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Learning for Life

Project Summary

Batch details	PGP-DSE PUNE JUL'20
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Domain of Project	Healthcare
Proposed project title	Diabetes Patient Readmission Prediction Analysis of 100,000 Clinical Database Patient Records
Group Number	Group 3
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Mentor Name	Srikar Muppidi

Date: 30 / 03 / 2021

Signature of the Mentor Leader

Signature of the Team

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Project Details

OVERVIEW:

Hospital readmissions pose additional costs and discomfort for the patient and their occurrences are indicative of deficient health service quality, Hence, efforts are generally made by medical professionals in order to prevent them. These endeavors are especially critical in the case of chronic conditions, such as diabetes. Recent developments in machine learning have been successful at predicting readmissions from the medical history of diabetic patients. These approaches rely on a large number of clinical variables and machine learning models achieving superior prediction performance. In this project, the relationship between diabetes and the various patient attributes is examined. Further, several prediction models are built based on different sets of attributes of the patient.

Business Problem Understanding:

Business Understanding:

It is increasingly recognized that the management of Hyperglycemia (High Blood Sugar) in the hospitalized patient has a significant bearing on the outcome, in terms of both morbidity and mortality. This recognition has led to the development of formalized protocols in the intensive care unit (ICU) setting with rigorous glucose targets in many institutions.

In particular, we examined the use of HbA1c as a marker of attention to diabetes care in a large number of individuals identified as having a diagnosis of diabetes mellitus. We hypothesize that measurement of HbA1c is associated with a reduction in readmission rates in individuals admitted to the hospital.

Business Objective:

A hospital readmission is when a patient who is discharged from the hospital, gets re-admitted again within a certain period of time. Hospital readmission rates for certain conditions are now considered an indicator of hospital quality, and also affect the cost of care adversely. Determining which factors are the strongest predictors of hospital readmission in diabetic patients & the efficiency and accuracy of the model in predicting hospital readmission with limited features.

Approach:

According to the problem definition we have to build a classification model as our target variable is a categorical variable. After applying various techniques of EDA, Feature Engineering into a single data source we would build our machine learning model and check and compare the performance of the different models by evaluating it through the evaluation metrics used in the classification model. Post the model building phase we would try to further improve the efficiency of our models through feature selection and hyper parameter tuning.

Conclusions:

The hospital data of in-patients having diabetes as an existing condition in conjunction with other medical illnesses were analyzed to build a predictive model to identify patients who had a higher likelihood of being readmitted. Some of the key factors that drove readmission based on the tuned RF model are discharge_disposition_id, number_diagnoses, race, diag1_complications Features, A1C result, and glipizide. Using the model, Clinical results, and medication details may be helpful for physicians in the diagnosis in some way but they may provide redundant information we needed for prediction as we have the health service records already. Based on the information provided with these three variables, it can be stated that patients in the top decile have 58 % (According to Random Forest Algo.) Higher likelihood of being readmitted.

TOPIC SURVEY IN BRIEF

1. Problem understanding:

For any healthcare organization, patient readmissions present a major challenge. Currently, one in every five patients who are discharged from the hospital is readmitted in less than 30 days. Hospital readmissions are expensive and more often than not they are avoidable, but avoiding them is still a major challenge for healthcare organizations. Also, the legislation penalizes healthcare organizations with comparatively higher readmission rates, so reducing the readmission rate becomes a necessity. While the reasons behind readmissions of patients are manifold, they are the outcome of inadequate follow-up care or poor discharge procedures. Big data analytics can be taken into account to eliminate unnecessary readmissions that can be avoided by proper post-discharge care. Machine learning can provide doctors with daily updates on patients' status, predict which patients are more likely to need readmission, and how they might be able to reduce the risk of readmission.

2. Current solution to the problem:

At this point, Hospitals can make sure that each patient is provided the highest quality care, keep patients under observation in their homes or do follow up appointments to make sure the patients have been given the proper care and are not at risk of being readmitted. Apart from this there is no clear-cut way for Hospitals to lower the rates of patient readmissions.

3. Proposed solution to the problem:

With this Machine Learning Model, we aim to provide Hospitals with a tool to narrow down the number of patients the hospital needs to keep their watch on and make sure that they can mitigate the risk of patient readmission.

Find the key area, gaps identified in the topic survey where the project can add value to the customers and business:

We can solve a problem for Hospitals which reduces the man hours that need to be put into follow ups and observation of patients with a prediction model, which can narrow down the patients the Hospital needs to pay more attention to.

Data Description:

Encounter ID - Unique identifier of an encounter

Patient number - Unique identifier of a patient

Race – Race of patient (Caucasian, Asian, African American, Hispanic, and other)

Gender - Male, Female, and unknown/invalid

Age - Grouped in 10-year intervals: 0-10, 10-20, etc.

Weight - Weight in pounds

Admission type - Integer identifier corresponding to 9 distinct values, for example, emergency, urgent, elective, new-born and not available

Discharge disposition - Integer identifier corresponding to 29 distinct values, for example, discharged to home, expired, and not available

Admission source - Integer identifier corresponding to 21 distinct values, for example, physician referral, emergency room, and transfer from a hospital

Time in hospital - Integer number of days between admission and discharge

Payer code - Integer identifier corresponding to 23 distinct values, for example, Blue Cross\Blue Shield, Medicare, and self-pay

Medical specialty - Integer identifier of a specialty of the admitting physician, corresponding to 84 distinct values, for example, cardiology, internal medicine, family\general practice, and surgeon

Number of lab procedures - Number of lab tests performed during the encounter

Number of procedures - Number of procedures (other than lab tests) performed during the encounter

Number of medications - Number of distinct generic names administered during the encounter

Number of outpatient visits - Number of outpatient visits of the patient in the year preceding the encounter

Number of emergency visits - Number of emergency visits of the patient in the year preceding the encounter

Number of inpatient visits - Number of inpatient visits of the patient in the year preceding the encounter

Diagnosis 1 - The primary diagnosis (coded as first three digits of ICD 9); 848 distinct values

Diagnosis 2 - Secondary diagnosis (coded as first three digits of ICD 9); 923 distinct values

Diagnosis 3 - Additional secondary diagnosis (coded as first three digits of ICD 9); 954 distinct values

Number of diagnoses - Number of diagnoses entered to the system

Glucose serum test result - Indicates the range of the result or if the test was not taken.

A1c test result - Indicates the range of the result or if the test was not taken.

Metformin - sold under the brand name Glucophage among others, is the first-line medication for the treatment of type 2 diabetes, particularly in people who are overweight.

Repaglinide - is used alone or with other medications to control high blood sugar along with a proper diet and exercise program. It is used in people with type 2 diabetes.

Nateglinide - is a drug for the treatment of type 2 diabetes

Chlorpropamide - is an oral antihyperglycemic agent used for the treatment of non-insulin-dependent diabetes mellitus (NIDDM).

Glimepiride - is an oral diabetes medicine that is used together with diet and exercise to improve blood sugar control in adults with type 2 diabetes mellitus.

Acetohexamide - is a first-generation sulfonylurea medication used to treat diabetes mellitus type 2, particularly in people whose diabetes cannot be controlled by diet alone.

Glipizide - sold under the brand name Glucotrol among others, is an anti-diabetic medication of the sulfonylurea class used to treat type 2 diabetes

Glyburide - is a diabetes medicine used to help control blood sugar levels and treat type 2 diabetes.

Tolbutamide - is a first-generation potassium channel blocker, sulfonylurea oral hypoglycemic medication. This drug may be used in the management of type 2 diabetes if diet alone is not effective.

Pioglitazone - is a diabetes drug (thiazolidinedione-type, also called "glitazones") used along with a proper diet and exercise program to control high blood sugar in patients with type 2 diabetes.

Rosiglitazone - is an insulin sensitizing agent and thiazolidinedione that is indicated for the treatment of type 2 diabetes.

Acarbose - is an anti-diabetic drug used to treat diabetes mellitus type 2 and, in some countries, prediabetes.

Miglitol - is an oral anti-diabetic drug that acts by inhibiting the ability of the patient to break down complex carbohydrates into glucose.

Troglitazone - is an antidiabetic and anti-inflammatory drug, and a member of the drug class of the thiazolidinediones. It was prescribed for people with diabetes mellitus type 2.

Tolazamide - is an oral blood glucose lowering drug used for people with Type 2 diabetes. It is part of the sulfonylurea family.

Citoglipton (Sitagliptin) - Sitagliptin is a diabetes drug that works by increasing levels of natural substances called incretins. Incretins help to control blood sugar by increasing insulin release, especially after a meal. They also decrease the amount of sugar your liver makes.

Glyburide-Metformin - The combination of glyburide and metformin is used to treat type 2 diabetes (condition in which the body does not use insulin normally and therefore cannot control the amount of sugar in the blood) in people whose diabetes cannot be controlled by diet and exercise alone.

Glipizide-Metformin - Glipizide and Metformin combination is used to treat high blood sugar levels that are caused by a type of diabetes mellitus or sugar diabetes called type 2 diabetes

Glimepiride-Pioglitazone - Pioglitazone and glimepiride combination is used with proper diet and exercise to treat high blood sugar levels caused by type 2 diabetes. Pioglitazone works by helping your body use insulin better. Glimepiride stimulates the release of insulin from the pancreas which will help your body turn food into energy

Metformin-Rosiglitazone - Rosiglitazone and metformin combination is used to treat a type of diabetes mellitus called type 2 diabetes. It is used together with a proper diet and exercise to help control blood sugar levels.

Metformin-Pioglitazone - Metformin/pioglitazone is used to improve blood sugar control in adults with type 2 diabetes. It's used along with diet and exercise. Metformin/pioglitazone isn't used to treat type 1 diabetes.

24 features for medications - The feature indicates whether the drug was prescribed or there was a change in the dosage. Values: “up” if the dosage was increased during the encounter, “down” if the dosage was decreased, “steady” if the dosage did not change, and “no” if the drug was not prescribed

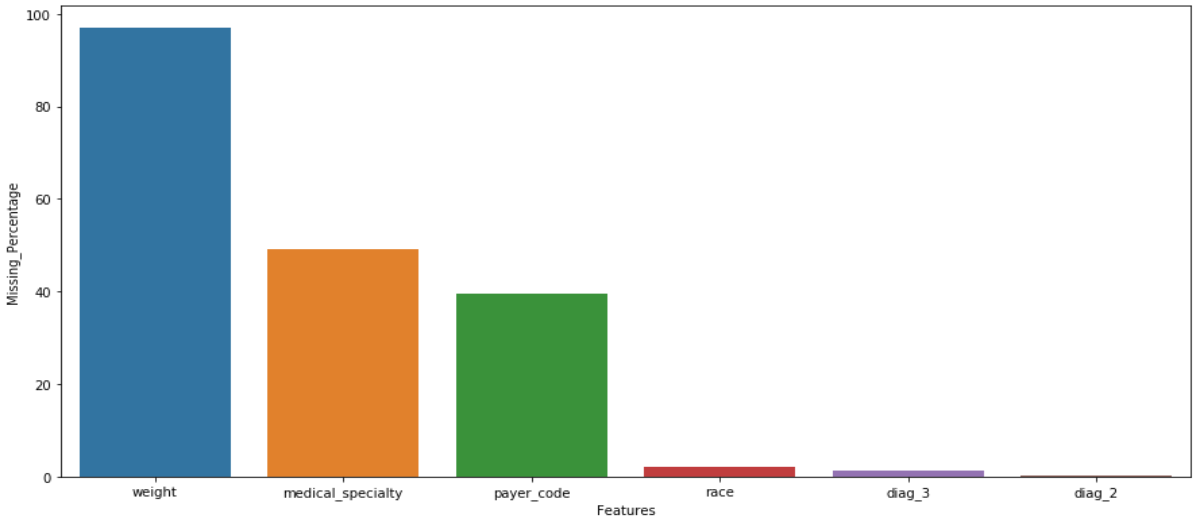
Change of medications - Indicates if there was a change in diabetic medications (either dosage or generic name).

Diabetes medications - Indicates if there was any diabetic medication prescribed

Readmitted - Whether the Patient was Readmitted or not OR whether the Patient was readmitted within 30 days or not.

Data Pre-Processing and Preparation:

NULL Handling:



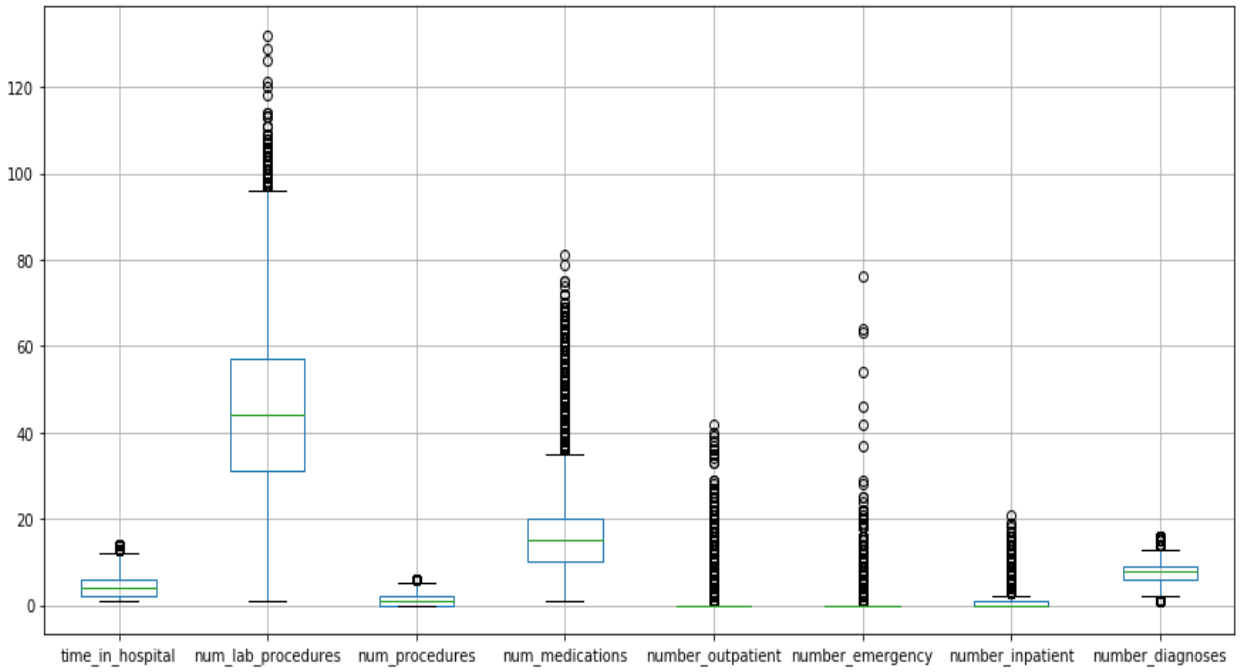
There are no traditional "**Null Values**" in the data rather there are some values which are missing that have been filled with "**?**". We have treated these values in following ways:

- In case of the "**race**" variable - Categorized the missing values to the already existing "**Others**" category
- In case of the "**weight**" variable - dropping the variable altogether where 97% values were missing
- In case of the "**payer_code**" variable - dropped the variable as here were too many existing classes making accurate imputation of missing values almost impossible
- In case of the "**medical_speciality**" variable - dropped the variable as here were too many existing classes making accurate imputation of missing values almost impossible.

In the case of diag_2 and diag_3 variables we have been able to impute those values with the Feature Engineering.

	Features	Missing_Percentage
0	weight	96.858479
1	medical_specialty	49.082208
2	payer_code	39.557416
3	race	2.233555
4	diag_3	1.398306
5	diag_2	0.351787

Outlier Handling:



As this is real world patient data, the outliers are the main patients who are affecting our Target.

For example, patients with a greater number of inpatient records are getting readmitted, patients who have gone through more lab procedures are less likely to get readmitted.

Thus, we have chosen not to do outlier treatment so as to preserve the integrity of the dataset which is linked to real world outcomes.

Exploratory Data Analysis & Business Insights:

UNIVARIATE:

We can see from the data that on average, a patient spends about 4.3 days in the hospital, and around 76% of the patients we have in the data are of the Caucasian race i.e., White, with African Americans patients in the data being around 19%. As for the "**Gender**" of the patients we have a more even distribution with around 53% Female patients and 47% Male Patients.

The data categorizes the "**Age"** of the patients in the 10-year intervals, i.e., 10-20, 20-30, etc. with the majority of patients in the data are between the ages of 50 and 90. We have around 97% Missing values in the "**Weight**" column, deeming it unfit for consideration.

We have 71518 unique patients with some of them having multiple visits. We were able to create a new feature **'Patient_Visits'** by calculating based on the unique patient numbers how many visits the patient has had over the span of the 10 years in which the data was collected.

We have 3 variables "**Admission_type_id**", "**Admission_source_id**" and "**Discharge_dispostion_id**" which have been pre-encoded with unique classifications for the type circumstance of the Patient's Admission and Discharge from the Hospital. We know from the data that the most common admission types are Emergency & Urgent admissions along with elective admission, the most common sources of admission is again Emergency or through Referrals. The most common types of discharge granted to patients being discharged to their homes or transferred to another facility.

We changed the mapping of these labels to a more manageable number of classes for the three variables, especially in the case of "**Admission_source_id**" and "**Discharge_dispostion_id**" where there were around 30 classes which we were able to reduce down to 4 and 7 categories respectively.

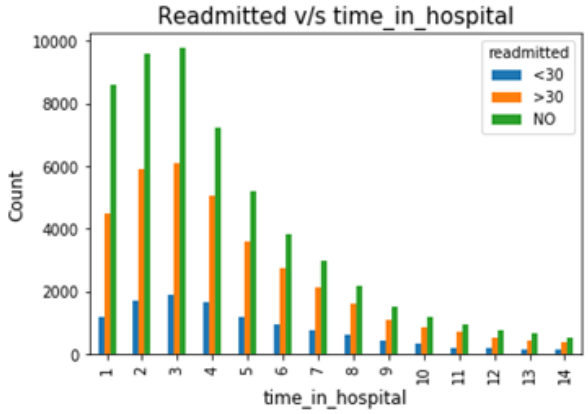
The "**payer_code**" is the identifier of the mode of payment by the patients i.e through insurance provider, blue cross or self-pay, etc with MC or Medicaid being the most common mode of payment amongst the patients.

We can see from the analysis of the Drugs in the data, the majority of the patients are being prescribed one or more of the drugs with a steady dosage, with the exception of the drugs **'Examide'** and **'Citoglipton'** where there are no patients being prescribed either drug.

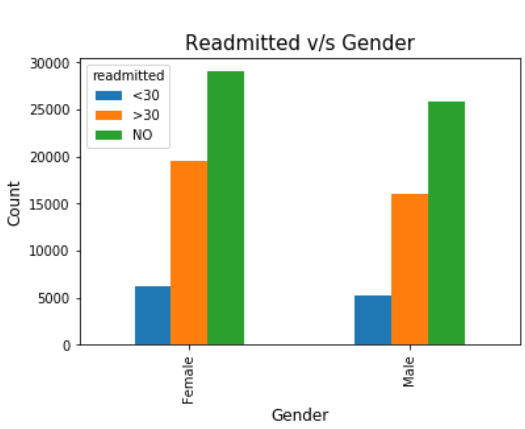
As for the target variable "**Readmitted**", we have 54864 patients who were not readmitted while 35545 patients having to be readmitted after 30 days and 11357 patients having to be readmitted before 30 days from date of discharge.

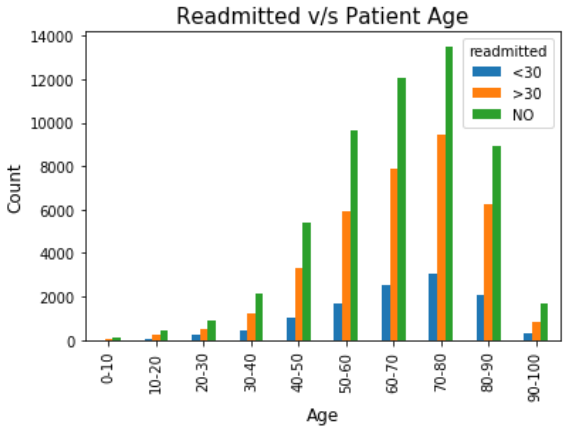
BIVARIATE:

From the bi-variate analysis done with the target variable, the main inferences we can draw are that the higher the "**time_in_hospital**" i.e., the duration the patients were admitted in the hospital for, the lower the likelihood of their re-admission, meaning that the patients who were under hospital care for longer, are less likely to be readmitted.



Another inference or insight we have gained is that the "**Age**" and "**Gender**" are also critical factors with respect to the likelihood of readmission for the patients, the higher **Age** increases the likelihood of readmission, and in case of **Gender**, Females have more likelihood of being readmitted.





Feature Engineering:

Feature engineering is about creating new input features from your existing ones. These features can be used to improve the performance of machine learning algorithms.

In our analysis we have implemented feature engineering techniques on a few features in order to gain more insights from our data.

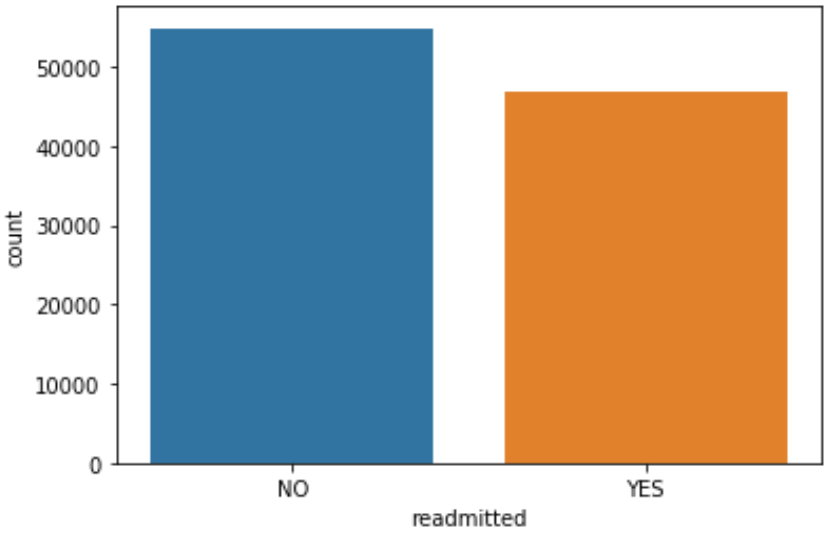
New Features Created / Transformed from existing Features for making Interpretations:

- **Readmitted (Target Variable)**
- **Admission_type_id**
- **Admission_source_id**
- **Discharge_disposition_id**
- **Diagnosis Kind**
- **Diagnosis Complications**

We made the decision after building our first base models, to change the Target Variable "**Readmitted**" from a multi-class variable into a binary **'Yes'** or **'No'** i.e. whether a patient was readmitted or not.

This was done to increase the clarity of our primary objective which was the prediction of patient readmission and also solve the problem of class distribution in the Target Variable.

Readmitted:



We changed the mapping of the labels in the "**Admission_type_id**", "**Admission_source_id**" and "**Discharge_dispostion_id**" by clubbing together similar classifications into one main classification label and were able to reduce the number of labels in each of these variables to more interpretable and more accurate representation.

Admission_type_id:

admission_type_id	description	new_id
1	Emergency	1
2	Urgent	1
3	Elective	2
4	Newborn	3
5	Not Available	5
6	NULL	5
7	Trauma Center	4
8	Not Mapped	5

Admission_source_id:

admission_source_id	description	new_id	new_category
1	Physician Referral	1	Referral
2	Clinic Referral	1	Referral
3	HMO Referral	1	Referral
4	Transfer from a hospital	2	Transfer
5	Transfer from a Skilled Nursing Facility (SNF)	2	Transfer
6	Transfer from another health care facility	2	Transfer
7	Emergency Room	3	ER
8	Court/Law Enforcement	4	Other
9	Not Available	4	Other
10	Transfer from critial access hospital	2	Transfer
11	Normal Delivery	4	Other
12	Premature Delivery	4	Other
13	Sick Baby	4	Other
14	Extramural Birth	4	Other
15	Not Available	4	Other
17	NULL	4	Other
18	Transfer From Another Home Health Agency	2	Transfer
19	Readmission to Same Home Health Agency	2	Transfer
20	Not Mapped	4	Other
21	Unknown/Invalid	4	Other
22	Transfer from hospital inpt/same fac reslt in a sep claim	2	Transfer
23	Born inside this hospital	4	Other
24	Born outside this hospital	4	Other
25	Transfer from Ambulatory Surgery Center	2	Transfer
26	Transfer from Hospice	2	Transfer

Discharge_dispostion_id:

discharge_disposition_id	description	new_id	new_category
1	Discharged to home	1	Discharged
2	Discharged/transferred to another short term hospital	2	Transferred
3	Discharged/transferred to SNF	2	Transferred
4	Discharged/transferred to ICF	2	Transferred
5	Discharged/transferred to another type of inpatient care institution	2	Transferred
6	Discharged/transferred to home with home health service	2	Transferred
7	Left AMA	3	Left
8	Discharged/transferred to home under care of Home IV provider	6	Hospice
9	Admitted as an inpatient to this hospital	4	Admitted
10	Neonate discharged to another hospital for neonatal aftercare	2	Transferred
11	Expired	5	Expired
12	Still patient or expected to return for outpatient services	1	Discharged/ Only Outpatient
13	Hospice / home	6	Hospice
14	Hospice / medical facility	6	Hospice
15	Discharged/transferred within this institution to Medicare approved swing bed	2	Transferred
16	Discharged/transferred/referred another institution for outpatient services	2	Transferred
17	Discharged/transferred/referred to this institution for outpatient services	2	Transferred
18	NULL	7	Other
19	Expired at home. Medicaid only, hospice.	5	Expired
20	Expired in a medical facility. Medicaid only, hospice.	5	Expired
21	Expired, place unknown. Medicaid only, hospice.	5	Expired
22	Discharged/transferred to another rehab fac including rehab units of a hospital .	2	Transferred
23	Discharged/transferred to a long term care hospital.	2	Transferred
24	Discharged/transferred to a nursing facility certified under Medicaid but not certified under Medicare.	2	Transferred
25	Not Mapped	7	Other
26	Unknown/Invalid	7	Other
30	Discharged/transferred to another Type of Health Care Institution not Defined Elsewhere	2	Transferred
27	Discharged/transferred to a federal health care facility.	2	Transferred
28	Discharged/transferred/referred to a psychiatric hospital of psychiatric distinct part unit of a hospital	2	Transferred
29	Discharged/transferred to a Critical Access Hospital (CAH).	2	Transferred

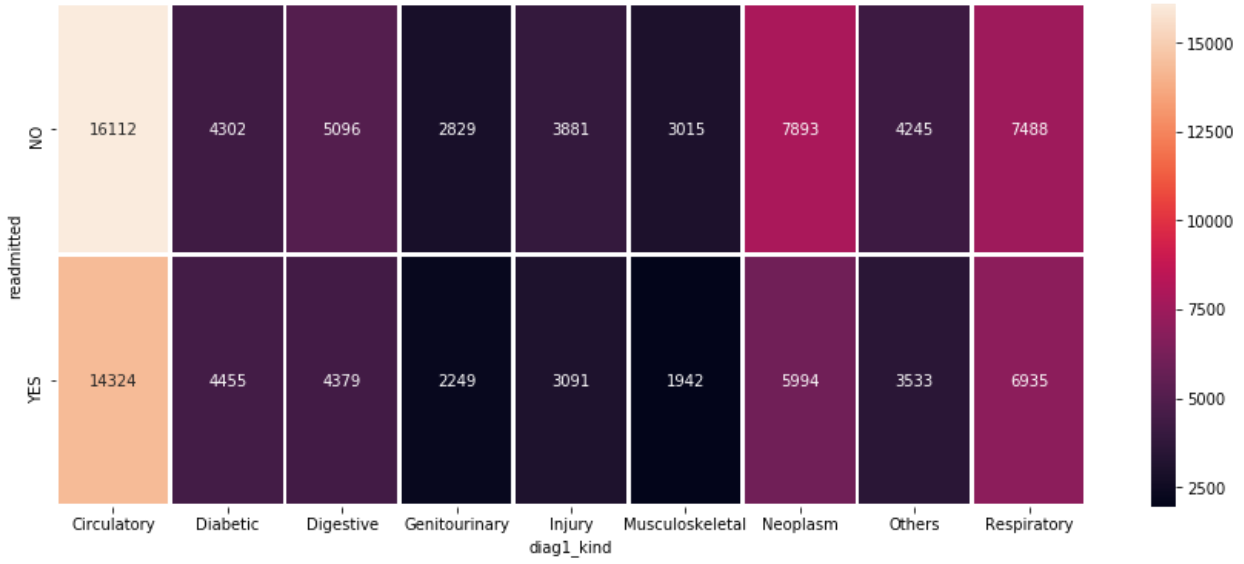
"**Diagnosis Kind**" , "**Diagnosis Complications**" Features are created based on the ICD-9 (International Classification of Diseases) Codes which are shared under the diagnoses noted down. These ICD-9 Codes are the method of capturing the diagnoses in US Hospitals.

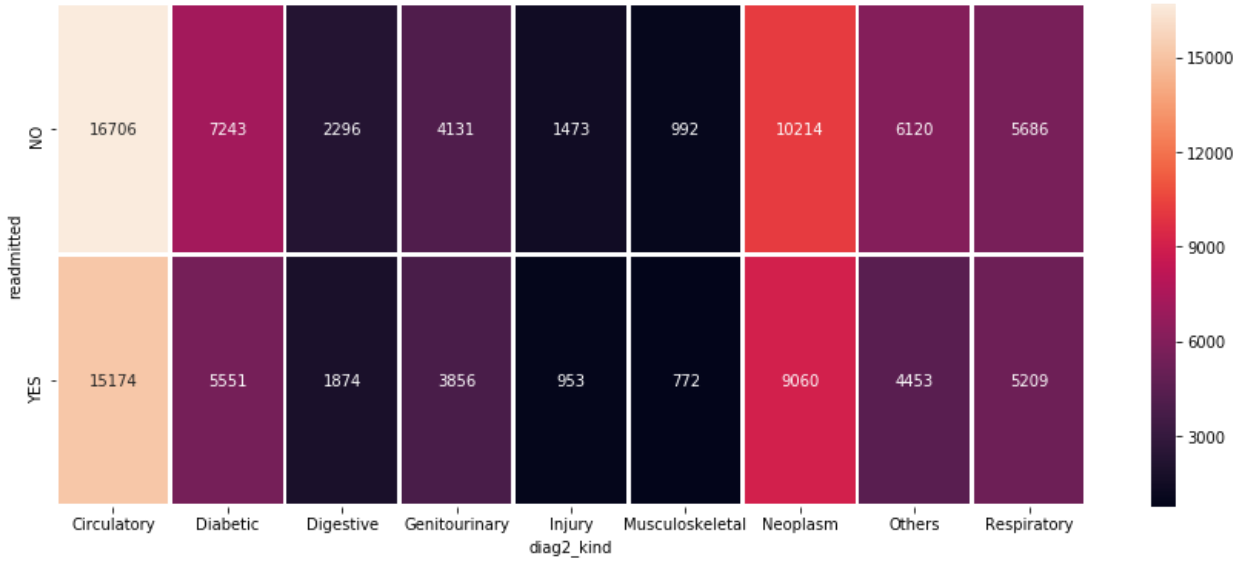
Diagnosis Kind:

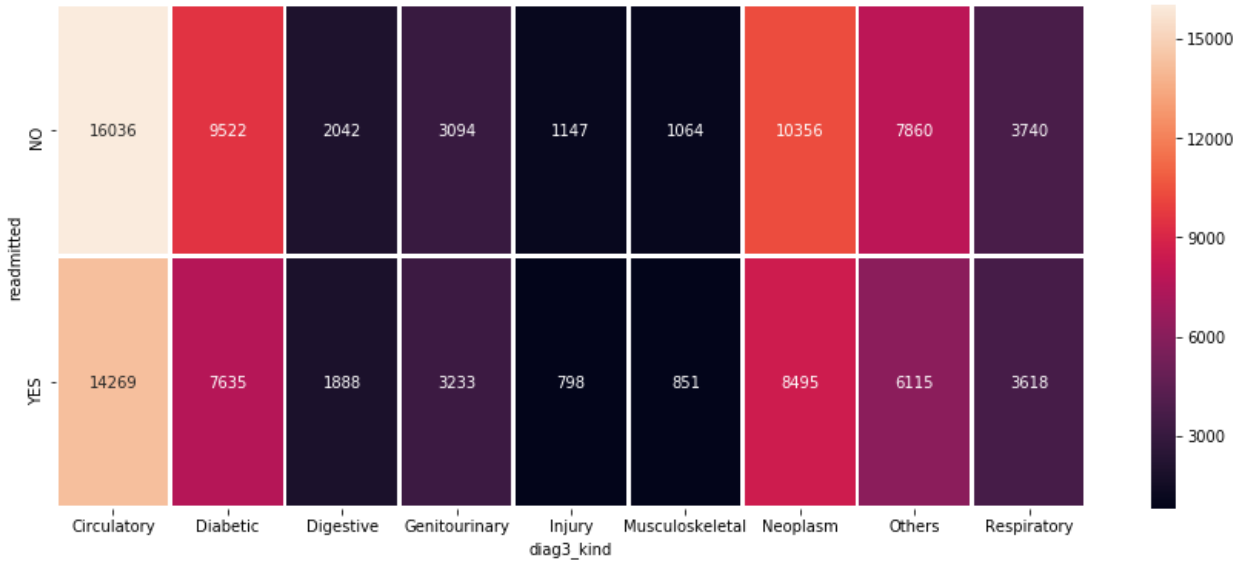
The code-mapping for Diagnosis Kind is described below:

Group name	icd9 codes
Circulatory	390–459, 785
Respiratory	460–519, 786
Digestive	520–579, 787
Diabetes	250.xx
Injury	800–999
Musculoskeletal	710–739
Genitourinary	580–629
Neoplasms	140–239,780, 781, 784, 790–799
	240–279, without 250
	680–709, 782
	001–139
	290–319
Other	E–V
	280–289
	320–359
	630–679
	360–389
	740–759

We could see here how the Diagnosis Kind was affecting my Target of Readmission:







Based on the above graphs we could see that the people getting diagnosed are getting detected by the 3rd diagnosis, as the number of diabetic kind diagnoses are increasing from 1st to 2nd to 3rd Diagnostic Test.

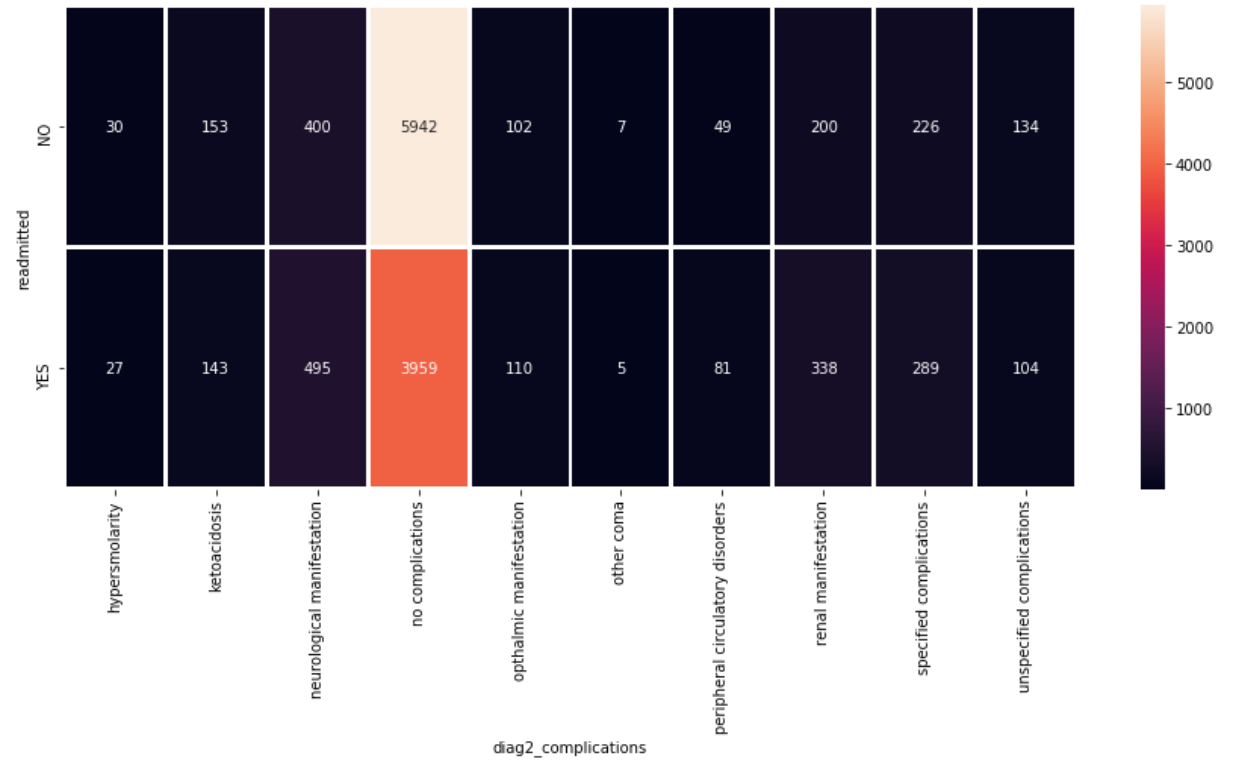
This might be a reason for the increase in readmission percentage of the patients!

Diabetes Complications:

The Codes mapped for Diagnosis Complications are only considered here towards Diabetes Patients and None was assigned for others. The Mapping is as given below:

Diabetes Complications	icd9 codes
Diabetes mellitus without mention of complications	250.0x
Diabetes with ketoacidosis	250.1x
Diabetes with hyperosmolarity	250.2x
Diabetes with other coma	250.3x
Diabetes with renal manifestations	250.4x
Diabetes with ophthalmic manifestations	250.5x
Diabetes with neurological manifestation	250.6x
Diabetes with peripheral circulatory disorders	250.7x
Diabetes with other specified manifestations	250.8x
Diabetes with unspecified complications	250.9x

We could see here how the Diagnosis Kind was affecting my Target of Readmission: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YES
30
153
400
5942
102
7
49
200
226
134
27
143
495
3959
110
5
81
338
289
104
hypersmolarity
ketoacidosis
neurological manifestation
no complications
opthalmic manifestation
other coma
peripheral circulatory disorders
renal manifestation
specified complications
unspecified complications
diag2_complications
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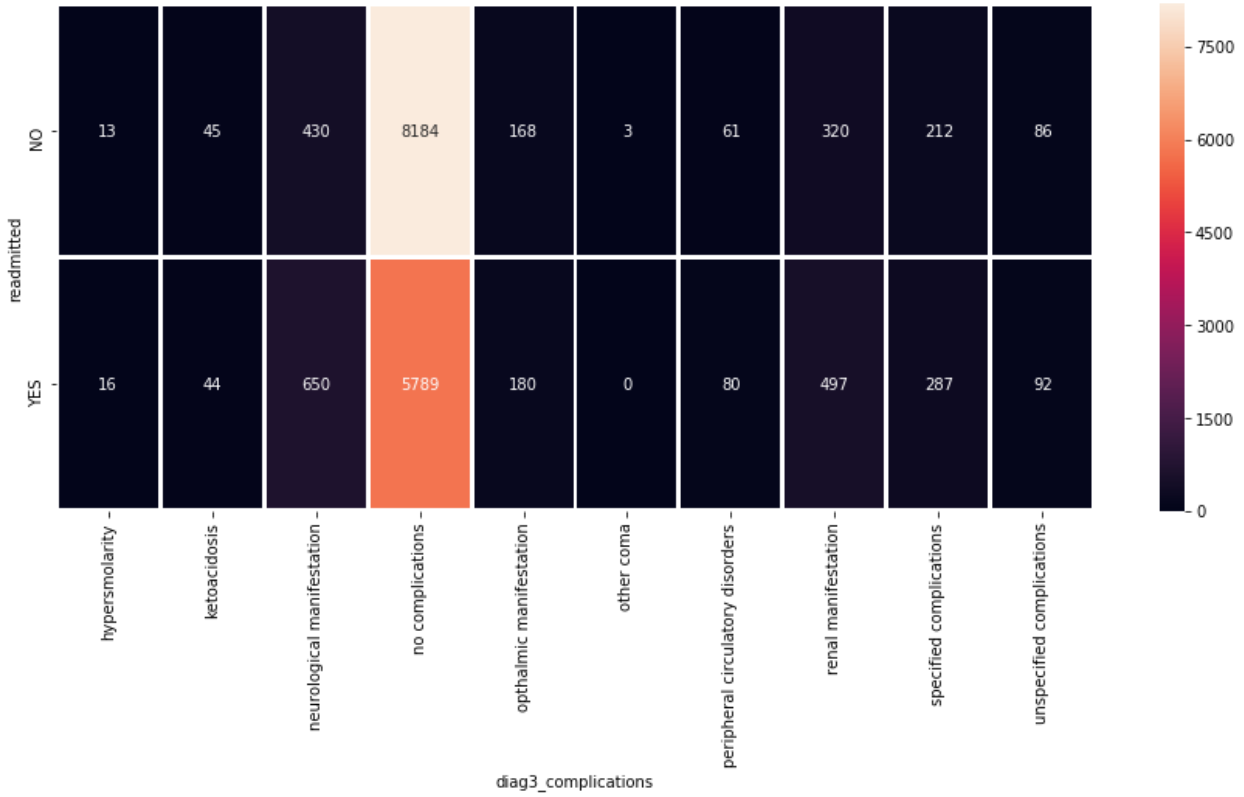
4000
3000
2000
1000


readmitted
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3
61
320
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86
16
44
650
5789
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0
80
497
287
92
hypersmolarity
ketoacidosis
neurological manifestation
no complications
opthalmic manifestation
other coma
peripheral circulatory disorders
renal manifestation
specified complications
unspecified complications
diag3_complications
7500
6000
4500
3000
1500
0

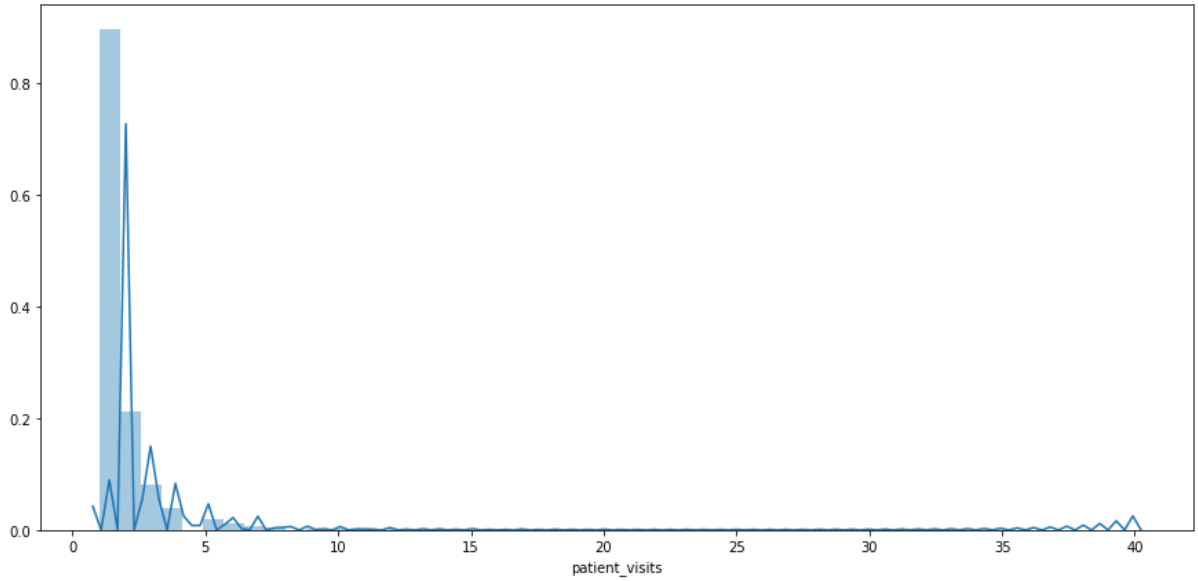
We could see that major diagnoses of Diabetic people are related to Ketoacidosis and Neurological manifestations.

Ketoacidosis is a serious complication of diabetes that occurs when your body produces high levels of blood acids called ketones. The condition develops when your body can't produce enough insulin. Insulin plays a major role for Glucose (Sugar) to enter the cells which in turn provides Energy!

Neurologic disorders are a common and often disabling aspect of diabetes mellitus. Pain and sensory disturbances, weakness and paralysis and symptoms of autonomic dysfunction may be experienced by the diabetic patient.

These might be the Major Focus Areas for the Hospital for preemptive care Measures to be taken which would in turn reduce the Patient Readmission.

Patient Visits: A new feature of Patient Visits was manufactured from the patient number. As this data is around 9 years from 1999-2008, the first occurrence of individual patients is given as count 1 and then the count was given in an incremental fashion for each patient.



Based on this new information gained from the **codes** and **patient_nbr**, we made new features of Kind and Complications for each diagnosis 1, 2 and 3 and patient_visits. Post this, we chose to drop the ICD codes and patient_nbr which were not giving any other information.

Basic Model:

Decision Tree Model :

```
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics

decision_tree = DecisionTreeClassifier(random_state=10)

decision_tree = decision_tree.fit(Xtrain,ytrain)

ypred = decision_tree.predict(Xtest)

print('Classification Report :\n',metrics.classification_report(ytest,ypred))
```

```
Classification Report :
               precision    recall  f1-score   support

           0       0.59      0.58      0.59     15979
           1       0.40      0.40      0.40     10458
           2       0.15      0.15      0.15      3411

    accuracy                           0.47     29848
   macro avg       0.38      0.38      0.38     29848
weighted avg       0.47      0.47      0.47     29848
```

Random Forest Model :

```
from sklearn.ensemble import RandomForestClassifier

rf_model = RandomForestClassifier(n_estimators=100,random_state=10)

rf_model.fit(Xtrain,ytrain)

ypred = rf_model.predict(Xtest)

print('Classification Report :')
print(metrics.classification_report(ytest,ypred))
```

```
Classification Report :
              precision    recall  f1-score   support

           0       0.61      0.84      0.70     15979
           1       0.49      0.37      0.42     10458
           2       0.42      0.01      0.03      3411

    accuracy                           0.58     29848
   macro avg       0.51      0.41      0.38     29848
weighted avg       0.55      0.58      0.53     29848
```

We can see that the Accuracy and F1 Score is better in Random Forest Model!

MODEL TUNING:

After the Data Preparation, Exploratory Data Analysis and Feature Engineering, Data Encoding and building our base models which were the "**Decision Tree Classifier**" and the "**Random Forest Classifier**", we now further tune the model to optimize our key metrics which are **Precision**, i.e. the proportion of positive instances that were correctly predicted and **Recall,** i.e the proportion of actual positive cases that were correctly predicted, also sometimes called '*True Positive Rate (TPR)*' or *'Sensitivity'*. We will do the Model Tuning in the following ways:

1. Run Statistical Tests to find out the Significant Features in our Data.

Performing Statistical Test to check the Individual Feature Effects on Target

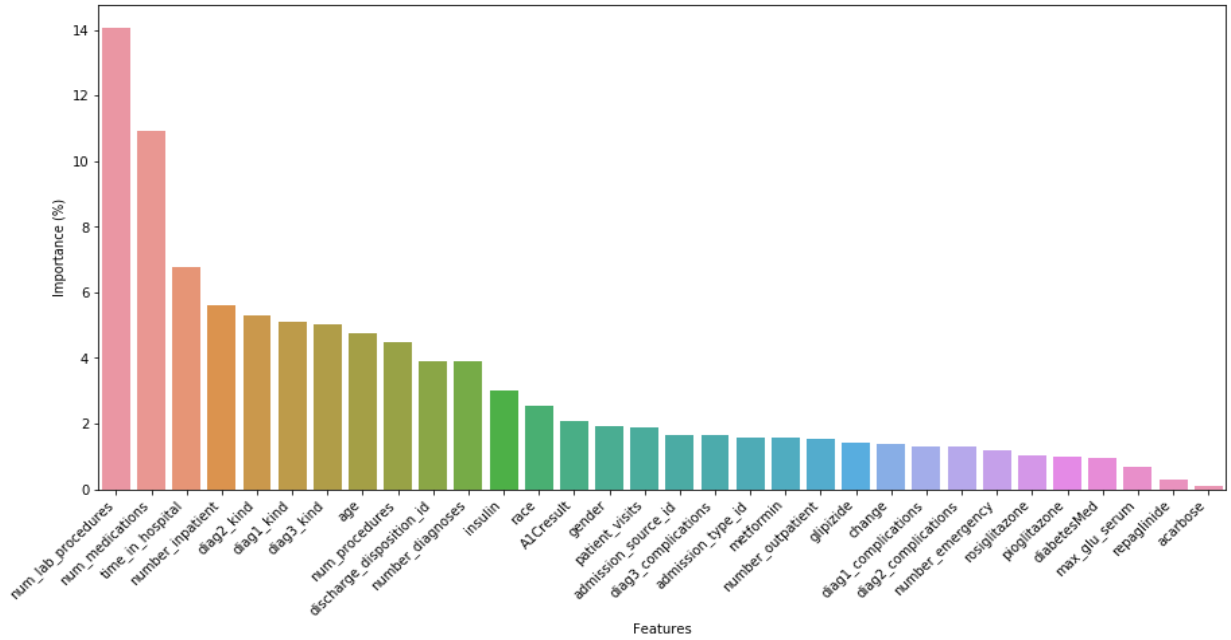
T-Test on Numerical & ANOVA Columns on Categorical and adding to Feature_list not affect my target!

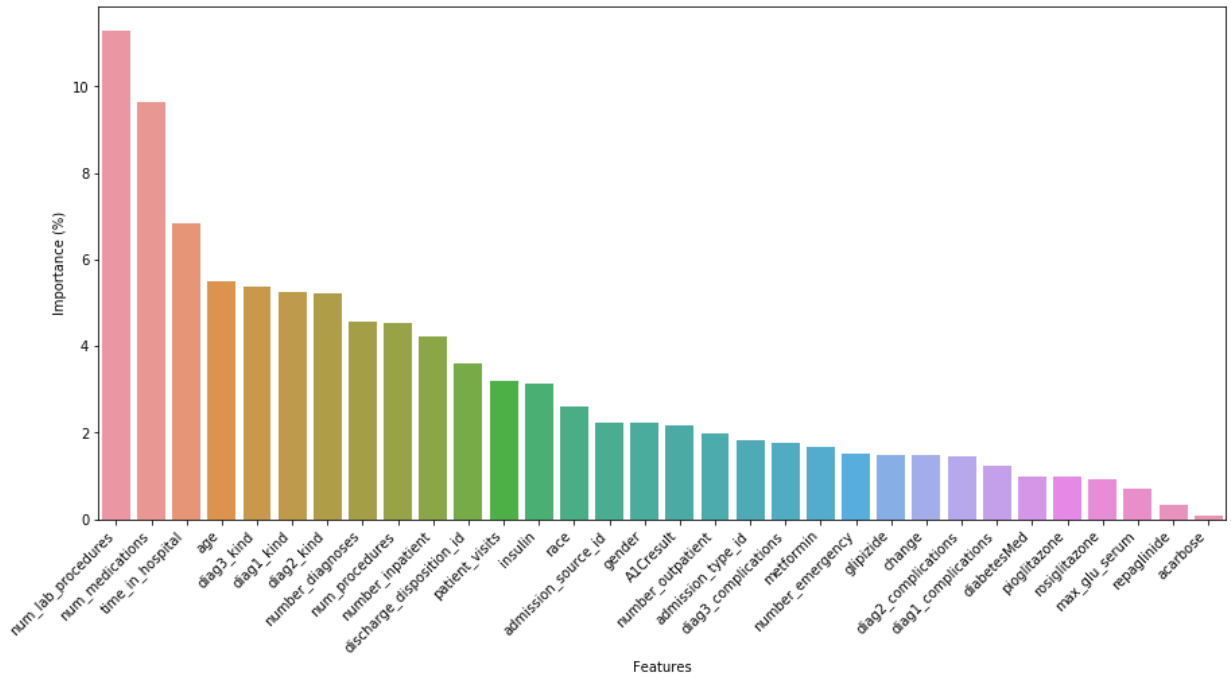
```
# H0 : Feature has NO Effect on Target
# H1 : Feature has a Clear Effect on Target

def statistical_test(df,target):
    cat_cols = df.select_dtypes('object').columns
    num_cols = df.select_dtypes(np.number).columns

    feature_list = []

    for i in num_cols:
        g1 = df[df[target]=='NO'][i]
        g2 = df[df[target]=='YES'][i]
        ts,pv = stats.ttest_ind(g1,g2)
        if(pv<0.05):
            feature_list.append(i)
            print('{} :--> p_value::{} is Affecting Readmission'.format(i,pv))
        else:
            print('{} is NOT Affecting Readmission'.format(i))

    for j in cat_cols: #Excluding Target for analysis
        table = pd.crosstab(df[j],df[target])
        ts,pv,dfreedom,exp = stats.chi2_contingency(table)
        if (pv<0.05):
            feature_list.append(j)
            print('{} :--> p_value::{} has a Clear Effect on {}'.format(j,pv,target))
        else:
            print('{} is Not Affecting {}'.format(j,target))

    return feature_list

# Function Built for Statistical Test!
```

```
['time_in_hospital', 'patient_visits', 'num_lab_procedures',
 'num_procedures', 'num_medications', 'number_outpatient',
 'number_emergency', 'number_inpatient', 'number_diagnoses', 'race',
 'gender', 'age', 'admission_type_id', 'discharge_disposition_id',
 'admission_source_id', 'diag1_kind', 'diag2_kind', 'diag3_kind',
 'diag1_complications', 'diag2_complications', 'diag3_complications',
 'max_glu_serum', 'A1Cresult', 'metformin', 'repaglinide', 'glipizide',
 'pioglitazone', 'rosiglitazone', 'acarbose', 'insulin', 'change',
 'diabetesMed', 'readmitted'],
```

The Following Features are obtained as Significant.

2. Finding out the Feature Importance of our Base Models.

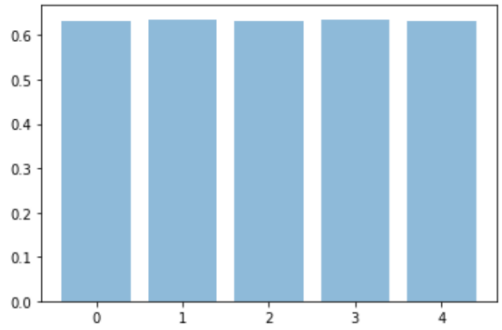




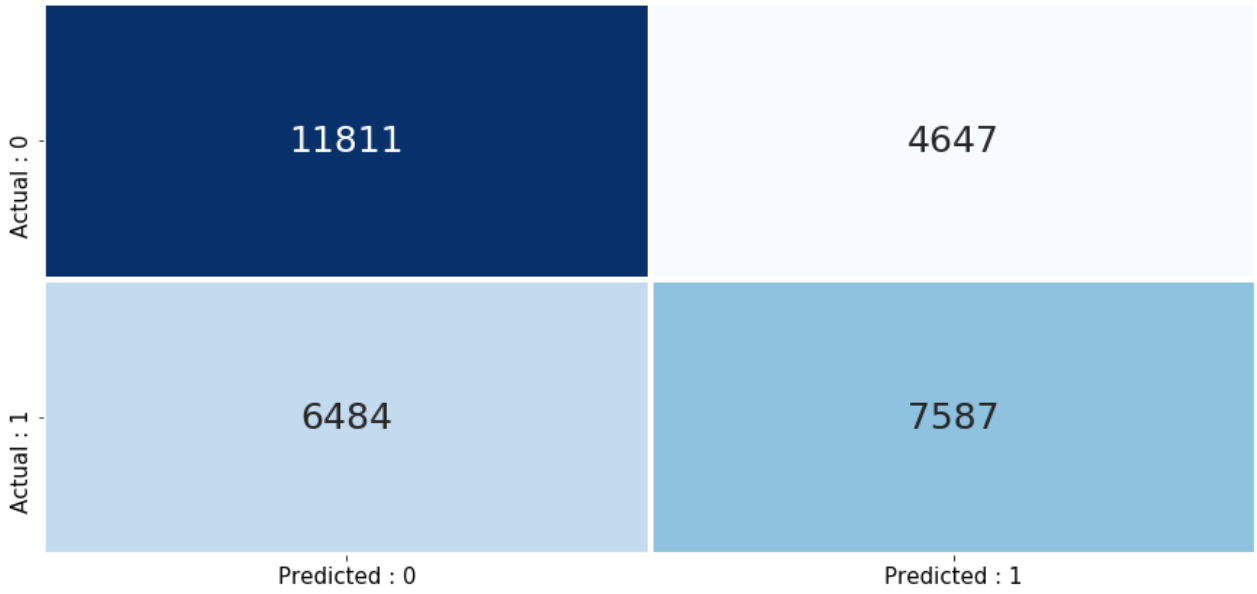
3. Creating a New Data frame with only the Significant Features and Build new Models on this Data frame.

4. Making sure the data is not Overfitting or Underfitting with use of "**Stratified K-Fold**" and "**Cross Validation Score**".

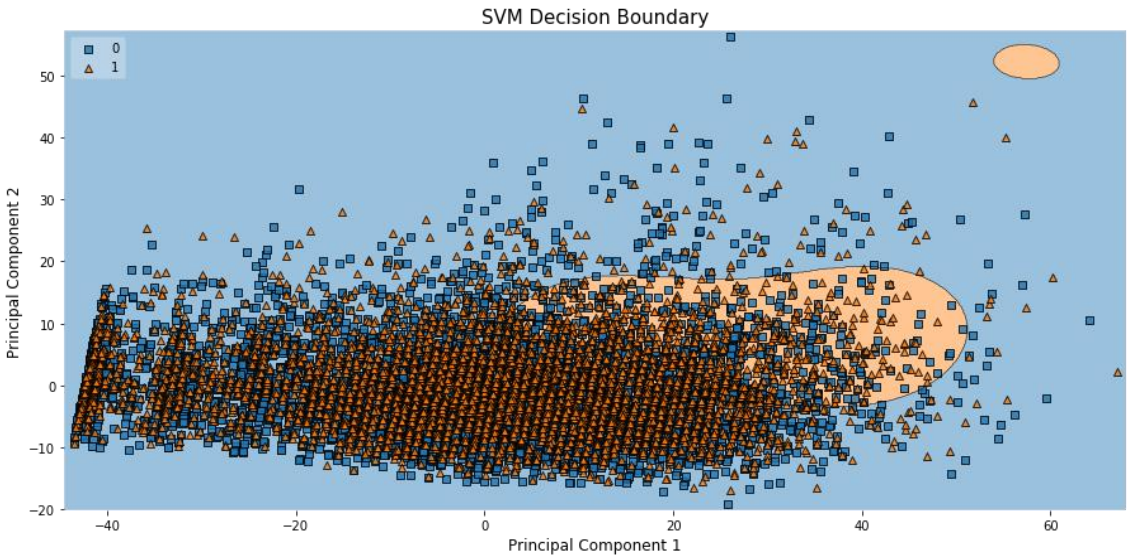
```
RandomForestClassifier(random_state=10) Cross Validation Scores : [0.63171194 0.63522145 0.63276479 0.63592335 0.63266882]
```



5. Plotting a **Confusion Matrix** to see the Distribution of Correctly and Incorrectly Classified Data Points for each Model.



6. Using **PCA** (Principal Component Analysis) and a **SVM** (Support Vector Machine) on the data to gauge the Decision Boundary of the SVM Classifier.



As the Data is not Linear, we have not pursued PCA.

7. Implementing Boosting Algorithms like "**Ada Boost**", "**Gradient Boosting**" and "**XGBoost**" to try and improve on key metrics.

Boosting Algorithms

```
# Lets try boosting to see the improvement in performance!
```

```
ada_model = AdaBoostClassifier(n_estimators=100,random_state =10)
ada_model.fit(Xtrain,ytrain)
ada_pred = ada_model.predict(Xtest)

print('Classification Report :')
print(metrics.classification_report(ytest,ada_pred))
```

```
Classification Report :
              precision    recall  f1-score   support

           0       0.63      0.75      0.69     49375
           1       0.63      0.49      0.55     42212

    accuracy                           0.63     91587
   macro avg       0.63      0.62      0.62     91587
weighted avg       0.63      0.63      0.62     91587
```

```
from sklearn.ensemble import GradientBoostingClassifier

gb_model = GradientBoostingClassifier(n_estimators=100,max_depth=3,random_state=10)
gb_model.fit(Xtrain,ytrain)
gb_pred = gb_model.predict(Xtest)

print('Classification Report :')
print(metrics.classification_report(ytest,gb_pred))
```

```
Classification Report :
              precision    recall  f1-score   support

           0       0.64      0.75      0.69     49375
           1       0.63      0.50      0.56     42212

    accuracy                           0.64     91587
   macro avg       0.64      0.63      0.63     91587
weighted avg       0.64      0.64      0.63     91587
```

```
xgb_model = XGBClassifier()
xgb_model.fit(Xtrain,ytrain)
xgb_pred = xgb_model.predict(Xtest)

print('Classification Report :')
print(metrics.classification_report(ytest,xgb_pred))
```

```
Classification Report :
              precision    recall  f1-score   support

           0       0.64      0.76      0.70     16458
           1       0.64      0.51      0.57     14071

    accuracy                           0.64     30529
   macro avg       0.64      0.63      0.63     30529
weighted avg       0.64      0.64      0.64     30529
```

8. Implementing Feature Selection Techniques on the Data, such as **SFS** (Sequential Feature Selection) to further optimise the key metrics.

SFS on Decision Tree Model

```
# Lets Try Sequential Feature Selector to find the best features for Decision Tree Model based on Recall!
from mlxtend.feature_selection import SequentialFeatureSelector as SFS

dt_sfs = SFS(estimator = DecisionTreeClassifier(),forward = True, scoring = "recall", verbose = 2, k_features = 'best',cv=10

dt_sfsmodel = dt_sfs.fit(Xtrain, ytrain)
print("Features: ", dt_sfsmodel.k_feature_names_)
print("Recall Score: ", dt_sfsmodel.k_score_)

dt_best_features = list(dt_sfsmodel.k_feature_names_)
```

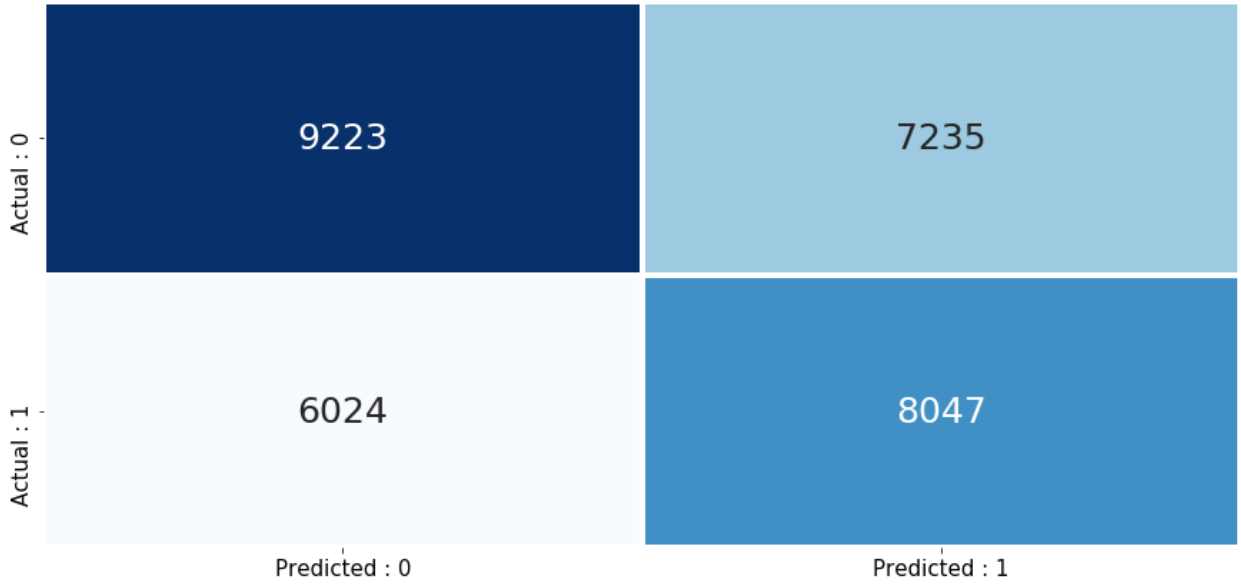
```
1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    1.5s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:    4.5s finished

[2021-03-30 10:47:03] Features: 30/32 -- score: 0.5321961620469082[Parallel(n_jobs=1)]: Using backend SequentialBackend with
1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    1.3s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    2.6s finished

[2021-03-30 10:47:06] Features: 31/32 -- score: 0.5315565031982942[Parallel(n_jobs=1)]: Using backend SequentialBackend with
1 concurrent workers.

Features:  ('number_diagnoses', 'race', 'discharge_disposition_id', 'diag1_complications', 'A1Cresult', 'glipizide', 'pioglit
azone')
Recall Score:  0.579317697228145
```

9. Conducting Hyper Parameter Tuning on the data with "**Randomized Search CV**" to get the best parameters for the models and deploying the tuned models.

Decision Tree Hyperparameter Tuning!

```
parameters = [{'criterion' : ['entropy','gini'],
               'max_depth' : range(5,18),
               'min_samples_split' : range(10,50)}]

dt_search = RandomizedSearchCV(DecisionTreeClassifier(random_state=10),param_distributions=parameters,cv = 5)
dt_search.fit(nXtrain,nytrain)
print('Best Parameters :',dt_search.best_params_)

dt_tune = DecisionTreeClassifier(criterion=dt_search.best_params_['criterion'],max_depth=dt_search.best_params_['max_depth']
dt_tune_model = dt_tune.fit(nXtrain,nytrain)
dt_tune_pred_train = dt_tune_model.predict(nXtrain)
dt_tune_pred_test = dt_tune_model.predict(nXtest)

print('Classification Report :\n',metrics.classification_report(nytest,dt_tune_pred_test))

print('\nChecking for Overfitting/Underfitting:')
print('\t\tTraining Accuracy Score \t:',metrics.accuracy_score(nytrain,dt_tune_pred_train))
print('\t\tTesting Accuracy Score \t:',metrics.accuracy_score(nytest,dt_tune_pred_test))

# Handled Overfitting!
```

```
Best Parameters : {'min_samples_split': 42, 'max_depth': 9, 'criterion': 'entropy'}
Classification Report :
              precision    recall  f1-score   support

           0       0.60      0.56      0.58     16458
           1       0.53      0.57      0.55     14071

    accuracy                           0.57     30529
   macro avg       0.57      0.57      0.57     30529
weighted avg       0.57      0.57      0.57     30529


Checking for Overfitting/Underfitting:
                Training Accuracy Score         : 0.5755678468147233
                Testing Accuracy Score  : 0.5656916374594648
```



REFERENCE Notes for Project Team:

Original owner of data	Center for Clinical and Translational Research, Virginia Commonwealth University
Data set information	The dataset represents 10 years (1999-2008) of clinical care at 130 US hospitals and integrated delivery networks. It includes over 50 features representing patient and hospital outcomes.
Any past relevant articles using the dataset	Impact of HbA1c Measurement on Hospital Readmission Rates: Analysis of 70,000 Clinical Database Patient Records
Reference	https://www.hindawi.com/journals/bmri/2014/781670/
Link to web page	https://archive.ics.uci.edu/ml/datasets/Diabetes+130-US+hospitals+for+years+1999-2008

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