Imports

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from scipy import stats
import collections
from sklearn.preprocessing import StandardScaler, RobustScaler, MinMaxScaler
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score, acc
from sklearn.model_selection import train_test_split
from sklearn.utils import resample
import warnings

#importing packages for modeling
from sklearn.linear_model import LogisticRegression, RidgeClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import make_pipeline


%matplotlib inline
warnings.filterwarnings('ignore')
```

In [2]:
```
target_names=['Non-Persistent', 'Persistent']
```

Dataset

In [3]:
```
xls = pd.ExcelFile('Healthcare_dataset.xlsx')
df = pd.read_excel(xls, 'Dataset')
```

In [4]:
```
df.head()
```

Out[4]:

	Ptid	Persistency_Flag	Gender	Race	Ethnicity	Region	Age_Bucket	Ntm_Speciality	Ntm
0	P1	Persistent	Male	Caucasian	Not Hispanic	West	>75	GENERAL PRACTITIONER	
1	P2	Non-Persistent	Male	Asian	Not Hispanic	West	55-65	GENERAL PRACTITIONER	
2	P3	Non-Persistent	Female	Other/Unknown	Hispanic	Midwest	65-75	GENERAL PRACTITIONER	
3	P4	Non-Persistent	Female	Caucasian	Not Hispanic	Midwest	>75	GENERAL PRACTITIONER	
4	P5	Non-Persistent	Female	Caucasian	Not Hispanic	Midwest	>75	GENERAL PRACTITIONER	

5 rows × 69 columns

Data Understanding

In [5]:
```
df.shape
```

Out[5]:
```
(3424, 69)
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['Ptid', 'Persistency_Flag', 'Gender', 'Race', 'Ethnicity', 'Region',
       'Age_Bucket', 'Ntm_Speciality', 'Ntm_Specialist_Flag',
       'Ntm_Speciality_Bucket', 'Gluco_Record_Prior_Ntm',
       'Gluco_Record_During_Rx', 'Dexa_Freq_During_Rx', 'Dexa_During_Rx',
       'Frag_Frac_Prior_Ntm', 'Frag_Frac_During_Rx', 'Risk_Segment_Prior_Ntm',
       'Tscore_Bucket_Prior_Ntm', 'Risk_Segment_During_Rx',
       'Tscore_Bucket_During_Rx', 'Change_T_Score', 'Change_Risk_Segment',
       'Adherent_Flag', 'Idn_Indicator', 'Injectable_Experience_During_Rx',
       'Comorb_Encounter_For_Screening_For_Malignant_Neoplasms',
       'Comorb_Encounter_For_Immunization',
       'Comorb_Encntr_For_General_Exam_W_O_Complaint,_Susp_Or_Reprtd_Dx',
       'Comorb_Vitamin_D_Deficiency',
       'Comorb_Other_Joint_Disorder_Not_Elsewhere_Classified',
       'Comorb_Encntr_For_Oth_Sp_Exam_W_O_Complaint_Suspected_Or_Reprtd_Dx',
       'Comorb_Long_Term_Current_Drug_Therapy', 'Comorb_Dorsalgia',
       'Comorb_Personal_History_Of_Other_Diseases_And_Conditions',
       'Comorb_Other_Disorders_Of_Bone_Density_And_Structure',
       'Comorb_Disorders_of_lipoprotein_metabolism_and_other_lipidemias',
       'Comorb_Osteoporosis_without_current_pathological_fracture',
       'Comorb_Personal_history_of_malignant_neoplasm',
       'Comorb_Gastro_esophageal_reflux_disease',
       'Concom_Cholesterol_And_Triglyceride_Regulating_Preparations',
       'Concom_Narcotics', 'Concom_Systemic_Corticosteroids_Plain',
       'Concom_Anti_Depressants_And_Mood_Stabilisers',
       'Concom_Fluoroquinolones', 'Concom_Cephalosporins',
       'Concom_Macrolides_And_Similar_Types',
       'Concom_Broad_Spectrum_Penicillins', 'Concom_Anaesthetics_General',
       'Concom_Viral_Vaccines', 'Risk_Type_1_Insulin_Dependent_Diabetes',
       'Risk_Osteogenesis_Imperfecta', 'Risk_Rheumatoid_Arthritis',
       'Risk_Untreated_Chronic_Hyperthyroidism',
       'Risk_Untreated_Chronic_Hypogonadism', 'Risk_Untreated_Early_Menopause',
       'Risk_Patient_Parent_Fractured_Their_Hip', 'Risk_Smoking_Tobacco',
       'Risk_Chronic_Malnutrition_Or_Malabsorption',
       'Risk_Chronic_Liver_Disease', 'Risk_Family_History_Of_Osteoporosis',
       'Risk_Low_Calcium_Intake', 'Risk_Vitamin_D_Insufficiency',
       'Risk_Poor_Health_Frailty', 'Risk_Excessive_Thinness',
       'Risk_Hysterectomy_Oophorectomy', 'Risk_Estrogen_Deficiency',
       'Risk_Immobilization', 'Risk_Recurring_Falls', 'Count_Of_Risks'],
      dtype='object')
```

In [7]:
```
df.values
```

Out[7]:
```
array([['P1', 'Persistent', 'Male', ..., 'N', 'N', 0],
```

```
       ['P2', 'Non-Persistent', 'Male', ..., 'N', 'N', 0],
       ['P3', 'Non-Persistent', 'Female', ..., 'N', 'N', 2],
       ...,
       ['P3422', 'Persistent', 'Female', ..., 'N', 'N', 1],
       ['P3423', 'Non-Persistent', 'Female', ..., 'N', 'N', 0],
       ['P3424', 'Non-Persistent', 'Female', ..., 'N', 'N', 1]],
      dtype=object)
```

In [8]:
```
df.dtypes
```

Out[8]:
```
Ptid                            object
Persistency_Flag                object
Gender                          object
Race                            object
Ethnicity                       object
                                 ...
Risk_Hysterectomy_Oophorectomy  object
Risk_Estrogen_Deficiency        object
Risk_Immobilization             object
Risk_Recurring_Falls            object
Count_Of_Risks                   int64
Length: 69, dtype: object
```

In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3424 entries, 0 to 3423
Data columns (total 69 columns):
 #   Column                                                    Non-Null Count
Dtype
---  ------                                                    --------------
-----
 0   Ptid                                                      3424 non-null
object
 1   Persistency_Flag                                          3424 non-null
object
 2   Gender                                                    3424 non-null
object
 3   Race                                                      3424 non-null
object
 4   Ethnicity                                                 3424 non-null
object
 5   Region                                                    3424 non-null
object
 6   Age_Bucket                                                3424 non-null
object
 7   Ntm_Speciality                                            3424 non-null
object
 8   Ntm_Specialist_Flag                                       3424 non-null
object
 9   Ntm_Speciality_Bucket                                     3424 non-null
object
 10  Gluco_Record_Prior_Ntm                                    3424 non-null
object
 11  Gluco_Record_During_Rx                                    3424 non-null
object
 12  Dexa_Freq_During_Rx                                       3424 non-null
int64
 13  Dexa_During_Rx                                            3424 non-null
```

```
object
 14  Frag_Frac_Prior_Ntm                                          3424 non-null
object
 15  Frag_Frac_During_Rx                                          3424 non-null
object
 16  Risk_Segment_Prior_Ntm                                       3424 non-null
object
 17  Tscore_Bucket_Prior_Ntm                                      3424 non-null
object
 18  Risk_Segment_During_Rx                                       3424 non-null
object
 19  Tscore_Bucket_During_Rx                                      3424 non-null
object
 20  Change_T_Score                                               3424 non-null
object
 21  Change_Risk_Segment                                          3424 non-null
object
 22  Adherent_Flag                                                3424 non-null
object
 23  Idn_Indicator                                                3424 non-null
object
 24  Injectable_Experience_During_Rx                              3424 non-null
object
 25  Comorb_Encounter_For_Screening_For_Malignant_Neoplasms       3424 non-null
object
 26  Comorb_Encounter_For_Immunization                            3424 non-null
object
 27  Comorb_Encntr_For_General_Exam_W_O_Complaint,_Susp_Or_Reprtd_Dx  3424 non-null
object
 28  Comorb_Vitamin_D_Deficiency                                  3424 non-null
object
 29  Comorb_Other_Joint_Disorder_Not_Elsewhere_Classified         3424 non-null
object
 30  Comorb_Encntr_For_Oth_Sp_Exam_W_O_Complaint_Suspected_Or_Reprtd_Dx  3424 non-null
object
 31  Comorb_Long_Term_Current_Drug_Therapy                        3424 non-null
object
 32  Comorb_Dorsalgia                                             3424 non-null
object
 33  Comorb_Personal_History_Of_Other_Diseases_And_Conditions     3424 non-null
object
 34  Comorb_Other_Disorders_Of_Bone_Density_And_Structure         3424 non-null
object
 35  Comorb_Disorders_of_lipoprotein_metabolism_and_other_lipidemias  3424 non-null
object
 36  Comorb_Osteoporosis_without_current_pathological_fracture    3424 non-null
object
 37  Comorb_Personal_history_of_malignant_neoplasm                3424 non-null
object
 38  Comorb_Gastro_esophageal_reflux_disease                      3424 non-null
object
 39  Concom_Cholesterol_And_Triglyceride_Regulating_Preparations  3424 non-null
object
 40  Concom_Narcotics                                             3424 non-null
object
 41  Concom_Systemic_Corticosteroids_Plain                        3424 non-null
object
 42  Concom_Anti_Depressants_And_Mood_Stabilisers                 3424 non-null
object
 43  Concom_Fluoroquinolones                                      3424 non-null
```

```
object
 44  Concom_Cephalosporins                                  3424 non-null
object
 45  Concom_Macrolides_And_Similar_Types                    3424 non-null
object
 46  Concom_Broad_Spectrum_Penicillins                      3424 non-null
object
 47  Concom_Anaesthetics_General                            3424 non-null
object
 48  Concom_Viral_Vaccines                                  3424 non-null
object
 49  Risk_Type_1_Insulin_Dependent_Diabetes                 3424 non-null
object
 50  Risk_Osteogenesis_Imperfecta                           3424 non-null
object
 51  Risk_Rheumatoid_Arthritis                              3424 non-null
object
 52  Risk_Untreated_Chronic_Hyperthyroidism                 3424 non-null
object
 53  Risk_Untreated_Chronic_Hypogonadism                    3424 non-null
object
 54  Risk_Untreated_Early_Menopause                         3424 non-null
object
 55  Risk_Patient_Parent_Fractured_Their_Hip                3424 non-null
object
 56  Risk_Smoking_Tobacco                                   3424 non-null
object
 57  Risk_Chronic_Malnutrition_Or_Malabsorption             3424 non-null
object
 58  Risk_Chronic_Liver_Disease                             3424 non-null
object
 59  Risk_Family_History_Of_Osteoporosis                    3424 non-null
object
 60  Risk_Low_Calcium_Intake                                3424 non-null
object
 61  Risk_Vitamin_D_Insufficiency                           3424 non-null
object
 62  Risk_Poor_Health_Frailty                               3424 non-null
object
 63  Risk_Excessive_Thinness                                3424 non-null
object
 64  Risk_Hysterectomy_Oophorectomy                         3424 non-null
object
 65  Risk_Estrogen_Deficiency                               3424 non-null
object
 66  Risk_Immobilization                                    3424 non-null
object
 67  Risk_Recurring_Falls                                   3424 non-null
object
 68  Count_Of_Risks                                         3424 non-null
int64
dtypes: int64(2), object(67)
memory usage: 1.8+ MB
```

Data Exploratory

In [10]:

```
df.columns=[x.lower() for x in df.columns]
```

In [11]:
```
cat_corr = df.apply(lambda x : pd.factorize(x)[0]).corr(method='pearson', min_periods=1
np.abs(cat_corr).sort_values(by=['persistency_flag'], ascending=False)
```

Out[11]:

	persistency_flag
persistency_flag	1.000000
dexa_during_rx	0.491823
dexa_freq_during_rx	0.395247
comorb_long_term_current_drug_therapy	0.352760
comorb_encounter_for_screening_for_malignant_neoplasms	0.322320
...	...
risk_untreated_early_menopause	0.005279
risk_family_history_of_osteoporosis	0.003492
risk_osteogenesis_imperfecta	0.002636
risk_segment_during_rx	0.000700
frag_frac_prior_ntm	0.000318

69 rows × 1 columns

In [12]:
```
df.isnull().sum()
```

Out[12]:
```
ptid                              0
persistency_flag                  0
gender                            0
race                              0
ethnicity                         0
                                 ..
risk_hysterectomy_oophorectomy    0
risk_estrogen_deficiency          0
risk_immobilization               0
risk_recurring_falls              0
count_of_risks                    0
Length: 69, dtype: int64
```

In [13]:
```
def uniquevals(col):
    print(f'Details of the particular col {col} is : {df[col].unique()}')

def valuecounts(col):
    print(f'Valuecounts of the particular col {col} is : {df[col].value_counts()}')



for col in df.columns:
    uniquevals(col)
    print("-"*75)
```

```
Details of the particular col ptid is : ['P1' 'P2' 'P3' ... 'P3422' 'P3423' 'P3424']
---------------------------------------------------------------------------
```

```
Details of the particular col persistency_flag is : ['Persistent' 'Non-Persistent']
----------------------------------------------------------------------------
Details of the particular col gender is : ['Male' 'Female']
----------------------------------------------------------------------------
Details of the particular col race is : ['Caucasian' 'Asian' 'Other/Unknown' 'African Am
erican']
----------------------------------------------------------------------------
Details of the particular col ethnicity is : ['Not Hispanic' 'Hispanic' 'Unknown']
----------------------------------------------------------------------------
Details of the particular col region is : ['West' 'Midwest' 'South' 'Other/Unknown' 'Nor
theast']
----------------------------------------------------------------------------
Details of the particular col age_bucket is : ['>75' '55-65' '65-75' '<55']
----------------------------------------------------------------------------
Details of the particular col ntm_speciality is : ['GENERAL PRACTITIONER' 'Unknown' 'END
OCRINOLOGY' 'RHEUMATOLOGY'
 'ONCOLOGY' 'PATHOLOGY' 'OBSTETRICS AND GYNECOLOGY'
 'PSYCHIATRY AND NEUROLOGY' 'ORTHOPEDIC SURGERY'
 'PHYSICAL MEDICINE AND REHABILITATION' 'SURGERY AND SURGICAL SPECIALTIES'
 'PEDIATRICS' 'PULMONARY MEDICINE' 'HEMATOLOGY & ONCOLOGY' 'UROLOGY'
 'PAIN MEDICINE' 'NEUROLOGY' 'RADIOLOGY' 'GASTROENTEROLOGY'
 'EMERGENCY MEDICINE' 'PODIATRY' 'OPHTHALMOLOGY' 'OCCUPATIONAL MEDICINE'
 'TRANSPLANT SURGERY' 'PLASTIC SURGERY' 'CLINICAL NURSE SPECIALIST'
 'OTOLARYNGOLOGY' 'HOSPITAL MEDICINE' 'ORTHOPEDICS' 'NEPHROLOGY'
 'GERIATRIC MEDICINE' 'HOSPICE AND PALLIATIVE MEDICINE'
 'OBSTETRICS & OBSTETRICS & GYNECOLOGY & OBSTETRICS & GYNECOLOGY'
 'VASCULAR SURGERY' 'CARDIOLOGY' 'NUCLEAR MEDICINE']
----------------------------------------------------------------------------
Details of the particular col ntm_specialist_flag is : ['Others' 'Specialist']
----------------------------------------------------------------------------
Details of the particular col ntm_speciality_bucket is : ['OB/GYN/Others/PCP/Unknown' 'E
ndo/Onc/Uro' 'Rheum']
----------------------------------------------------------------------------
Details of the particular col gluco_record_prior_ntm is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col gluco_record_during_rx is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col dexa_freq_during_rx is : [  0   2   7   3   5  20  13   1
6  12   4  10  25  11  18  21  15  28
  22  37  14   8   9  17  81  42  16  30  19  45  27  24  58  26  23  33
 110  36  34  88  66  32 118  48  69  38  40  68  52  50 146  44  35  39
 108  54  72  29]
----------------------------------------------------------------------------
Details of the particular col dexa_during_rx is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col frag_frac_prior_ntm is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col frag_frac_during_rx is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_segment_prior_ntm is : ['VLR_LR' 'HR_VHR']
----------------------------------------------------------------------------
Details of the particular col tscore_bucket_prior_ntm is : ['>-2.5' '<=-2.5']
----------------------------------------------------------------------------
Details of the particular col risk_segment_during_rx is : ['VLR_LR' 'Unknown' 'HR_VHR']
----------------------------------------------------------------------------
Details of the particular col tscore_bucket_during_rx is : ['<=-2.5' 'Unknown' '>-2.5']
----------------------------------------------------------------------------
Details of the particular col change_t_score is : ['No change' 'Unknown' 'Worsened' 'Imp
roved']
----------------------------------------------------------------------------
```

```
Details of the particular col change_risk_segment is : ['Unknown' 'No change' 'Worsened'
'Improved']
----------------------------------------------------------------------------
Details of the particular col adherent_flag is : ['Adherent' 'Non-Adherent']
----------------------------------------------------------------------------
Details of the particular col idn_indicator is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col injectable_experience_during_rx is : ['Y' 'N']
----------------------------------------------------------------------------
Details of the particular col comorb_encounter_for_screening_for_malignant_neoplasms is
: ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col comorb_encounter_for_immunization is : ['Y' 'N']
----------------------------------------------------------------------------
Details of the particular col comorb_encntr_for_general_exam_w_o_complaint,_susp_or_repr
td_dx is : ['Y' 'N']
----------------------------------------------------------------------------
Details of the particular col comorb_vitamin_d_deficiency is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col comorb_other_joint_disorder_not_elsewhere_classified is :
['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col comorb_encntr_for_oth_sp_exam_w_o_complaint_suspected_or_r
eprtd_dx is : ['Y' 'N']
----------------------------------------------------------------------------
Details of the particular col comorb_long_term_current_drug_therapy is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col comorb_dorsalgia is : ['Y' 'N']
----------------------------------------------------------------------------
Details of the particular col comorb_personal_history_of_other_diseases_and_conditions i
s : ['Y' 'N']
----------------------------------------------------------------------------
Details of the particular col comorb_other_disorders_of_bone_density_and_structure is :
['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col comorb_disorders_of_lipoprotein_metabolism_and_other_lipid
emias is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col comorb_osteoporosis_without_current_pathological_fracture
is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col comorb_personal_history_of_malignant_neoplasm is : ['N'
'Y']
----------------------------------------------------------------------------
Details of the particular col comorb_gastro_esophageal_reflux_disease is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col concom_cholesterol_and_triglyceride_regulating_preparation
s is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col concom_narcotics is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col concom_systemic_corticosteroids_plain is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col concom_anti_depressants_and_mood_stabilisers is : ['N'
'Y']
----------------------------------------------------------------------------
Details of the particular col concom_fluoroquinolones is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col concom_cephalosporins is : ['N' 'Y']
----------------------------------------------------------------------------
```

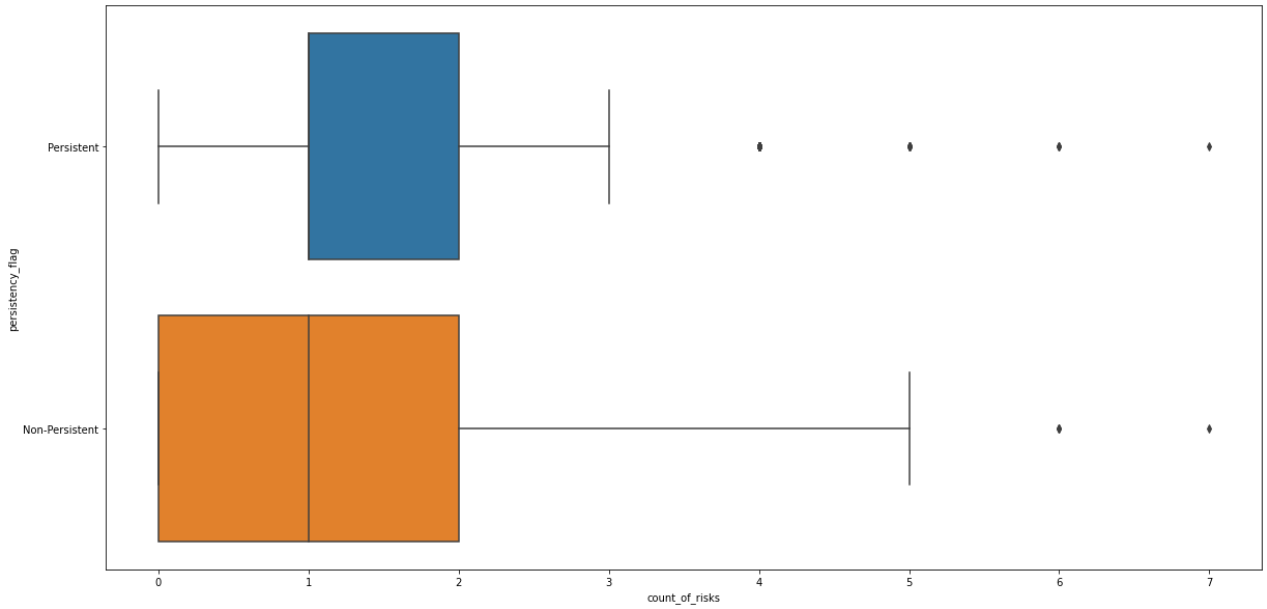
```
Details of the particular col concom_macrolides_and_similar_types is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col concom_broad_spectrum_penicillins is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col concom_anaesthetics_general is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col concom_viral_vaccines is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_type_1_insulin_dependent_diabetes is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_osteogenesis_imperfecta is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_rheumatoid_arthritis is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_untreated_chronic_hyperthyroidism is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_untreated_chronic_hypogonadism is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_untreated_early_menopause is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_patient_parent_fractured_their_hip is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_smoking_tobacco is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_chronic_malnutrition_or_malabsorption is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_chronic_liver_disease is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_family_history_of_osteoporosis is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_low_calcium_intake is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_vitamin_d_insufficiency is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_poor_health_frailty is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_excessive_thinness is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_hysterectomy_oophorectomy is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_estrogen_deficiency is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_immobilization is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col risk_recurring_falls is : ['N' 'Y']
----------------------------------------------------------------------------
Details of the particular col count_of_risks is : [0 2 1 3 4 5 6 7]
----------------------------------------------------------------------------
```

In [14]:

```
plt.figure(figsize=(20,10))
var ="count_of_risks"
sns.boxplot(x=var,y ="persistency_flag",data=df)
```

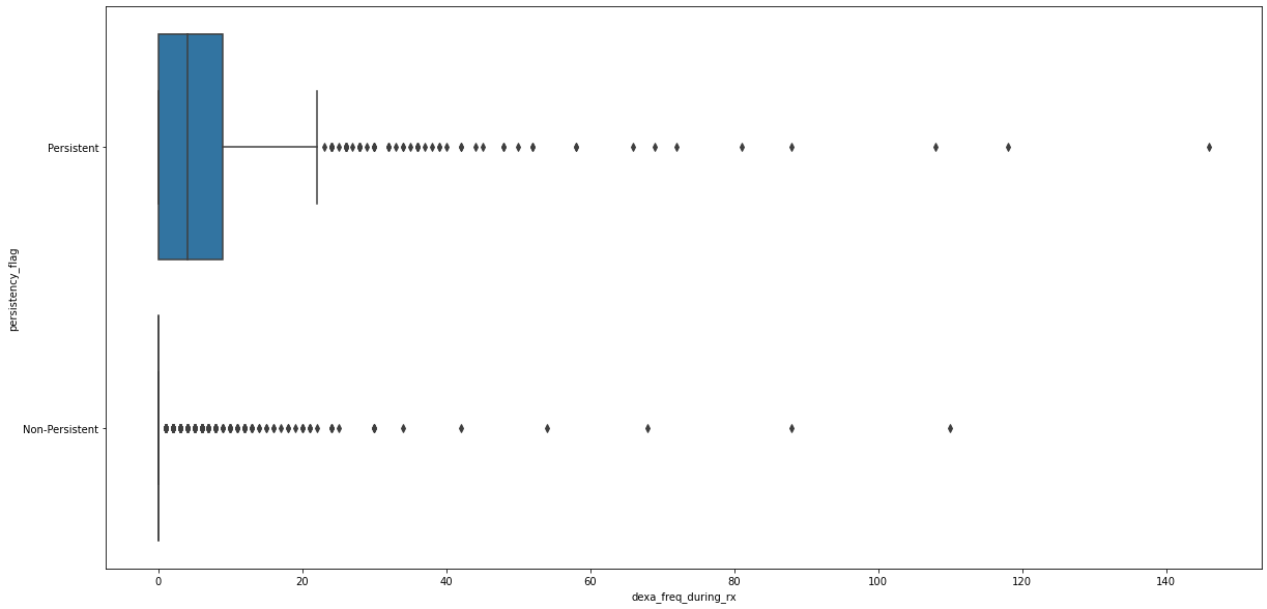
Out[14]:

```
<AxesSubplot:xlabel='count_of_risks', ylabel='persistency_flag'>
```



In [15]:
```
plt.figure(figsize=(20,10))
var ="dexa_freq_during_rx"
sns.boxplot(x=var,y ="persistency_flag",data=df)
```

Out[15]:
```
<AxesSubplot:xlabel='dexa_freq_during_rx', ylabel='persistency_flag'>
```



In [16]:
```
print("Count of risks skweness: ",df["count_of_risks"].skew())
```

```
Count of risks skweness:  0.8797905232898707
```

In [17]:
```
print("dexa_freq_during_rx skweness: ",df["dexa_freq_during_rx"].skew())
```

```
dexa_freq_during_rx skweness:  6.8087302112992285
```

In [18]:
```
#standardizing dexa_freq_during_rx df
dexa_scaled = StandardScaler().fit_transform(df['dexa_freq_during_rx'][:,np.newaxis]);
low_range = dexa_scaled[dexa_scaled[:,0].argsort()][:10]
high_range= dexa_scaled[dexa_scaled[:,0].argsort()][-10:]
```

```
print('outer range (low) of the distribution:')
print(low_range)
print('\nouter range (high) of the distribution:')
print(high_range)
```

```
outer range (low) of the distribution:
[[-0.3707352]
 [-0.3707352]
 [-0.3707352]
 [-0.3707352]
 [-0.3707352]
 [-0.3707352]
 [-0.3707352]
 [-0.3707352]
 [-0.3707352]
 [-0.3707352]]

outer range (high) of the distribution:
[[ 7.98784109]
 [ 8.11076133]
 [ 8.47952205]
 [ 9.58580421]
 [10.44624589]
 [10.44624589]
 [12.90465068]
 [13.15049116]
 [14.13385307]
 [17.57561978]]
```

In [19]:

```
scaler = RobustScaler()
df['dexa_freq_during_rx'] = scaler.fit_transform(df['dexa_freq_during_rx'].values.resha
```

In [20]:

```
scaler = RobustScaler()
df['count_of_risks'] = scaler.fit_transform(df['count_of_risks'].values.reshape(-1,1))
```

In [21]:

```
''' Detection '''
# IQR
Q1 = np.percentile(df['dexa_freq_during_rx'], 25,
                   interpolation = 'midpoint')

Q3 = np.percentile(df['dexa_freq_during_rx'], 75,
                   interpolation = 'midpoint')
IQR = Q3 - Q1

print("Old Shape: ", df.shape)

# Upper bound
upper = np.where(df['dexa_freq_during_rx'] >= (Q3+1.5*IQR))
# Lower bound
lower = np.where(df['dexa_freq_during_rx'] <= (Q1-1.5*IQR))

print("lower",lower[0])
print("Upper",upper[0])

''' Removing the Outliers '''
df.drop(upper[0], inplace = True)
```

```
df.drop(lower[0], inplace = True)

print("New Shape: ", df.shape)

df = df.reset_index(drop=True)
```

```
Old Shape:  (3424, 69)
lower []
Upper [  32   33   62   65   89  101  110  116  164  180  186  194  198  201
  217  241  246  256  264  282  292  303  327  340  349  358  368  369
  373  378  382  390  415  417  426  433  448  457  462  464  480  495
  496  497  505  514  517  541  545  549  563  575  588  589  592  599
  603  605  613  640  646  651  653  656  657  678  684  688  700  705
  710  711  726  728  729  730  759  760  764  765  785  786  804  814
  823  834  847  849  864  870  873  885  909  915  925  926  930  937
  946  978  982  991  994 1006 1008 1016 1042 1061 1073 1074 1076 1113
 1118 1119 1128 1134 1141 1148 1151 1196 1240 1265 1267 1270 1272 1273
 1280 1283 1286 1291 1315 1359 1360 1363 1365 1370 1372 1396 1398 1404
 1448 1474 1513 1524 1533 1539 1546 1550 1554 1555 1564 1566 1570 1576
 1599 1628 1641 1642 1647 1654 1662 1671 1691 1703 1724 1732 1734 1746
 1752 1773 1782 1783 1788 1793 1803 1815 1826 1833 1834 1836 1838 1848
 1852 1854 1870 1876 1895 1901 1904 1909 1910 1914 1915 1919 1920 1928
 1936 1943 1948 1949 1952 1956 1959 1963 1964 1965 1968 1970 1971 1975
 1982 1983 1988 1993 1996 1997 2000 2002 2005 2006 2009 2010 2011 2013
 2015 2016 2020 2024 2028 2029 2030 2031 2033 2034 2038 2041 2042 2043
 2044 2046 2049 2054 2057 2058 2059 2060 2062 2065 2066 2069 2075 2081
 2083 2086 2087 2132 2134 2139 2142 2151 2161 2163 2168 2169 2170 2171
 2172 2175 2176 2178 2181 2186 2187 2189 2192 2196 2197 2205 2207 2213
 2214 2215 2217 2220 2227 2231 2233 2235 2236 2237 2238 2239 2240 2247
 2255 2262 2263 2264 2271 2272 2275 2278 2279 2280 2285 2289 2294 2298
 2307 2308 2310 2314 2320 2321 2323 2324 2325 2327 2329 2330 2331 2332
 2333 2335 2336 2337 2338 2350 2356 2359 2364 2376 2379 2381 2390 2393
 2413 2416 2422 2425 2428 2429 2430 2432 2447 2459 2469 2478 2503 2528
 2529 2537 2556 2557 2558 2560 2562 2567 2569 2570 2575 2578 2580 2582
 2591 2595 2598 2603 2606 2608 2609 2611 2612 2617 2625 2631 2635 2640
 2644 2654 2660 2675 2676 2681 2686 2696 2698 2710 2713 2715 2727 2733
 2751 2753 2757 2789 2790 2791 2794 2799 2802 2804 2806 2809 2814 2819
 2821 2822 2828 2833 2880 2882 2894 2895 2906 2910 2920 2927 2940 2944
 2945 2952 2957 2959 2960 2984 2996 2998 3013 3021 3022 3023 3042 3044
 3046 3048 3052 3058 3066 3068 3080 3100 3131 3138 3159 3172 3177 3236
 3281 3309 3311 3325 3363 3378 3382 3384 3396 3400 3411 3414]
New Shape:  (2964, 69)
```

In [22]:

```
''' Detection '''
# IQR
Q1 = np.percentile(df['count_of_risks'], 25,
                   interpolation = 'midpoint')

Q3 = np.percentile(df['count_of_risks'], 75,
                   interpolation = 'midpoint')
IQR = Q3 - Q1

print("Old Shape: ", df.shape)

# Upper bound
upper = np.where(df['count_of_risks'] >= (Q3+1.5*IQR))
# Lower bound
lower = np.where(df['count_of_risks'] <= (Q1-1.5*IQR))
```

```
print("lower",lower[0])
print("Upper",upper[0])

''' Removing the Outliers '''
df.drop(upper[0], inplace = True)
df.drop(lower[0], inplace = True)

print("New Shape: ", df.shape)

df = df.reset_index(drop=True)
```

```
Old Shape:  (2964, 69)
lower []
Upper [ 281  318  327  507  655  665  678  705  733  952 1001 1126 1590 1624
 1836 2227 2234 2450 2611 2702 2755 2888]
New Shape:  (2942, 69)
```

In [23]:

```
df.describe
```

Out[23]:

```
<bound method NDFrame.describe of        ptid persistency_flag  gender           race
ethnicity   region  \
0        P1       Persistent    Male      Caucasian  Not Hispanic     West
1        P2   Non-Persistent    Male          Asian  Not Hispanic     West
2        P3   Non-Persistent  Female  Other/Unknown      Hispanic  Midwest
3        P4   Non-Persistent  Female      Caucasian  Not Hispanic  Midwest
4        P5   Non-Persistent  Female      Caucasian  Not Hispanic  Midwest
...     ...              ...     ...            ...           ...      ...
2937  P3420       Persistent  Female      Caucasian  Not Hispanic    South
2938  P3421       Persistent  Female      Caucasian  Not Hispanic    South
2939  P3422       Persistent  Female      Caucasian  Not Hispanic    South
2940  P3423   Non-Persistent  Female      Caucasian  Not Hispanic    South
2941  P3424   Non-Persistent  Female      Caucasian  Not Hispanic    South

     age_bucket        ntm_speciality ntm_specialist_flag  \
0           >75  GENERAL PRACTITIONER              Others
1         55-65  GENERAL PRACTITIONER              Others
2         65-75  GENERAL PRACTITIONER              Others
3           >75  GENERAL PRACTITIONER              Others
4           >75  GENERAL PRACTITIONER              Others
...         ...                   ...                 ...
2937        >75  GENERAL PRACTITIONER              Others
2938        >75               Unknown              Others
2939        >75         ENDOCRINOLOGY          Specialist
2940      55-65               Unknown              Others
2941      65-75               Unknown              Others

          ntm_speciality_bucket  ... risk_family_history_of_osteoporosis  \
0     OB/GYN/Others/PCP/Unknown  ...                                   N
1     OB/GYN/Others/PCP/Unknown  ...                                   N
2     OB/GYN/Others/PCP/Unknown  ...                                   N
3     OB/GYN/Others/PCP/Unknown  ...                                   N
4     OB/GYN/Others/PCP/Unknown  ...                                   N
...                         ...  ...                                 ...
2937  OB/GYN/Others/PCP/Unknown  ...                                   N
2938  OB/GYN/Others/PCP/Unknown  ...                                   N
2939               Endo/Onc/Uro  ...                                   N
2940  OB/GYN/Others/PCP/Unknown  ...                                   N
2941  OB/GYN/Others/PCP/Unknown  ...                                   N
```

```
     risk_low_calcium_intake  risk_vitamin_d_insufficiency  \
0                          N                            N
1                          N                            N
2                          Y                            N
3                          N                            N
4                          N                            N
...                      ...                          ...
2937                       N                            Y
2938                       N                            N
2939                       N                            Y
2940                       N                            N
2941                       N                            Y

     risk_poor_health_frailty risk_excessive_thinness  \
0                           N                       N
1                           N                       N
2                           N                       N
3                           N                       N
4                           N                       N
...                       ...                     ...
2937                        N                       N
2938                        N                       N
2939                        N                       N
2940                        N                       N
2941                        N                       N

     risk_hysterectomy_oophorectomy risk_estrogen_deficiency  \
0                                 N                        N
1                                 N                        N
2                                 N                        N
3                                 N                        N
4                                 N                        N
...                             ...                      ...
2937                              N                        N
2938                              N                        N
2939                              N                        N
2940                              N                        N
2941                              N                        N

     risk_immobilization risk_recurring_falls count_of_risks
0                      N                    N          -0.5
1                      N                    N          -0.5
2                      N                    N           0.5
3                      N                    N           0.0
4                      N                    N           0.0
...                  ...                  ...           ...
2937                   N                    N           0.0
2938                   N                    N          -0.5
2939                   N                    N           0.0
2940                   N                    N          -0.5
2941                   N                    N           0.0

[2942 rows x 69 columns]>
```

In [24]:

```
df.groupby(['persistency_flag']).mean().T
```

Out[24]:

persistency_flag	Non-Persistent	Persistent
dexa_freq_during_rx	0.085491	0.662570

persistency_flag	Non-Persistent	Persistent
count_of_risks	0.074744	0.155866

In [25]:
```
df.groupby(['gender']).mean().T
```

Out[25]:

gender	Female	Male
dexa_freq_during_rx	0.263874	0.215800
count_of_risks	0.099494	0.098266

In [26]:
```
df.groupby(['race']).mean()
```

Out[26]:

race	dexa_freq_during_rx	count_of_risks
African American	0.246377	0.168478
Asian	0.135266	0.021739
Caucasian	0.266445	0.098297
Other/Unknown	0.204167	0.125000

In [27]:
```
df.groupby(['ethnicity']).mean().T
```

Out[27]:

ethnicity	Hispanic	Not Hispanic	Unknown
dexa_freq_during_rx	0.279835	0.260417	0.264069
count_of_risks	0.265432	0.097342	0.000000

In [28]:
```
df.groupby(['age_bucket']).mean().T
```

Out[28]:

age_bucket	55-65	65-75	<55	>75
dexa_freq_during_rx	0.242229	0.297880	0.273973	0.242208
count_of_risks	0.118167	0.097039	0.089041	0.093106

In [29]:
```
df.groupby(['ntm_speciality']).mean().T
```

Out[29]:

ntm_speciality	CARDIOLOGY	CLINICAL NURSE SPECIALIST	EMERGENCY MEDICINE	ENDOCRINOLOGY	GASTROENTEROLOGY
dexa_freq_during_rx	0.285714	0.0	0.0	0.392265	0.0
count_of_risks	0.380952	-0.5	0.0	0.279006	0.0

2 rows × 35 columns

In [30]:
```
df.groupby(['ntm_specialist_flag']).mean().T
```

Out[30]:

ntm_specialist_flag	Others	Specialist
dexa_freq_during_rx	0.215145	0.330765
count_of_risks	0.056370	0.164812

In [31]:
```
df.groupby(['ntm_speciality_bucket']).mean().T
```

Out[31]:

ntm_speciality_bucket	Endo/Onc/Uro	OB/GYN/Others/PCP/Unknown	Rheum
dexa_freq_during_rx	0.442907	0.215274	0.221349
count_of_risks	0.170415	0.053639	0.185658

In [32]:
```
df.groupby(['risk_chronic_liver_disease']).mean().T
```

Out[32]:

risk_chronic_liver_disease	N	Y
dexa_freq_during_rx	0.260132	0.452381
count_of_risks	0.096482	0.714286

In [33]:
```
df.groupby(['risk_family_history_of_osteoporosis']).mean().T
```

Out[33]:

risk_family_history_of_osteoporosis	N	Y
dexa_freq_during_rx	0.258113	0.287671
count_of_risks	0.045283	0.590753

In [34]:
```
df.groupby(['risk_low_calcium_intake']).mean().T
```

Out[34]:

risk_low_calcium_intake	N	Y
dexa_freq_during_rx	0.261069	0.259259
count_of_risks	0.090502	0.819444

In [35]:
```
df.groupby(['risk_vitamin_d_insufficiency']).mean().T
```

Out[35]:

risk_vitamin_d_insufficiency	N	Y
dexa_freq_during_rx	0.223363	0.303468
count_of_risks	-0.175866	0.409321

In [36]:
```
df.groupby(['risk_excessive_thinness']).mean().T
```

Out[36]:

risk_excessive_thinness	N	Y
dexa_freq_during_rx	0.261946	0.218579
count_of_risks	0.085908	0.737705

In [37]:
```
df.groupby(['risk_hysterectomy_oophorectomy']).mean().T
```

Out[37]:

risk_hysterectomy_oophorectomy	N	Y
dexa_freq_during_rx	0.261650	0.222222
count_of_risks	0.089748	0.722222

In [38]:
```
df.groupby(['risk_estrogen_deficiency']).mean().T
```

Out[38]:

risk_estrogen_deficiency	N	Y
dexa_freq_during_rx	0.261052	0.259259
count_of_risks	0.097682	0.666667

In [39]:
```
df.groupby(['risk_immobilization']).mean().T
```

Out[39]:

risk_immobilization	N	Y
dexa_freq_during_rx	0.262002	0.027778
count_of_risks	0.096416	0.833333

In [40]:
```
df.groupby(['risk_recurring_falls']).mean().T
```

Out[40]:

risk_recurring_falls	N	Y
dexa_freq_during_rx	0.259901	0.321212
count_of_risks	0.087634	0.718182

In [ ]:

In [ ]:

Data Wrangling Transformation

In [41]:
```
df = df.drop(['ptid'], axis=1)
```

In [42]:
```
mapper = {'N': 0, 'Y':1}
df = df.replace(mapper)
```

In [43]:
```
df['persistency_flag'] = df['persistency_flag'].replace(['Non-Persistent', 'Persistent'
df.head()
```

Out[43]:

	persistency_flag	gender	race	ethnicity	region	age_bucket	ntm_speciality	ntm_speciali
0	1	Male	Caucasian	Not Hispanic	West	>75	GENERAL PRACTITIONER	
1	0	Male	Asian	Not Hispanic	West	55-65	GENERAL PRACTITIONER	
2	0	Female	Other/Unknown	Hispanic	Midwest	65-75	GENERAL PRACTITIONER	
3	0	Female	Caucasian	Not Hispanic	Midwest	>75	GENERAL PRACTITIONER	
4	0	Female	Caucasian	Not Hispanic	Midwest	>75	GENERAL PRACTITIONER	

5 rows × 68 columns

Data Exploratory (After Transformation)**

In [44]:
```
np.abs(df.corr()).sort_values(by=['persistency_flag'], ascending=False)
```

Out[44]:

	persistency_flag	gluco_record_prio
persistency_flag	1.000000	0.0
dexa_freq_during_rx	0.414876	0.0
dexa_during_rx	0.374966	0.0
comorb_long_term_current_drug_therapy	0.342776	0.0
comorb_encounter_for_screening_for_malignant_neoplasms	0.268339	0.0
comorb_encounter_for_immunization	0.268305	0.0
comorb_encntr_for_general_exam_w_o_complaint,_susp_or_reprtd_dx	0.257895	0.0
concom_systemic_corticosteroids_plain	0.249048	0.3
concom_viral_vaccines	0.227004	0.0
comorb_other_disorders_of_bone_density_and_structure	0.227003	0.0
concom_anaesthetics_general	0.220619	0.1
concom_cephalosporins	0.217821	0.1

	persistency_flag	gluco_record_prio
comorb_other_joint_disorder_not_elsewhere_classified	0.215937	0.0
gluco_record_during_rx	0.212778	0.3
comorb_gastro_esophageal_reflux_disease	0.207985	0.0
concom_macrolides_and_similar_types	0.192350	0.0
comorb_personal_history_of_other_diseases_and_conditions	0.189565	0.0
concom_narcotics	0.188391	0.1
concom_broad_spectrum_penicillins	0.186610	0.0
concom_fluoroquinolones	0.181213	0.1
comorb_dorsalgia	0.179925	0.0
comorb_encntr_for_oth_sp_exam_w_o_complaint_suspected_or_reprtd_dx	0.164096	0.0
comorb_personal_history_of_malignant_neoplasm	0.157273	0.0
comorb_vitamin_d_deficiency	0.151592	0.0
comorb_disorders_of_lipoprotein_metabolism_and_other_lipidemias	0.147411	0.0
comorb_osteoporosis_without_current_pathological_fracture	0.132641	0.0
idn_indicator	0.125887	0.0
concom_cholesterol_and_triglyceride_regulating_preparations	0.125322	0.0
risk_smoking_tobacco	0.115573	0.0
concom_anti_depressants_and_mood_stabilisers	0.111728	0.1
frag_frac_during_rx	0.102944	0.0
injectable_experience_during_rx	0.097495	0.0
count_of_risks	0.071565	0.1
risk_vitamin_d_insufficiency	0.069520	0.0
risk_rheumatoid_arthritis	0.059501	0.0
risk_poor_health_frailty	0.055891	0.0
risk_untreated_chronic_hypogonadism	0.045216	0.0
risk_immobilization	0.042316	0.0
risk_chronic_malnutrition_or_malabsorption	0.031632	0.0
risk_chronic_liver_disease	0.029426	0.0
risk_excessive_thinness	0.023628	0.0
risk_estrogen_deficiency	0.023250	0.0
risk_recurring_falls	0.020356	0.0
risk_untreated_chronic_hyperthyroidism	0.017246	0.0
risk_family_history_of_osteoporosis	0.016878	0.0

	persistency_flag	gluco_record_prio
risk_hysterectomy_oophorectomy	0.016192	0.0
risk_patient_parent_fractured_their_hip	0.015073	0.0
risk_low_calcium_intake	0.013116	0.0
risk_type_1_insulin_dependent_diabetes	0.007144	0.0
frag_frac_prior_ntm	0.005521	0.0
risk_untreated_early_menopause	0.004193	0.0
gluco_record_prior_ntm	0.003027	1.0
risk_osteogenesis_imperfecta	0.002022	0.0

53 rows × 53 columns

Creating Dummy values

In [45]:
```
X=df.drop(['persistency_flag'],axis=1)
y=df['persistency_flag']

X = pd.get_dummies(X)
X.columns=[x.lower() for x in X.columns]
X_train,X_test,y_train,y_test=train_test_split(X,y,random_state=42,test_size=0.3, strat
```

In [46]:
```
df_train = X_train.copy()
df_train['persistency_flag'] = y_train
df_train.head()
```

Out[46]:

	gluco_record_prior_ntm	gluco_record_during_rx	dexa_freq_during_rx	dexa_during_rx	frag_frac_pri
1493	1	1	0.0	0	
1375	0	0	0.0	0	
1217	1	1	0.0	0	
1157	1	1	0.0	0	
2766	0	0	0.0	0	

5 rows × 131 columns

In [47]:
```
classes=df_train['persistency_flag'].value_counts()
normal_share=round(classes[0]/df_train['persistency_flag'].count()*100,2)
fraud_share=round(classes[1]/df_train['persistency_flag'].count()*100, 2)
print("Non-Persistent : {} %".format(normal_share))
print("Persistent : {} %".format(fraud_share))
```

```
Non-Persistent : 69.6 %
```

```
Persistent : 30.4 %
```

In [48]:
```
fig = px.histogram(df_train, x="persistency_flag", color="persistency_flag", title="Per
fig.show()
```

In [49]:
```
# Upsampling
df_minority_upsampled = resample(df_train[df_train['persistency_flag'] == 1],
                                 replace=True,     # sample with replacement
                                 n_samples=len(df_train[df_train['persistency_flag'] ==
                                 random_state=123) # reproducible results

# Combine majority class with upsampled minority class
df_train = pd.concat([df_train[df_train['persistency_flag'] == 0], df_minority_upsample

# Display new class counts
df_train.persistency_flag.value_counts()
```

Out[49]:
```
0    1433
1    1433
Name: persistency_flag, dtype: int64
```

In [50]:
```
X_train=df_train.drop(['persistency_flag'],axis=1)
y_train=df_train['persistency_flag']
```

In [51]:
```
fig = px.histogram(df_train, x="persistency_flag", color="persistency_flag", title="Per
fig.show()
```

Models Building

In [58]:
```
def evaluation_metrics(y_test, y_pre, target_names):
    #scores
    print("Accuracy :",accuracy_score(y_test,y_pre))
    print("Precision :",precision_score(y_test,y_pre))
    print("Recall :",recall_score(y_test,y_pre))
    print("F1 Score :",f1_score(y_test,y_pre))

    print(classification_report(y_test, y_pre, target_names=target_names))

    #AUC
    fpr, tpr, _ = roc_curve(y_test,  y_pre)
    auc = roc_auc_score(y_test, y_pre)
    print("AUC :", auc)

    #ROC
    plt.plot(fpr,tpr,label="uc={:.3f})".format(auc))
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlabel('False positive rate')
```

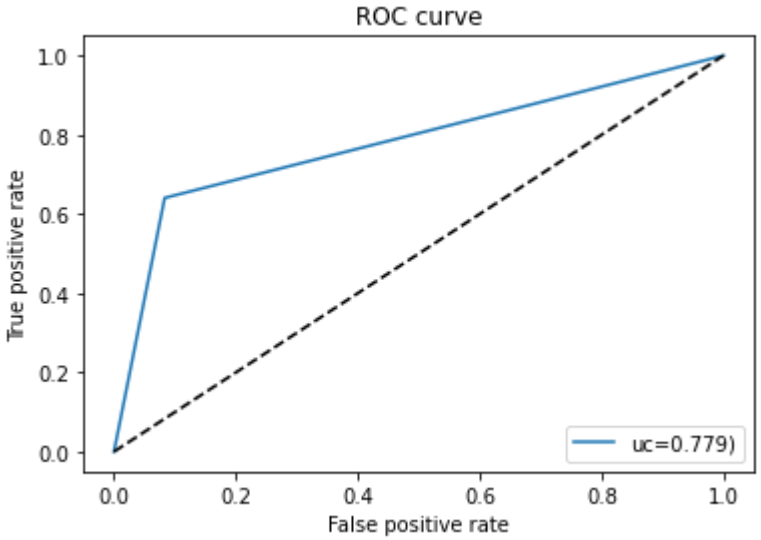
```
    plt.ylabel('True positive rate')
    plt.title('ROC curve')
    plt.legend(loc=4)
    plt.show()

    #CM matrix
    matrix = confusion_matrix(y_test, y_pre)
    cm = pd.DataFrame(matrix, index=target_names, columns=target_names)

    sns.heatmap(cm, annot=True, cbar=None, cmap="Blues", fmt = 'g')
    plt.title("Confusion Matrix"), plt.tight_layout()
    plt.ylabel("True Class"), plt.xlabel("Predicted Class")
    plt.show()
```

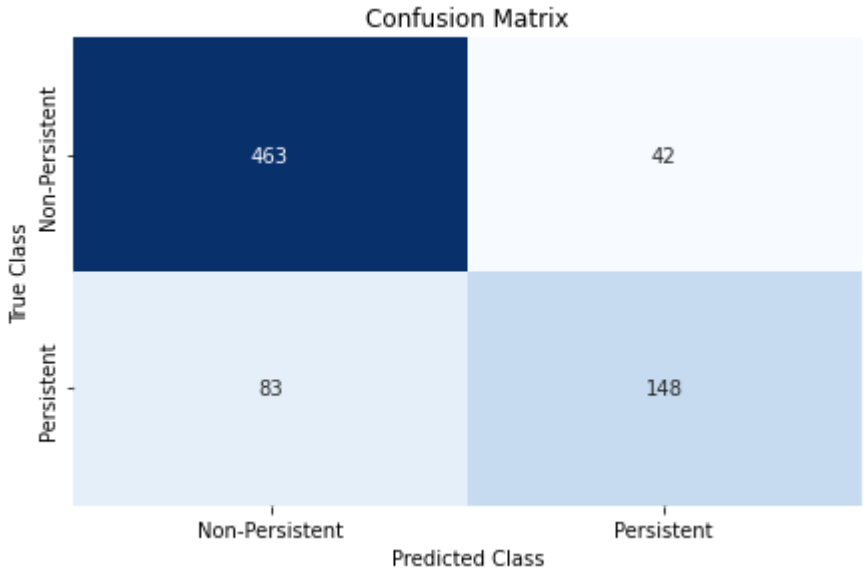
Logistic Regression

In [59]:

```
def log(X_train,X_test,y_train,y_test):
    model=LogisticRegression()
    model.fit(X_train,y_train)
    y_pre=model.predict(X_test)
    evaluation_metrics(y_test, y_pre, target_names)

log(X_train,X_test,y_train,y_test)
```

```
Accuracy : 0.8301630434782609
Precision : 0.7789473684210526
Recall : 0.6406926406926406
F1 Score : 0.7030878859857482
                precision    recall  f1-score   support

Non-Persistent       0.85      0.92      0.88       505
    Persistent       0.78      0.64      0.70       231

      accuracy                           0.83       736
     macro avg       0.81      0.78      0.79       736
  weighted avg       0.83      0.83      0.83       736

AUC : 0.7787621619304788
```



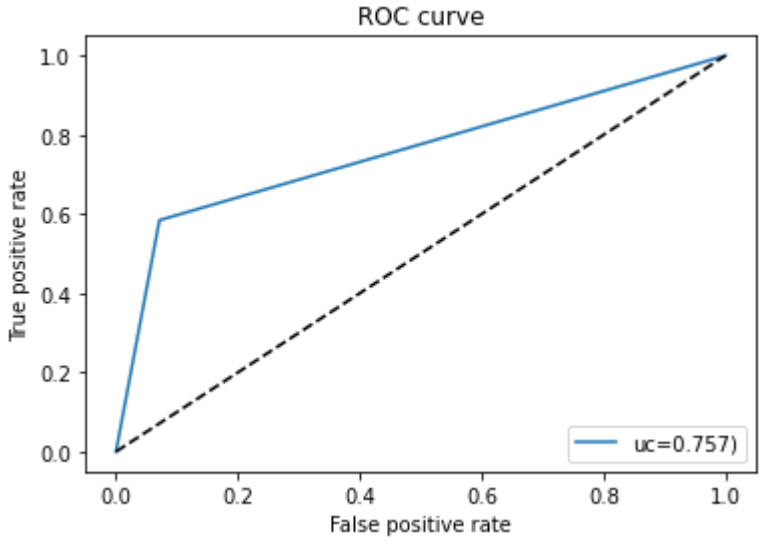


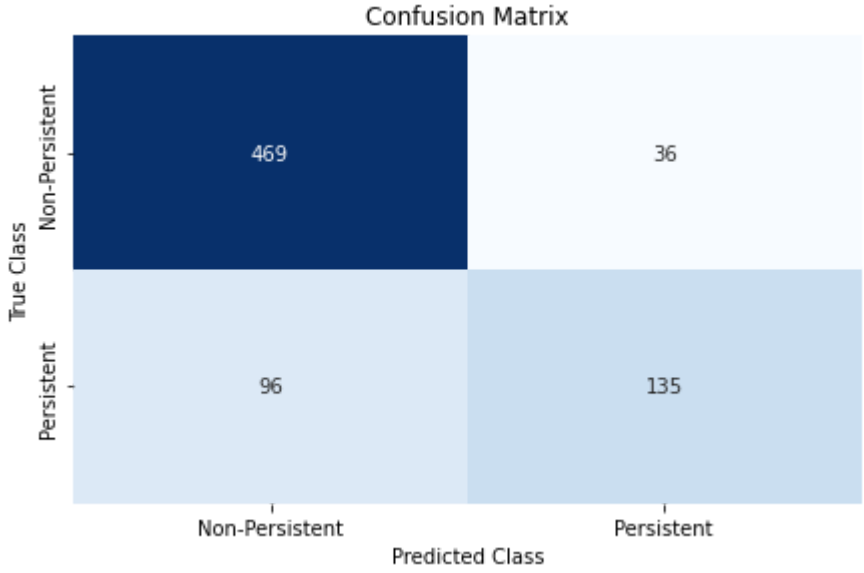
RidgeClassifier

In [60]:
```
def Ridge(X_train,X_test,y_train,y_test):
    #train the model
    model = RidgeClassifier(random_state=2)
    model.fit(X_train, y_train)
    #predictions
    y_pre = model.predict(X_test)
    evaluation_metrics(y_test, y_pre, target_names)
```

In [61]:
```
Ridge(X_train,X_test,y_train,y_test)
```

```
Accuracy : 0.8206521739130435
Precision : 0.7894736842105263
Recall : 0.5844155844155844
F1 Score : 0.6716417910447761
                precision    recall  f1-score   support

Non-Persistent       0.83      0.93      0.88       505
    Persistent       0.79      0.58      0.67       231

      accuracy                           0.82       736
     macro avg       0.81      0.76      0.77       736
  weighted avg       0.82      0.82      0.81       736

AUC : 0.7565642278513565
```





RandomForestClassifier

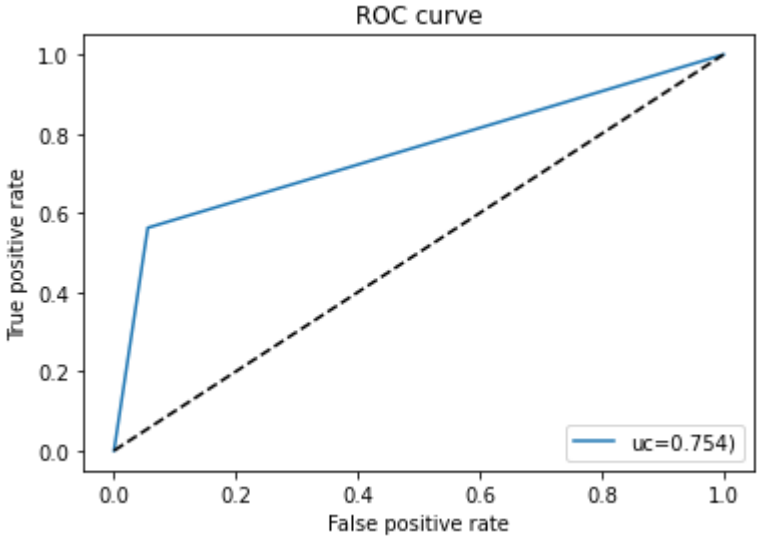
In [63]:
```
def RF(X_train,X_test,y_train,y_test):
  #train the model
  model = RandomForestClassifier(random_state=2)
  model.fit(X_train, y_train)
  #predictions
  y_pre = model.predict(X_test)
  evaluation_metrics(y_test, y_pre, target_names)
```

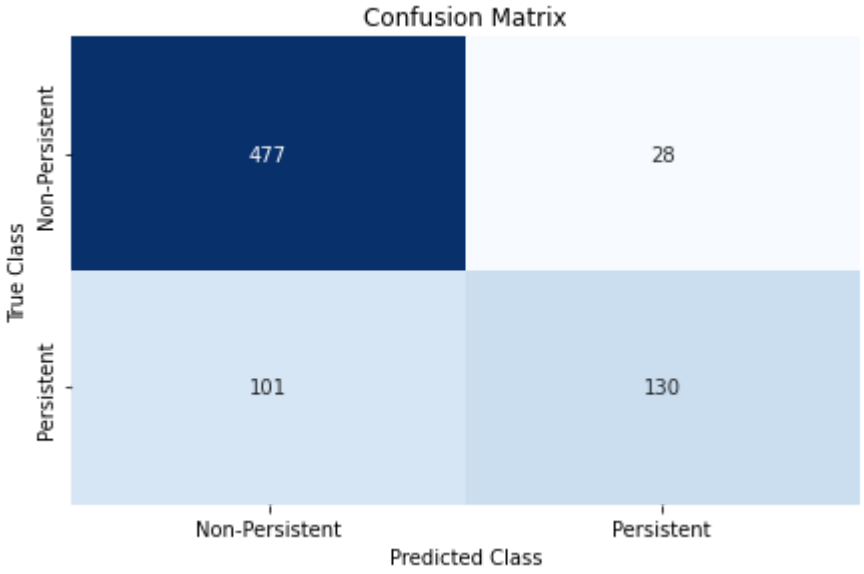
In [64]:
```
RF(X_train,X_test,y_train,y_test)
```

```
Accuracy : 0.8247282608695652
Precision : 0.8227848101265823
Recall : 0.5627705627705628
F1 Score : 0.6683804627249357
               precision    recall  f1-score   support

Non-Persistent       0.83      0.94      0.88       505
    Persistent       0.82      0.56      0.67       231
```

```
              accuracy                           0.82       736
             macro avg       0.82      0.75      0.77       736
          weighted avg       0.82      0.82      0.81       736
```

```
AUC : 0.7536625091080535
```





Conclusion

- Approximately all the classifiers have same result, but the Ridge CLassifier and the Random Forest were the best one.
- These two models have around 82% Accuracy.
- Ridge Classifier has 78% Precision, 58% Recall, & 67% F1 Score.
- Random Forest has 82% Precision, 56% Recall, & 66% F1 Score.
- We can also see the results for each classifier as well.

Model Deployment

In [73]:
```
from sklearn.ensemble import StackingClassifier
```

In [74]:
```
def Stacking(X_train,X_test,y_train,y_test):
  #train the model
  estimators = [('rf', RandomForestClassifier(n_estimators=10, random_state=42)), ('svr
  model = StackingClassifier(estimators=estimators, final_estimator=LogisticRegression(
  model.fit(X_train, y_train)
  #predictions
  y_pre = model.predict(X_test)
  evaluation_metrics(y_test, y_pre, target_names)
```

In [75]:
```
###Stacking classifier
import pickle
estimators = [('rf', RandomForestClassifier(n_estimators=10, random_state=42)), ('svr',
final_model = StackingClassifier(estimators=estimators, final_estimator=LogisticRegress
final_model.fit(X, y)
filename = 'final_model.sav'
pickle.dump(final_model, open(filename, 'wb'))
```