A Data-Driven Approach to Improving Hospital Observation Unit Operations

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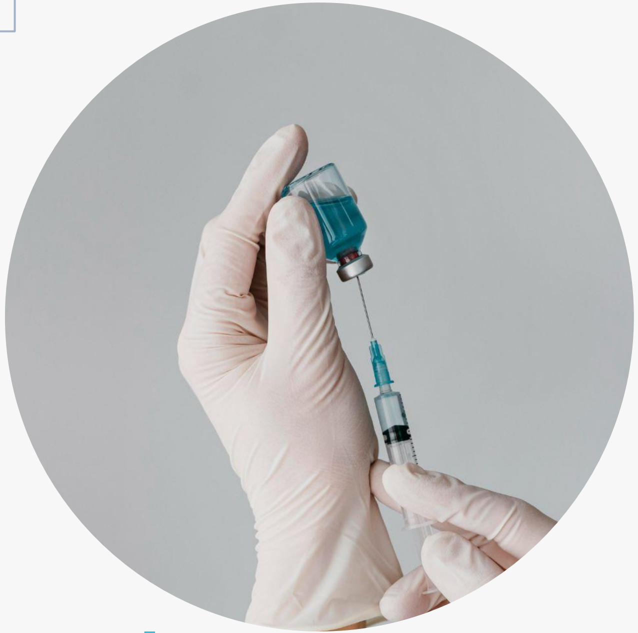
Problem Description



Problem Description

Problem statement

- Prolonged Average Length of Stay in the OU
- Outdated Patient Placement Protocols

  → *Patients being placed in inpatient beds due to OU capacity limitations*
- Inaccurate OU Exclusion List

Impact

- Suboptimal Resource Utilization
- Potential Medical Errors due to handoffs
- Limiting Revenue Generation

Research Questions: —What are the critical influencers of flipped rate?

—How can the OU patient flow be enhanced?

Dataset

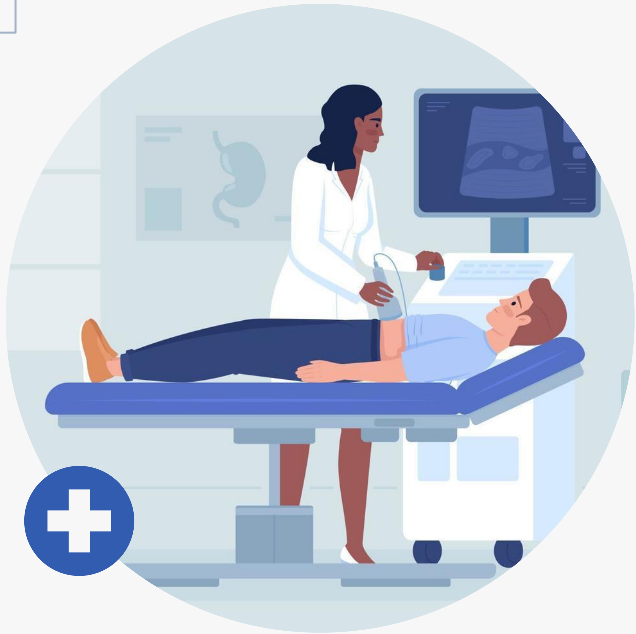
1111 observations - **13** variables

Age	Age of patients
Gender	Patient gender (Male/Female)
PrimaryInsurance Category	Insurance providers of the patient
Flipped	1- Observation -> Inpatient. 0- Observation -> Discharged
OU_LOS_hrs	Length of stay in the OU in hours
DGR01	Initial primary diagnosis-related group
BloodPressureLower	Diastolic, or lower, blood pressure
BloodPressureUpper	Systolic, or upper, blood pressure
BloodPressureDiff	Difference between systolic and diastolic blood pressure
Pulse	Patient Pulse
Pulse Oximetry	Measure level of oxygen in patient’s blood
Respirations	Number of breaths patients takes per minutes
Temperature	Patient’s temperature

02

Methodology

- Data Preprocessing
- Data Visualization
- Modeling & Applying ML Techniques



Data Preprocessing

1. Covert data to the correct type

As.factor (‘Gender’, ‘PrimaryInsuranceCategory’, ‘InitPatientClassAndFirstPostOUClass’, ‘Flipped’, ‘DRG01’ **)**

As.numeric (‘BloodPressureUpper’, ‘BloodPressurLower’ ‘BloodPressureDiff’, ‘Pulse’,‘PulseOximetry’, ‘Respirations’, ‘Temperature’ **)**

2. Handling Missing Values

‘BloodPressureUpper’, ‘BloodPressureDiff’, ‘PulseOximetry’, ‘Respirations’ and ‘Temperature’ (Numerical variables)

➜ Plot distributions ➜ Skewed ➜ Impute with Median

3. Dimension Reduction

Removing ‘ObservationRecordKey’ and ‘InitPatientClassAndFirstPostOUClass’ due to redundancy

Data Visualization

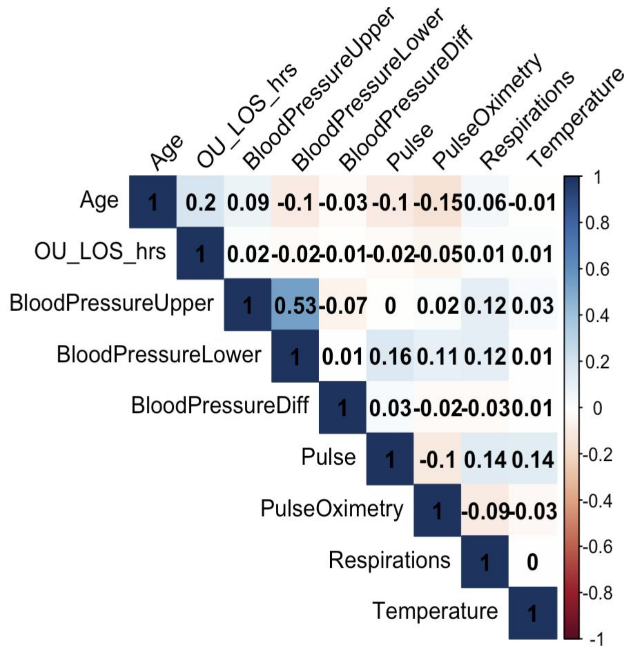


Figure 1: Correlation Heatmap

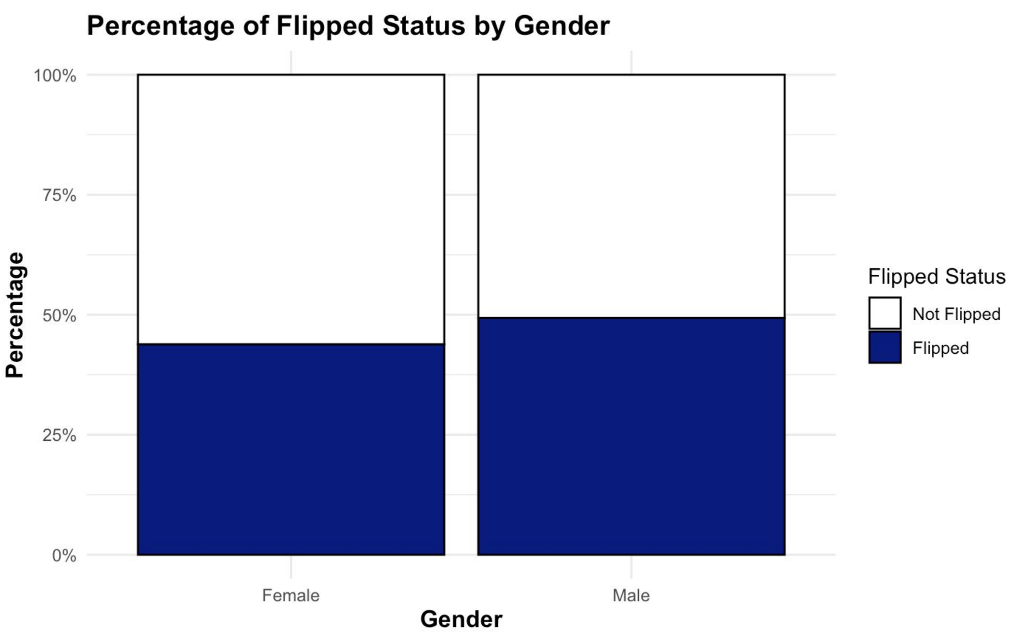


Figure 2: Proportion of Flipped and Non-Flipped patient by Gender

Data Visualization

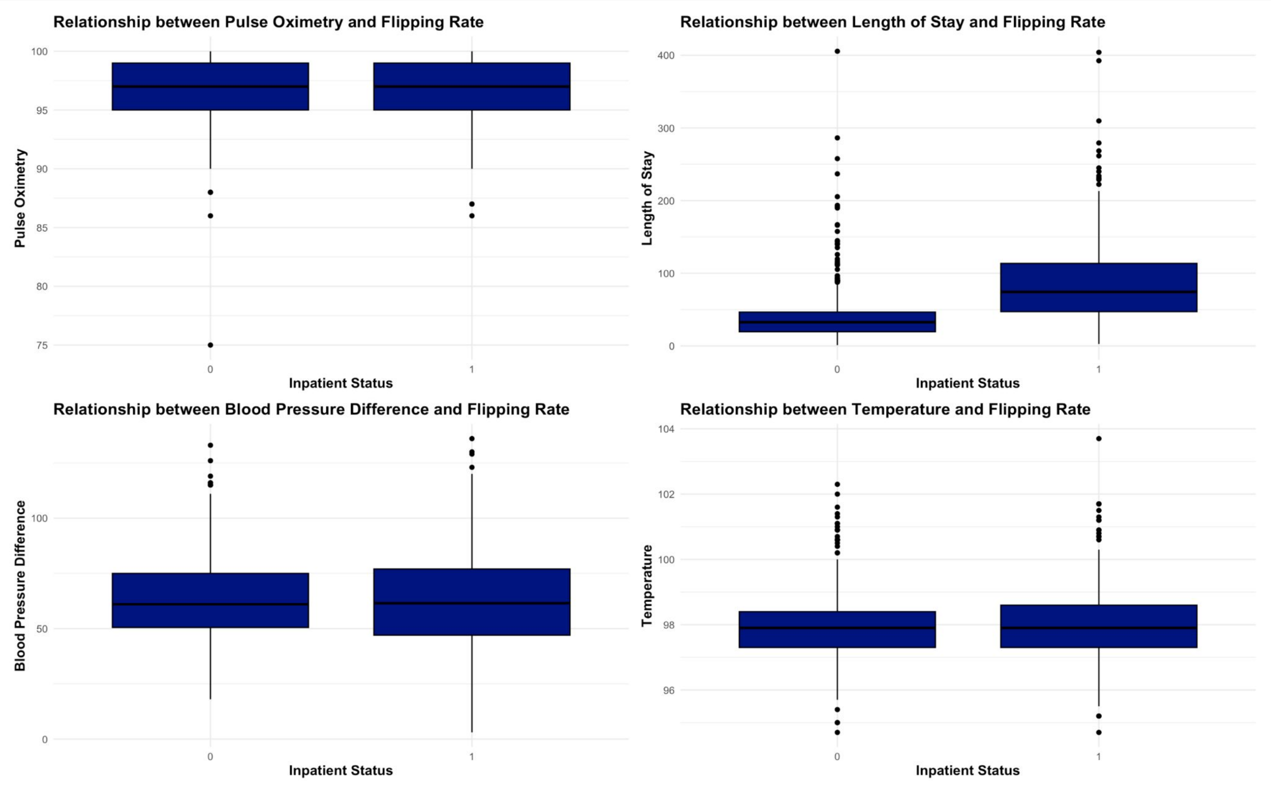


Figure 3: Box plots of Pulse Oximetry, Length of Stay, Blood Pressure Difference and Temperature for “Flipped” and “Non-Flipped” groups

Data Visualization

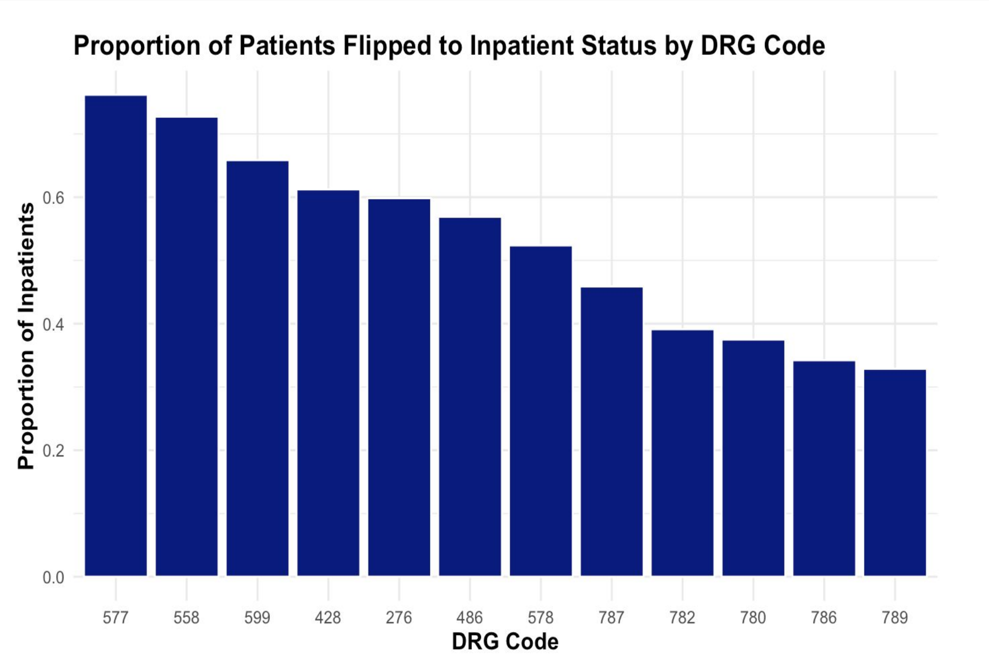


Figure 4: Bar Chart of the proportion of flipped patient by DRG code

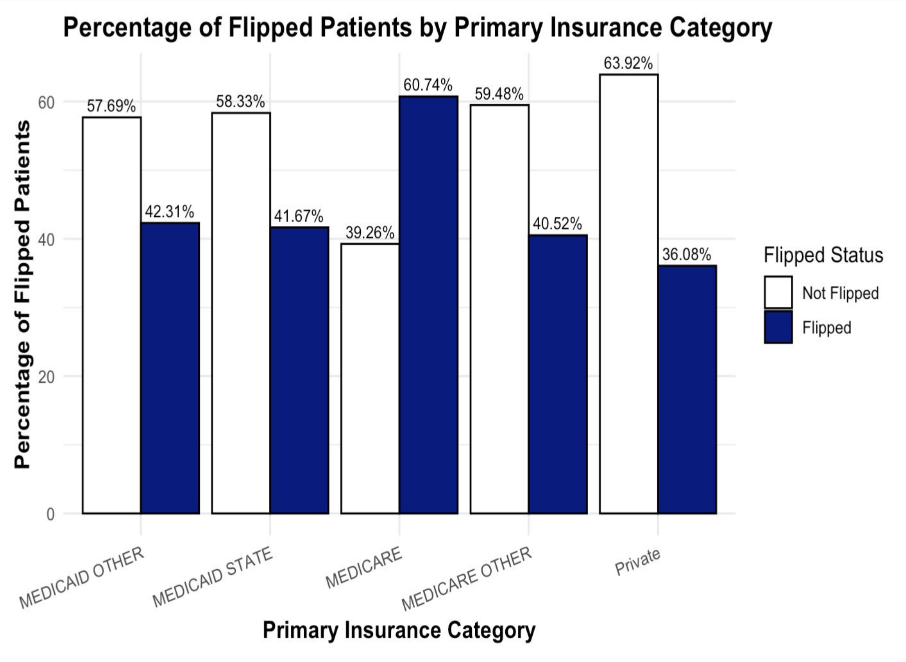


Figure 5: Bar Chart of flipping proportion by primary insurance company

Techniques

Logistic Regression

Classification Tree

Random Forest

Naive Bayes

Modeling & Applying Techniques

Q: What are the critical factors in predicting patient status flipping rate?

Logistic Model (Reduced): P(Flipped | Age, Primary Insurance Category, DRG Code, Length of Stay)

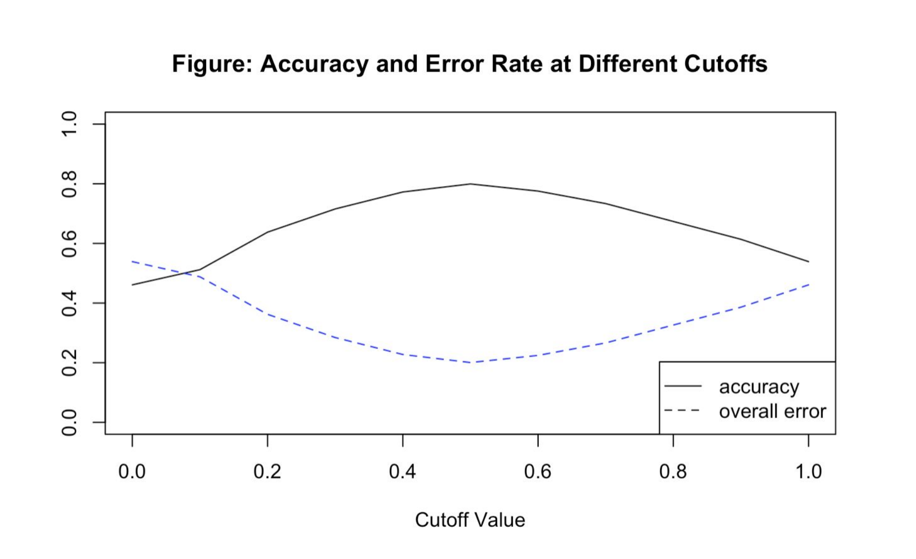


Figure 6: Accuracy Rate at different cutoffs

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Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 151  38
         1  29 116

               Accuracy : 0.7994
                 95% CI : (0.7524, 0.841)
    No Information Rate : 0.5389
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.5946

 Mcnemar's Test P-Value : 0.3284

            Sensitivity : 0.8389
            Specificity : 0.7532
         Pos Pred Value : 0.7989
         Neg Pred Value : 0.8000
             Prevalence : 0.5389
         Detection Rate : 0.4521
   Detection Prevalence : 0.5659
      Balanced Accuracy : 0.7961

       'Positive' Class : 0
```

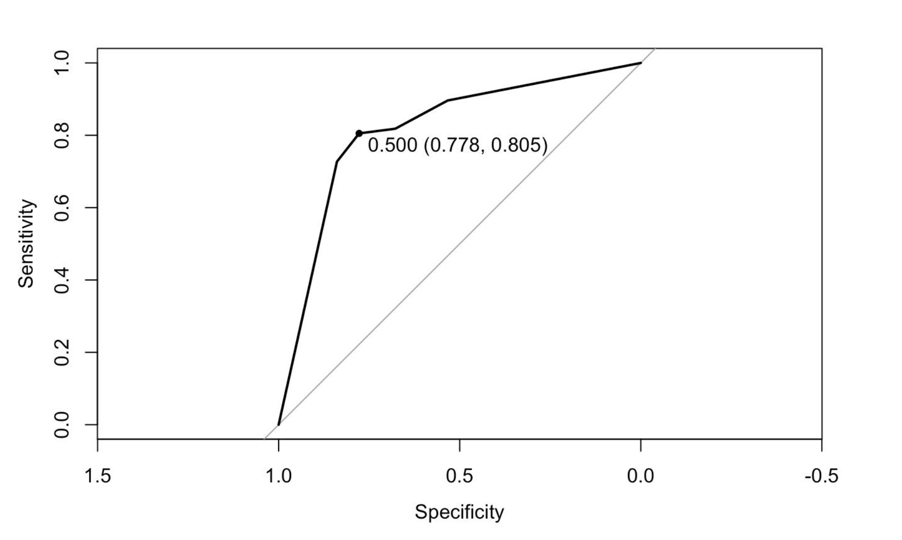
Figure 7: Confusion Matrix of chosen model

Technique Evaluation

	Logistic Regression	Classification Tree	Random Forest	Naive Bayes
Accuracy	0.7994	**0.7904**	0.7814	0.4611
Specificity	0.7532	**0.8052**	0.7792	0.6169

Figure 8: ROC Curve of Classification Tree

AUC = 0.816



03

Results

Results

Flipped Rate by DRG	
Congestive Heart Failure	0.2769
Pneumonia	-0.1277
Colitis	0.5
Pancreatitis	0.7473
GI Bleeding	-0.3
Urinary Tract Infection	-0.39
Syncope	-1.57
Edema	-0.65
Chest Pain	-1.3
Nausea	-0.93
Abdominal Pain	-1.04

Figure 9: Logistics Regression Coefficient of DRG

True Positive Rate by DRG	
Dehydration	91%
Congestive Heart Failure	88%
Pneumonia	67%
Colitis	71%
Pancreatitis	75%
GI Bleeding	75%
Urinary Tract Infection	93%
Syncope	84%
Edema	67%
Chest Pain	76%
Nausea	85%
Abdominal Pain	62%

Figure 10: Model's ability to correctly predict flipping rate by DRG

Results

	OU Patient Flow (weekly)			OU Patient Flow Using Model		
Type of patient	Percentage	Number of patient	Average OU LOS (day)	Percentage	Number of patient	Average OU LOS (day)
Post-surgery	33,30%	22	1	33,30%		1
Medicine service		44				
1. Remain in Observation status	55%	24,2	1,7	55%		1,7
2. Changed to Inpatient status	45%	19,8		**7%**	3,08	**1,4**
a) Not transfered to inpatient ward before discharge	75%	14,85	3,7	75%		**1,06**
b) Transfer to inpatient ward	25%	4,95	3,25	25%		**0,35**
Average Inpatient LOS (assumed)			5			0.54

Figure 11: OU Patient Flow before and after applying predictive model

Financial Input	
Average Revenue per Observation patient	$5.000
Average Revenue per Admitted patient	$11.000
Cost per day for an Observation bed	$650
Cost per day for an Inpatient bed	$100

Figure 12: Average Assumptions of Financial Input

Improvement Summary

	Case Study		Model	
	Cost per Case	Profit per Case	Cost per Case	Profit per Case
Observation status - Observation bed - Discharge	$1.755	$3.245	$1.755	$3.245
Observation status - Inpatient bed - Discharge	$270	$4.730	$270	$4.730
Observation status - Observation bed - Inpatient Status	$2.113	$8.888	$284	$10.716
Observation status - Inpatient bed - Inpatient status	$325	$10.675	$90	$10.910
Total	**$4.463**	**$27.538**	**$2.398**	**$29.602**

Figure 13: Cost-Benefit comparison before and after applying model

04

Recommendation

Recommendation

Adopt the predictive model

- Modify OU exclusion list based on DRG code that are most likely to flip based on both actual and model predicted result → **including Pancreatitis, Colitis, Urinary Tract Infection, Dehydration and Congestive Heart Failure** in OU exclusion list
- Model reduces the flipping rate from 45% to 7% -> a substantial decrease in operational disruption and improve patient care

Resource allocation

- With a lower flipping rate, there may be a reduced need for inpatient staff time -> reallocate of resources to the OU based on DRG groups' needs to improve utilization

Technology Integration

- Ensure that the predictive model is fully integrated into the hospital's electronic health record (EHR) system for ease of use by the ED, OU, and inpatient staff

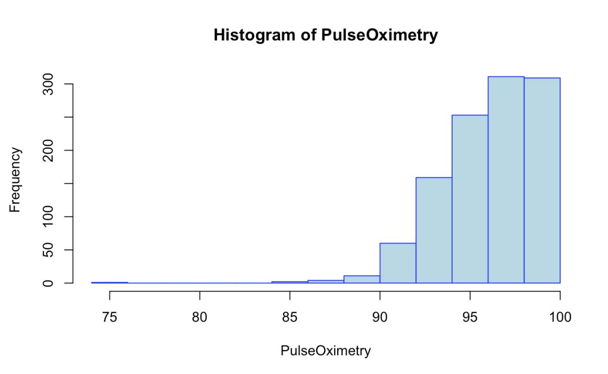
Performance Tracking

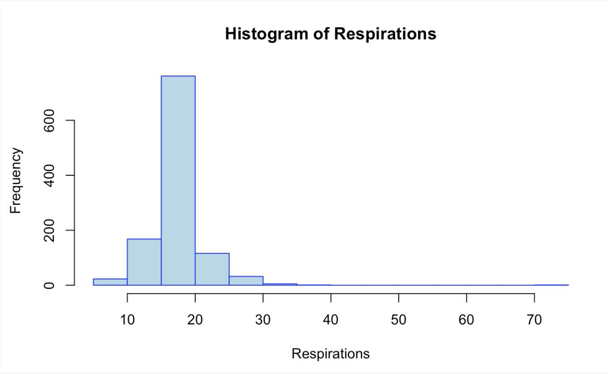
- Establish KPIs to track the model's impact on flipping rates, patient outcomes, and operational costs

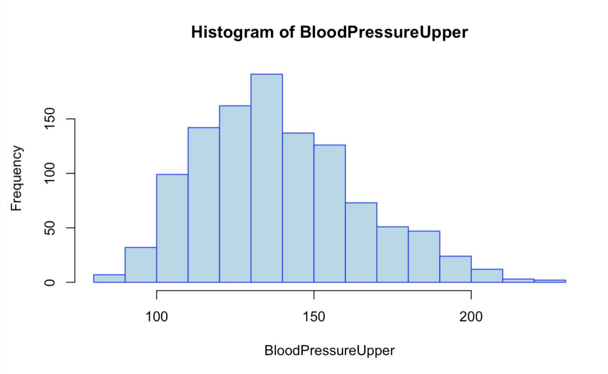
Thank You

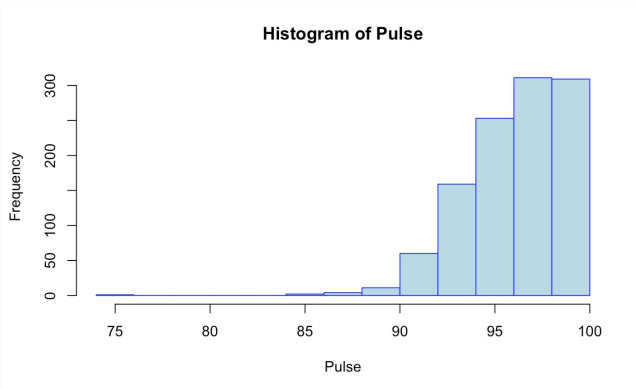
Appendix

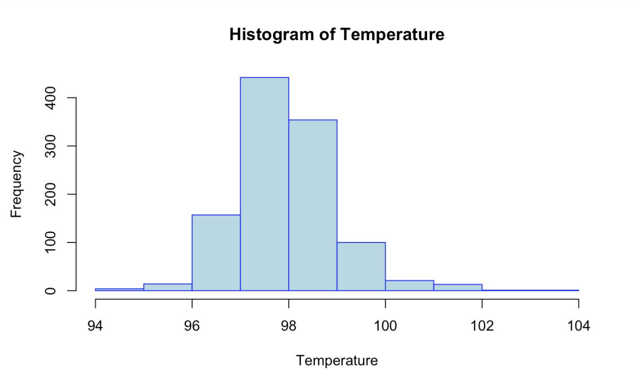
Appendix 1. Distributions of numeric variables with missing values











Appendix

Appendix 2. Logistic Model using Stepwise Selection Method

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Call:
glm(formula = Flipped ~ Age + PrimaryInsuranceCategory + OU_LOS_hrs +
    DRG01, family = binomial(link = "logit"), data = train.df)

Coefficients:
                                          Estimate Std. Error z value Pr(>|z|)
(Intercept)                              -0.309862   0.519741  -0.596 0.551052
Age                                      -0.015938   0.007087  -2.249 0.024519 *
PrimaryInsuranceCategoryMEDICAID STATE    0.075414   0.465948   0.162 0.871423
PrimaryInsuranceCategoryMEDICARE          0.980352   0.385009   2.546 0.010887 *
PrimaryInsuranceCategoryMEDICARE OTHER -0.028396   0.395753  -0.072 0.942799
PrimaryInsuranceCategoryPrivate           0.118560   0.360942   0.328 0.742553
OU_LOS_hrs                                0.030243   0.002792  10.832  < 2e-16 ***
DRG01428                                  0.276947   0.480179   0.577 0.564103
DRG01486                                 -0.127735   0.449622  -0.284 0.776338
DRG01558                                  0.504422   0.586525   0.860 0.389780
DRG01577                                  0.747287   0.767393   0.974 0.330156
DRG01578                                 -0.302138   0.520587  -0.580 0.561659
DRG01599                                 -0.390473   0.420089  -0.930 0.352629
DRG01780                                 -1.570000   0.322929  -4.862 1.16e-06 ***
DRG01782                                 -0.650213   0.734101  -0.886 0.375764
DRG01786                                 -1.299789   0.362122  -3.589 0.000331 ***
DRG01787                                 -0.929946   0.411921  -2.258 0.023972 *
DRG01789                                 -1.035670   0.360072  -2.876 0.004024 **
```
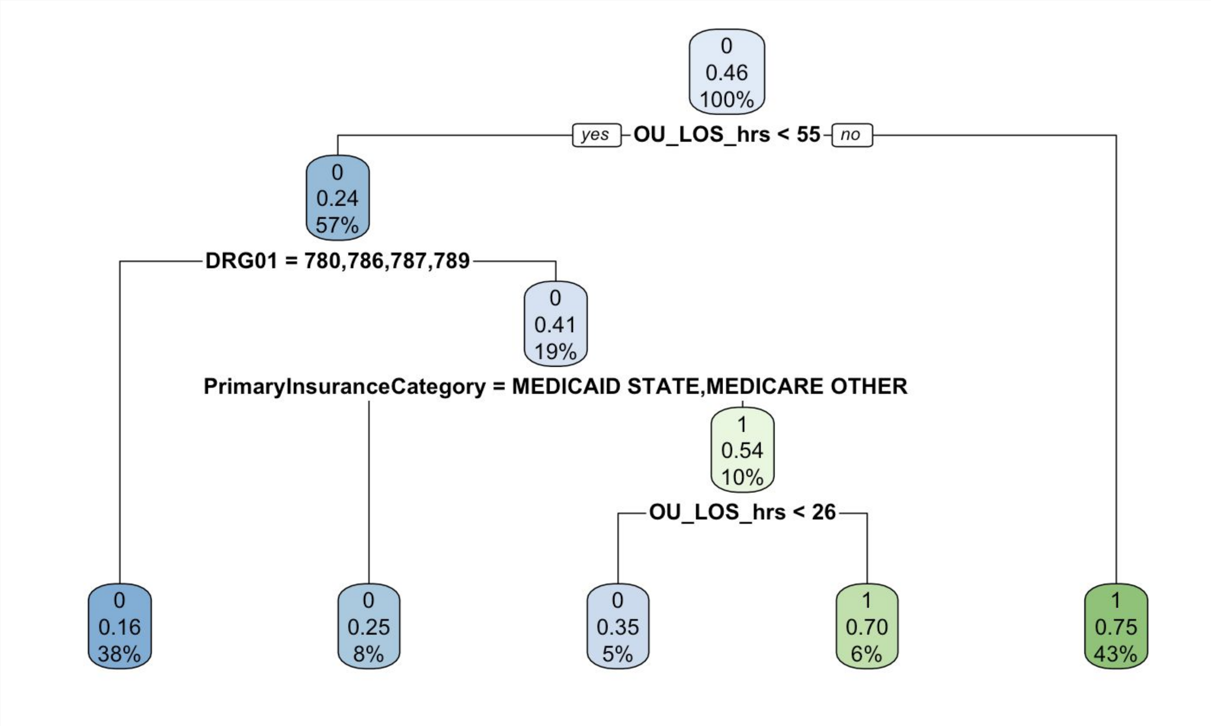

Appendix

Appendix 3. Confusion Matrix of Classification Tree

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 140  30
         1  40 124

               Accuracy : 0.7904
                 95% CI : (0.7428, 0.8328)
    No Information Rate : 0.5389
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.5803

 Mcnemar's Test P-Value : 0.2821

            Sensitivity : 0.7778
            Specificity : 0.8052
         Pos Pred Value : 0.8235
         Neg Pred Value : 0.7561
             Prevalence : 0.5389
         Detection Rate : 0.4192
   Detection Prevalence : 0.5090
      Balanced Accuracy : 0.7915

       'Positive' Class : 0
```

Appendix

Appendix 4. Classification Tree using the chosen model



Appendix

Appendix 5. Flipped Rate based on Tree Rules

	A	D	F	H	I	T	U	V	W	X	Y	Z	AA
1	ObservationRe	PrimaryInsuranceCatego	Flipped_nu	OU_LOS_hrs	DRG01	Flipped Predict	1 ---> 0		0 ---> 1				
2	905459x1	MEDICAID STATE	1	37,3	428	=IF(H2>55;1;IF(AND(H2<55;OR(I2=780;I2=786;I2=787;I2=789));0;IF(OR(D2="MEDICAID STATE";D2="MEDICARE OTHER");0;IF(H2<26;0;1))))							
3	131565z1	MEDICARE	1	96,3	786	1							
4	448887x1	MEDICAID STATE	1	112,8	558	1							
5	859289z1	Private	0	5,5	786	0							
6	170477x1	MEDICAID STATE	0	15,2	789	0							
7	784052z1	MEDICARE OTHER	1	117,2	578	1							
8	409162x1	MEDICARE OTHER	0	16,4	578	0							
9	154066z1	Private	1	106	577	1							
10	914486x2	MEDICARE	1	110,6	780	1							
11	055937z1	MEDICARE	1	392,5	276	1							
12	472260x1	MEDICAID STATE	1	161,3	276	1							
13	429637x2	MEDICARE OTHER	1	63,1	787	1							
14	254550x2	MEDICARE	1	90,5	780	1							
15	831147z1	Private	1	49,3	782	1							
16	476048z1	MEDICARE OTHER	1	57,8	276	1							
17	728164x2	MEDICARE OTHER	1	160,7	599	1							
18	454389z1	MEDICARE OTHER	0	40,7	787	0							
19	708909z1	Private	0	14,8	787	0							
20	271927z1	MEDICARE OTHER	1	158,5	780	1							

Appendix

Appendix 6. # of changed status

COUNT of Flipped Predict	Flipped Predict		
Flipped_nu	0	1	Total
0	118	62	180
1	23	131	154
Total	141	193	334
Changed to Inpatient status	=Y8/AA9	**7%**	

Appendix

Appendix 7. Average OU_LOS_hrs using model

AVERAGE of OU_LOS_hrs	Flipped Predict	
Flipped_nu	0	1
0	23,92118644	64,88064516
1	33,86521739	98,63816794
Average OU LOS (day) Changed to Inpatient status	=AE8/24	**1,4**