

Final Presentation HEALTHCARE - PERSISTENCY OF A DRUG

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Agenda

Executive Summary

Problem Statement

Approach

Data Cleaning

EDA

EDA Summary

Models

Recommendations



Problem Statement

- To identify the persistency of a drug, a pharmaceutical company approached to develop a model based on data analysis.
- Factors that affect the persistence of drugs should be identified, along with data insights with predictive analytics, to help the company for their smooth and efficient functioning, with the help of dataset provided by the company.



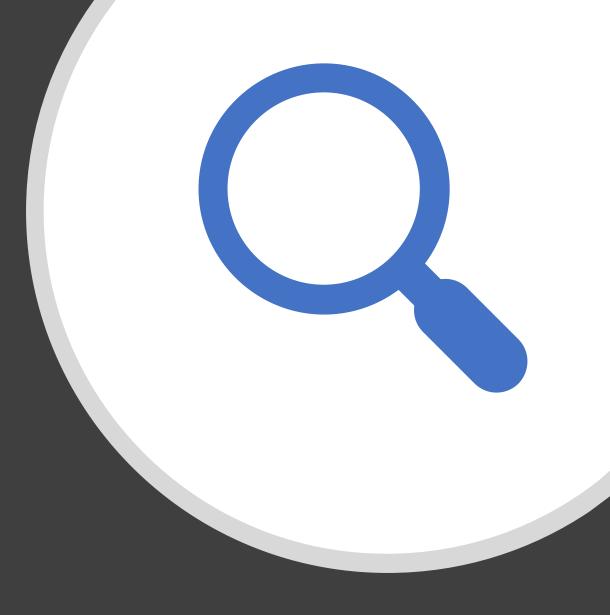
Approach

- Collect data
- Analyze the data
- Detect outliers
- Combine datasets
- Curate the data
- Feature engineering
- Detect correlations
- Analyze patterns
- Provide insights
- Tools used Microsoft Excel, Python, Microsoft Power BI



Data Cleaning

- Dataset details:
 - File name: Healthcare_dataset.xlsx
 - \triangleright No. of rows = 3424
 - \triangleright No. of columns = 69
 - Target variable = 'Persistency_Flag'
- There were no null values in the dataset.
- Some variables have large number of value counts, which is reduced by grouping same names, treating "Unknown" values, etc.
- A new dataset was created after data curation steps, with 2942 rows & 66 columns.

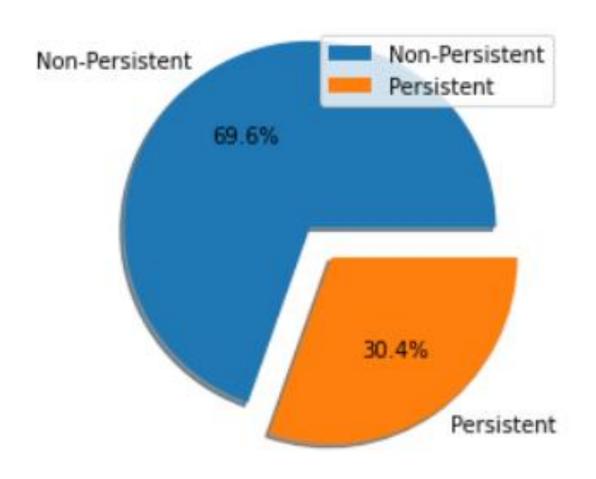


Exploratory Data Analysis

- 1. Basic Data Exploration
- 2. Demographic Analysis
 - Gender
 - > Age
 - Race
 - Region
 - > Ethnicity
- 3. Clinical Factors' Analysis
 - > T score
 - Risk Segment
 - Glucocorticoid Recency
 - Fragility Fracture Recency
- 4. Disease/Treatment Factors' Analysis
 - Comorbidity
 - Risk factors
 - Concomitancy



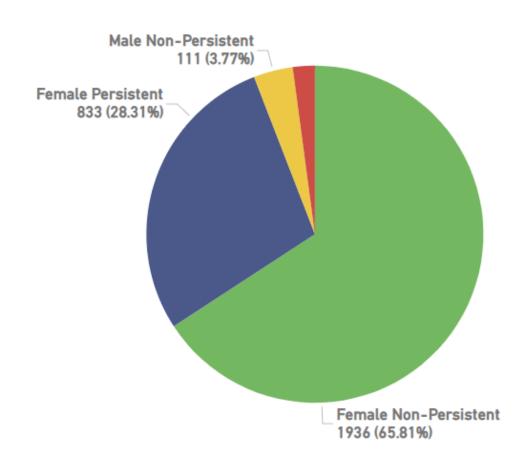
Target Variable Analysis





Gender Analysis

Patients' Count by Gender and Persistency_Flag



Gender Persistency_Flag

- Female Non-Persistent
- Female Persistent
- Male Non-Persistent
- Male Persistent

Age Group Analysis

Age_Bucket

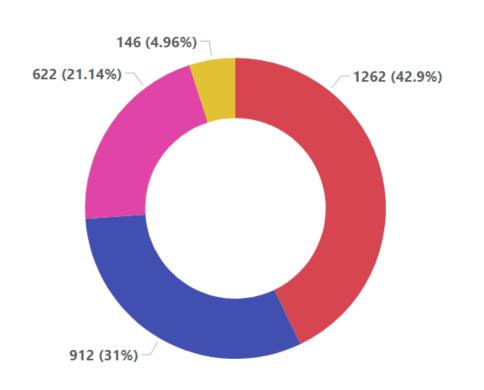
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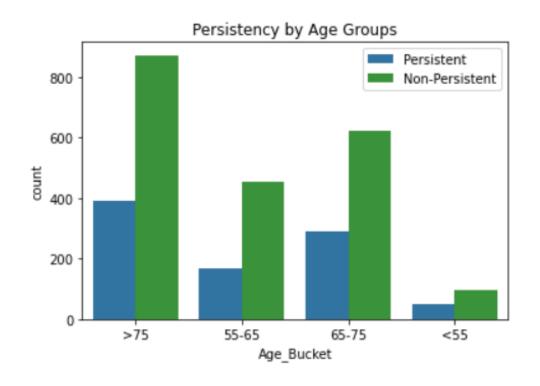
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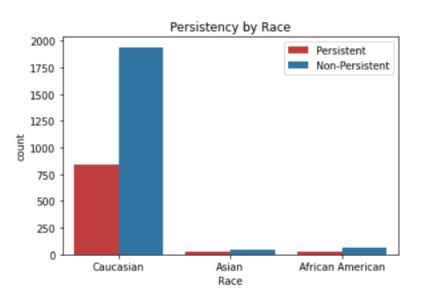
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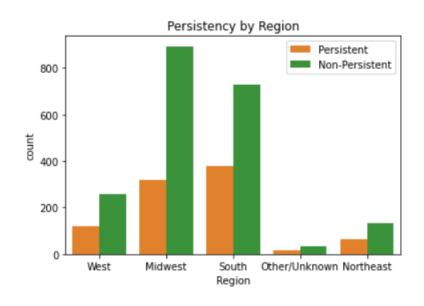
Age Group Count

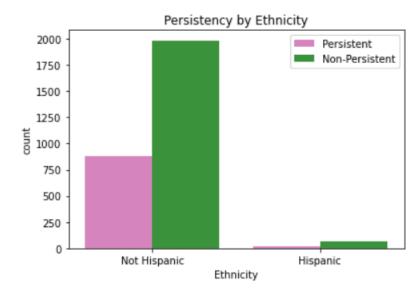




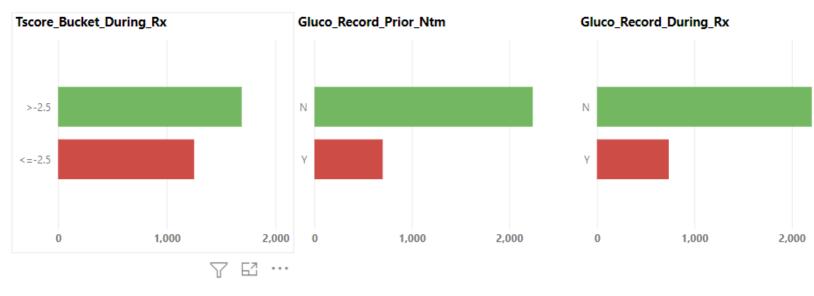
Race, Region & Ethnicity

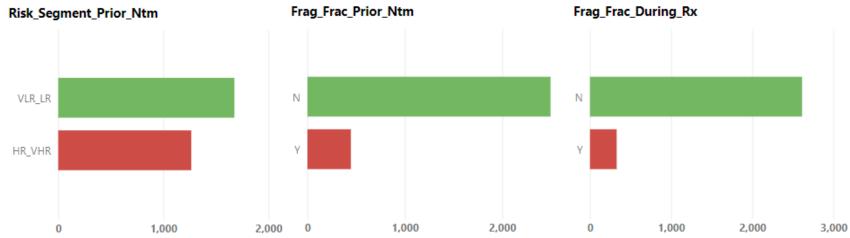






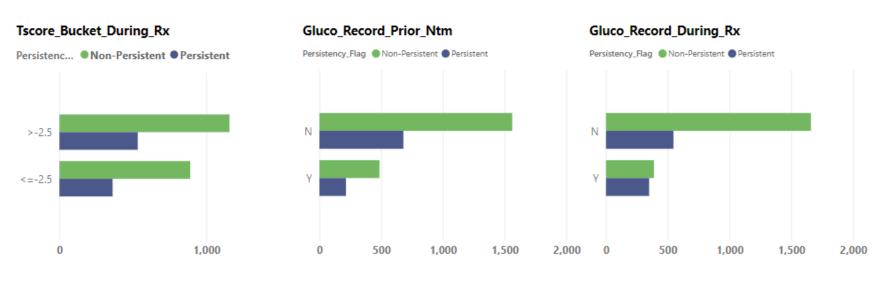
Clinical Factors

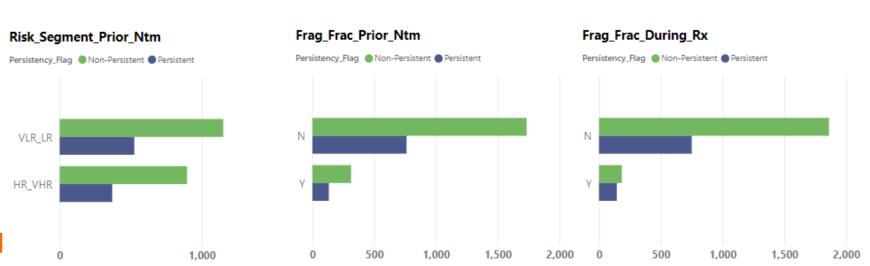




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Clinical Factors - Persistency





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Disease/Treatment Factors

- NTM-Comorbidity:
 Comorb_Disorders_of_lipoprotein_metabolism_and_ot
 her_lipidemias has highest influence.
- NTM-Risk Factors: Risk_Vitamin_D_Insufficiency has highest influence.
- NTM-Concomitancy: Concom_Narcotics has highest influence.

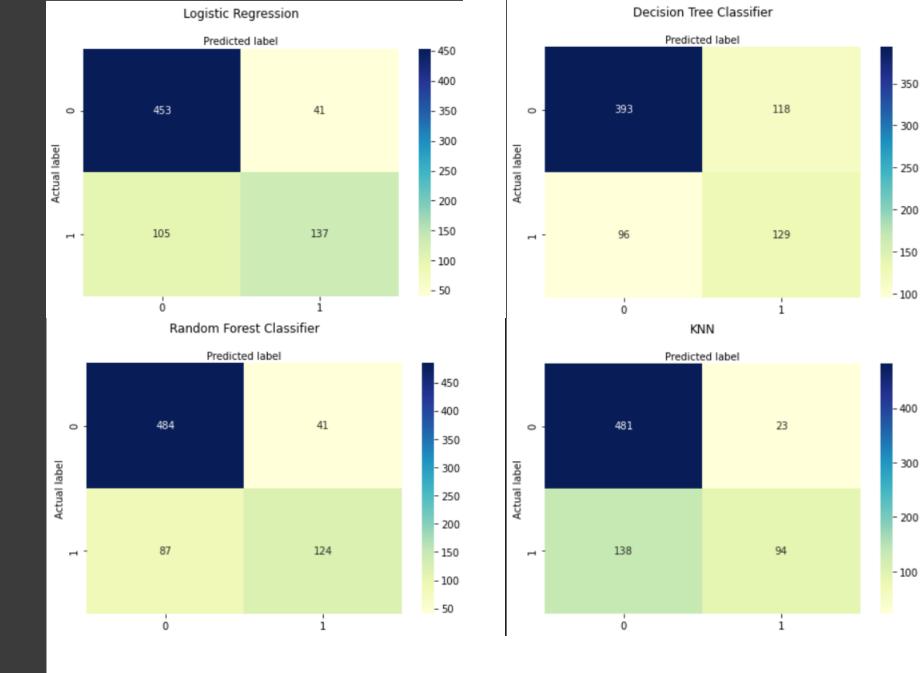


EDA Summary

- Drug Persistency is affected by many factors
- Patients older than 65 years show more persistency
- T-square also has influence in persistency
- Disease/Treatment factors:
 - Comorbidity
 - Risk factors
 - Concomitancy



Models





Models

| Model | Accuracy Score |
|------------------------------|----------------|
| 1. Logistic Regression | 80.16% |
| 2. Decision Tree Classifier | 70.92% |
| 3. Random Forest Classifier | 82.61% |
| 4. k-Nearest Neighbors (kNN) | 78.13% |



Classification Reports

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1. Logistic Regression 2. Decision Tree Classifier precision recall f1-score support precision recall f1-score support Non-Persistent Non-Persistent 0.80 0.77 0.79 511 0.81 0.92 0.86 494 Persistent Persistent 0.52 0.57 0.55 0.77 0.57 0.65 225 242 0.71 0.80 736 736 accuracy accuracy 0.74 0.79 0.76 736 macro avg 0.66 0.67 0.67 736 macro avg weighted avg 0.80 0.80 0.79 736 weighted avg 0.72 0.71 0.71 736 3. Random Forest Classifier **4. KNN**

| support | f1-score | recall | precision | | support | f1-score | recall | precision | |
|---------|----------|--------|-----------|----------------|---------|----------|--------|-----------|----------------|
| 504 | 0.86 | 0.95 | 0.78 | Non-Persistent | 525 | 0.88 | 0.92 | 0.85 | Non-Persistent |
| 232 | 0.54 | 0.41 | 0.80 | Persistent | 211 | 0.66 | 0.59 | 0.75 | Persistent |
| | | | | | | | | | |
| 736 | 0.78 | | | accuracy | 736 | 0.83 | | | accuracy |
| 736 | 0.70 | 0.68 | 0.79 | macro avg | 736 | 0.77 | 0.75 | 0.80 | macro avg |
| 736 | 0.76 | 0.78 | 0.79 | weighted avg | 736 | 0.82 | 0.83 | 0.82 | weighted avg |
| | | | | | | | | | |

Recommendations

- Classifier algorithms tend to produce more effective results
- These models help to categorize patients based on certain factors
- Random Forest Classifier produced most accurate results
- Factors that affect comorbidity, risks and concomitancy were also found out



Thank You

