

Week 8 Deliverables

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Problem Description

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

Data Understanding

- The dataset provides the factors impacting the patient's persistence to New Therapy Medication (NTM) by ABC pharmaceutical company prescribed by various physicians.
- The aim is to build a machine-learning model that classifies the patient into Persistent (Compliant) and Non-persistent (Non-Compliant).
- The dataset consists of 3242 records and is a an imbalanced dataset due to low number of Persistent records as compared to Non-persistent.
- There are no missing values in the dataset, other than 'unknown' values.
- Among the independent features, there are 2 features Dexa_Freq_During_Rx and Count_Of_Risks, that have outliers.

Data Understanding

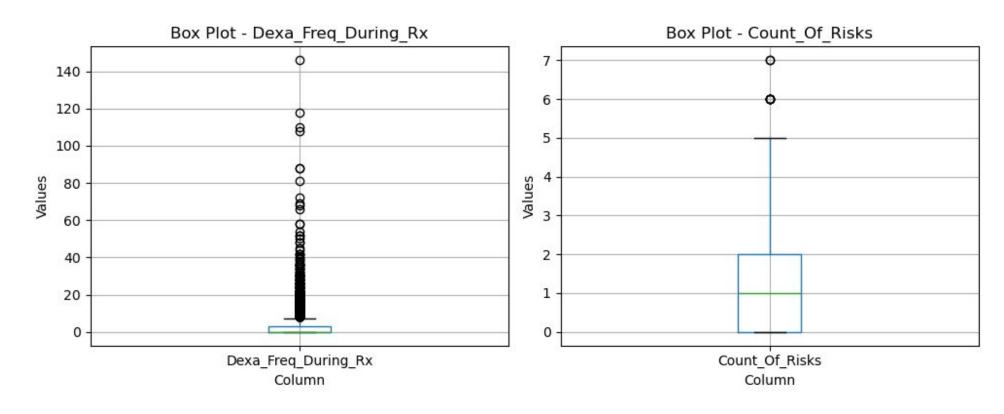
- The dataset contains a total of 69 features that are divided into multiple categories -
 - 1 Target variable: Persistency_Flag
 - 1 Unique identifier for each patient: Ptid
 - 6 Demographic variables of the each patient: Age_Bucket, Gender, Race, Ethnicity, Region,
 Idn_Indicator
 - 3 Physician Specialist attributes: Ntm_Speciality, Ntm_Specialist_Flag, Ntm_Specialist_Bucket
 - 13 Clinical factors: T-Score details, Risk_Segment details, Multiple risk factors count, DEXA details, Fragility fracture details, Glucocorticoid details
 - 45 Disease/Treatment factors: Injectable drugs, Risk factors, Comorbidities, Concomitancies,
 Adherence to therapy

Type of Data

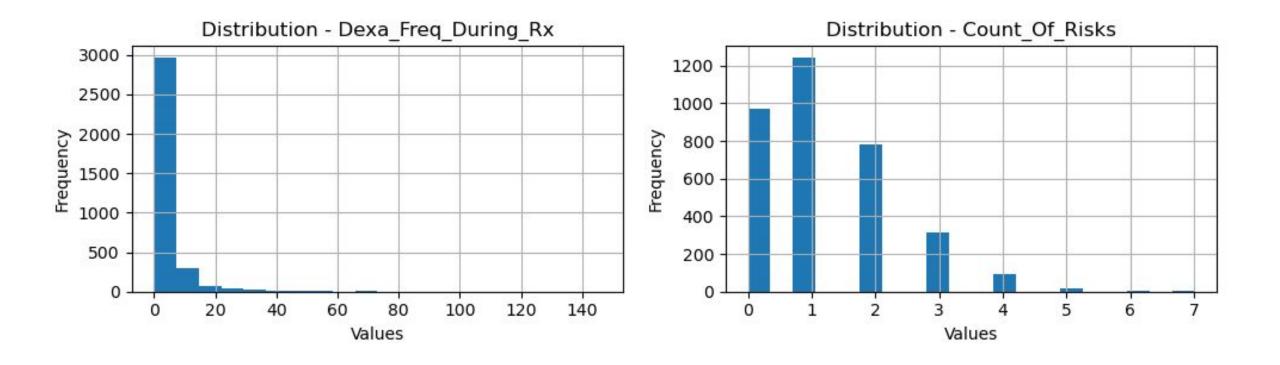
- The dataset contains high majority of categorical data rather than numerical data.
 - Categorical features: 66
 - Numerical features: 2
- Among the given features, 68 are independent variables and the target variable is the Persistency_Flag.

Problems in the Data - Outliers

- 2 of the features in the dataset contain outliers Dexa_Freq_During_Rx and Count_Of_Risks
- Data is positively skewed

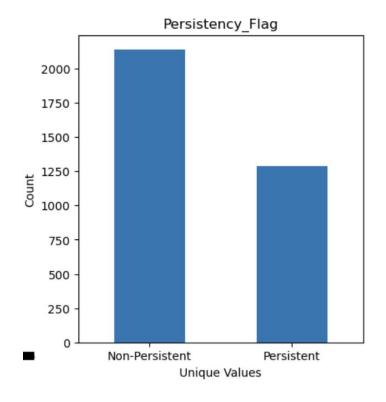


Problems in the Data - Outliers



Problems in the Data - Imbalance

• The target feature - *Persistency_Flag* is imbalanced with 2135 records **Persistent** and 1289 records **Non-persistent**.



Problems in the Data - Others

- NTM_Speciality feature has 36 unique categories.
- Count_Of_Risks feature has 8 unique values.
- Dexa_Freq_During_Rx has 58 unique values.

Handling Problems in Data

- Handling of outliers can be performed using below methods:
 - Winsorize This can be used to cap the lower and upper bound of the outliers.
 - Log Transformation Applying log to the data points will change the values but also help reduce skewness and make the data more normal.
 - Median Absolute Deviation(MAD) Approach is similar to Z-score but uses Median and Median Absolute Deviation statistics instead of Mean and Standard Deviation.
 - O **Box-Cox Transformation** Power transformation method that tries to stabilize variance and make the data more normally distributed. We can use the boxcox() method in python.
 - Square-root Transformation Takes the square root of each data point. It's often used to moderate right-skewed data and can make a more-normal distribution.
 - Inverse Transformation The inverse transformation is the reversal of a previous transformation, typically used to revert data to its original scale.

Handling Problems in Data (Continued)

- Since the dataset contains 2 different features for Physician specialist attribute, we can
 drop the Ntm_Speciality feature. We can use the Ntm_Speciality_Bucket feature as it
 consists of 3 different categories generalising the Ntm_Speciality feature.
- The different categories for *Count_Of_Risks* feature can be reduced to (0, 1, 2, 3 and >3) to reduce complexity.
- The values *Dexa_Freq_During_Rx* feature can be updated into different buckets (0 6], (6 12], (12 18], (18 24], (24 30] and (>30).
- The above 2 methods can also be considered as outlier handling methods.

Handling Problems in Data (Continued)

• Furthermore, to combat missing values in the Risk Segment during Rx column, we can take data from the Risk Segment Prior to Rx column. This is because, the taking the prescription and not taking it resulted in no change the majority (86%) of the time.

Handling Imbalanced Dataset

- Handling imbalanced dataset can be followed using below techniques -
 - Choose Appropriate Evaluation Metrics: Utilize proper evaluation metrics such as precision, recall, F1-score, etc. when training machine learning models. These metrics are particularly useful for imbalanced datasets as they consider both false positives and false negatives.
 - Resampling Techniques:
 - Oversampling and Undersampling: Balance the class distribution by either oversampling the minority class or undersampling the majority class.
 - Synthetic Minority Oversampling Technique (SMOTE): Apply SMOTE to generate synthetic instances of the minority class, creating a more balanced dataset. SMOTE helps mitigate the risk of overfitting on the original minority class.
 - Weighted Sampling: Implement weighted sampling during the training process. Assign higher weights to samples from the minority class to give them more influence during model training. This approach ensures that the model pays sufficient attention to the minority class.

Thank You

