Data Science Persistency of a Drug Project

Exploratory Data Analysis

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- Problem Understanding
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- Conclusion

Data Analysis Approach

One of the challenge for all Pharmaceutical companies is to understand the persistency of drug as per the physician prescription. To solve this problem ABC pharma company approached an analytics company to automate this process of identification.

- Explore and Understand the data
- Prepare and clean the data
- Analyze the data
- Find the features of drug persistency
- Give recommendations

Problem Understanding

Since the data is very large, we know that ABC pharmaceutical company wants to run the whole process faster and to get precise results.

We have considered and measured many factors that do or do not affect permanence.

DATA PREPARATION

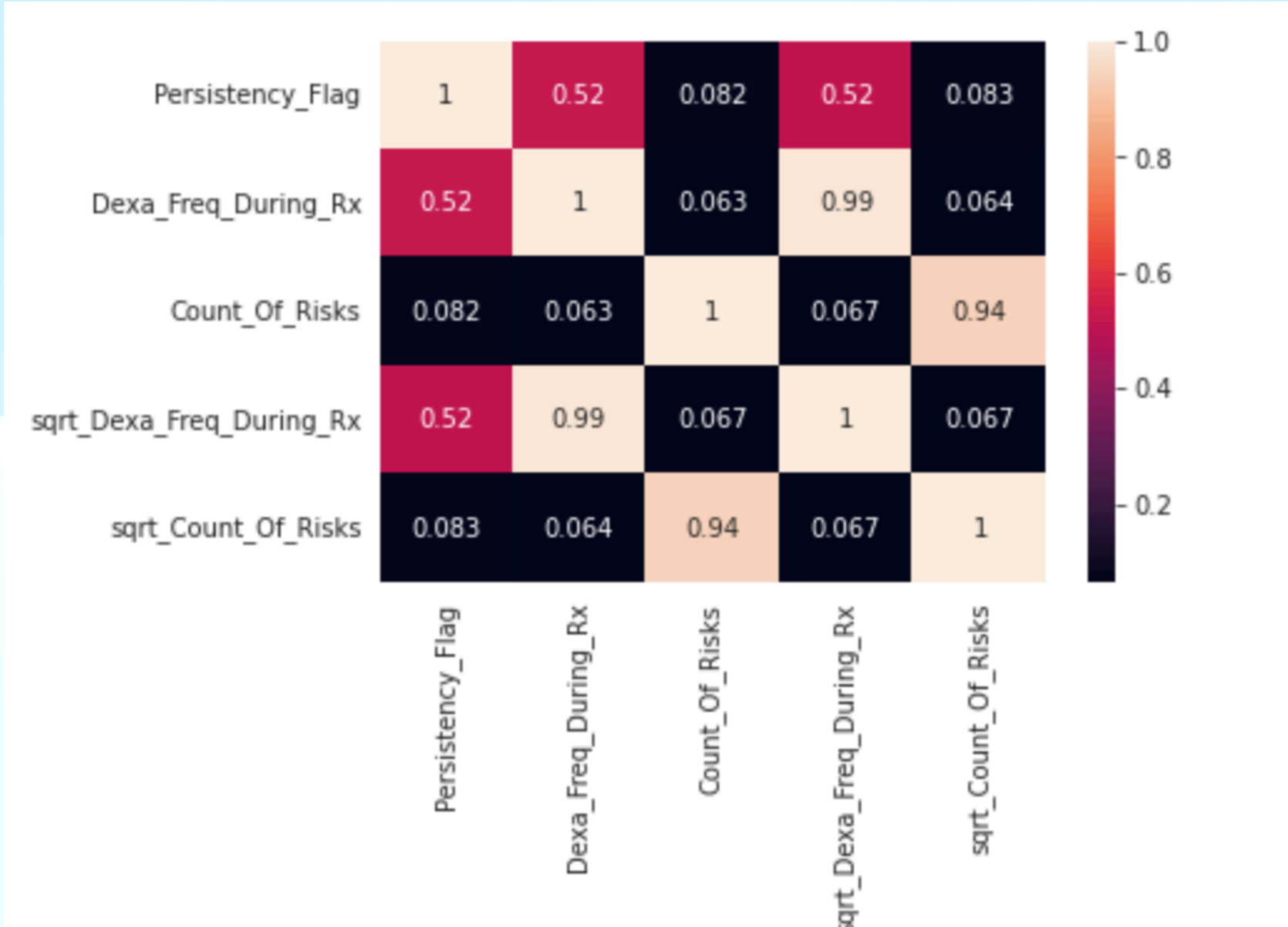
- We used pandas library and Google Colab Notebook
- Data was cleaned and prepared for analyzation.
- Approaches:
  - From null and missing values.
  - Virtualization of data.

EXPLORATORY DATA ANALYSIS

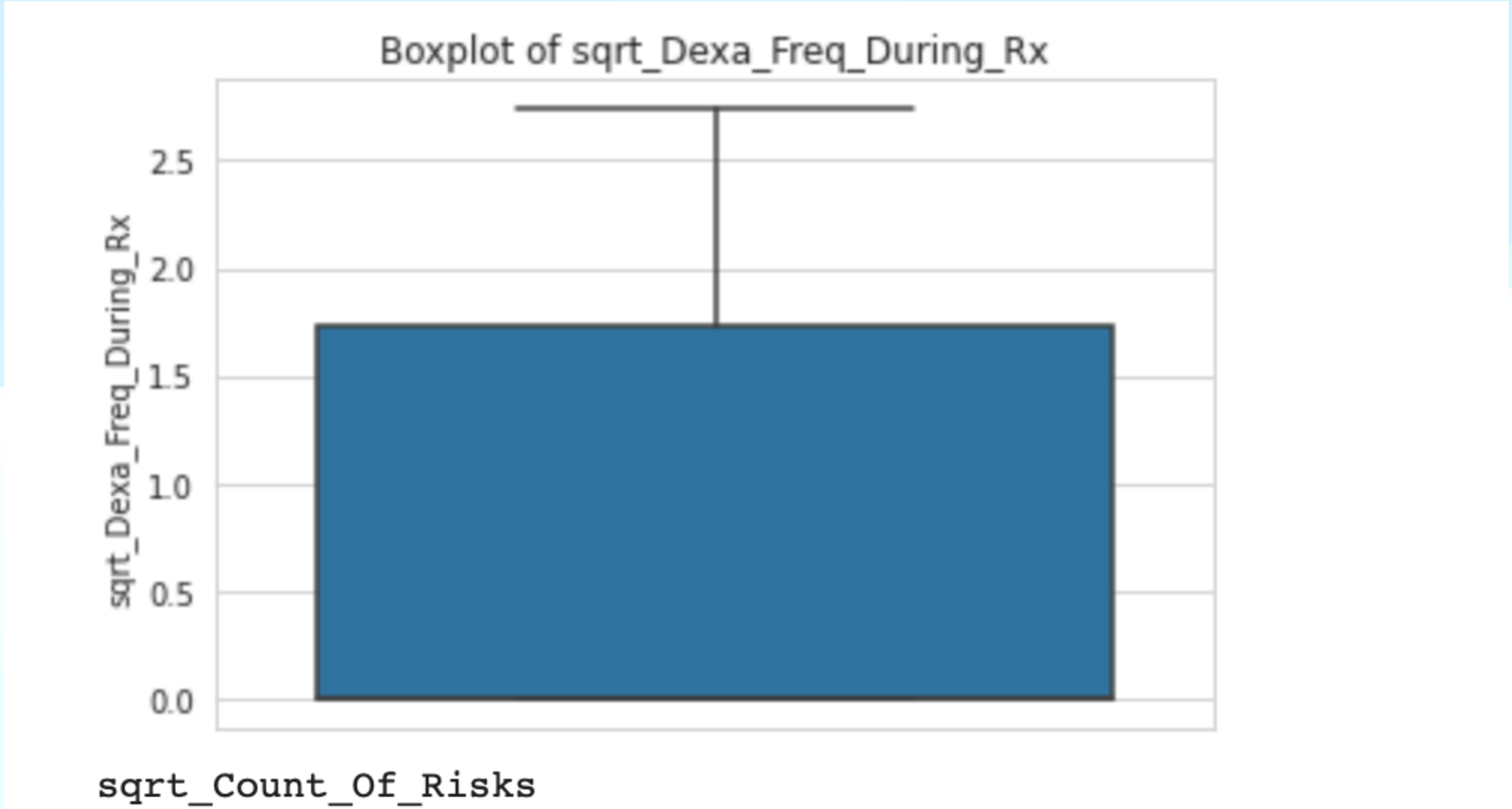
- The demographic data characteristics, gender, race, ethnicity, age, region etc are analyzed.
- Many graphics used for visualization.
- Some analyzes achieved very high accuracy rates.

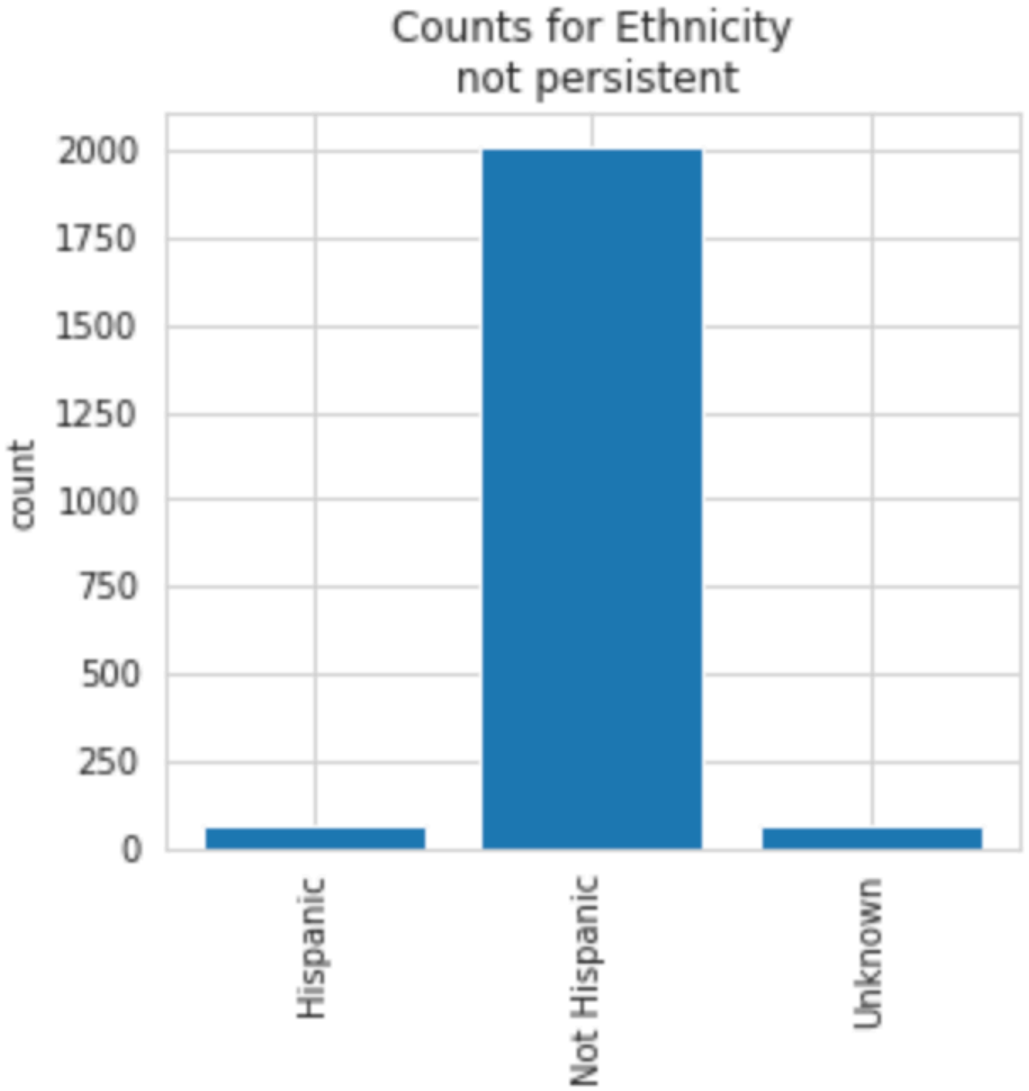
As a result of the analyzes made, we got different outputs every week and saved them.

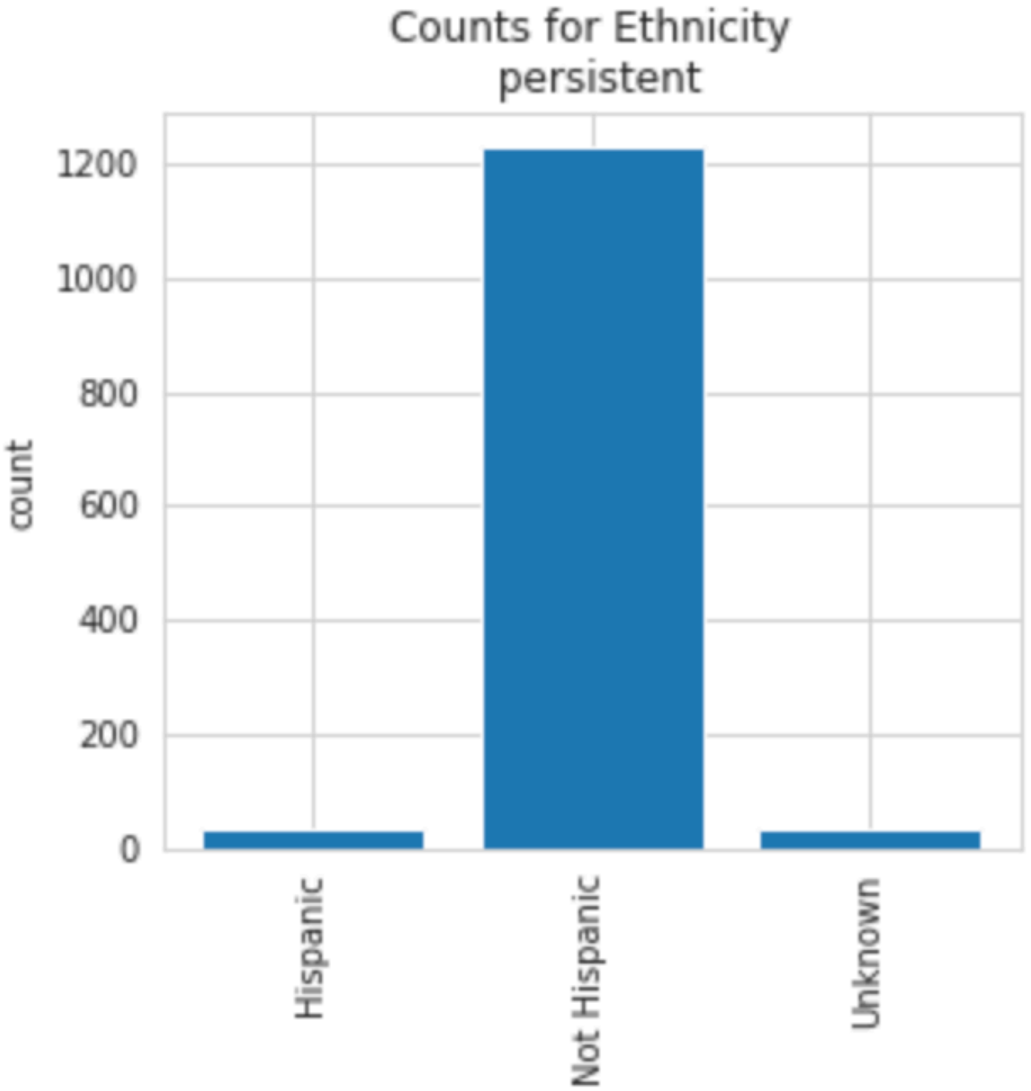
Heatmap


Persistency_Flag
Dexa_Freq_During_Rx
Count_Of_Risks
sqrt_Dexa_Freq_During_Rx
sqrt_Count_Of_Risks
1
0.52
0.082
0.52
0.083
0.52
1
0.063
0.99
0.064
0.082
0.063
1
0.067
0.94
0.52
0.99
0.067
1
0.067
0.083
0.064
0.94
0.067
1
Persistency_Flag
Dexa_Freq_During_Rx
Count_Of_Risks
sqrt_Dexa_Freq_During_Rx
sqrt_Count_Of_Risks
1.0
0.8
0.6
0.4
0.2

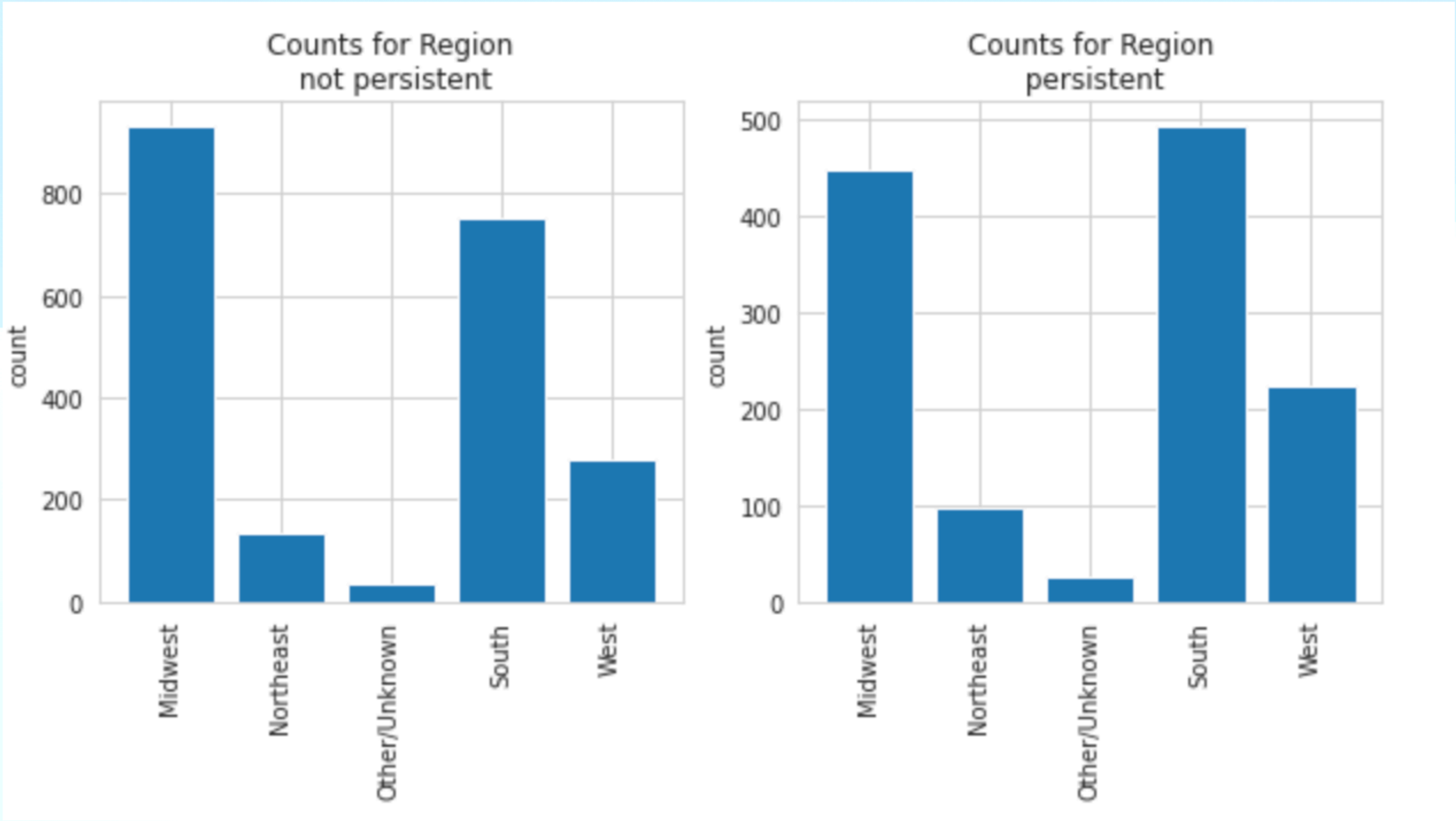
Outlier Test

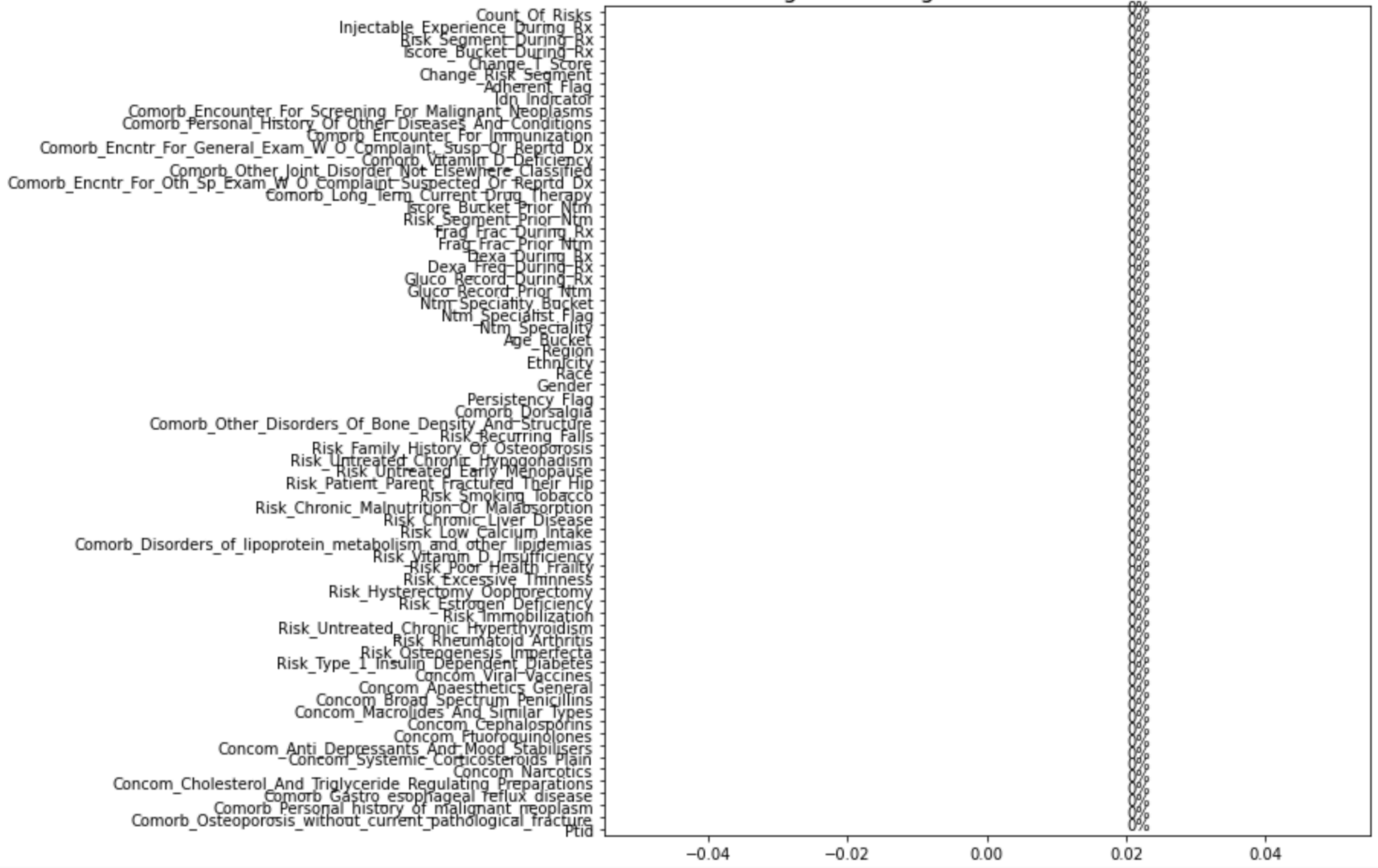



Counts for Ethnicity
not persistent
count
2000
1750
1500
1250
1000
750
500
250
0
Hispanic
Not Hispanic
Unknown

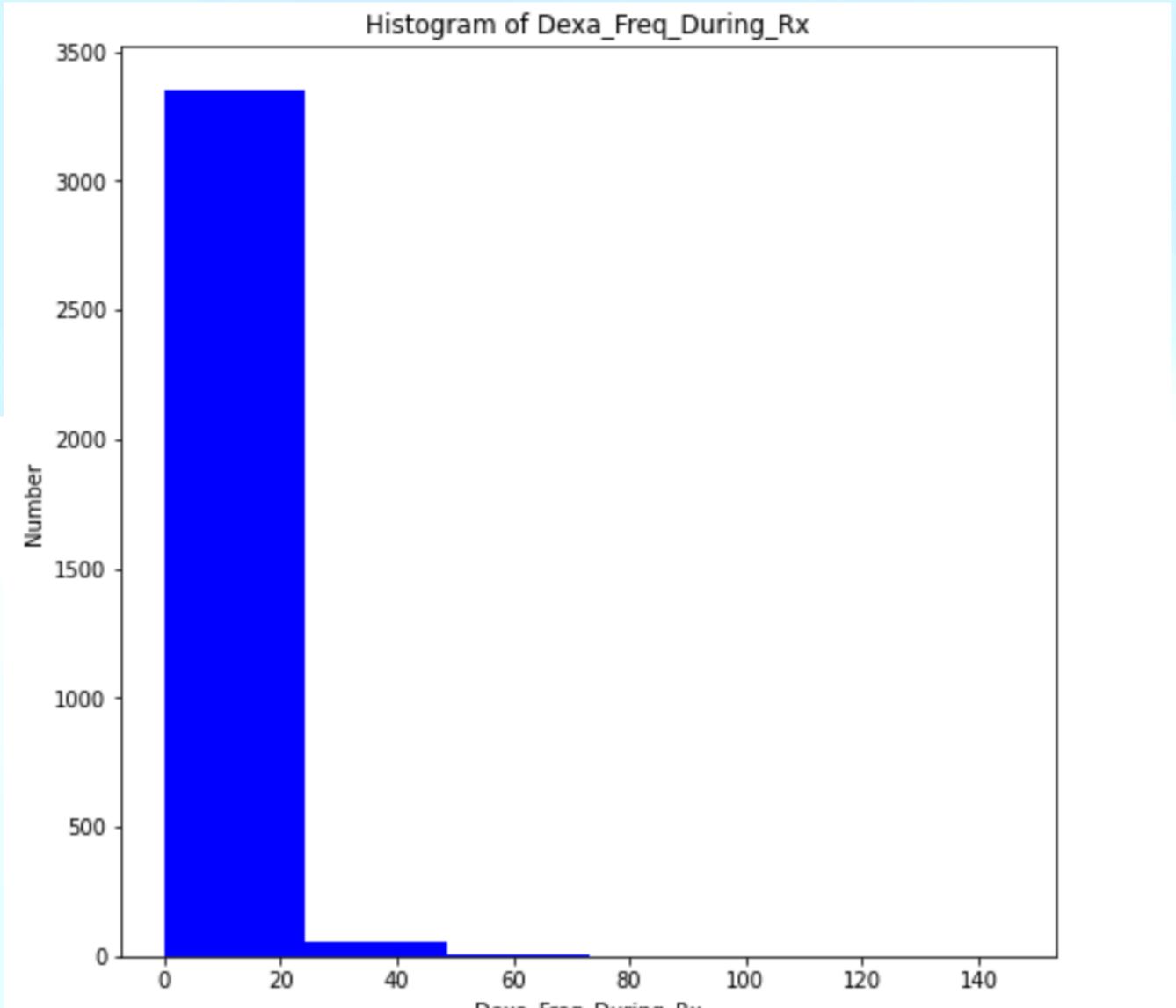

Counts for Ethnicity
persistent
count
1200
1000
800
600
400
200
0
Hispanic
Not Hispanic
Unknown

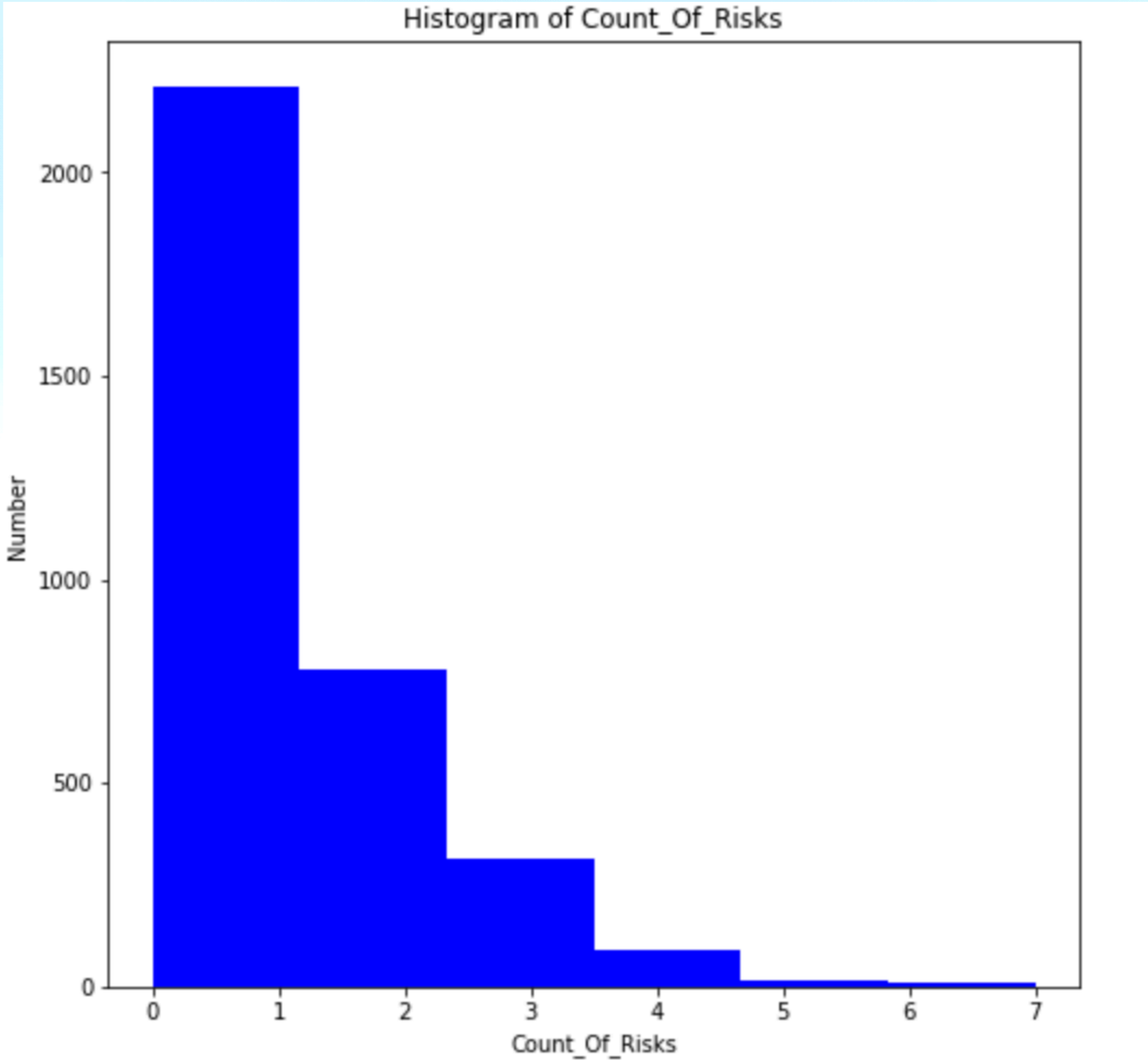
Persistency and Non-Persistent




Percentage of Missing Values Per Column in Train Set
Count_Of_Risks
Injectable_Experience_During_Rx
Risk_Segment_During_Rx
Tscore_Bucket_During_Rx
Change_T_Score
Change_Risk_Segment
Adherent_Flag
Idn_Indicator
Comorb_Encounter_For_Screening_For_Malignant_Neoplasms
Comorb_Personal_History_Of_Other_Diseases_And_Conditions
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
Tscore_Bucket_Prior_Ntm
Risk_Segment_Prior_Ntm
Frag_Frac_During_Rx
Frag_Frac_Prior_Ntm
Dexa_During_Rx
Dexa_Freq_During_Rx
Gluco_Record_During_Rx
Gluco_Record_Prior_Ntm
Ntm_Speciality_Bucket
Ntm_Specialist_Flag
Ntm_Speciality
Age_Bucket
Region
Ethnicity
Race
Gender
Persistency_Flag
Comorb_Dorsalgia
Comorb_Other_Disorders_Of_Bone_Density_And_Structure
Risk_Recurring_Falls
Risk_Family_History_Of_Osteoporosis
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_Low_Calcium_Intake
Comorb_Disorders_of_lipoprotein_metabolism_and_other_lipidemias
Risk_Vitamin_D_Insufficiency
Risk_Poor_Health_Frailty
Risk_Excessive_Thinness
Risk_Hysterectomy_Oophorectomy
Risk_Estrogen_Deficiency
Risk_Immobilization
Risk_Untreated_Chronic_Hyperthyroidism
Risk_Rheumatoid_Arthritis
Risk_Osteogenesis_Imperfecta
Risk_Type_1_Insulin_Dependent_Diabetes
Concom_Viral_Vaccines
Concom_Anaesthetics_General
Concom_Broad_Spectrum_Penicillins
Concom_Macrolides_And_Similar_Types
Concom_Cephalosporins
Concom_Fluoroquinolones
Concom_Anti_Depressants_And_Mood_Stabilisers
Concom_Systemic_Corticosteroids_Plain
Concom_Narcotics
Concom_Cholesterol_And_Triglyceride_Regulating_Preparations
Comorb_Gastro_esophageal_reflux_disease
Comorb_Personal_history_of_malignant_neoplasm
Comorb_Osteoporosis_without_current_pathological_fracture
Ptid
0%
−0.04
−0.02
0.00
0.02
0.04

Skrewed Histogram





EDA Summary

- We tried many ways to learn the permanence of the drugs on the patient, and as a result of the necessary analyzes, the effect of factors such as race, gender, origin was better understood. Apart from these, although there are many different factors, we achieved good results with a very good margin of precision as a result of the data we have.

Model Building

- Categorical data were converted into numerical data.
- Tree Classifier, Random Forest Classifier and LightGBM Classifier regression techniques were used.

Final Recommendation

- The Random Forest Classifier model is the most suitable model because it has the highest accuracy rate.

- It will give the best results in persistent and non-persistent drug effects compared to other models.