



# Data Science Project

**Project:** Healthcare - Persistency of a Drug  
**Week 10 Deliverables**

**Team Name:** Team Healthy Bones

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**Batch Code:** LISUM 10

**Country:** United States of America

**Specialization:** Data Science

**Submission Date:** August 9, 2022

**Submitted to:** Data Glacier

**Github Link:** [https://github.com/shonjeeyeon/DG\\_Week\\_10](https://github.com/shonjeeyeon/DG_Week_10)

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## Problem Description

A model will be established and deployed to automate identifying persistency of a certain pharmaceutical product.

Data of patients who take the medication will be used for analysis, and correlation between medication persistency and other factors such as patient demographics, provider attributes, clinical factors, and disease/treatment factors will be investigated. Finally, an optimal model to predict persistency based on above features will be developed.

## Data Understanding

The dataset includes 3,424 records of patients on a certain medication. 69 features pertaining the demographics of the patient, attributes of the prescriber, and clinical/disease/treatment factors of the disease progression are present.

The client requested to build a model to predict a patient's drug persistency, so the column 'Persistent' will be the target variable. The prediction will use a classification process since the values of the target column are binary ('Persistent' vs. 'Non-Persistent')

## Link to the Repository

[https://github.com/shonjeeyeon/DG\\_Week\\_10](https://github.com/shonjeeyeon/DG_Week_10)

# Exploratory Data Analysis (EDA)

## Summary of Actions

- Prior to EDA, 'risk', 'concom', and 'comorb' columns were added.
  - These columns refer to each patient's sum of risk factors, concomitant treatments, and comorbidities. ('Y's and 'N's were converted to 1 and 0 prior to the calculation)
  - There are a substantial number of risks, concomitances, and comorbidities listed in the dataset. Moreover, relatively small portion of patients has each of the conditions.
  - Therefore, incorporating the features in larger groups might help reduce computational efforts and improve predictability.
  - The original features used in the calculations will be maintained because some of the conditions may contribute more to the persistency compared to the rest of the condition.
- Count plots, violin plots and box plots were plotted with hue=persistency\_flag to compare count, mean, and range of values between persistent and non-persistent populations.

## Findings

- Persistent group has higher mean number of comorbidities and concomitances compared to the non-persistent counterpart.
- Patient groups who have had concomitant encounters for below reasons have higher persistency levels:
  - General exam without complaints
  - Immunizations
- Patients who have cancer have higher persistency level.
- Persistent group has higher mean number of DEXA scans compared to the non-persistent group. Persistent group also has higher proportion of patient who has had at least one DEXA scan compared to non-persistent group.
- Prescribers with certain specializations (e.g. Oncology and Endocrinology) have higher proportion of persistent patients compared to the others.

## **Model Recommendations**

- This is a classification project, so using classifiers such as Linear Regression Classifier, Naive Bayes, K-Neighbors, Random Forest Classifier, Support Vector Machines, or XGBoost is recommended.
- To save computational efforts, starting from simple Linear Regression then trying kernel or ensemble models is recommended.
- The dataset has a substantial number of features, so using PCA or RFE to choose most important features is recommended.

# Data Intake Report

Name: Healthcare – Persistency of a Drug

Report date: August 9, 2022

Internship Batch: LISUM 10

Version:<1.0>

Data intake by: Jeeyeon Shon

Data intake reviewer:

Data storage location:

[https://github.com/shonjeeyeon/DG\\_Week\\_8/blob/main/Healthcare\\_dataset.csv](https://github.com/shonjeeyeon/DG_Week_8/blob/main/Healthcare_dataset.csv)

(Original xlsx file:

[https://drive.google.com/file/d/1P\\_oMc6gOBlhW6dY5PxaqxV2swdHMuooK/view](https://drive.google.com/file/d/1P_oMc6gOBlhW6dY5PxaqxV2swdHMuooK/view))

## Tabular data details:

Healthcare\_dataset.csv

<b>Total number of observations</b>	3,424
<b>Total number of files</b>	1
<b>Total number of features</b>	69
<b>Base format of the file</b>	.csv
<b>Size of the data</b>	892 KB

## Proposed Approach:

- Ptid can be used to identify and remove duplicate observations
- The dataset has been deidentified already
- No missing values, however there are practical missing values such as 'unknown'. These values should be imputed appropriately
- Most of the features are categorical; will need encoding to enable ML

## Summary of Columns and Data Types

Bucket	Variable	index #	Dtype	Notes
Target	Persistency	1	Object	Non-Persistent: 62.35% Persistent: 37.65% (→ Imbalanced data)
Unique Row ID	Patient ID	0		
Demographics	Gender	2		
	Race	3		NaN='Other/Unknown' (2.85%) Mode='Caucasian' (91.94%)
	Ethnicity	4		NaN='Unknown' (2.66%) Mode='Non-Hispanic' (94.48%)
	Region	5		NaN='Other/Unknown' (1.75%) Mode='Midwest' (40.39%)
	Age Bucket	6		
Prescriber Attributes	Ntm_Speciality	7		NaN='Unknown' (9.05%) Mode='General Practitioner' (44.83%)
	Ntm_Specialist_Flag	8		

	Ntm_Speciality_Bucket	9																		
Clinical Factors	Gluco_Record_Prior_Ntm	10																		
	Gluco_Record_During_Rx	11																		
	Dexa_Freq_During_Rx	12	int64	<ul style="list-style-type: none"><li>• Outlier issues</li><li>• The data is <b>skewed</b> (6.81)</li></ul> <table><tr><td>Count</td><td>3,424</td></tr><tr><td>Mean</td><td>3.02</td></tr><tr><td>Std</td><td>8.14</td></tr><tr><td>Min</td><td>0.00</td></tr><tr><td>25%</td><td>0.00</td></tr><tr><td>50%</td><td>0.00</td></tr><tr><td>75%</td><td>3.00</td></tr><tr><td>Max</td><td>146.00</td></tr></table>	Count	3,424	Mean	3.02	Std	8.14	Min	0.00	25%	0.00	50%	0.00	75%	3.00	Max	146.00
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Frag_Frac_Prior_Ntm	14																			
Frag_Frac_During_Rx	15																			
Risk_Segment_Prior_Ntm	16																			
Tscore_Bucket_Prior_Ntm	17																			
Risk_Segment_During_Rx	18		NaN='Unknown' (43.72%) The other two categories have very few differences in percentages																	



			HR_VHR	28.18%	
			VLR_LR	28.10%	
	Tscore_Bucket_During_Rx	19	NaN='Unknown' ( <b>43.72%</b> ) <b>The other two categories have very few differences in percentages</b>		
			<=-2.5	29.70%	
			>-2.5	26.56%	
	Change_T_Score	20	NaN='Unknown' ( <b>43.72%</b> ) Mode='No Change' (48.48%)		
	Change_Risk_Segment	21	NaN='Unknown' ( <b>65.01%</b> ) Mode='No Change' (30.72%)		
Disease/ Treatment Factors	Adherent_Flag	22			
	Idn_Indicator	23			
	Injectable_Experience_During_Rx	24			
	Comorbidities columns (Column names start with 'Comorb_')	25-38			
	Concomitant drugs use columns (Column names start with 'Concom_')	39-48			
	Risk factors columns	49-67			

	Count_of_Risks	68	Dtype: int64	<ul style="list-style-type: none"><li>• Outlier issues</li><li>• The data is <b>skewed</b> (0.88)</li></ul> <table><tr><td>Count</td><td>3,424</td></tr><tr><td>Mean</td><td>1.24</td></tr><tr><td>Std</td><td>1.09</td></tr><tr><td>Min</td><td>0.00</td></tr><tr><td>25%</td><td>0.00</td></tr><tr><td>50%</td><td>1.00</td></tr><tr><td>75%</td><td>2.00</td></tr><tr><td>Max</td><td>7.00</td></tr></table>	Count	3,424	Mean	1.24	Std	1.09	Min	0.00	25%	0.00	50%	1.00	75%	2.00	Max	7.00
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## Problems and Suggested Actions

Problem	Column	Details	Actions Taken	Rationale
Missing Data	Race	NaN='Other/Unknown' (2.85%) Mode='Caucasian' (91.94%)	Impute mode	The Modes are high in proportion while the NaNs are relatively small in proportion.
	Ethnicity	NaN='Unknown' (2.66%) Mode='Non-Hispanic' (94.48%)		
	Region	NaN='Other/Unknown' (1.75%) Mode='Midwest' (40.39%)		
	Ntm_Speciality	NaN='Unknown' (9.05%) Mode='General Practitioner' (44.83%)	Keep 'Unknown' as a separate value	The value 'Unknown' is relatively high in proportion (9.05%), while the category has many values with smaller proportions (as small as <1%). Therefore, it will be

				prudent to leave the unknown as it is.
>40% Missing Data	Risk_Segment_During_Rx	NaN='Unknown' (43.72%)	Delete columns	The columns have very high proportion of 'Unknown'. Imputation may cause serious distortion of the data.
	Tscore_Bucket_During_Rx	NaN='Unknown' (43.72%)		
	Change_T_Score	NaN='Unknown' (43.72%)		
	Change_Risk_Segment	NaN='Unknown' (65.01%)		
Outliers/ Skews	Dexa_Freq_During_Rx	<ul style="list-style-type: none"> <li>• Outlier issues</li> <li>• The data is <b>skewed</b> (6.81)</li> </ul>	Remove outliers, and try skewness reduction strategies as needed	<p>Outliers were removed using quantiles and it reduced the skewness. Then, square root was used to additionally reduce skew.</p> <p>Skews after above steps are: 1.28 for Dexa_Freq_During_Rx, and 0.38 for Count_of_Risks</p>
	Count_of_Risks	<ul style="list-style-type: none"> <li>• Outlier issues</li> <li>• The data is <b>skewed</b> (0.88)</li> </ul>		

Basic Cleaning	All columns	Will need to remove upper cases, special characters, or spaces	Use df.replace() to clean the column names	df.replace() used to remove upper cases, special characters, and spaces
Typo in Value	Ntm_Speciality	'OBSTETRICS & OBSTETRICS & GYNECOLOGY & OBSTETRICS & GYNECOLOGY'	Use df.replace() to correct the value	Replaced with 'OBSTETRICS AND GYNECOLOGY'
Imbalanced Target Data	Persistency	Non-Persistent: 62.35% Persistent: 37.65%	Use SMOTE	SMOTE will be implemented during the process of model development
Encoding	Applies to every categorical column	Categorical values are written in alphabet, which ML cannot process	Label or one hot encoding	Values will be encoded after EDA