Data Science Intern at Data Glacier

Project: Healthcare - Persistency of a drug (Data Science)

Deliverables

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ALL SUBMITTED TO DATA GLACIERS				

Table of Contents:

1. Project Plan

WEEKS	DATE	PROGRESS
Week 7	July 19, 2023	Problem Statement and Data Processing
Week 8	July 26, 2023	Data preparation, Input and output
Week 9	Aug 2, 2023	Analysis
Week 10	Aug 9, 2023	
Week 11	Aug 16, 2023	EDA Presentation and proposed model technique
Week 12	Aug 23, 2023	Model Selection
Week 13	Aug 30, 2023	Final project report and code

2. Problem Statement

The pharmaceutical industry faces numerous challenges in understanding the persistency of drugs as per physician prescriptions. Ensuring that patients adhere to prescribed medications is crucial for their health outcomes and overall treatment effectiveness. However, non-adherence to prescribed medications can lead to suboptimal results, increased healthcare costs, and potential complications. To address this critical issue, ABC pharma company has decided to take a data-driven approach and has approached us to automate the process of identifying factors impacting drug persistency.

Our task is to analyze a comprehensive dataset containing a diverse set of variables related to patient demographics, provider attributes, clinical factors, disease/treatment factors, comorbidities, concomitancy, and adherence information. The primary objective is to gather insights and build a robust classification model that predicts whether a patient will exhibit persistency with the prescribed drug or not. The target variable, "Persistency_Flag," will serve as the ground truth for this classification task, where it is coded as 1 if the patient is persistent and 0 if the patient is nonpersistent between variables. Then build a model that classifies the dataset.

3. Data Collection

Healthcare_dataset.xlsx –

Total number of observations	27
Total number of files	2 – Feature Description and SDataset
Total number of features	27 & 3424
Base format of the file	xlsx
Size of the data	920kb

There was no missing values

4. Data Preparation

4.1 Data Manipulation - After collecting the data, we noticed that there is 'N' and 'Y' for most of the one-hot encoding categorical value, it needs to change to 0 and 1 in the following step to get an accurate overview of the data.

Before

```
data = pd.read_csv(sensitive_data_file)
data.head()
```

f_Osteoporosis	Risk_Low_Calcium_Intake	Risk_Vitamin_D_Insufficiency	Risk_Poor_Health_Frailty	Risk_Excessive_Thinness	Risk_
N	N	N	N	N	
N	N	N	N	N	
N	Y	N	N	N	
N	N	N	N	N	
N	N	N	N	N	

After

```
data = data.replace('N', 0)
data = data.replace('Y', 1)
data.head()
```

k_Family_History_Of_Osteoporosis	Risk_Low_Calcium_Intake	Risk_Vitamin_D_Insufficiency	Risk_Poor_Health_Frailty	Risk_Excess
0	0	0	0	
0	0	0	0	
0	1	0	0	
0	0	0	0	
0	0	0	0	

4.2 Data Verification – After manipulating the data to getting an accurate view of our data, we verified the data types and check for any duplicate value(s)

```
[ ]  # Check if there are any duplicate values:

     duplicates = data.duplicated()

     if duplicates.any():
         print("Duplicates exist in the DataFrame.")
     else:
         print("No duplicates found in the DataFrame.")

     No duplicates found in the DataFrame.

[ ]  # Double check if there are any null (NA) values:

     Null_Values = data.isnull().sum()

     if Null_Values.any():
         print("Null values exist in the DataFrame.")
     else:
         print("No null values exist in the DataFrame.")

     No null values exist in the DataFrame.
```

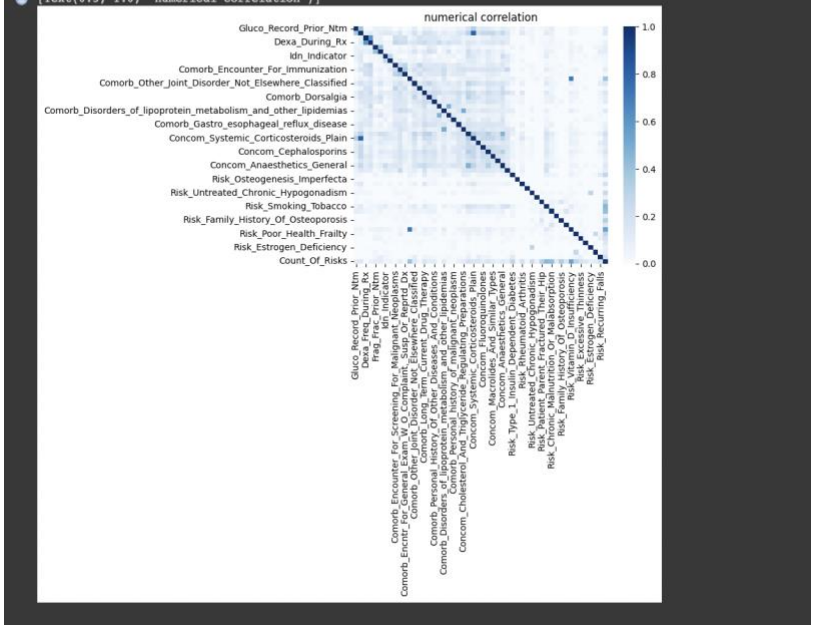
5. Analysis

To properly classify our data, we analyzed our dataset to have a deeper understanding of each category to give us a better approach to building our model. We analyzed the data into four different categories.

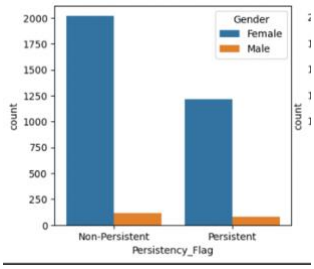
5.1 Numerical Values Analysis

Numerical Values Analysis

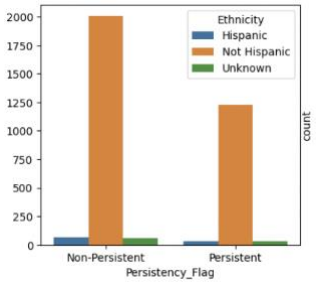
```
[ ] numerical = [col for col in data.columns if data[col].dtype == 'int64']
    data_numerical = data[numerical]

    sns.heatmap(data_numerical.corr(),cmap='Blues',vmin=0,vmax=1).set(title='numerical correlation')

    [Text(0.5, 1.0, 'numerical correlation')]
```



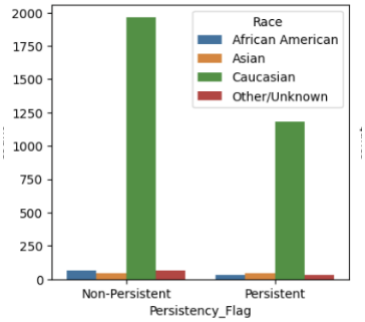
5.2 Patient Demographic Analysis – We grouped the patients by their gender, Ethnicity, Race, Region, and Age then plotted a graph for better visualization.



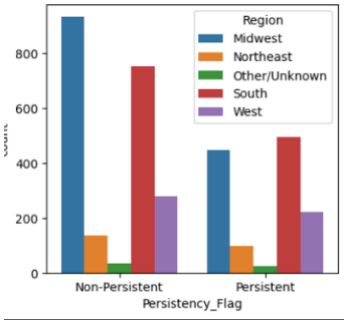
Gender



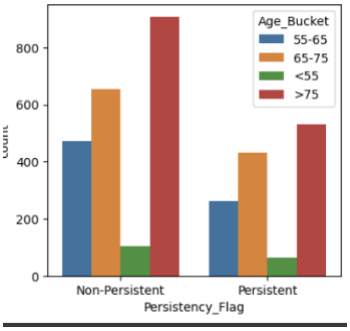
Ethnicity



Race



Region



Age

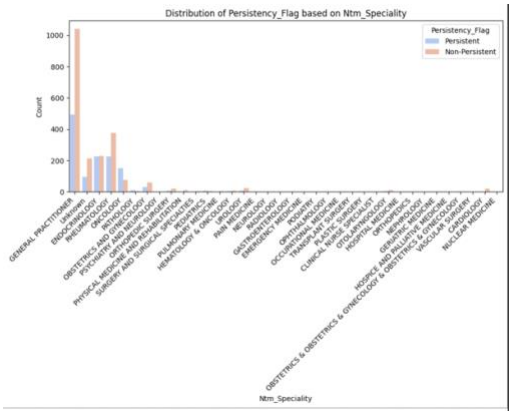
Findings

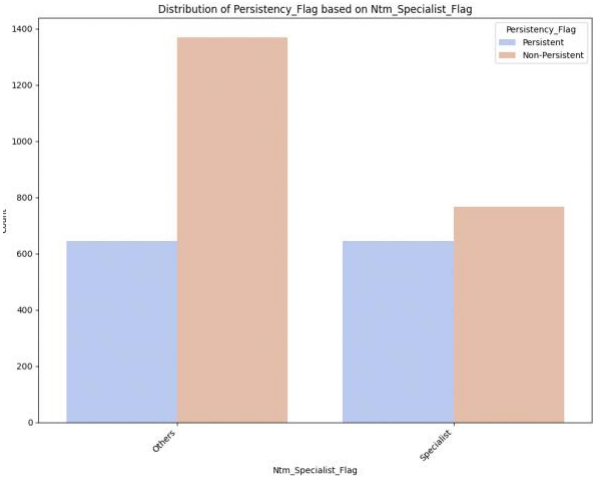
Based on the graphs above:
1) There is higher persistency and non-persistency counts in Females than in Males with non-persistency being higher.
2) There is higher persistency and non-persistency counts in Caucasians among all other races with non-persistency being higher.
3) There is higher persistency and non-persistency counts in Non-Hispanic people among all other ethnicities with non-persistency being higher.
4) The highest persistency counts in order among regions is in the South, Midwest, and West regions. And the highest non-persistency counts in order is in the Midwest, South, and West regions.
5) The highest persistency and non-persistency counts in order are among patients of the following age groups: >75, 65-75, and 55-65.

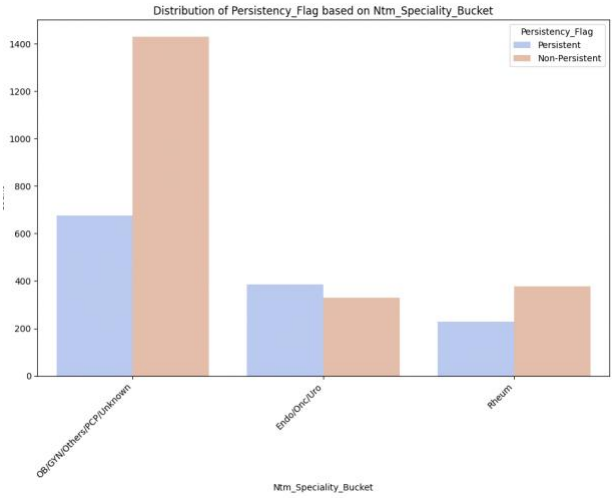
5.3 Physician/Provider Analysis - NTM Rx is the medication prescribed by the physician.

- Ntm_Speciality: Physician Specialty
- Ntm_Specialist_Flag: If physician is a specialist or not.
- Ntm_Speciality_Bucket: has 3 separate groups:
    - OB/GYN/Others/PCP/Unknown = Obstetrics and Gynecology, other specialties, Primary Care Physicians, and those of unknown specialty.
    - Endo/Onc/Uro: Endocrinology, Oncology, and Urology
    - Rheu: Rheumatology

We plotted three graphs to check if the physician's categorical features impact the persistency flag based on the categories above







FINDINGS

According to the graphs above:

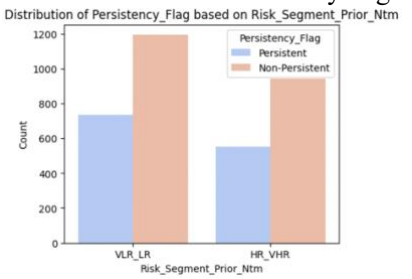
1) The highest non-persistency and persistency counts among patients occurred with those whose providers are general practitioners and rheumatologists with endocrinologists and unknown specialties coming next.
2) The highest non-persistency and persistency counts also occurred among patients whose providers' flag was categorized as non-specialists.
3) The highest non-persistency and persistency counts also occurred among patients whose providers' bucket was categorized as OB/GYN/Others/PCP/Unknown.

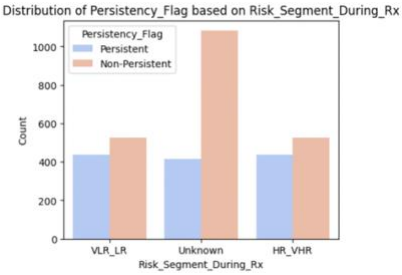
Based on this information, it's hard to detect what specialty led to the most non-persistency. However, generally, those who were general practitioners or non-specialists had higher non-persistency patient counts.

5.4 Risk Factors and Change, Adherence to Therapy, & T-score Change Analysis

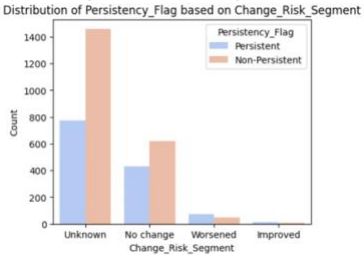
With this analysis, we looked for other factors that may influence target variable and plotted their graphs to visualize them. They include.

- Risk_Segment_Prior_Ntm & Risk_Segment_During_Rx: The risk segment of patients before they started their treatment (prior to receiving the NTM medication) with VLR_LR and HR_VHR representing Very Low Risk/Low Risk and Very High Risk/High Risk respectively.

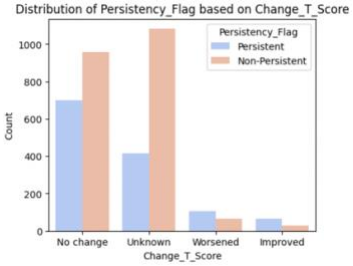




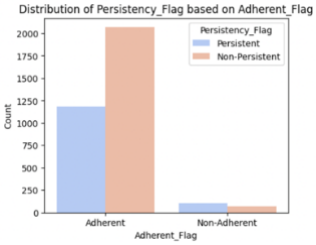
- Change_Risk_Segment: If there was any change in Risk Segment.



- Change_T_Score: The T-score is a measurement used to assess bone density in the context of osteoporosis. This value indicates the change in the patient's bone density relative to that of a healthy adult.



- Adherent Flag: Adherence status of patients to their prescribed therapies and whether they followed the prescribed medication.



FINDINGS

According to graphs above:

1) There are higher non-persistency counts among patients who have low risk factors prior to taking their medication.

2) There are higher non-persistency counts among patients who have low risk and unknown factors during taking their medication.

3) Both the change in risk segment and the change in T-score are mostly either unknown or had no change with the count being higher for patients who were non-persistent.

4) Although many patients were adherent to their medication, there was still higher non-persistency among them.