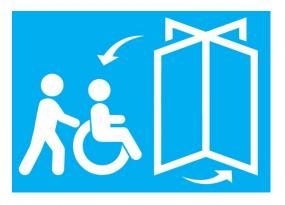


# Diabetes Readmission Prediction





## Introduction

Readmission Rate

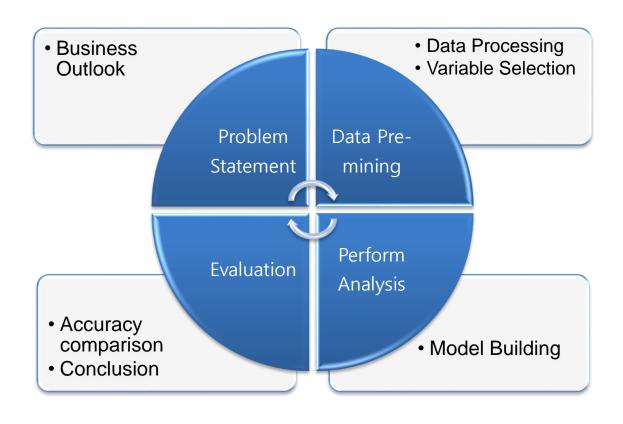
A hospitalization that occurs within 30 days after a discharge.

Why Is Readmission Important?

Reduce cost of care and medical disputes.

Improve patients' safety and health.

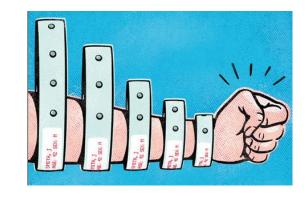
## **Methodology/ Process**





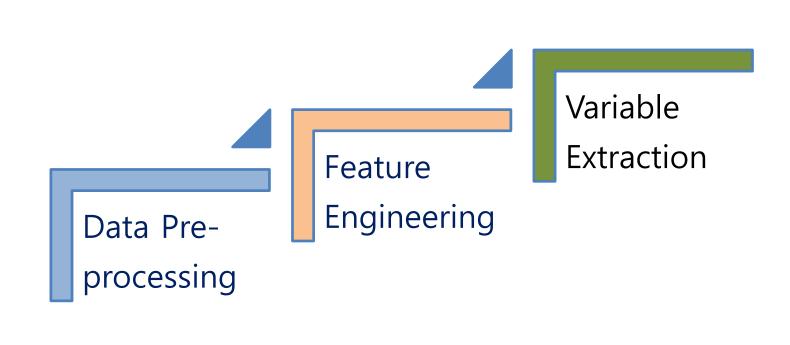


- Identify the major factors that contribute to hospital readmi ssions.
- ❖ Goal: To make effective prediction on readmissions which will enable hospitals to identify and target patients at the higher risk.





## **Data Pre-mining**



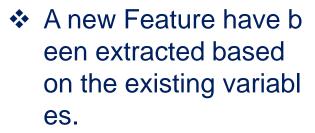




## **Data Pre-processing**

- Dataset was given with 34650 records and 45 variable es out of which one is target variable.
- Categorize Diagnosis into 18 groups.
- Re-categorize Age group.
- Drop variables which has more than 50% of null Values.

## **Feature Engineering**



Days \_Spent : No. of days spent in hospital







❖ By using the chisq test between the various extracted variables and the target variables, could able to find the most useful variables.



❖ Remove irrelevant variables (EX: patient ID)

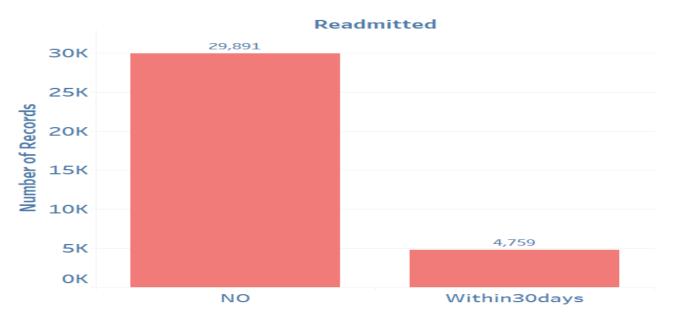








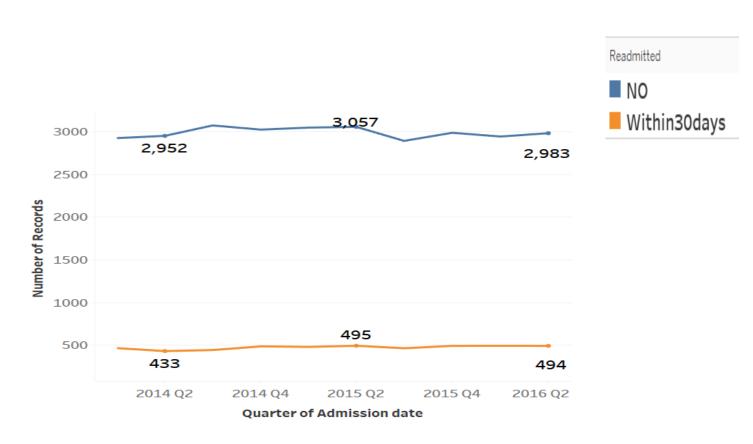




Smote has been used to oversample the minority class data.



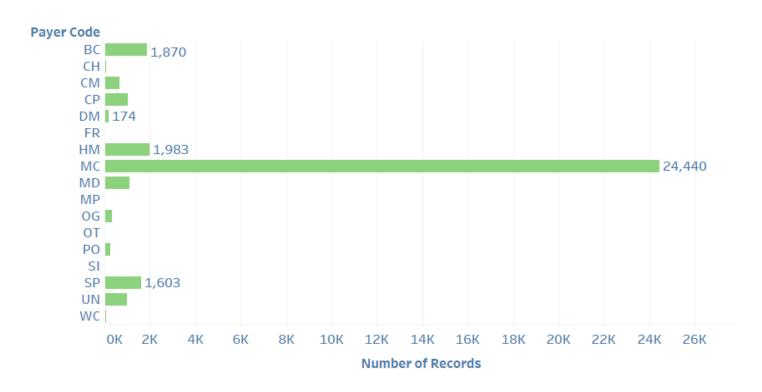
## No. of Patient Records Trend



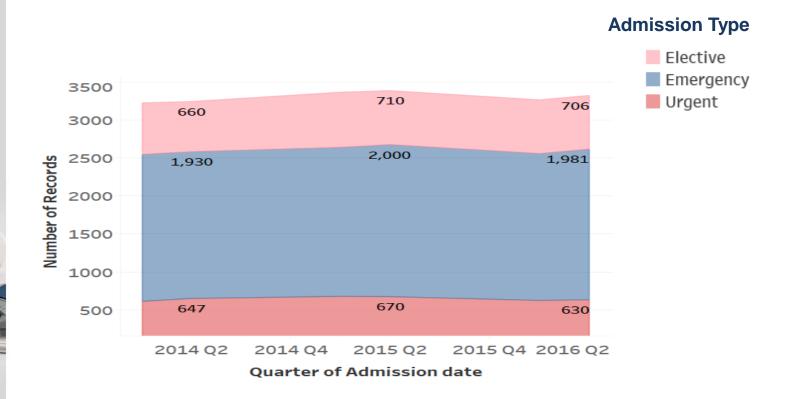




## No. of Records Significantly varying with Payer



## **Admission Type Trend**

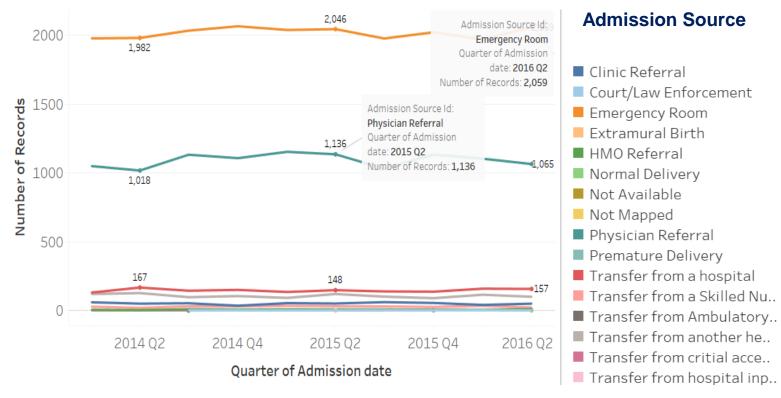


### **Admission Sources**

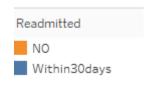


- Clinic Referral
- Court/Law Enforcement
- Emergency Room
- Extramural Birth
- HMO Referral
- Normal Delivery
- Not Available
- Not Mapped
- Physician Referral
- Premature Delivery
- Transfer from a hospital
- Transfer from a Skilled Nu..
- Transfer from Ambulatory..
- Transfer from another he..
- Transfer from critial acce..
- Transfer from hospital inp...

## **Admission Source Trend**

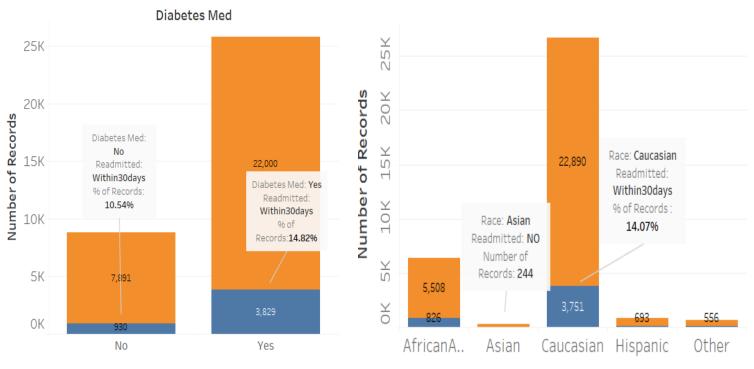


## No. of Patients read mitted who were on Diabetes Medicine



## No. of Patients readmitted Vs Race



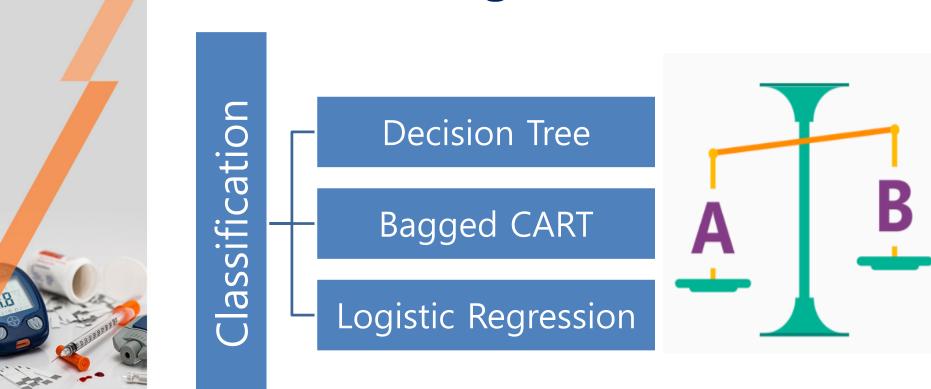


## **Model Building**





## **Model Building Methods**





- Easy to interpret.
- Useful in Data exploration.
- Less data cleaning required.



perc. under	perc. over	Recall	Accuracy	
0	300	16.23%	74.42%	

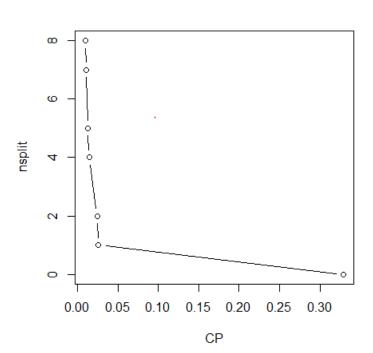






### Variables actually used in tree construction:

- > A1Cresult
- discharge\_disposition\_id
- > max\_glu\_serum
- num\_diagnoses
- num\_lab\_procedures
- > race





- Reduce the variance of our predictions.
- ❖ There are various implementations of bagging models Random forest is one of them.

Model Performance using "treebag":

perc. under	perc. over	Recall	Accuracy
50	50 400		68.05%
100	500	14.40%	76.69%





## **Random Forest**



- Handle large data set with higher dimensionality.
- Identify most significant variables i.e. the model outputs Importance of variable.
- ❖ The sub-trees are learned so that the resulting predictions from all of the subtrees have less correlation.

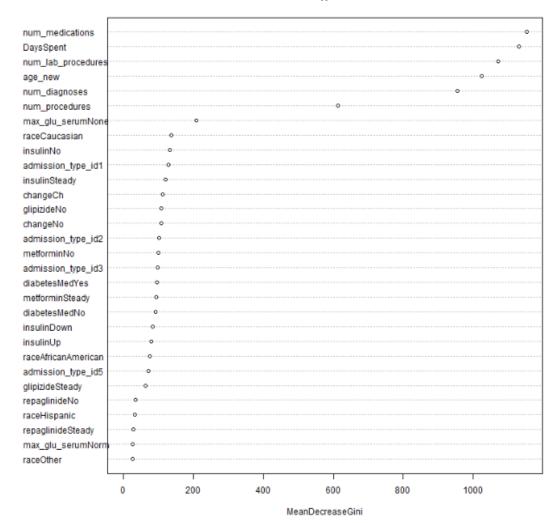


### Model Performance:

perc. under	perc. over	Recall	Accuracy
0	300	9.81%	78.09%
50	400	48.41%	62.10%
50	500	61.57%	55.19%
28	500	65.59%	51.67%



## Important Variable Plot





## **Logistic Regression**

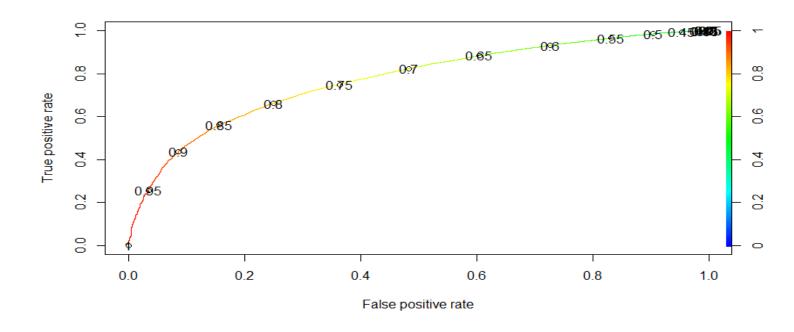
- Have probability for reference.
- ❖ The threshold value determines whether the probability value should be assigned to True or False.

### **Model Performance:**

perc. under	perc. over	Threshold Level	Recall	Accuracy
28	550	0.7	66.87%	52.78%
		0.68	69.87%	51.07%
		0.6775	70.61%	50.58%
33	450	0.66	68.98%	50.89%

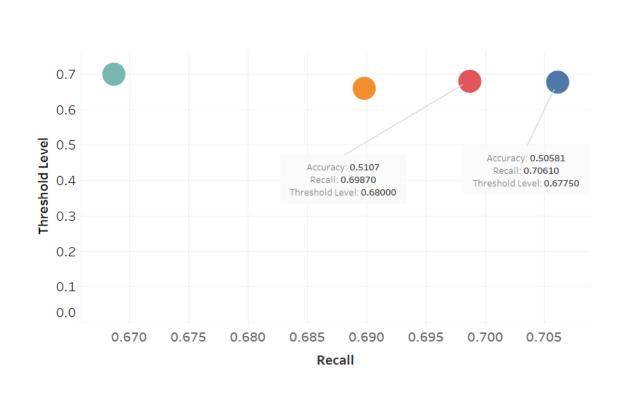
## **ROC Curve**

AUC = 77.12%



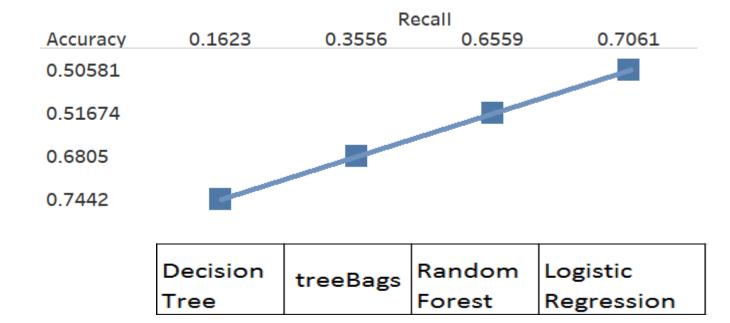


### Threshold Level Vs Recall & Accuracy





## **Model Performance**







## Conclusion

- The readmission groups are related to admission source, admission type, discharge disposition and number of inpatient visits.
- ❖ Instead of tracking all attributes, hospitals are suggested to focus on number of patient's inpatient visits, admission source, admission type, discharge disposition.
- Hospitals are advised to concern not only inpatient treatment but also continuing care after discharge.

