Readmission to Hospital Predictor for Diabetic Patients

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Summary

This project builds a classification model using logistic regression to analyze various diabetic patient features to predict whether or not the patient will be readmitted to the hospital again.

Introduction

For this project, we are trying to answer the predictive question: Given a diabetic patient's demographic, medication history and management of diabetes during hospital stay, can we predict if they will be readmitted to the hospital or not?

Due to COVID-19, it is critical to reduce the burden on the health care system and prevent readmission rates from increasing to make space for COVID-19 cases. Our predictor aims to look at the diabetes management and diagnosis during a patient's hospital stay to understand how much this affects their readmission. Analysis with machine learning models will identify features more likely to predict patient readmission so that hospital management has an idea of where to improve their protocols to better manage diabetic patients during their hospital stay to provide effective care and prevent readmission during this critical time.

Methods

The R programming language (R Core Team 2020) and Python programming language (Van Rossum and Drake 2009) were used to perform the analysis. The following R and Python packages were also used to perform the analysis:

- knitr (Xie 2020)
- tidyverse (Wickham et al. 2019)

- numpy (Harris et al. 2020)
- pandas (McKinney and others 2010)
- altair and altair_saver (VanderPlas et al. 2018)
- hashlib (Rossum and Drake Jr, n.d.b)
- matplotlib (Hunter 2007)
- iPython (Pérez and Granger 2007)
- scikit (Pedregosa et al. 2011)
- requests (Chandra and Varanasi 2015)
- zipfile (Rossum and Drake Jr, n.d.e)
- urllib (Rossum and Drake Jr, n.d.c)
- io (Rossum and Drake Jr, n.d.a)
- pandas profiling (Brugman 2019)
- warnings (Rossum and Drake Jr, n.d.d)

For statistical analysis specifically:

- StackOverflow (Whidden, n.d.)
- store_vals_function (Kolhatkar, n.d.)
- plot formatting (Ostblom, n.d.)

The code used to perform the project and create this report can be found here (https://github.com/UBC-MDS/group29).

Data

The data are submitted on behalf of the Center for Clinical and Translational Research, Virginia Commonwealth University, a recipient of NIH CTSA grant UL1 TR00058, and a recipient of the CERNER data. This dataset was collected from 1998-2008 among 130 hospitals and integrated delivery networks throughout the United States of America.

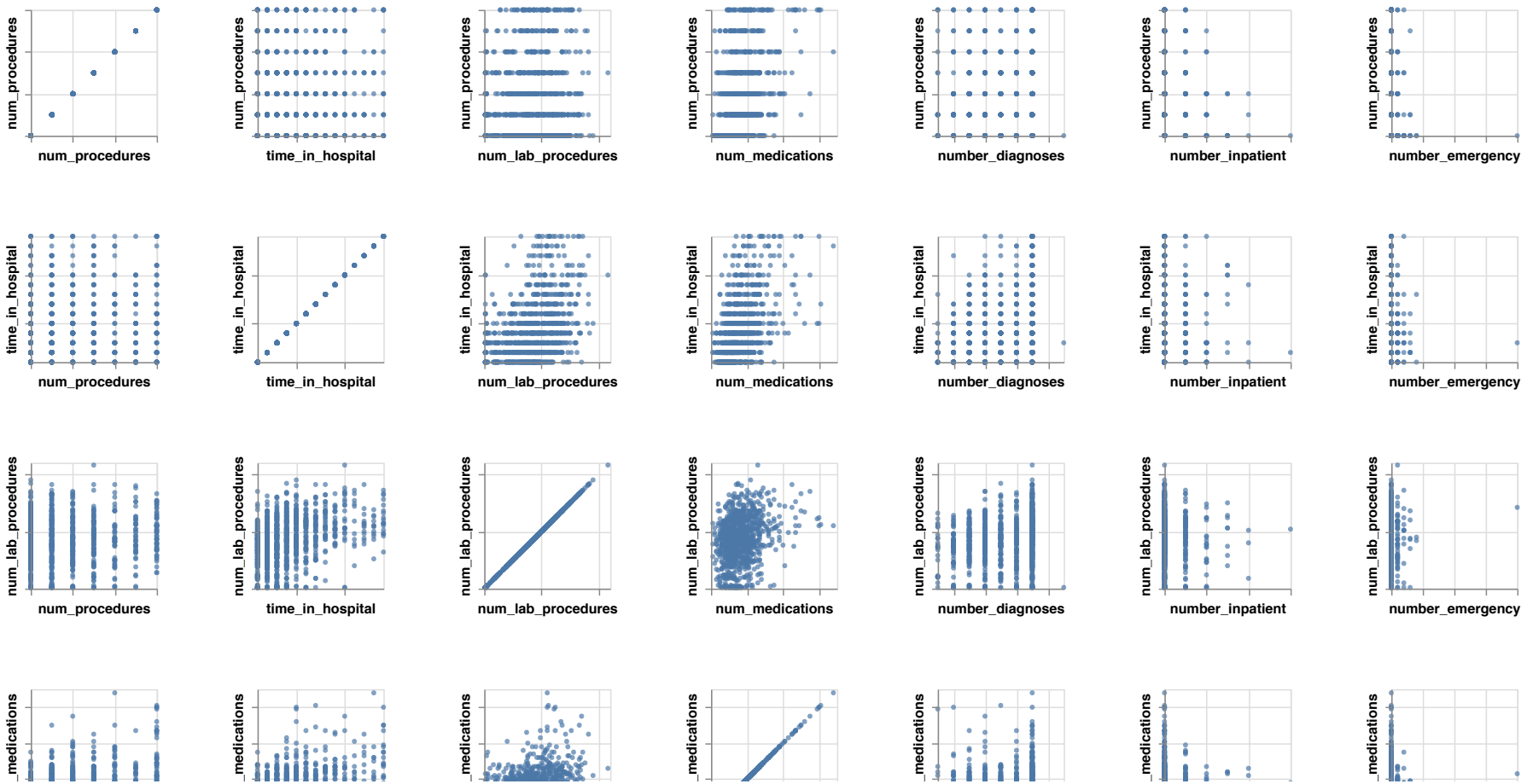
This data set was sourced from the UCI Machine Learning Repository (Strack et al. 2014a) and can be found here (https://archive.ics.uci.edu/ml/datasets/diabetes+130-us+hospitals+for+years+1999-2008#). Research from this collected data was used to assess diabetic care during hospitalization and determine if patients were likely to be readmitted or not. The paper by (Strack et al. 2014b) can be found here (https://www.hindawi.com/journals/bmri/2014/781670/). Each row corresponds a unique encounter with a diabetic patient, totaling 74,036,643 unique encounters. Details about each column feature of information collected during these unique encounters can be found here (https://www.hindawi.com/journals/bmri/2014/781670/tab1/).

Analysis

After data cleaning, machine learning model logistic regression was tested against radial basis function kernel with support vector machine (RBF SVM) and a baseline dummy classifier method. Logistic regression was determined as the best model in terms of fit and score time, accuracy, and f1 score. Continuing with logistic regression, hyperparameters were optimized and our model was then used to predict diabetic patient readmission (found in the readmitted target column of the data set). The code used to perform the analysis can be found here (https://github.com/UBC-MDS/group29/tree/main/src).

Results and Discussion

Through exploratory data analysis, we determined that some of the features were not informative to answering our question or contained many missing values. Feature information was confirmed through Pandas Profiling which can be found here (https://github.com/UBC-MDS/group29/blob/main/reports/figures/pandas_profiling.html) as well as correlation between specific features and potential class imbalance based on the target readmitted column. Correlation between certain numerical values shown in Pandas Profiling was confirmed when we analyzed interactions between the features.



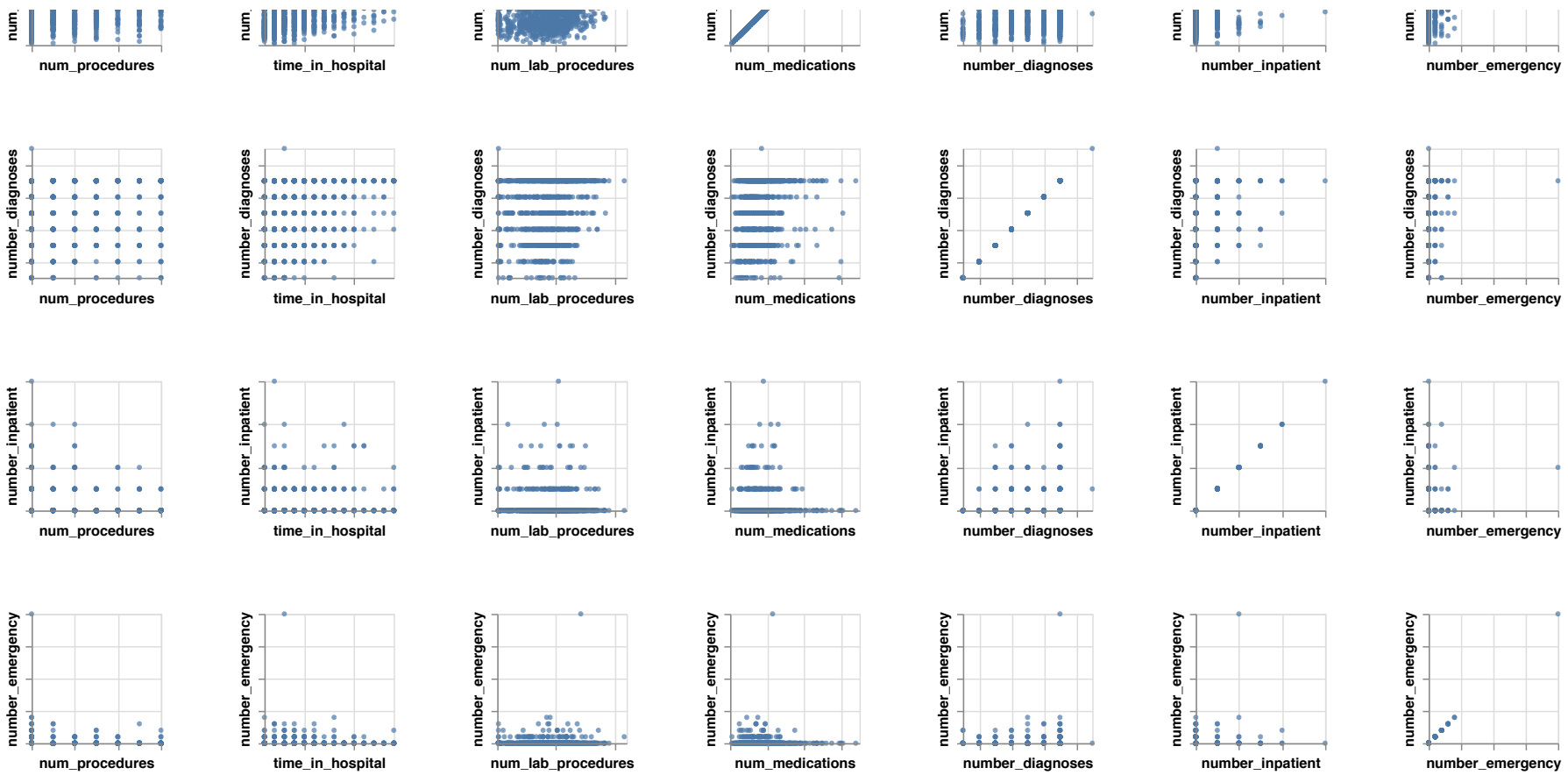


Figure 1. Interactions and Correlation of Numeric Features

Data cleaning was done to address non-informative features, class imbalance, NAN values, and duplicate encounters, and this code can be found here (https://github.com/UBC-MDS/group29/blob/main/src/processingdata.py). Particularly, the distribution of race was reviewed to determine that there was no significant difference between different races in patient readmission and therefore the race column was removed from our analysis.

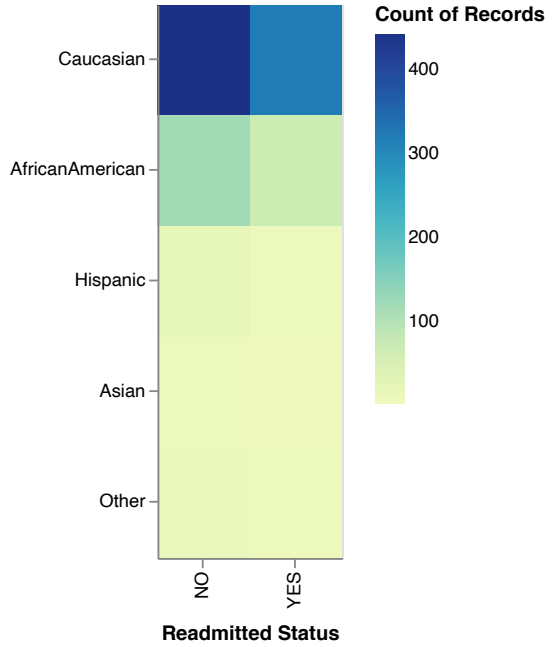


Figure 2. Distribution of Race and Readmission Status

Several of the numerical features were reviewed by plotting the distribution of the feature for the two different target classes against each other and found the primary diagnosis of the patient, days spent in hospital, number of medications taken and the frequency of lab procedures to be most informative of predicting readmission status. The importance of the primary diagnosis feature is that if the primary diagnosis is diabetes perhaps patients received better care during their first encounter and thus do not get readmitted (Strack et al. 2014b).

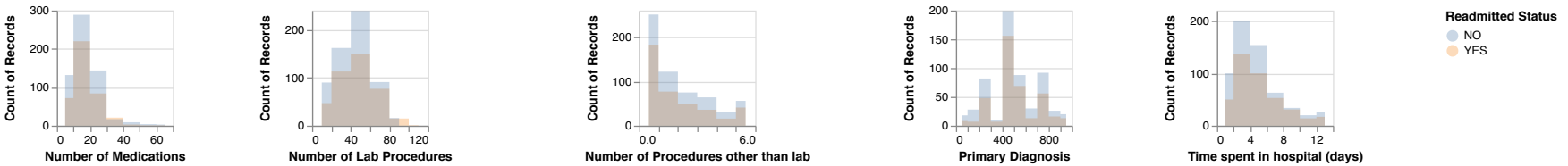


Figure 3. Distribution of Numeric Features and Readmission Status

Several of the categorical features were also reviewed in a similar format to the numerical features analysis, and found that metformin, insulin, and Hemoglobin A1C levels were most informative of predicting readmission status. Testing for hemoglobin levels may have resulted in applicable changes to the medications and thus better management of diabetes during their hospital stay, preventing readmission (“Insulin, Medicines, &Amp; Other Diabetes Treatments” 2016).

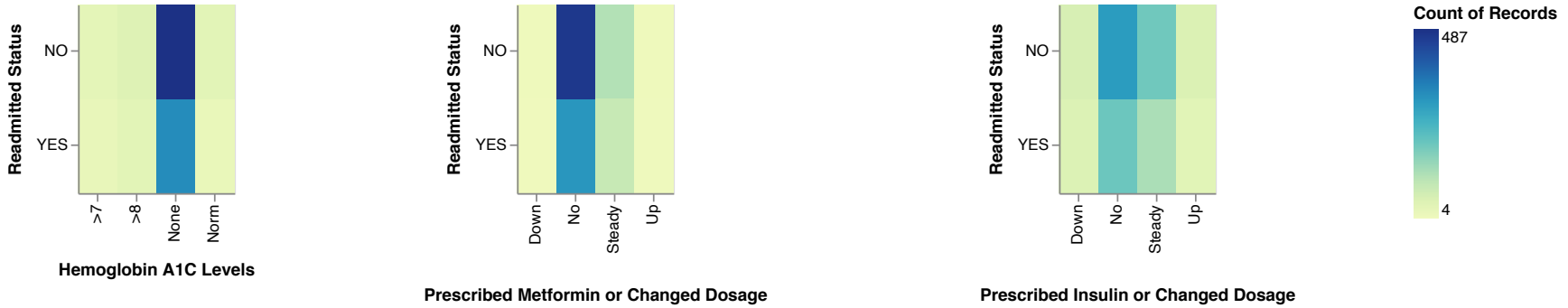


Figure 4. Distribution of Categorical Features and Readmission Status

After exploratory data analysis and data cleaning, machine learning models were tested with our data set, and logistic regression (balanced) was determined as the best model to move forward with in our analysis based on fit and score time, accuracy, and f1 scores as shown in Table 1. The code used to perform machine learning can be found here (https://github.com/UBC-MDS/group29/blob/main/src/explore_script4.py).

Table 1. Classifier Models and Their Associated Times and Scores

Time or Score	Dummy Classifier	RBFSVM	Logistic Regression	Logistic Regression (balanced)
fit_time	0.0259	0.0736	0.1097	0.1086
score_time	0.0296	0.0495	0.0293	0.0290
test_accuracy	0.5212	0.6238	0.5837	0.5650
train_accuracy	0.5194	0.7009	0.8441	0.8459
test_f1	0.4259	0.3212	0.4342	0.4909
train_f1	0.4216	0.4742	0.7972	0.8204
test_recall	0.4275	0.2170	0.3857	0.5063
train_recall	0.4225	0.3253	0.7387	0.8479
test_precision	0.4250	0.6473	0.5041	0.4826
train_precision	0.4210	0.8771	0.8659	0.7947
test_average_precision	0.4250	0.6473	0.5041	0.4826
train_average_precision	0.4210	0.8771	0.8659	0.7947

Time or Score	Dummy Classifier	RBFSVM	Logistic Regression	Logistic Regression (balanced)
test_roc_auc	0.4919	0.5978	0.5924	0.5915
train_roc_auc	0.4943	0.8670	0.9143	0.9162

Hyperparameter optimization was performed and identified potential improvements for our model in future use. From the confusion matrix, we can see that there is a high amount of false positives and false negatives. From the receiver operating characteristic curve with area under the curve (ROC curve with AUC), and the red point showing our threshold at 0.5, our model is performing at 0.54 where AUC = 1.0 is a perfect classification. These results suggest that our model could be improved by choosing a different classifier or testing other scoring methods for our optimization besides f1-score. Our model performed average on the test data, and will therefore require improvements before implementation on deployment data for use in clinical studies. Details about these improvements can be found in the Future Improvements section of this report.

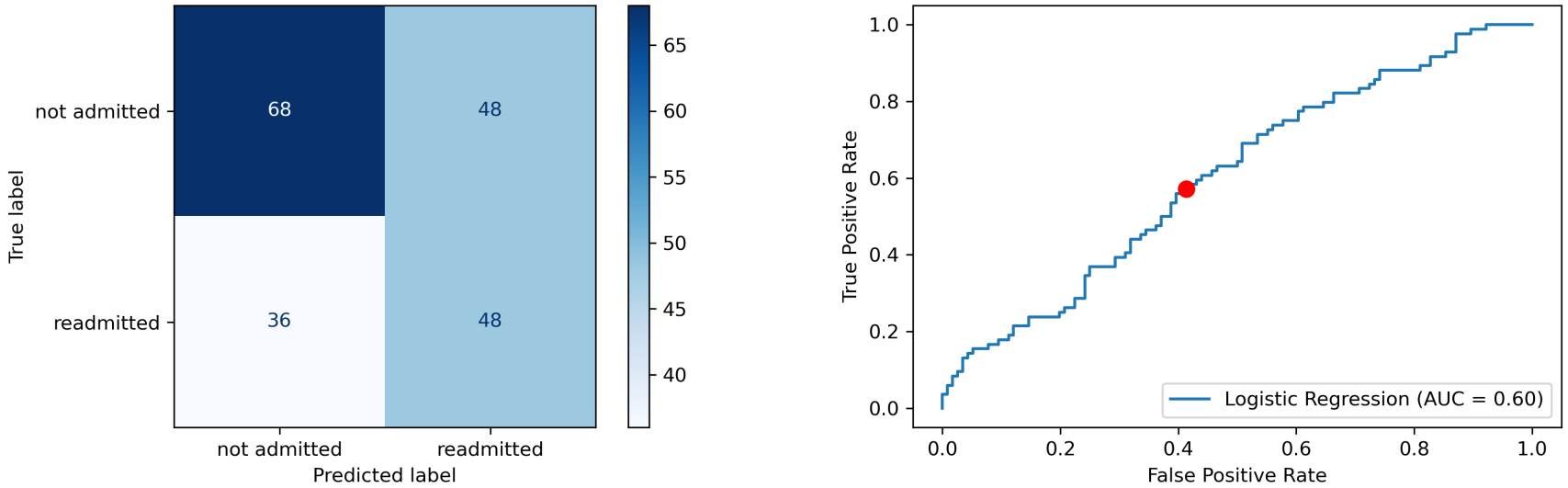


Figure 5. Confusion Matrix and ROC AUC Curve Results From Logistic Regression (Balanced)

Completing our analysis using our model on test data, the top 10 features most indicative of patient readmission were found by having the highest associated coefficients as shown in Table 2. These results suggest the health care system begin implementing changes in these specific features, particularly in admission type ID, in order to manage diabetic patient readmission more effectively.

Table 2. Top 10 Features Most Indicative of Patient Readmission

Features	Coefficients

Features	Coefficients
admission_type_id	0.2663170
discharge_disposition_id	0.2435044
admission_source_id	0.2473305
time_in_hospital	0.0084882
num_lab_procedures	0.0297474
num_procedures	0.0265883
num_medications	0.0958197
number_outpatient	0.2936842
number_emergency	0.1059684
number_inpatient	0.7724087

Future Improvements

To improve our model in the future to further analyze patient readmission, we can recommend three main suggestions. First, rather than subsetting our data to take a representative and random sample of 1000, we can take a larger subset or even use our entire data set of roughly 70,000 observations. Our reasoning for subsetting the data was to reduce fit and score time of our models. In future models, the use of a larger data set will provide more accurate predictions, reduce bias, and identify outliers that may skew our results. Second, other classifier models such as random forest could be used to test against our logistic regression model to improve predictions. The use of logistic regression assumes there is a linear relationship between the independent and dependent variables, which may not be the case in our project. Random forest is non-parametric and will bypass this linearity assumption associated with logistic regression. Third, our model analyzes a binary classification of readmission although the original data set was a multi-classification of readmission (not readmitted, readmitted for less than 30 days, readmitted for more than 30 days). By using a multi-classification model instead, we can generate a more specific prediction and analyze the severity of features related to readmission time, making our conclusions more informative to improving the health care system.

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