Week 9: Problem Understanding

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Project Life Cycle

Tasks	**08/11/2021** **Week 0**	**15/11/2021** **Week 1**	**22/11/2021** **Week 2**	**29/11/2021** **Week 3**	**6/12/2021** **Week 4**
Week 7	🟩				
Week 8		🟩			
Week 9					
Week 10			🟩		
Week 11				🟩	
Week 12				🟩	🟩

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.

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.

Data Intake Report

Name: Health care- Data Science Specialization
Report date: 5 November 2021
Internship Batch: LISUM04
Version:1.0
Data intake by: Seyedeh Marzieh Hosseini
Data intake reviewer: Bao Khanh Nguyen
Data storage location:

Tabular data details: https://github.com/Khanhbao8695/HealthCar_DS2021

Total number of observations	3424
Total number of files	1
Total number of features	69
Base format of the file	xlsx
Size of the data	898KB

GitHub Repository:

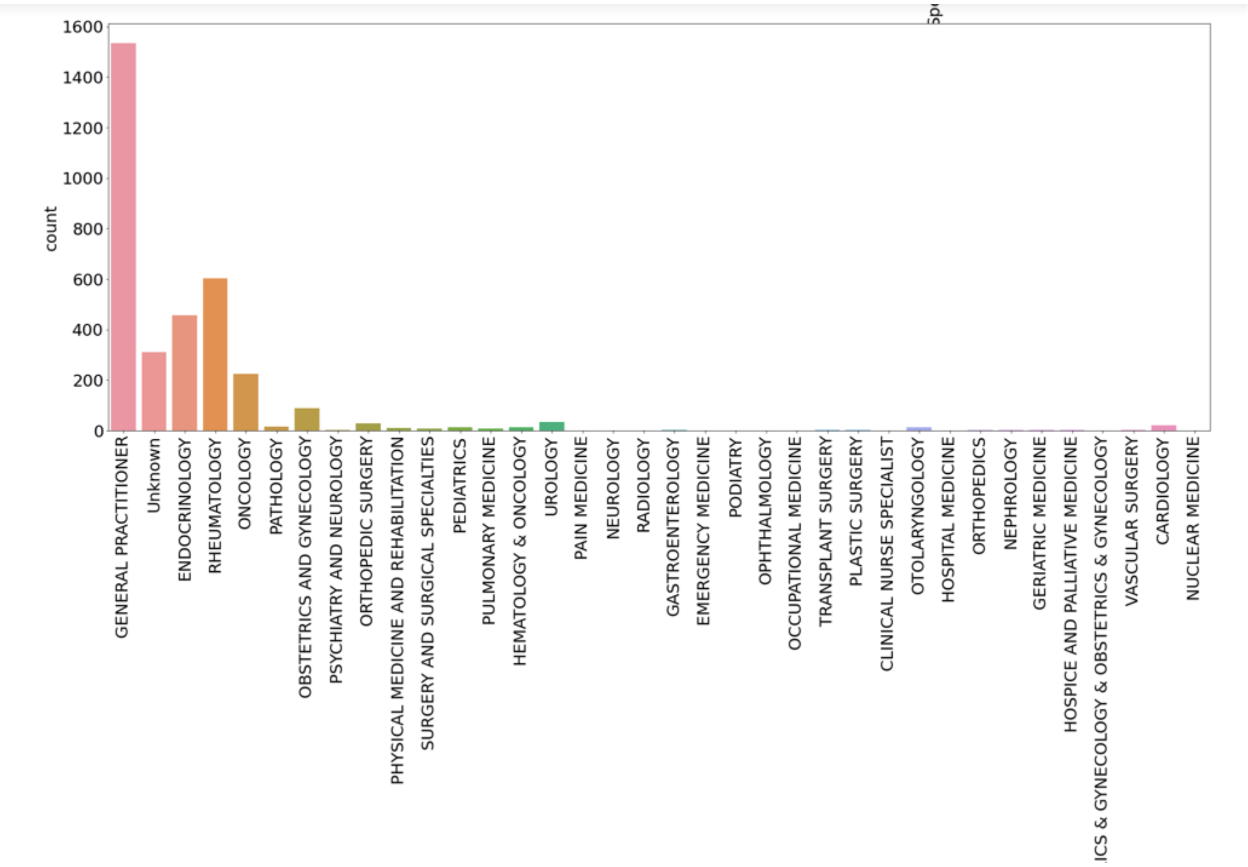
Project Link: https://github.com/Khanhbao8695/HealthCar_DS2021

Data Types

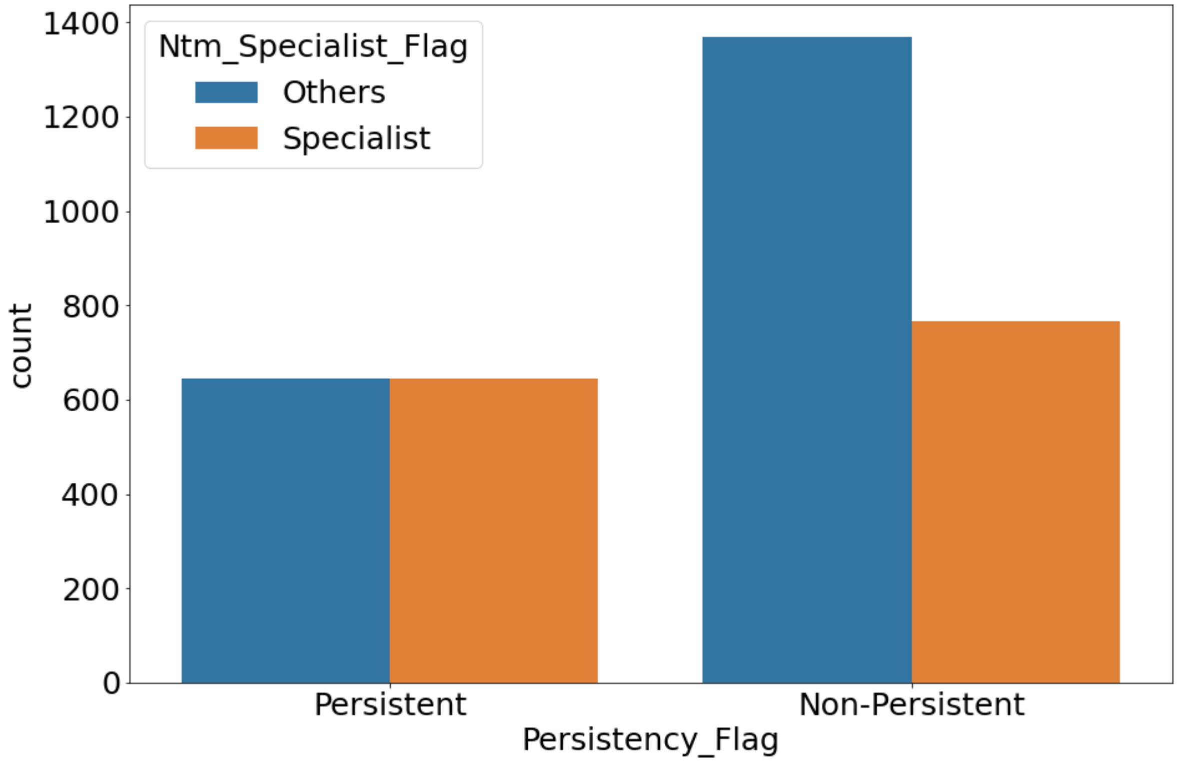
There are 69 features in this dataset from more than 3424 inputs. The majority of the data types in this dataset are "object" types with more than 67 features and only 2 features are “inte64” data type.

Data Problems

There are 69 features in this dataset and about 3424 rows. The majority of the data types in this dataset are "object" types with about 69 features and only 2 features are “inte64” data type. The first problem with the dataset is the high number of categorical columns. Therefore it is important to drop few columns that does not seem to impact the persistency factor to high extent. One example would be the NTM_Speciality features which are three similar columns, Ntm_Speciality, Ntm_Specialist_Flag and Ntm_Speciality_Bucket. These columns are about the speciality of the person who prescribes the drug. Further investigation of feature Ntm_speciality shows the number of general practitioner is very high compared to other specialists and other specialits does not play that much of role.



However, since there are three columns with similar information, its better to keep one. Additionally, its not clear if the speciality of the person who prescribed the medicine, is related to the persistency of drug. To investigate this, we plot the persistency and non_persistency of NTM_speciality flag. As can be seen in the second plot, the persistency is the same for the others and specialist flags. However, non-persistency is higher for other practioners than specialist. So to not lose additional information, we keep the NTM_speciality_flag .



Data cleaning

For numerical variables, the two columns, Dexa_Freq_During_Rx and the column Count_Of_Risks, contains outliers and skewness as shown in the figures that need to be taken into account.

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6.8087302112992285
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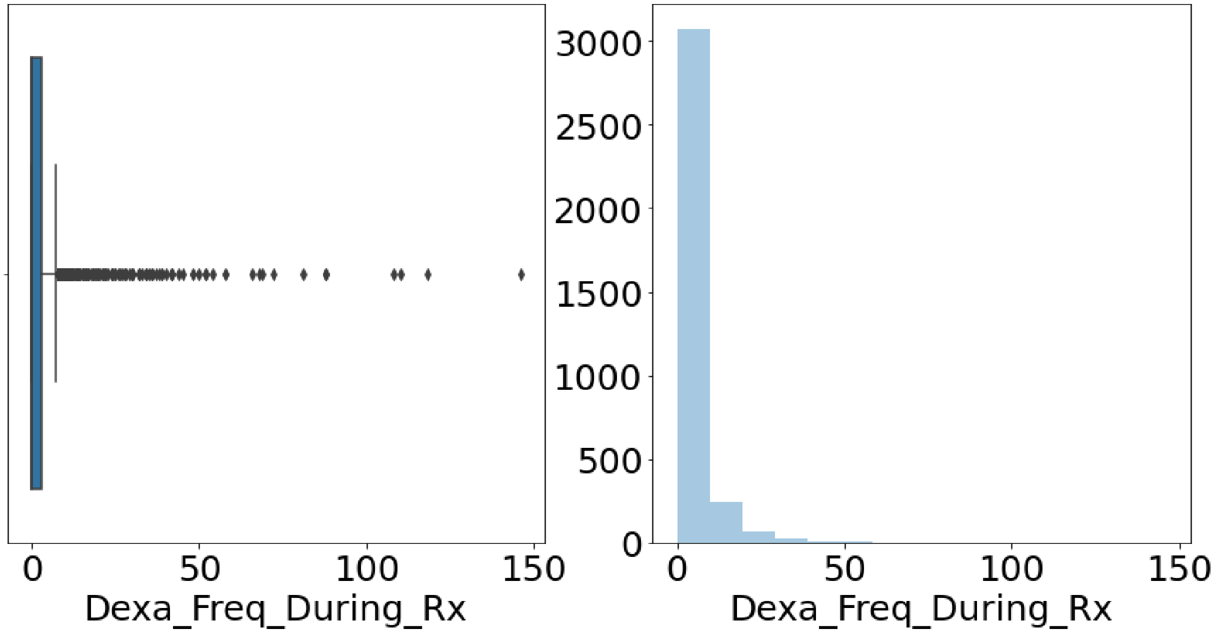
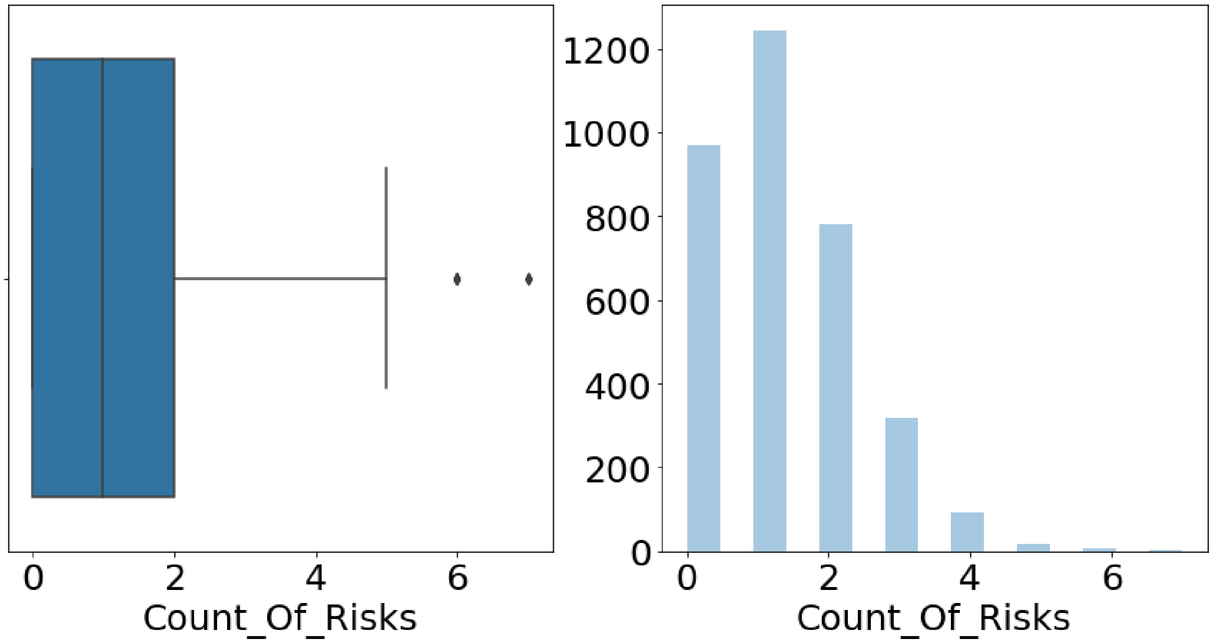


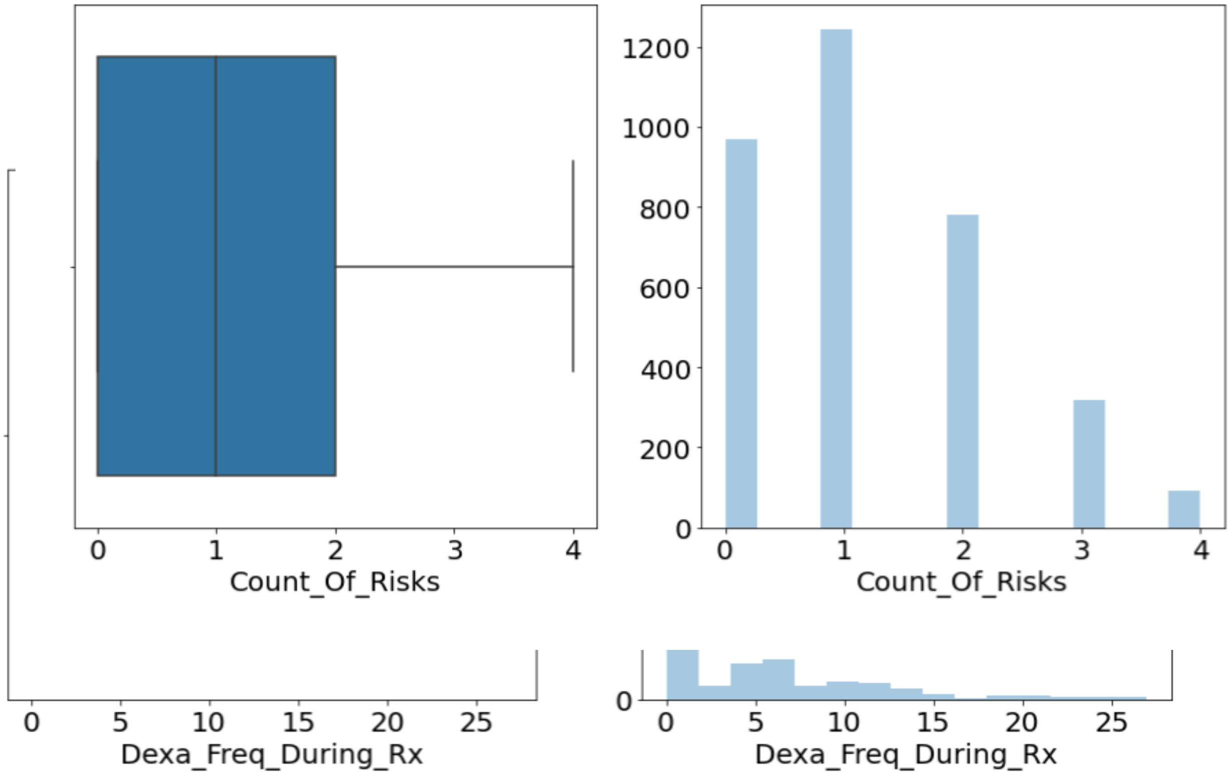
Additionally, for the Count_of_risks column, there are outliers as well.



Remove Outliers

My first approach is to use Z scores to remove outliers from count of risks and Dexa_Freq_During_Rx columns. Z score finds the relationship of each data point with standard deviation and mean of the group of data points. So Z score rescales data and look for data points which are too far from zero. However, this method did not get ride of the all of outliers in the Dexa_Freq_During_Rx column. As shown in the figure, there are still few outliers left

However, for the column count of risks, this method worked reasonably well as shown here.



IQR method

The second approach I used to remove the outliers, is the IQR method. The interquartile range is calculated in much the same way as the range. All one find is subtract the first quartile from the third quartile: IQR = Q3 – Q1. The interquartile range shows how the data is spread about the median. Anything outside of the range of (Q1 - 1.5 IQR) and (Q3 + 1.5 IQR) is considered an outlier and should be eliminated.

I applied this method on both columns, and the filtered dataset reduced to the 2964 rows at the end.