

Exploratory Data Analysis and Proposed Modeling Technique

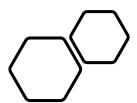
Healthcare – Persistency of a drug



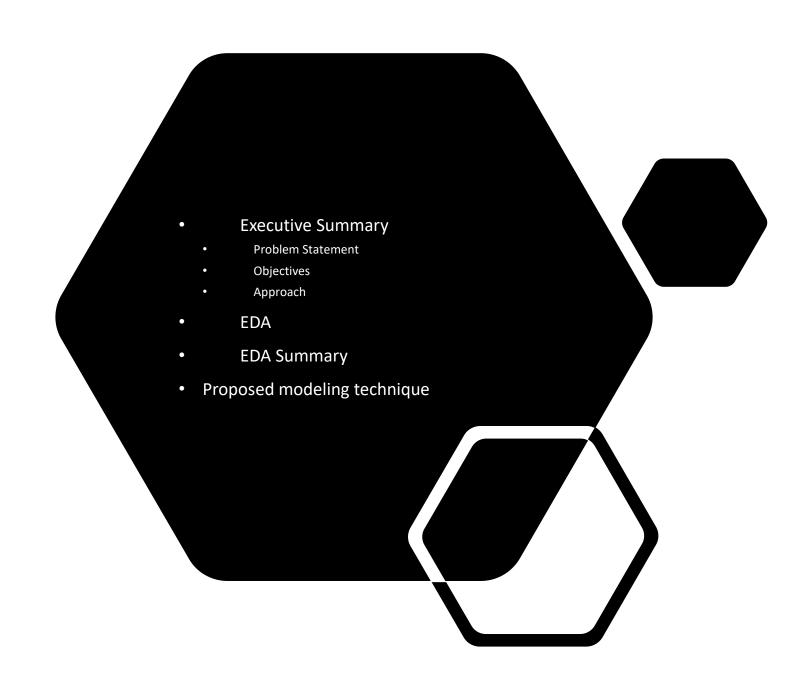
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Group FTR

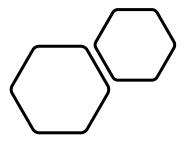
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Agenda



Executive Summary



Problem statement

• One of the challenge for all Pharmaceutical companies is to understand the persistency of drugs as per the physician prescription. To solve this problem ABC pharma company would like the process Automated.

Objectives

• The overall aim of the analysis part of the project is to provide insights into factors that impact the persistency of drugs, which afterwards will lay the foundation on building a suitable classification model and also propose some modelling technique to be used.

Approach

- Understanding the dataset
- Identifying the most impactful factors
- Making recommendations.
- Proposed modeling technique



Data Understanding						
data.head()		Bucket Variable Unique Row Id Patient ID	Variable Description Unique ID of each patient			
		Target Variable Persistency_Flag	Flag indicating if a patient was persistent or not			
Ptid Persistency_Flag Gender Race Ethnicity Region / P1 Persistent Male Caucasian Not Hispanic West	Age_Bucket Ntm_Speciality Ntm_Specialist_Flag Ntm_Speciality_Bucket Risk_Family_History_0 >75 GENERAL PRACTITIONER Others OB/GYN/Others/PCP/Unknown	Race Region	Age of the patient during their therapy Race of the patient from the patient table Region of the patient from the patient table			
Hispanic	PRACITIONER	Demographics Ethnicity	Ethnicity of the patient from the patient table			
1 P2 Non-Persistent Male Asian Not Hispanic West	55-65 GENERAL Others OB/GYN/Others/PCP/Unknown Others OB/GYN/Others/PCP/Unknown	Gender IDN Indicator	Gender of the patient from the patient table Flag indicating patients mapped to IDN			
2 P3 Non-Persistent Female Other/Unknown Hispanic Midwest	65-75 GENERAL Others OB/GYN/Others/PCP/Unknown	Provider Attributes NTM - Physician Specialty	Specialty of the HCP that prescribed the NTM Rx			
	PRACIIIONER	NTM - T-Score	T Score of the patient at the time of the NTM Rx (within 2 years prior from rxdate)			
3 P4 Non-Persistent Female Caucasian Not Hispanic Midwest	>75 GENERAL Others OB/GYN/Others/PCP/Unknown GENERAL OUT OB/GYN/Others/PCP/Unknown	Change in T Score	Change in Tscore before starting with any therapy and after receiving therapy (Worsened, Remained Same, Improved, Unknown)			
4 P5 Non-Persistent Female Caucasian Hispanic Mildwest	>75 OCHARIAL Others OB/GYN/Others/PCP/Unknown	NTM - Risk Segment	Risk Segment of the patient at the time of the NTM Rx (within 2 years days prior from rxdate)			
5 rows × 69 columns		Change in Risk Segment	Change in Risk Segment before starting with any therapy and after receiving therapy (Worsened, Remained Same, Improved, Unknown)			
		NTM - Multiple Risk Factors	Flag indicating if patient falls under multiple risk category (having more than 1 risk) at the time of the NTM Rx (within 365 days prior from rxdate)			
		NTM - Dexa Scan Frequency Clinical Factors	Number of DEXA scans taken prior to the first NTM Rx date (within 365 days prior from rxdate)			
		NTM - Dexa Scan Recency	Flag indicating the presence of Dexa Scan before the NTM Rx (within 2 years prior from rxdate or between their first Rx and Switched Rx; whichever is smaller and applicable)			
		Dexa During Therapy	Flag indicating if the patient had a Dexa Scan during their first continuous therapy			
		NTM - Fragility Fracture Recency	Flag indicating if the patient had a recent fragility fracture (within 365 days prior from rxdate)			
		Fragility Fracture During Therapy	Flag indicating if the patient had fragility fracture during their first continuous therapy			

 The dataset contains 3424 rows and 69 columns.



Disease/Treatment Factor and chronic, based on the ICD codes. For chronic disease NTM - Comorbidity we are taking complete look back from the first Rx date of NTM therapy and for acute diseases, time period before the NTM OP Rx with one year lookback has been applied

NTM - Glucocorticoid Recency

NTM - Injectable Experience

NTM - Risk Factors

Glucocorticoid Usage During Therapy

Concomitant drugs recorded prior to starting with a NTM - Concomitancy therapy(within 365 days prior from first rxdate)

first OP Rx

Flag indicating usage of Glucocorticoids (>=7.5mg strength)

Flag indicating if the patient had a Glucocorticoid usage

Flag indicating any injectable drug usage in the recent 12

Risk Factors that the patient is falling into. For chronic Risk Factors complete lookback to be applied and for non-

chronic Risk Factors, one year lookback from the date of

Comorbidities are divided into two main categories - Acute

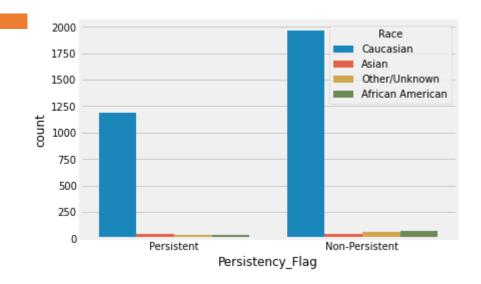
in the one year look-back from the first NTM Rx

during the first continuous therapy

months before the NTM OP Rx

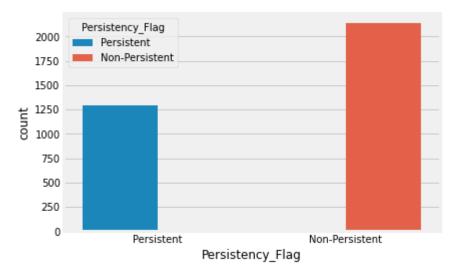
Adherence Adherence for the therapies

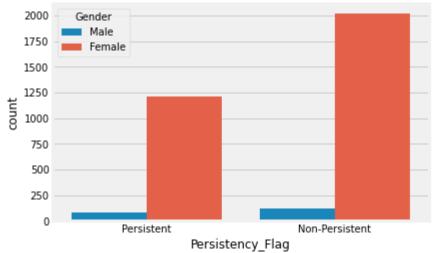
Exploratory data analysis



- The number of cases where the drugs proved to be nonpersistent were higher compared to number od persistency cases.
- The dataset reveal that more females partook in this analysis than male.
- People of Caucasian race when compered to other races were the most common in the study.





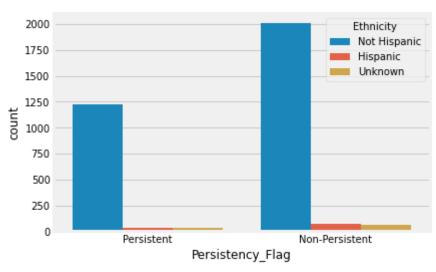


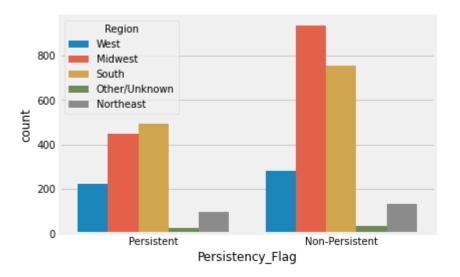


- The non-Hispanic ethnic group were the most common in the study.
- There were more people from the Midwest and South region compared to other regions.

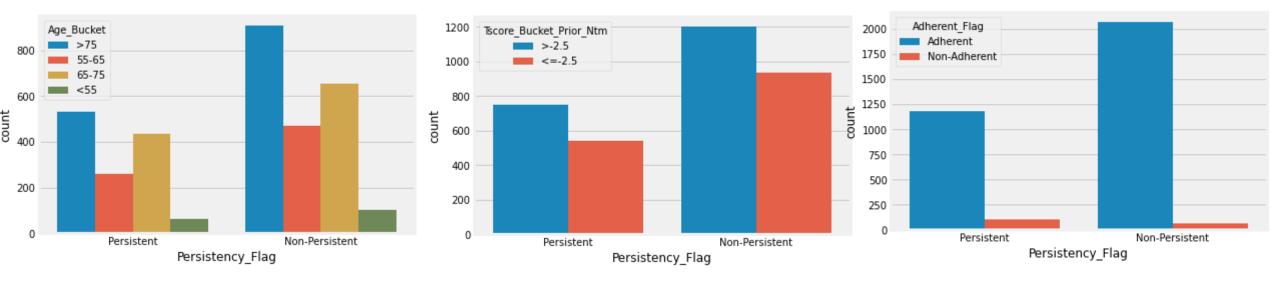
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Exploratory data analysis

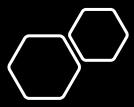




Exploratory data analysis

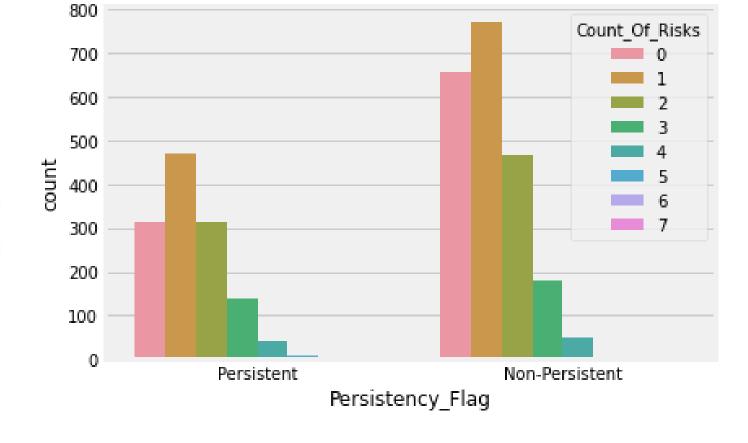


- For this study, the majority of people selected are greater than 75 years of age.
- People with a Tscore of >-2.5 have a higher chance of drug being non-persistent.





Exploratory data analysis



 The chart reveals people with a lower count of risk have a higher chance of drug being nonpersistent.





Summary and recommendation

EDA SUMMARY

- The dataset contains 3424 rows and 69 columns.
- The number of cases where the drugs proved to be non-persistent were higher compared to number od persistency cases.
- The dataset reveal that more females partook in this analysis than male.
- People of Caucasian race when compered to other races were the most common in the study.
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- For this study, most people selected are greater than 75 years of age.
- People with a Tscore of >-2.5 have a higher chance of drug being non-persistent.





Proposed modeling technique

The project is aimed at using certain factors relative to a patient in classifying successfully whether a drug is persistent or not. From the machine learning aspect of things, the task is a classification task and a binary classification task to be specific. For this project, we will focus on state-of-the-art machine learning classification models to build our drug persistency classifier. They include:

- 1. Logistic regression model
- 2. Support vector machines (SVM)
- 3. K-nearest neighbours (KNN)
- 4. Gradient Boost model





• Github Repo link: Ovuowo-Rukevwe/-Healthcare-Persistency-of-a-Drug (github.com)

Repository details



Thank You

