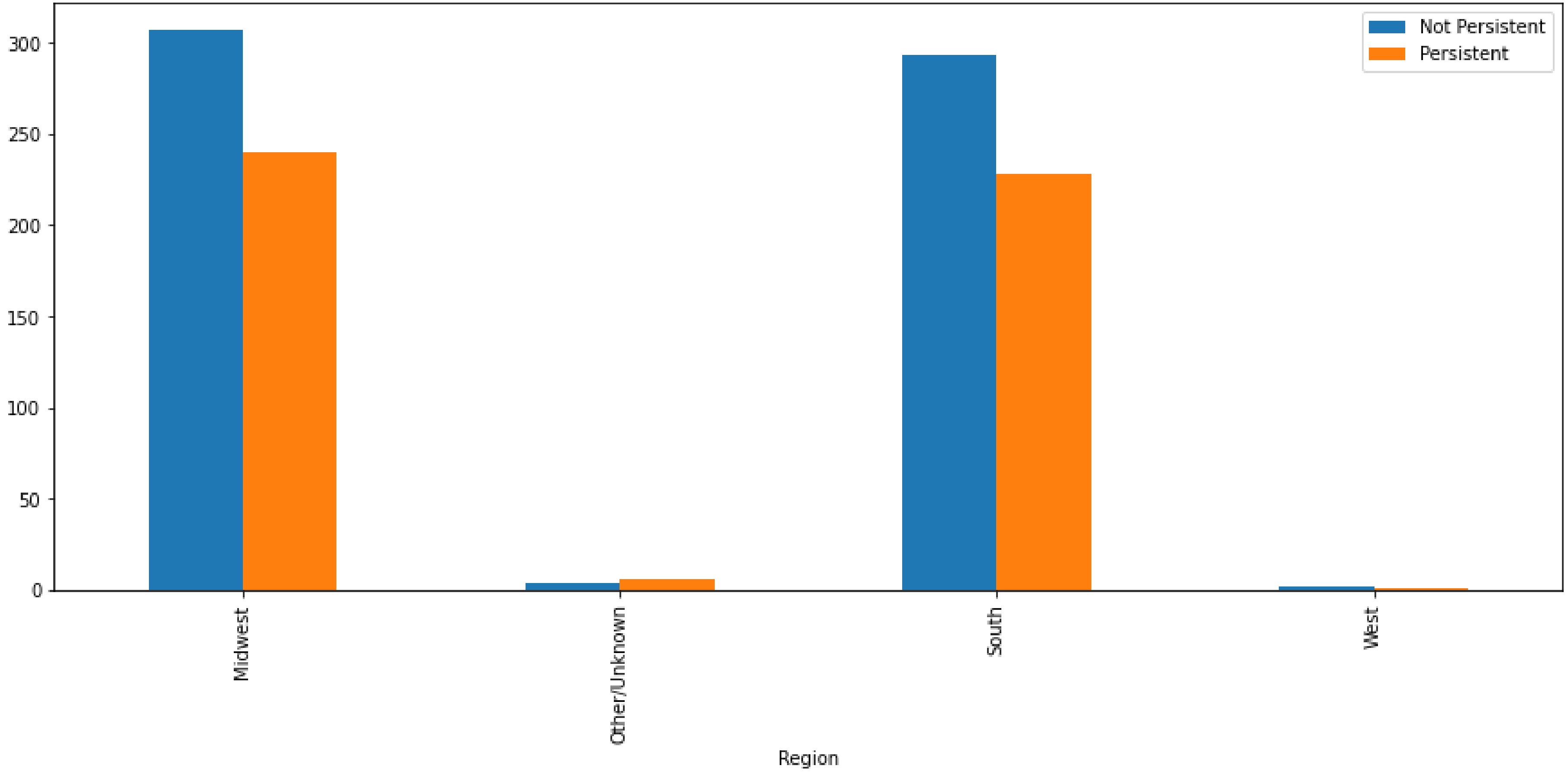

**Group of people under 55 years old tend to have higher persistent compared to other groups**

# EDA (4): Number of Risks and Persistent with drugs




**It shows that the number of risk arises when patients are not persistent with their drugs**

# EDA (5): Regions and Persistent with drugs



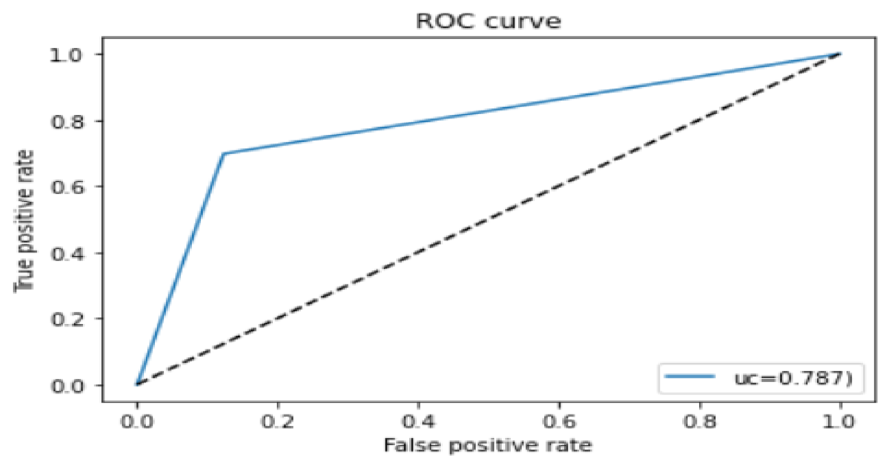

**South and Midwest Regions have both higher Persistent and Non-Persistent Drugs**

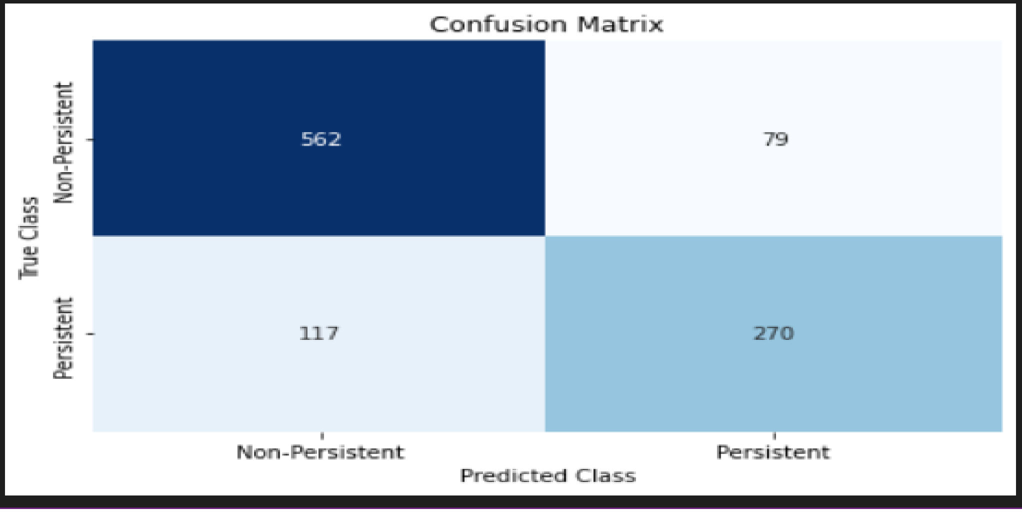
# Model Suggestion

- We will develop four different classification models:
  - Linear Models: Logistic Regression
  - Model for Ensemble: XGBoost Classifier
  - Model for Boosting: AdaBoost Classifier
  - Other models

# Model Creation-Logistic Regression

```
Accuracy : 0.8093385214007782
Precision : 0.7736389684813754
Recall : 0.6976744186046512
F1 Score : 0.733695652173913
                precision    recall  f1-score   support

Non-Persistent       0.83      0.88      0.85       641
    Persistent       0.77      0.70      0.73       387

      accuracy                           0.81      1028
     macro avg       0.80      0.79      0.79      1028
  weighted avg       0.81      0.81      0.81      1028

AUC : 0.7872147444037296
```

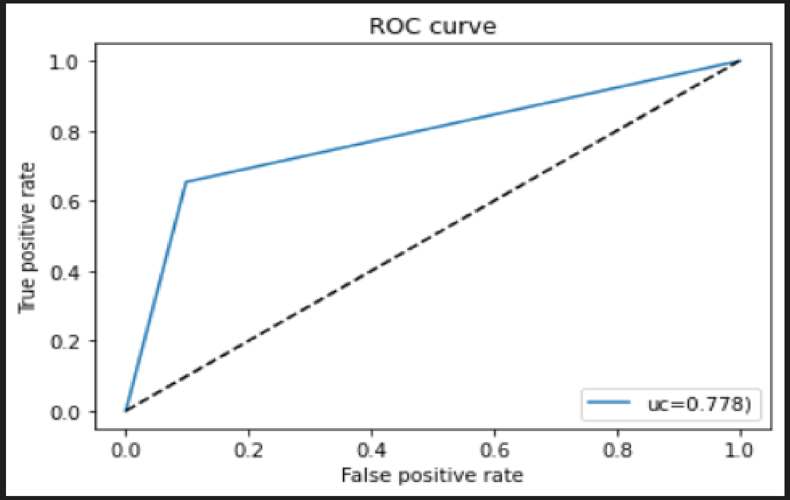


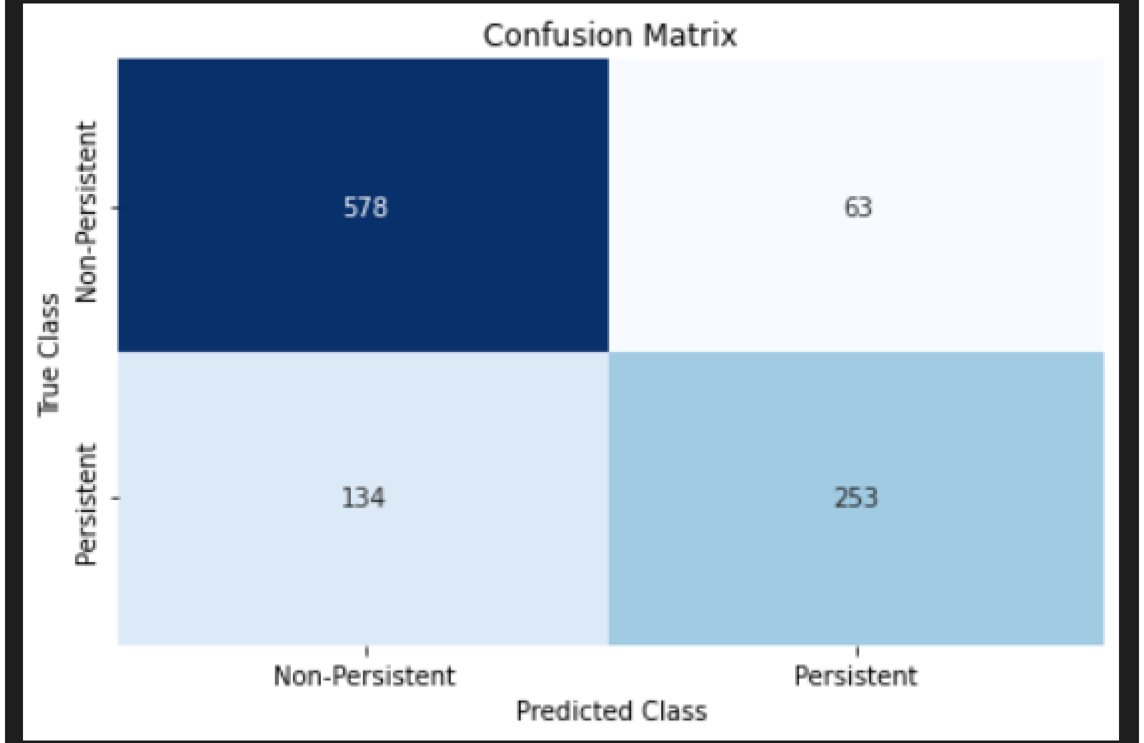

Logistic Regression Model shows the Accuracy, Recall, Precision ,f1 score and Support of Non-Persistent and Persistence of drugs.

# Model Creation- Ridge Classifier

```
Accuracy : 0.8083657587548638
Precision : 0.8006329113924051
Recall : 0.6537467700258398
F1 Score : 0.7197724039829304
               precision    recall  f1-score   support

Non-Persistent       0.81      0.90      0.85       641
    Persistent       0.80      0.65      0.72       387

      accuracy                           0.81      1028
     macro avg       0.81      0.78      0.79      1028
  weighted avg       0.81      0.81      0.80      1028

AUC : 0.7777314193342927
```

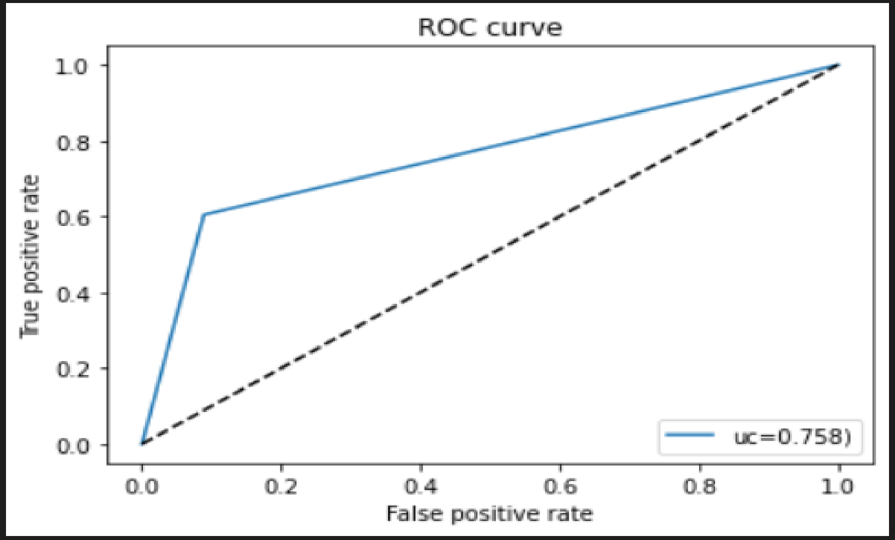



Ridge Classifier Model shows the Accuracy, Recall, Precision ,f1 score and Support of Non-Persistent and Persistence of drugs.

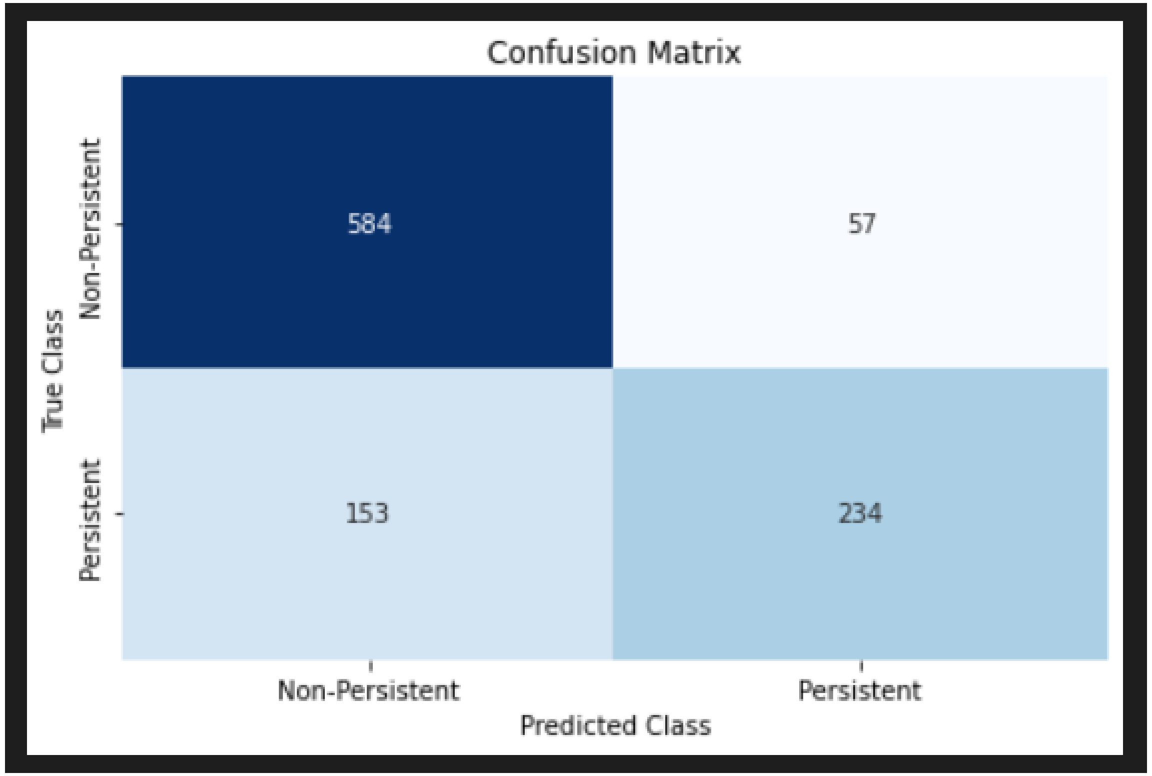


# Model Creation-SDG Classifier

```
Accuracy : 0.7957198443579766
Precision : 0.8041237113402062
Recall : 0.6046511627906976
F1 Score : 0.6902654867256637
               precision    recall  f1-score   support

Non-Persistent       0.79      0.91      0.85       641
    Persistent       0.80      0.60      0.69       387

      accuracy                           0.80      1028
     macro avg       0.80      0.76      0.77      1028
  weighted avg       0.80      0.80      0.79      1028

AUC : 0.75786380292421
```

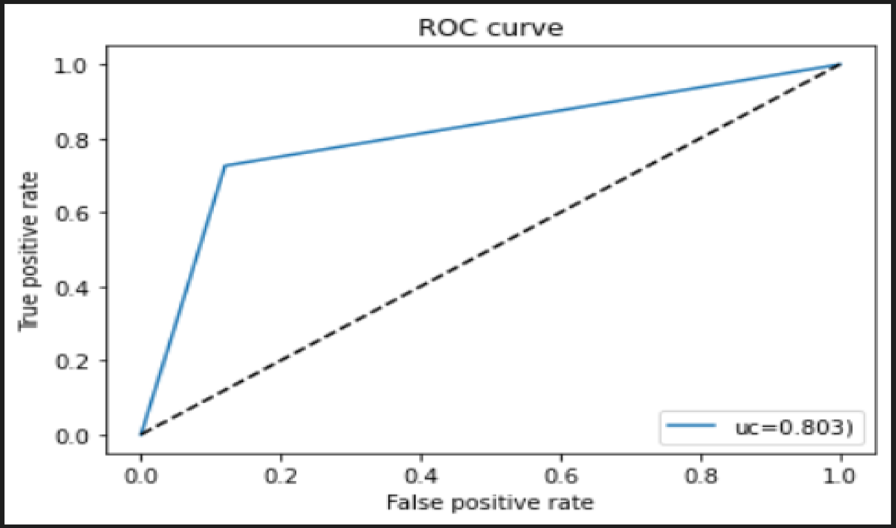



SDG Classifier Model shows the Accuracy, Recall, Precision ,f1 score and Support of Non-Persistent and Persistence of drugs.

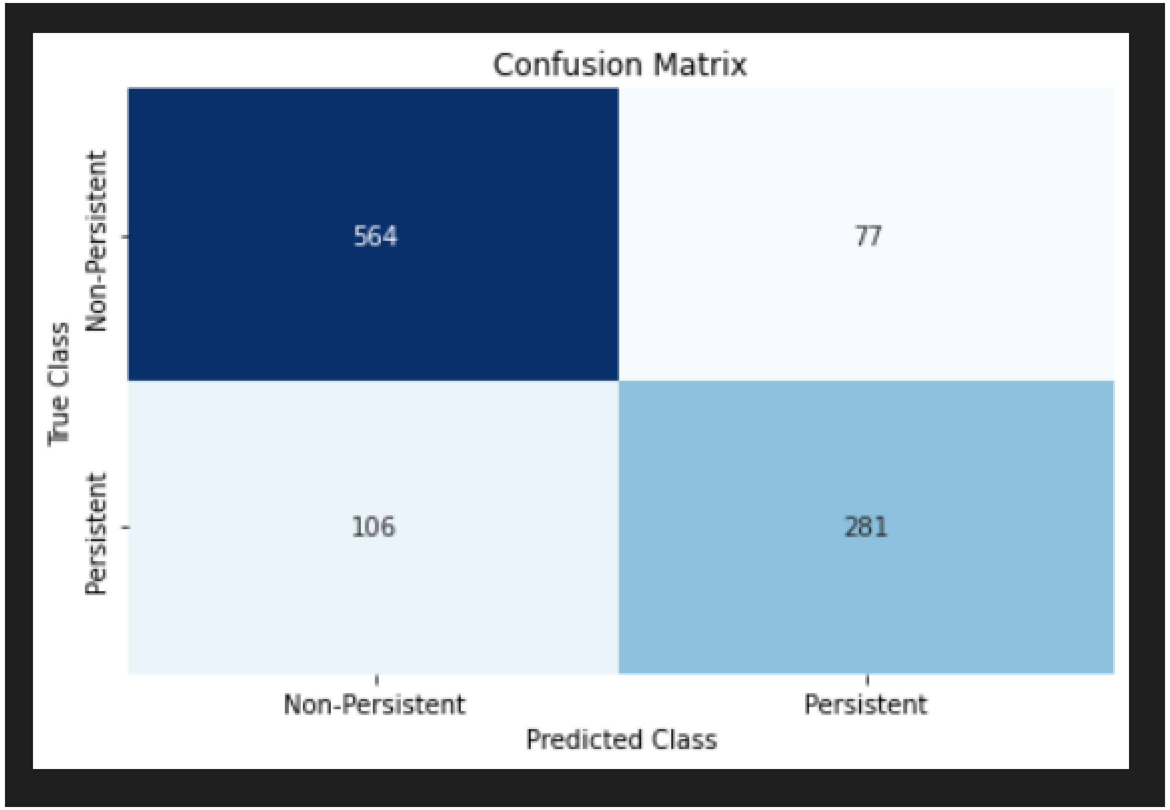


# Random Forest Classifier

```
Accuracy : 0.8219844357976653
Precision : 0.7849162011173184
Recall : 0.7260981912144703
F1 Score : 0.7543624161073826
                precision    recall  f1-score   support

Non-Persistent       0.84      0.88      0.86       641
    Persistent       0.78      0.73      0.75       387

      accuracy                           0.82      1028
     macro avg       0.81      0.80      0.81      1028
  weighted avg       0.82      0.82      0.82      1028

AUC : 0.8029866931111354
```



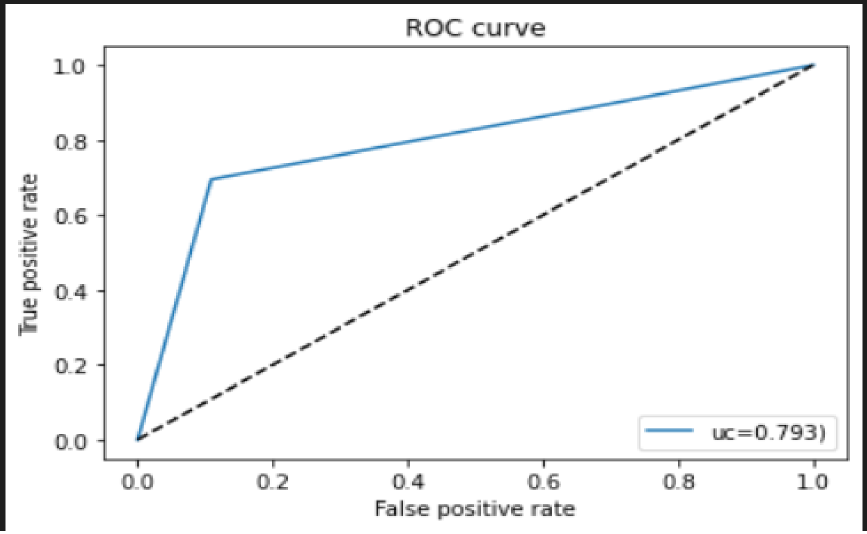

Random Forest Classifier Model shows the Accuracy, Recall, Precision ,f1 score and Support of Non-Persistent and Persistence of drugs.

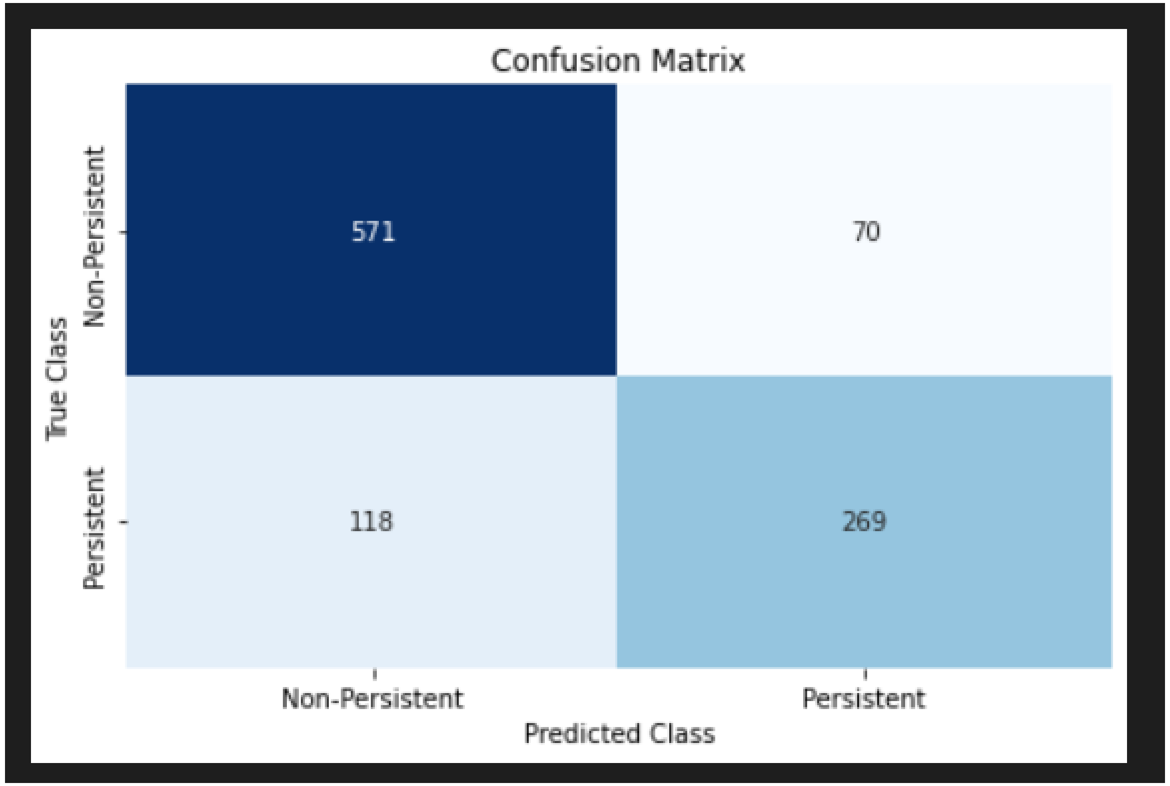


# Ada Boost Classifier

Ada boost classifier shows the Accuracy, Recall, Precision ,f1 score and Support of Non-Persistent and Persistence of drugs.

```
Accuracy : 0.8171206225680934
Precision : 0.7935103244837758
Recall : 0.6950904392764858
F1 Score : 0.7410468319559228
               precision    recall  f1-score   support

Non-Persistent      0.83      0.89      0.86       641
    Persistent      0.79      0.70      0.74       387

      accuracy                          0.82      1028
     macro avg      0.81      0.79      0.80      1028
  weighted avg      0.82      0.82      0.81      1028

AUC : 0.7929430355508794
```

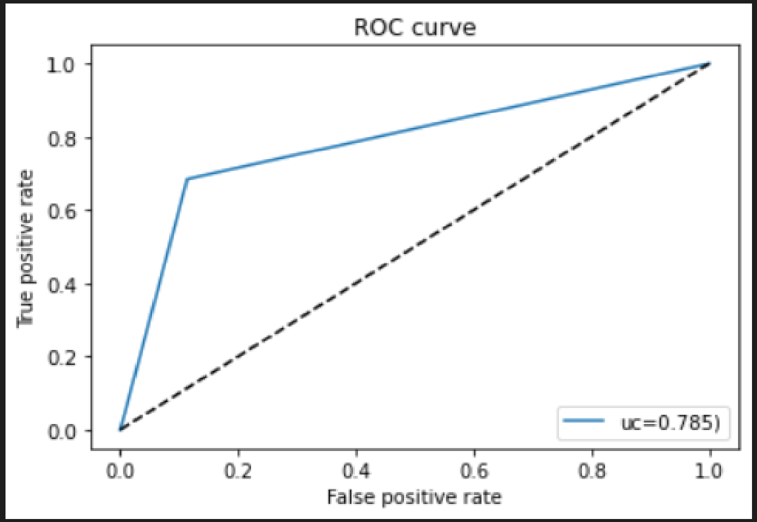


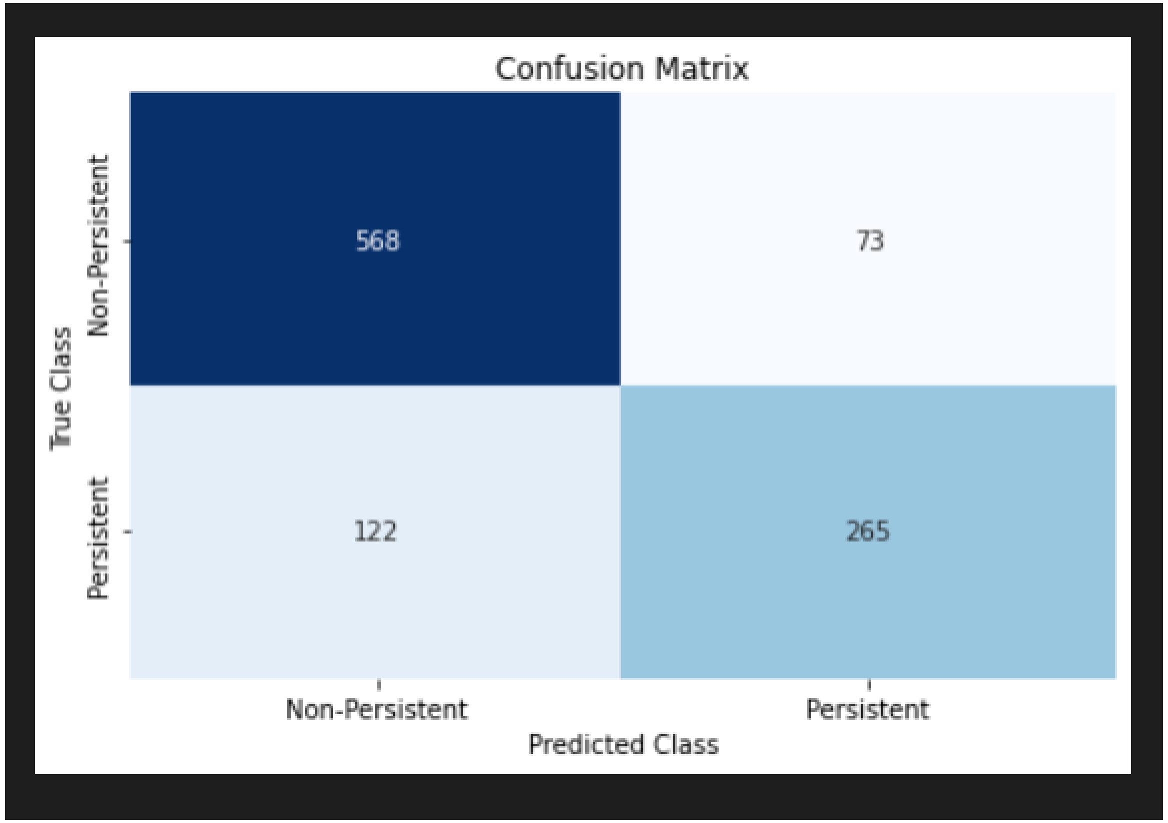



# Stacking Classifier

Stacking Classifier Model shows the Accuracy, Recall, Precision ,f1 score and Support of Non-Persistent and Persistence of drugs.

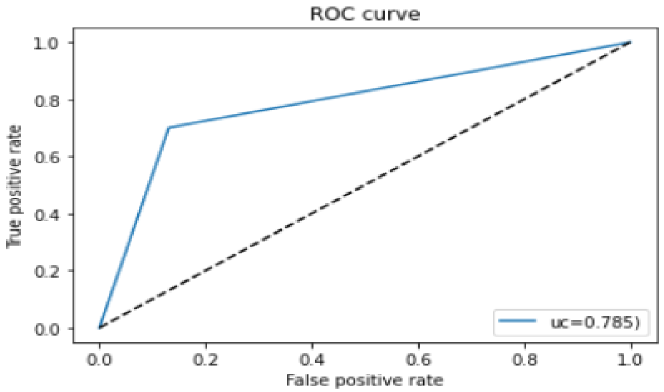
```
Accuracy : 0.8103112840466926
Precision : 0.7840236686390533
Recall : 0.6847545219638242
F1 Score : 0.7310344827586208
               precision    recall  f1-score   support

Non-Persistent       0.82      0.89      0.85       641
    Persistent       0.78      0.68      0.73       387

      accuracy                           0.81      1028
     macro avg       0.80      0.79      0.79      1028
  weighted avg       0.81      0.81      0.81      1028

AUC : 0.7854349832908045
```

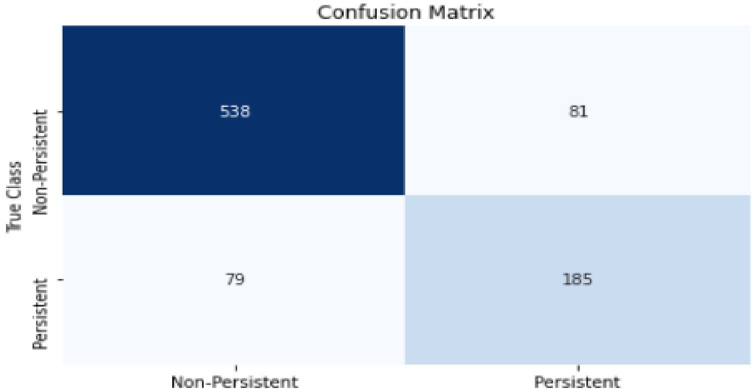


# XG Boost Classifier

```
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
```




XG Boost Classifier Model shows the Accuracy, Recall, Precision ,f1 score and Support of Non-Persistent and Persistence of drugs.

# Conclusion

- Approximately all the classifiers have same result, but three of them are the bests :
- Logistic Classifier (Linear) with Accuracy 81%, Recall 70%, 73% F1-Score, and 78% AUC
- AdaBoost Classifier (Ensemble/Boosting) with Accuracy 81%, Recall 69%, 74% F1-Score, and 79% AUC
- XGBoost Classifier (Ensemble/Boosting) with Accuracy 82%, Recall 73%, 75% F1-Score, and 80% AUC

# Thank You

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