



# Team 2

## Ward Admission Classification



Connor Mignone, Amanda Konet, Yilin Ye,  
Tonnar Castellano, Sarah Torrence

# EXECUTIVE SUMMARY

## Objectives

- Predict patient admission into hospital if test positive for COVID-19
- Avoid false negatives

## Conclusions

- Blood Test results are most important for predicting admission
- “Accurately” predict true positives

## Methodology

- Exploratory Data Analysis
- SMOTE and ROSE Oversampling
- KNN and Random Forests

## Next Steps

- More Data
- Predict admission by ward
  - (ICU, semi-intensive, regular)
- Dashboard for medical professionals

# OBJECTIVE

- Minimize the Externalities
- Save Hospital Resources
- Save Lives



# DATA

- Only COVID-19 positive patients
- 558 observations and 63 variables
- Limitations: missing patient medical history and symptoms





# ASSUMPTIONS

## Covid Positives Only

Model can only be used to predict admission of covid positive patients.

## Missing Tests

Imputed missing values based on assumption patients with no lab tests would have normal levels.

# METHODS/APPROACH


## Exploratory Data Analysis

Understanding lab tests, distributions of admitted patients

## Feature Engineering

Created features based on lab test variable groupings

## Modeling

Random Forest   
K Nearest Neighbors

## Data Cleaning

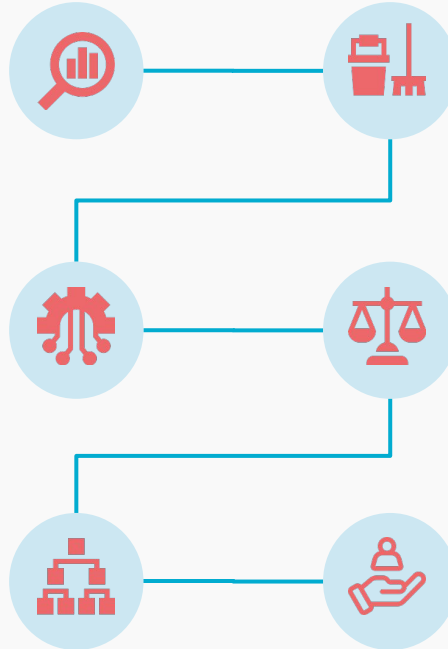
Handle missing data by removing columns or imputing values

## Balancing Train Set

Oversample admitted patients, undersample discharged patients

## Validation & Value

Estimate model results and value to the hospital

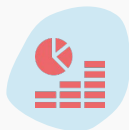


# DATA CLEANING



## Covid Positive

Filtered for only covid positive patients



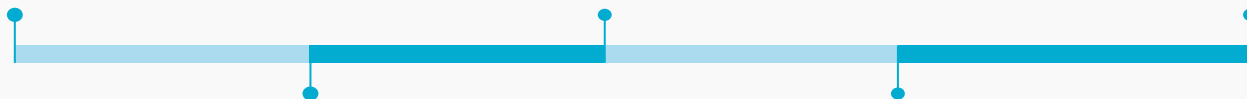
## Remove Same Values

Remove columns with no variation by patient



## Combined Wards

Admitted vs. Discharged



## Remove Missing Values

Remove columns with  $\geq 98\%$  missing values

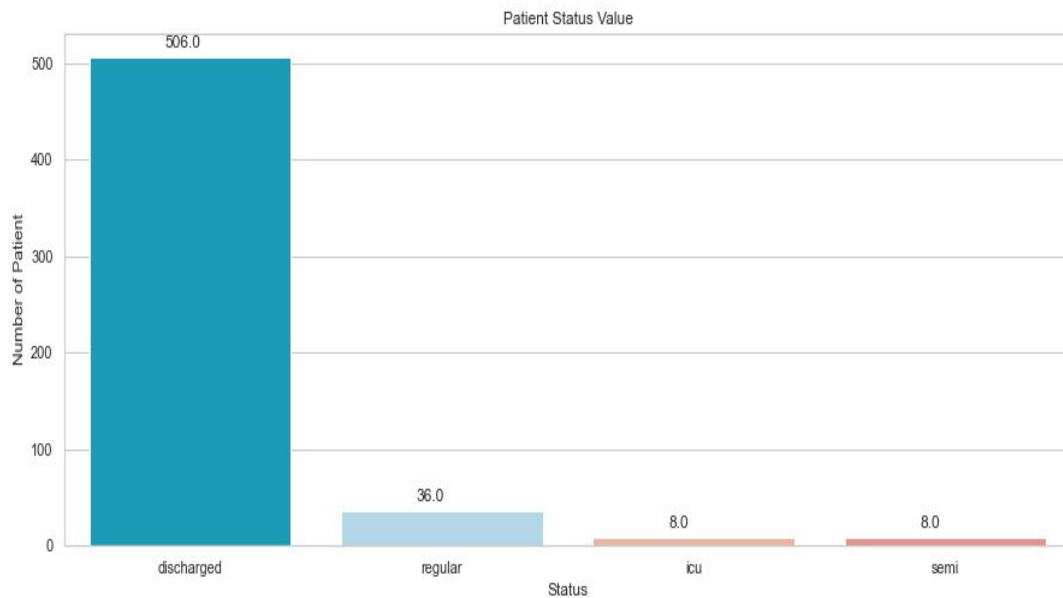


## Impute Missing Values

Randomly assign value from distribution  $N(0, 0.5)$

# PATIENT STATUS

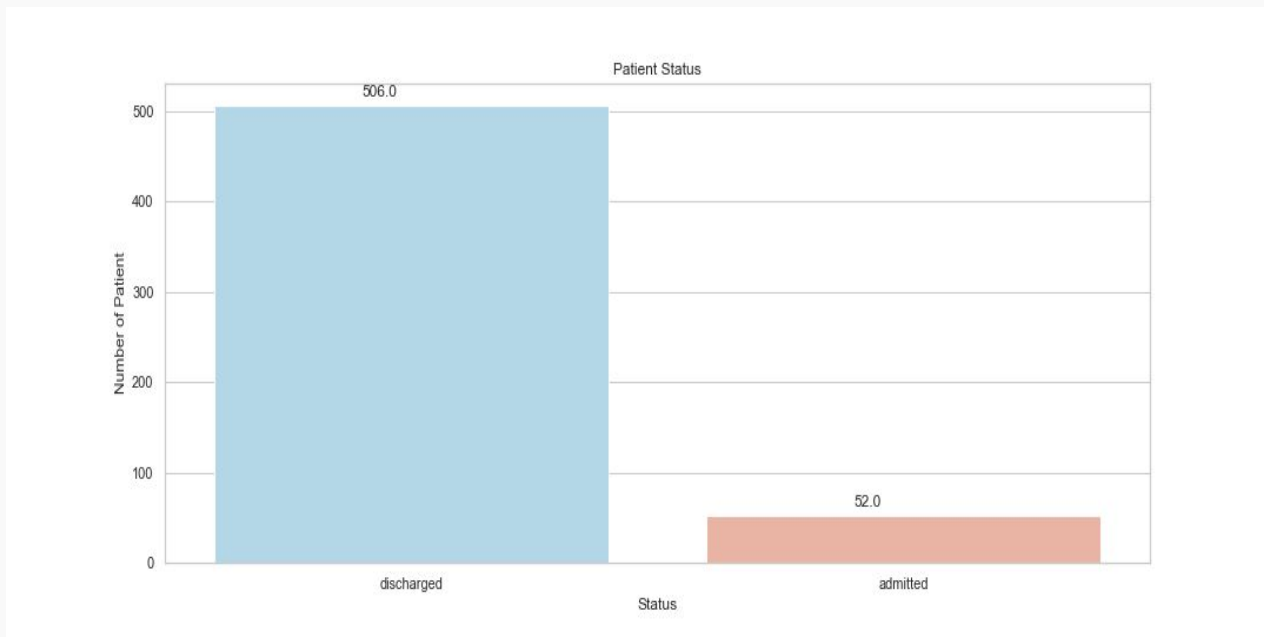
Before grouping





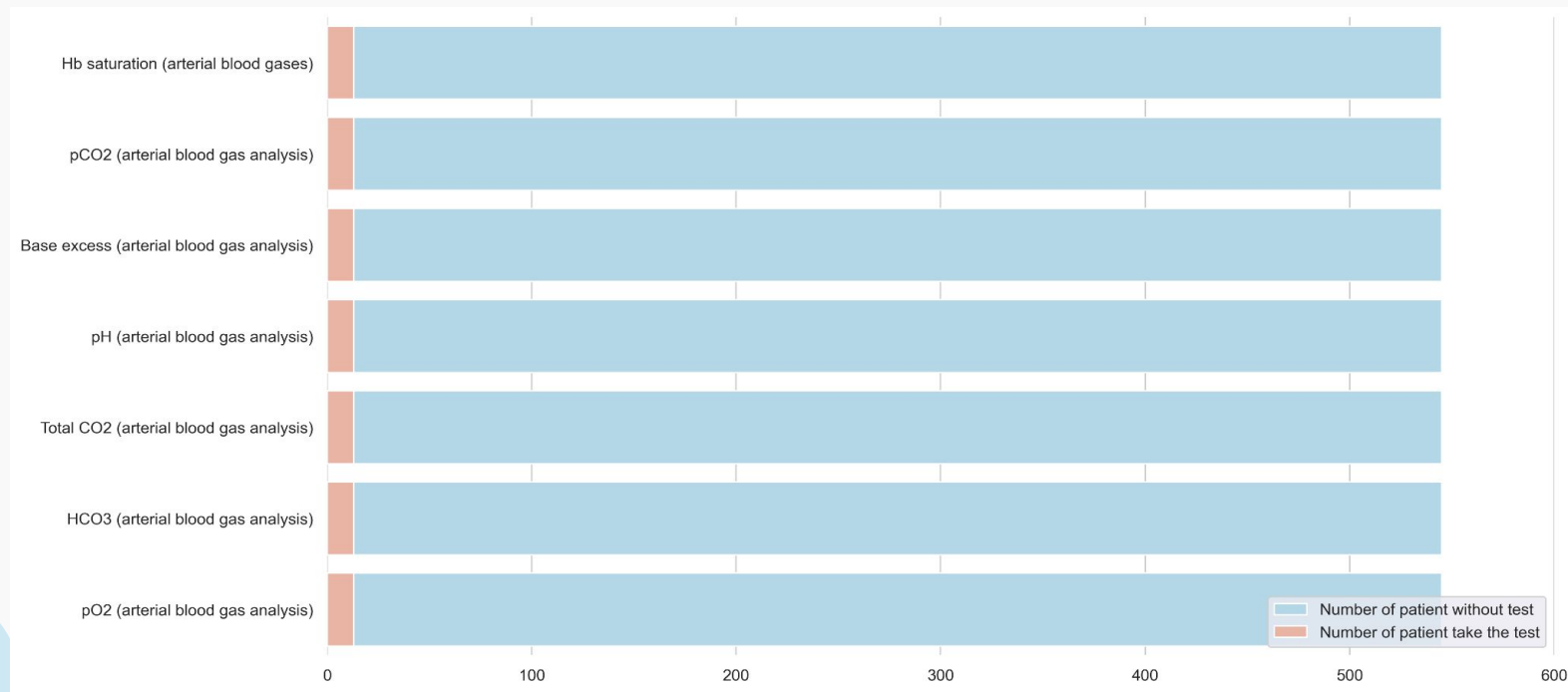
# PATIENT STATUS

After grouping



# GROUPED LAB TESTS

Ex. Blood gas grouping





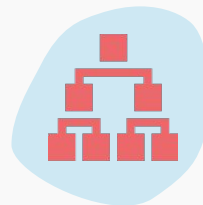
# FEATURE ENGINEERING

- Based on the ratio of missing value vs. non-missing value of each variable with respect to each patient, we grouped the variables with same ratio new feature groups
  - Binary: 1 indicates patient had test grouping done
- Lab groupings:
  - Urine test group
  - Virus test group: 1) whether virus tests given, 2) number of viruses detected
  - Blood test group
  - Blood gasses group: 1) arterial, 2) venous, 3) arterial & venous)
  - Bilirubin test group
  - Sodium & Potassium test group

# MODELING



**K-nearest Neighbors**



**Random Forest**

Combined over-and under-sampling using SMOTE, ROSE

Cross Validation

Grid Tuning

# TEST RESULTS

ROSE Sampling ( $p_{\text{admitted}} = 0.3$ ) with 5-fold Cross Validation

## K-Nearest Neighbors

Admission	True Discharged	True Admitted
Predicted Discharge	147	5
Predicted Admitted (k = 6)	6	10

## Random Forest

Admission	True Discharged	True Admitted
Predicted Discharge	145	2
Predicted Admitted (mtry = 8, trees = 10, min n = 5)	8	13

$N_{\text{test}} = 153$

# TEST RESULTS

## K-Nearest Neighbors

Test Metric	Scores
Accuracy	93.5%
Sensitivity / Recall (TPR)	66.7%
Specificity (TNR)	96.0%
Precision	0.625
F1	0.645

(k = 6)

## Random Forest 🏆

Test Metric	Scores
Accuracy	94.0%
Sensitivity / Recall (TPR)	<b>86.7%</b>
Specificity (TNR)	94.8%
Precision	0.612
F1	0.722

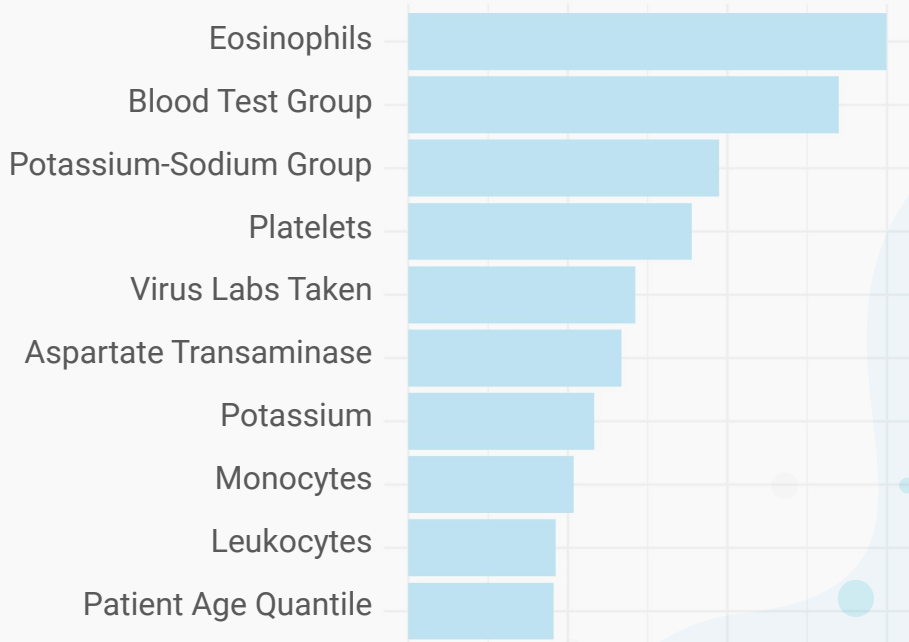
(mtry = 8, trees = 10, min n = 5)



# FEATURE IMPORTANCE

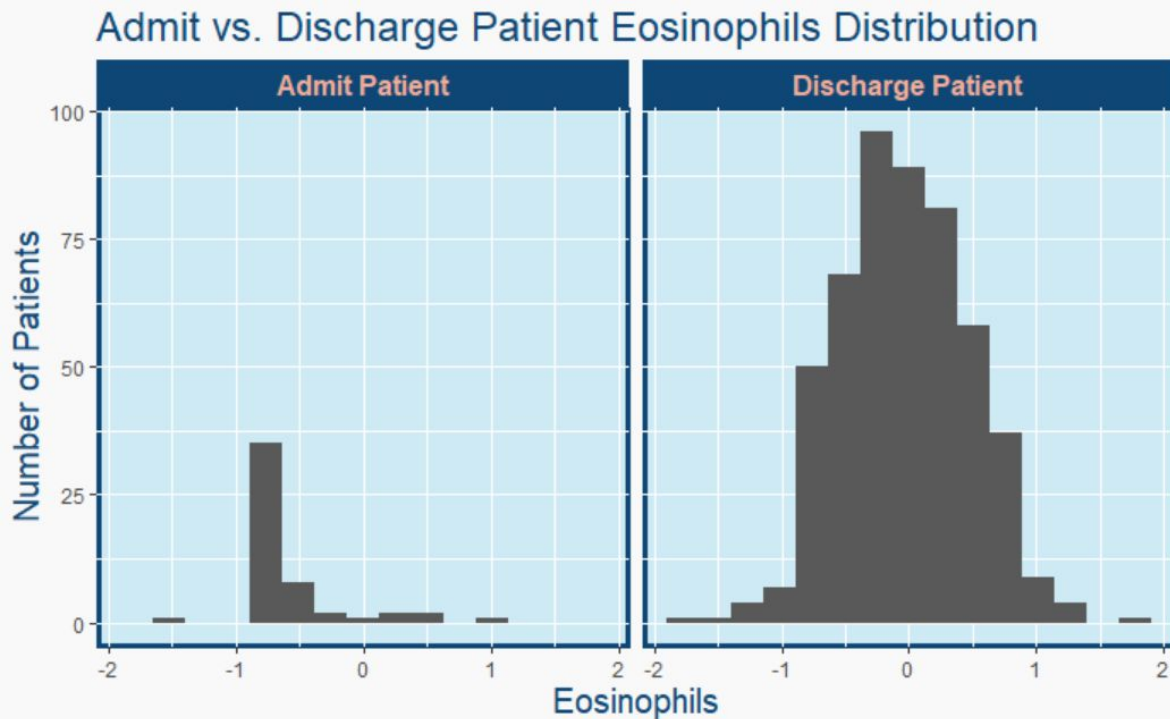
- Many important features related to blood tests:
  - Eosinophils
  - Whether blood tests were taken
  - Platelets
  - Monocytes
  - Leukocytes
- Other important features:
  - Whether sodium and potassium tests given
  - Whether other virus labs given
  - Patient age quantile

10 Most Important Features



# FEATURE IMPORTANCE

Low eosinophil (disease-fighting white blood cells) levels associated with mortality from COVID-19<sub>1</sub>

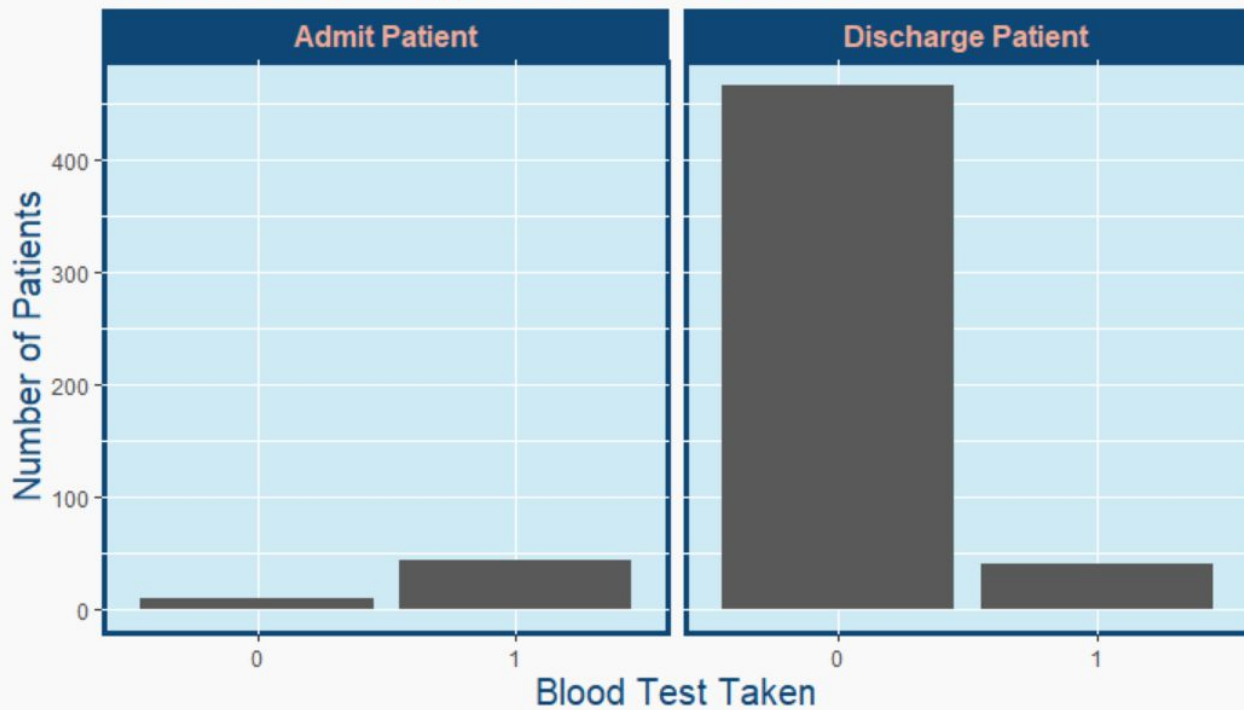




# FEATURE IMPORTANCE

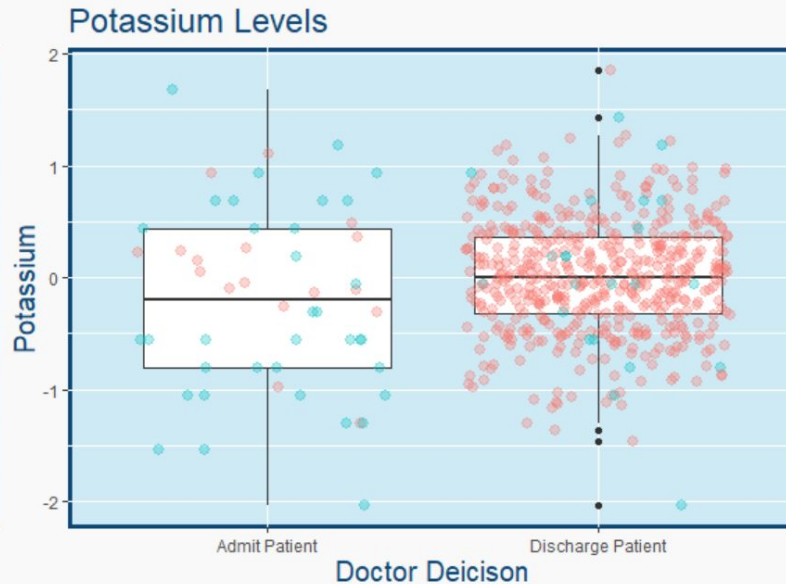
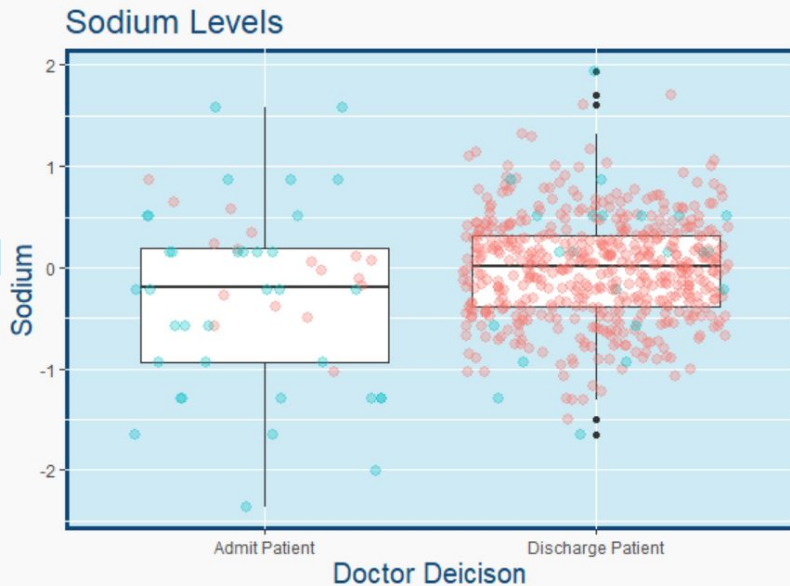
Most admitted patients had blood tests done

Admit vs. Discharge Patient Blood Test



# FEATURE IMPORTANCE

Low electrolyte levels associated with severe cases of COVID-19<sub>2</sub>



Salt Test Taken

- FALSE
- TRUE



# MODEL VALUE ADMITTANCE ASSUMPTIONS

- Our Model Admittance Rate: 13.69%
- Peak Hospitalization Rate: 15.2%
- Average Hospital Admittance Cost: \$25,175.50
- Average Death Cost: \$26,000
- Current Weekly Hospitalizations: 8,321
- Current Hospitalization Death Rate: 15%



# VALUE - SURFACE LEVEL

Current Cost of Weekly Admissions:

$$8321 \times 15.2\% \times \$26,000 = \$32,884,592.00$$

Current Weekly Cost of Model Admission:

$$8321 \times 13.69\% \times ((\$26000) + (\$26000) \times 15\%) = \$29,618,797.62$$

**Current Weekly Savings:**

$$\$32,884,592.00 - \$29,618,797.62 = \mathbf{\$3,265,794.38}$$

# VALUE SENSITIVITY ANALYSIS

Prediction Power	Model Admission Cost	Current Admission Cost	Savings
100%	\$29,618,797.62	\$32,884,592.00	\$3,265,794.38
90%	\$32,580,677.38	\$32,884,592.00	\$1,881,150.26
50%	\$44,428,196.43	\$32,884,592.00	\$(11,543,604.43)

# MODEL VALUE READMISSION ASSUMPTIONS

- The current COVID-19 readmission rate: 9%
- Our model false discharge rate: 1.1%
- Our model false admittance rate: 4.76%
- Our model true admittance rate: 7.7%
- Current Weekly Hospitalizations: 8321
- Current Weekly Readmissions:  $8321 \times .09 = 745$

# VALUE - MORE VARIABLES

*Current Weekly Cost:*

$$(8321 \times 15.2\% \times \$26,000) + (9\% \times 8321 \times 26000) = \$51,309,116.62$$

*Current Weekly Cost of Model False Discharge Error:*

$$((8321 \times 1.1\% \times ((\$26000) + (\$26000) \times 15\%)) + (8321 \times 9\% \times \$26000)) \times \mathbf{150\%} = \$33,649,529.64$$

*Current Weekly Cost of Model False Admit Error:*

$$8321 \times 4.76\% \times \$26000 = \$10,302,190.48$$

*Current Weekly Cost of Model True Admit:*

$$(7.7\% \times 8321 \times (26000 + (26000 \times 15\%))) + (\$26000 \times 9\% \times 8321) = \$38,628,578.30$$

**Current Weekly Savings:**

$$\$51,309,116.62 - (\$38,628,578.30 + \$33,649,529.64 + \$10,302,190.48) = \mathbf{-\$31,271,181.80}$$

# VALUE LIMITATIONS / SENSITIVITY ANALYSIS

## A Change of Assumptions:

- If we assume our model lowers the admittance rate to around 3%, we break even in costs.

Model Readmittance Rate	Model Cost	Current Cost	Savings
3.218302%	\$51,309,116.62	\$51,309,116.62	\$0
9% (Current)	\$32,735,210.24	\$51,309,116.62	\$(31,271,181.80)
1%	\$39,311,098.42	\$51,309,116.62	\$11,998,018.20



# LIMITATIONS



**Data Size**



**Grouped Classes**



**Patient medical history  
and symptoms**

# NEXT STEPS

- Predict on each ward (ICU, semi-intensive, regular)
- Extend to all patients, not just covid positive
- Create dashboard to assist hospital staff in admitting patients
- Collect readmission data



# Questions?



# Appendix





# MODELING DATASET

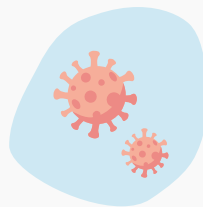
- Train/Test split
- Combined over-sampling majority and under-sampling minority
  - ROSE (balance such that minority proportion is one of:  $p = 0.3, 0.4, 0.5$ )
  - SMOTE (downsample majority 80%, upsample minority 50%)
- Cross-validation
  - 3-fold
  - 5-fold

# MODELING



## K-nearest Neighbors

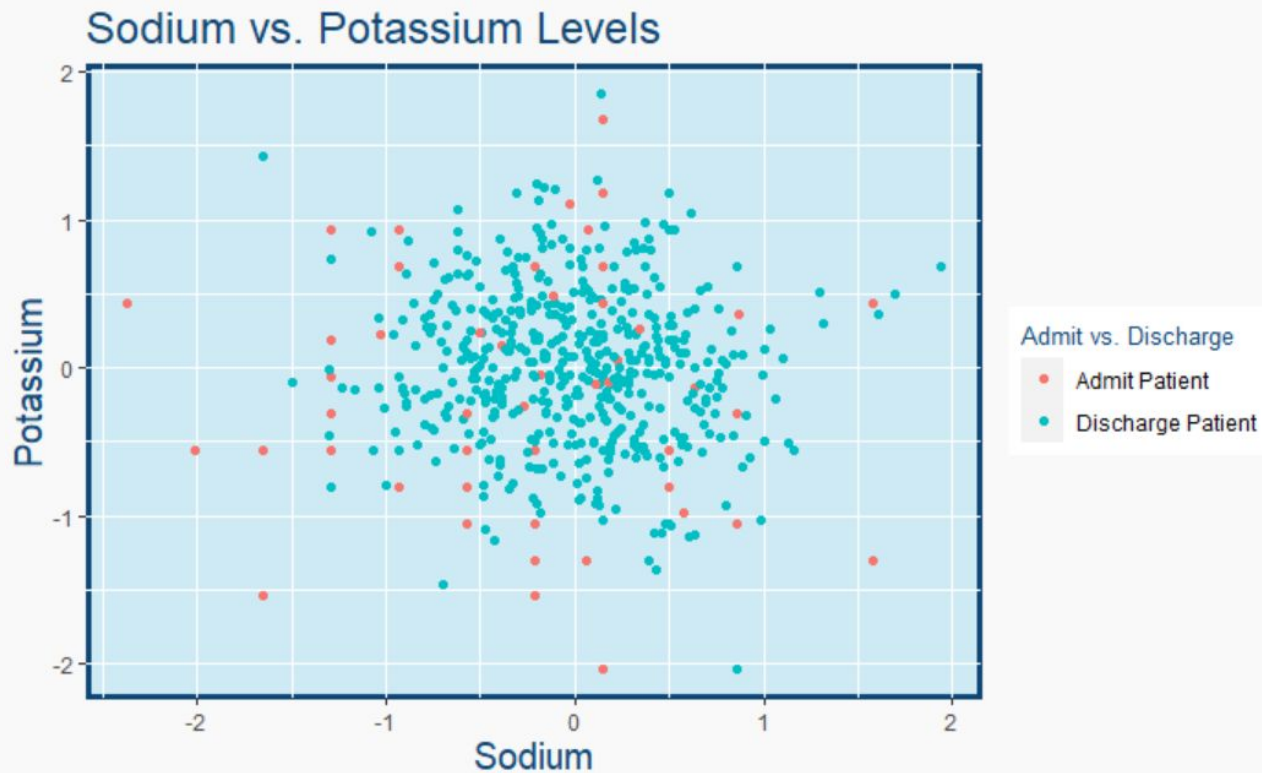
Parameter	Values
k	[2, 10] and every 5th value [20, 80]



## Random Forest

Parameter	Values
mtry	[2, 15]
Min n	[2, 15]
Trees	[10, 200]

# FEATURE IMPORTANCE



# CITATIONS

1. Yan et al. (2021) <https://www.sciencedirect.com/science/article/pii/S1939455121000156>
2. Lippi (2020) <https://pubmed.ncbi.nlm.nih.gov/32266828/>
3. <https://www.cdc.gov/coronavirus/2019-ncov/covid-data/covidview/index.html>
4. <https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2777028>
5. <https://jamanetwork.com/journals/jama/fullarticle/2774420>
6. <https://www.healthleadersmedia.com/clinical-care/dying-hospital-costs-more-surviving-inpatient-stay>





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