# Week 8 – Healthcare Project

## Group Name: Cool Data Scientists Team

Team Members Details:

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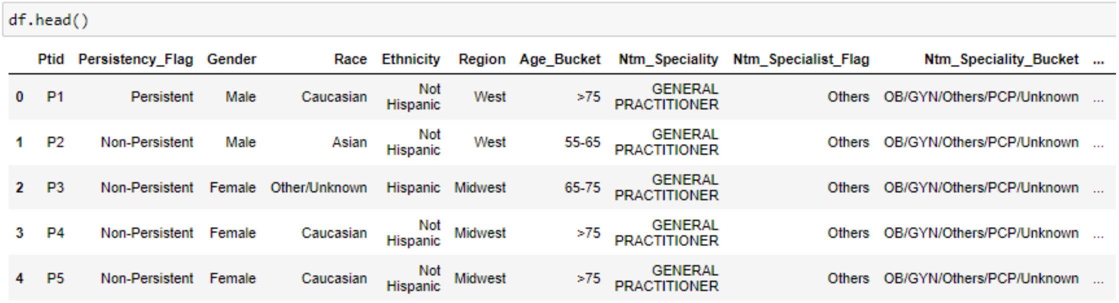
**Problem Description**

One of the challenges for Pharmaceutical companies is to understand the persistency of drug as per the physician prescription. This issue results in a bad impact on the pharmacies for all the categories; patients, physicians, and administration. However, the team of data scientist is capable of discovering the analyzing the dataset and detecting the factors that are impacting the primary factor which is the "persistency". By building a classification machine learning model, we will be able to classify the dataset and find the variables that affect the target variables "Persistency Flag".

## Data understanding

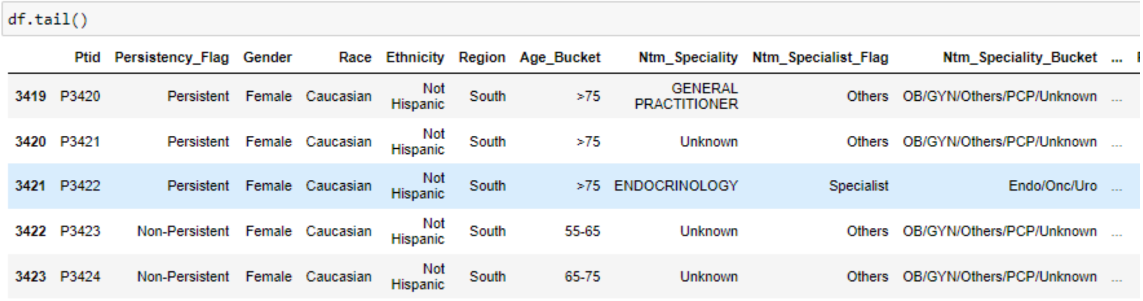
As a first step, we imported the dataset and copied it. Then we've looked at the first five and the last five entries.

The following pictures show how our dataset looks like:



```
df.head()
```

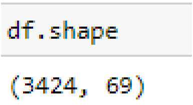
| | Ptid | Persistency_Flag | Gender | Race | Ethnicity | Region | Age_Bucket | Ntm_Speciality | Ntm_Specialist_Flag | Ntm_Speciality_Bucket | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | P1 | Persistent | Male | Caucasian | Not Hispanic | West | >75 | GENERAL PRACTITIONER | Others |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



```
df.tail()
```

| | Ptid | Persistency_Flag | Gender | Race | Ethnicity | Region | Age_Bucket | Ntm_Speciality | Ntm_Specialist_Flag | Ntm_Speciality_Bucket | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 3419 | P3420 | Persistent | Female | Caucasian | Not Hispanic | South | >75 | GENERAL PRACTITIONER | Others | OB/GYN/Others/PCP/Unknown | ... |
| 3420 | P3421 | Persistent | Female | Caucasian | Not Hispanic | South | >75 | Unknown | Others | OB/GYN/Others/PCP/Unknown | ... |
| 3421 | P3422 | Persistent | Female | Caucasian | Not Hispanic | South | >75 | ENDOCRINOLOGY | Specialist | Endo/Onc/Uro | ... |
| 3422 | P3423 | Non-Persistent | Female | Caucasian | Not Hispanic | South | 55-65 | Unknown | Others | OB/GYN/Others/PCP/Unknown | ... |
| 3423 | P3424 | Non-Persistent | Female | Caucasian | Not Hispanic | South | 65-75 | Unknown | Others | OB/GYN/Others/PCP/Unknown | ... |

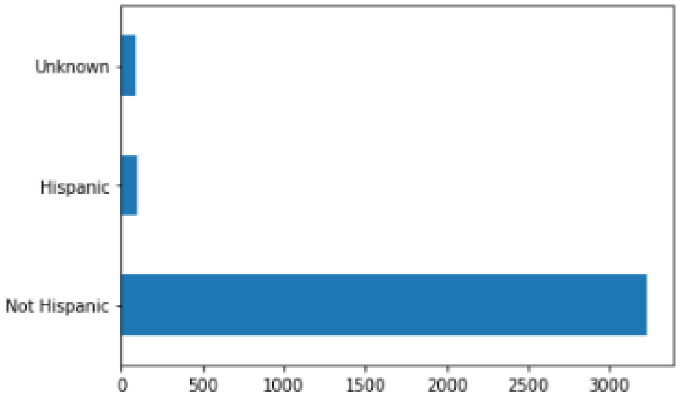
Totally we have 3424 observations and 69 features.



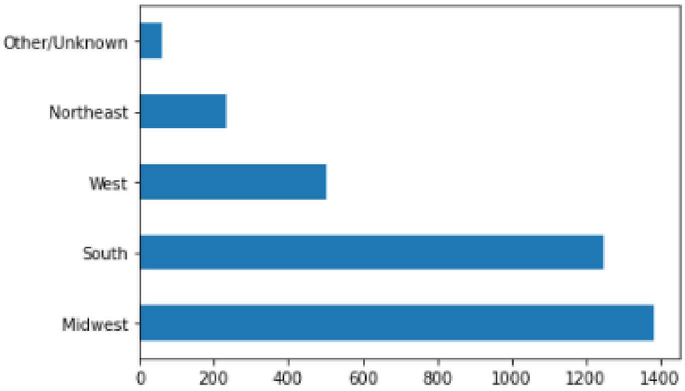
```
df.shape
(3424, 69)
```

For Demographics, we have the followings:

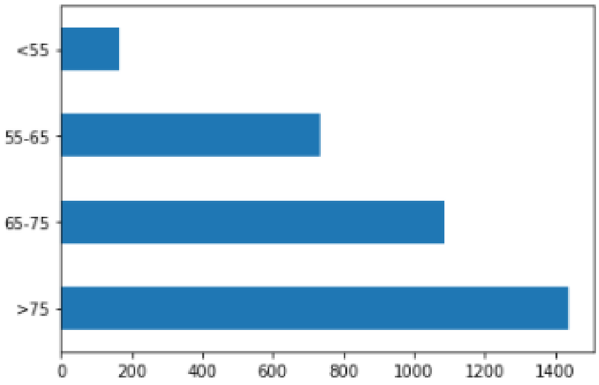
If we examine "Ethnicity", we see that "Non-Hispanic" people dominates the "Hispanic" people and also we have unknown values.



If we examine the “Region”, we see that patients are mostly “Midwest” and “South” region:

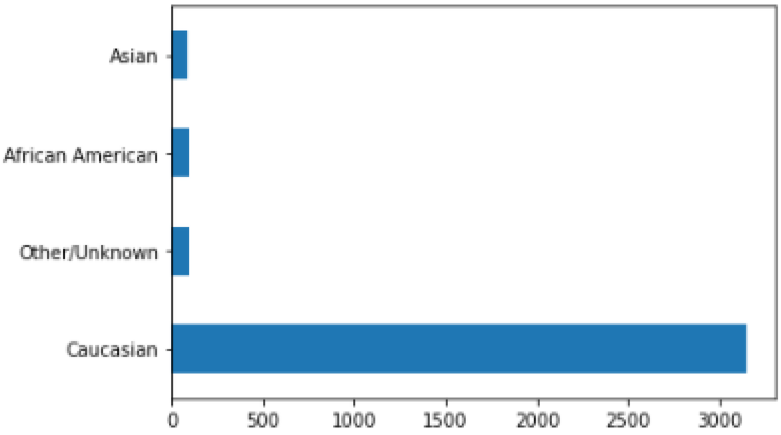


If we look at the “Age”, we see the following:

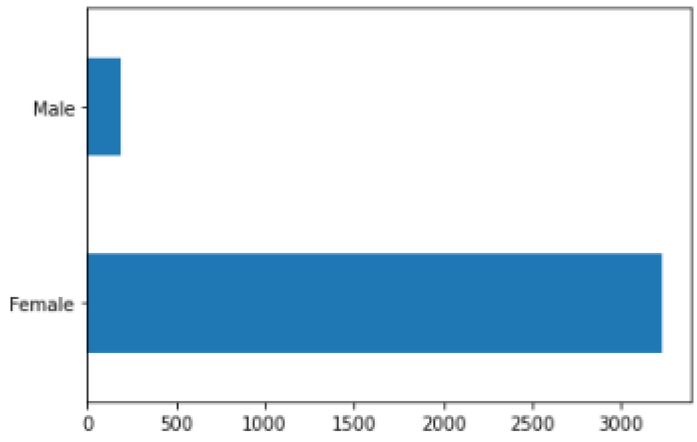


By looking at the above picture, it can be thought that being of age “>55” can be related to have persistency to drug.

If we look at the “Race”, we see that the Caucasians are dominated the other races.

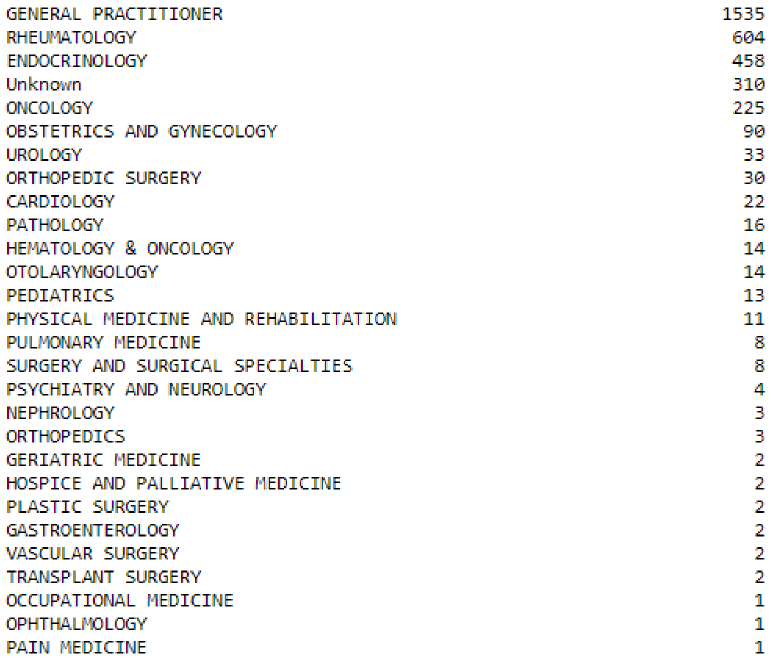


If we look at the “Gender”, by the following picture , the female patients are more than the male patients.



**Ntm Speciality** is the specialty of the HCP that prescribed the NTM Rx.

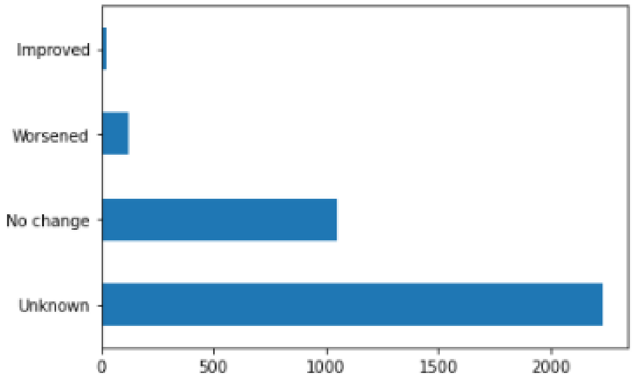
We see that General Practitioner, Rheumatology, Endocrinology and Oncology specialists prescribed the NTM Rx most.



```
GENERAL PRACTITIONER                               1535
RHEUMATOLOGY                                        604
ENDOCRINOLOGY                                       458
Unknown                                             310
ONCOLOGY                                            225
OBSTETRICS AND GYNECOLOGY                            90
UROLOGY                                              33
ORTHOPEDIC SURGERY                                   30
CARDIOLOGY                                           22
PATHOLOGY                                            16
HEMATOLOGY & ONCOLOGY                                14
OTOLARYNGOLOGY                                       14
PEDIATRICS                                           13
PHYSICAL MEDICINE AND REHABILITATION                 11
PULMONARY MEDICINE                                    8
SURGERY AND SURGICAL SPECIALTIES                      8
PSYCHIATRY AND NEUROLOGY                              4
NEPHROLOGY                                            3
ORTHOPEDICS                                           3
GERIATRIC MEDICINE                                    2
HOSPICE AND PALLIATIVE MEDICINE                       2
PLASTIC SURGERY                                       2
GASTROENTEROLOGY                                      2
VASCULAR SURGERY                                      2
TRANSPLANT SURGERY                                    2
OCCUPATIONAL MEDICINE                                 1
OPHTHALMOLOGY                                         1
PAIN MEDICINE                                         1
```

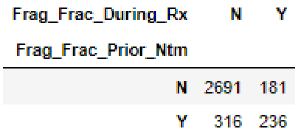
## Clinical Factors:

**Risk Segment:** We have compared the risk segments prior NTM and during NTM and examine how it changes:



We have done similar computations for all other clinical factors.

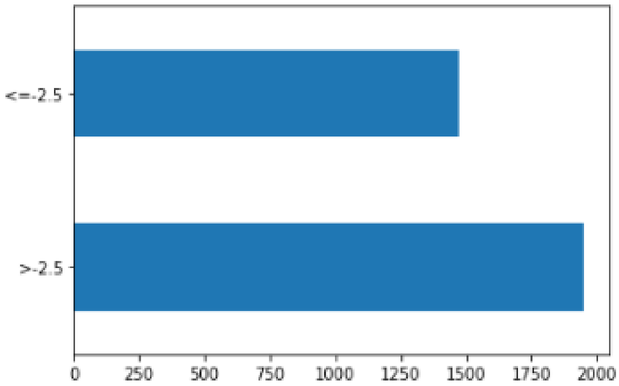
For instance, we have examined the Fragility and we have obtained the following cross- table:



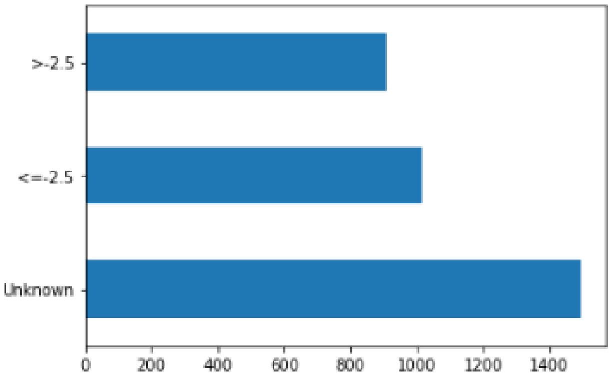
| Frag_Frac_During_Rx | N | Y |
|---|---|---|
| Frag_Frac_Prior_Ntm | | |
| N | 2691 | 181 |
| Y | 316 | 236 |

## T-scores:

We have compared the “T-scores”. The following picture shows the prior to NTM:



The following shows the “T-scores” during the Rx:



Besides, we have examined the Disease and Treatment Factors. They are all Yes/No information and we have decided which of the variables can affect the persistency to drug:

By comparing the results, we see that the followings can affect the target variable:

1) Comorb_Encounter_For_Screening_For_Malignant_Neoplasms

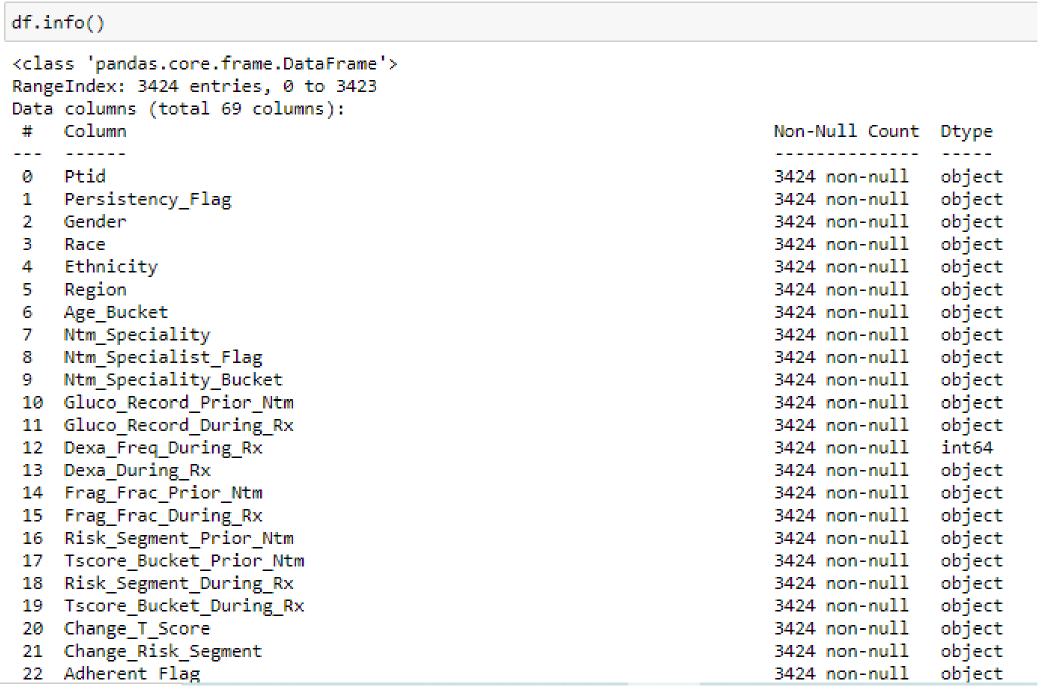
2) Comorb_Disorders_of_lipoprotein_metabolism_and_other_lipidemias

3) Comorb_Encounter_For_Immunization.

Similarly, we think that Vitamin D-insufficiency can affect the target variable.

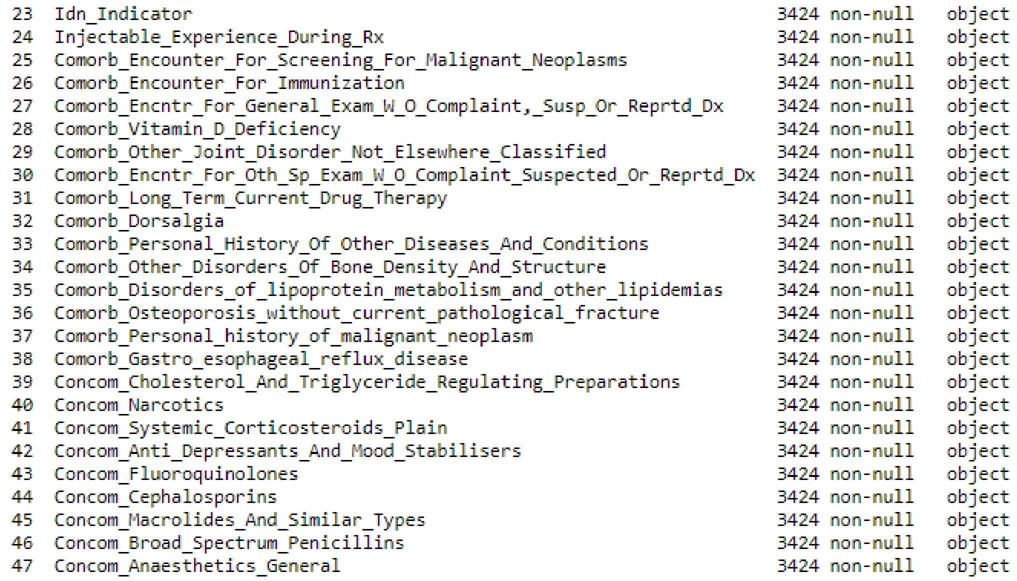
## What type of data you have got for analysis?

When we've checked the types of the variables, we obtained the following result:

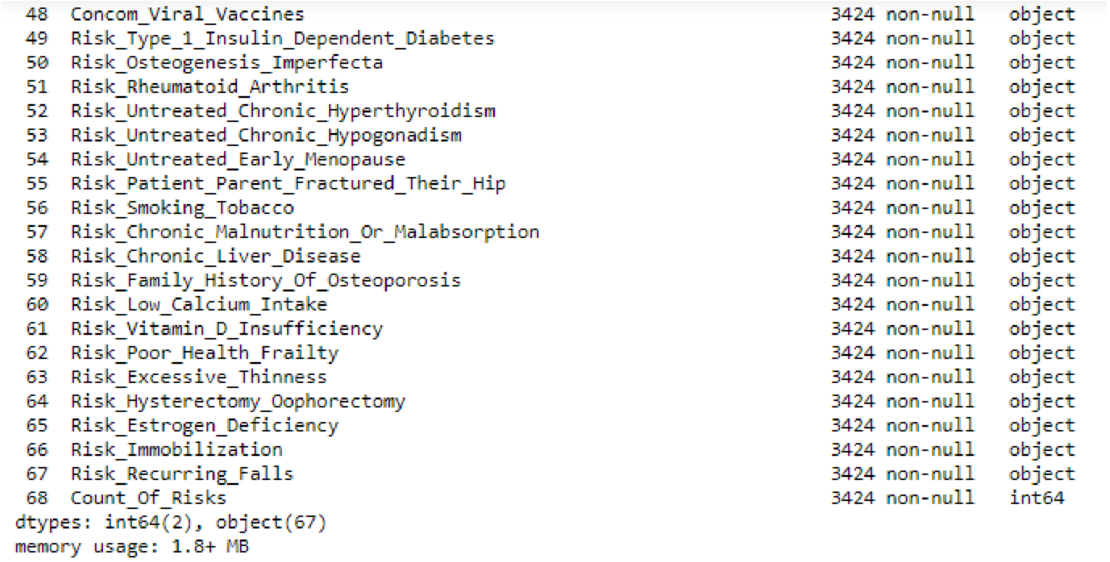


```
df.info()
```

```
<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
```



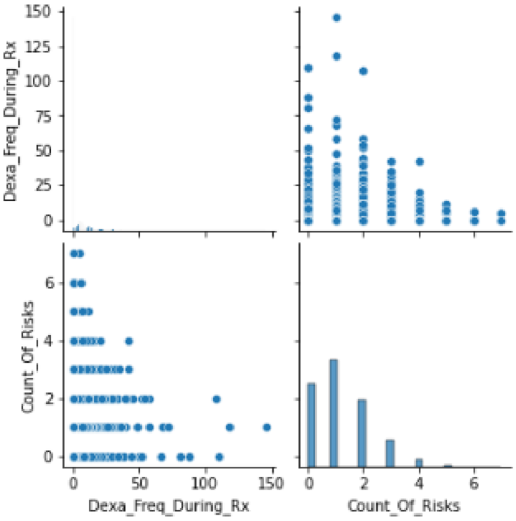
```
 23  Idn_Indicator                                                  3424 non-null   object
 24  Injectable_Experience_During_Rx                                3424 non-null   object
 25  Comorb_Encounter_For_Screening_For_Malignant_Neoplasms         3424 non-null   object
 26  Comorb_Encounter_For_Immunization                              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
```

We have that those 67 features are of object type and just 2 of them are int64 type.

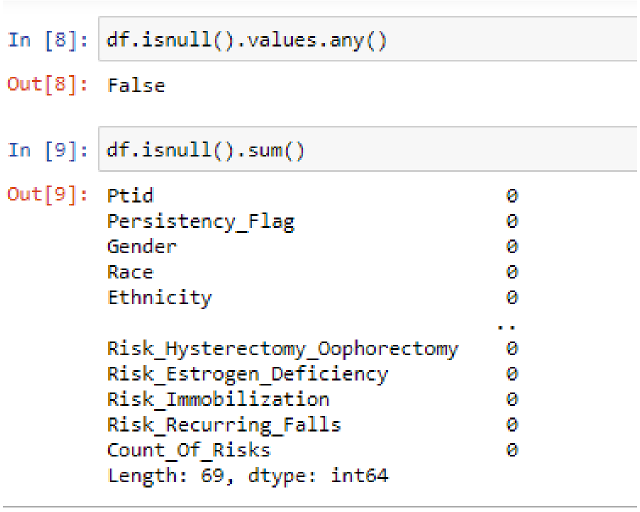
And we have determined the relation between these two numerical variables:



## What are the problems in the data ( number of NA values, outliers , skewed etc):

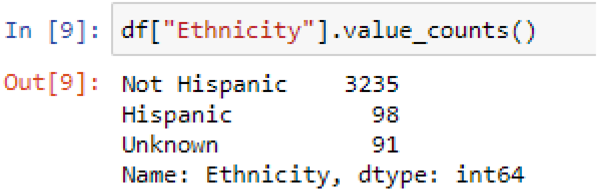
## NA Values:

When we checked that whether there is any NA value, we have obtained the following:

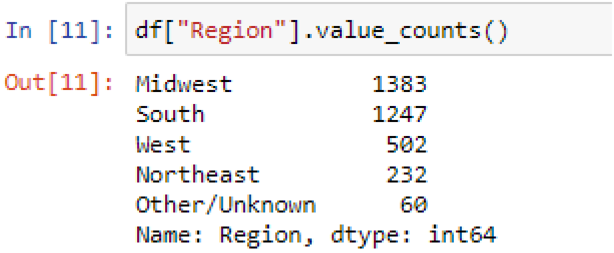


```
In [8]:  df.isnull().values.any()

Out[8]:  False

In [9]:  df.isnull().sum()

Out[9]:  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
```

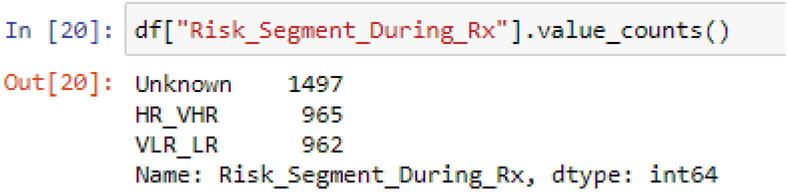
Even if we don’t have any NA values, we have “Unknown” variables. The followings are only examples of some of them:



```
In [9]:  df["Ethnicity"].value_counts()

Out[9]:  Not Hispanic    3235
         Hispanic          98
         Unknown           91
         Name: Ethnicity, dtype: int64
```



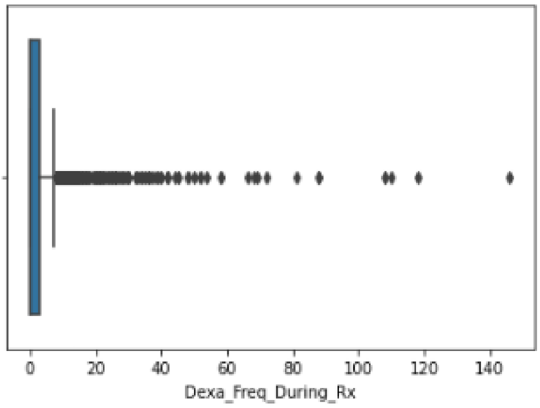
```
In [11]:  df["Region"].value_counts()

Out[11]:  Midwest          1383
          South            1247
          West              502
          Northeast         232
          Other/Unknown      60
          Name: Region, dtype: int64
```



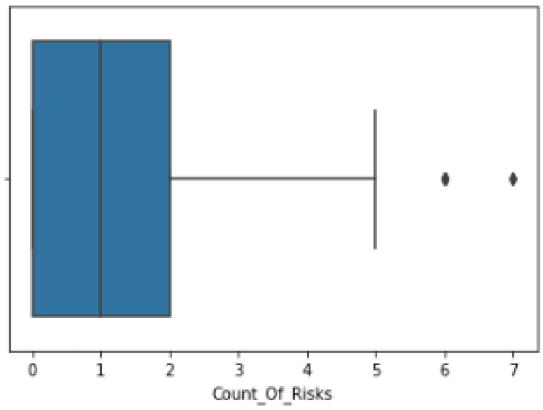
```
In [20]:  df["Risk_Segment_During_Rx"].value_counts()

Out[20]:  Unknown    1497
          HR_VHR      965
          VLR_LR      962
          Name: Risk_Segment_During_Rx, dtype: int64
```

## Outliers:

To detect the outliers, we’ve used boxplot.



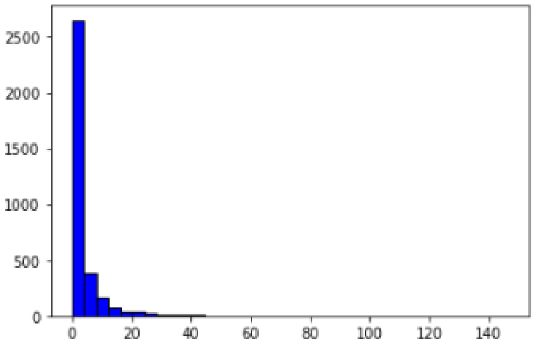
We have 460 outliers in “Dexa_Freq_During_Rx” variable.



We have 8 outliers in “Count_Of_Risks” variable.

**Skewed Data:**

We have the following histogram graphs:



As seen in the above, since the tail is on the right side, we can say that “Dexa_Freq_During_Rx” variable has right-skewed distribution. Hence, we can conclude that the mean value is greater than the mode.

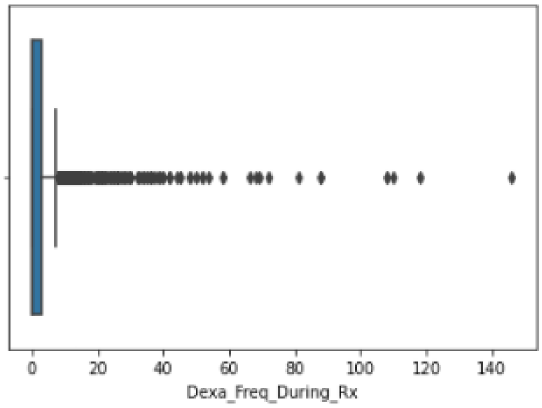
## What approaches you are trying to apply on your data set to overcome problems like NA value, outlier etc and why?

**For NA values**: Since all of the NA values are in object types we prefer to ignore these values.

For instance, we have NA values in “Ethnicity”. If we change the Unknown values with “Hispanic” or “Non-Hispanic” it can change the result of the dataset.

**For Outliers:**

As seen in the following picture, the outliers of the "**Dexa_Freq_During_Rx**" variable are place on the right-hand side of the upper bound. So, if we replace them with the mean value can change the type of the dataset. But instead, we have discussed on suppressing them with the upper bound.



On the other hand, the number of the outliers of the "**Count_Of_Risks**" variable is just 8. So, we can use mean value or suppress them with the upper bound.

## Github Repo link

https://github.com/melis-ta/Healthcare