

# Predict COVID-19 Hospitalization Based on Patient Basic Info

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## Introduction

- Predict whether a confirmed Covid-19 patient will be hospitalized
- Provide timely and dedicated care to prevent hospitalization
- The result can also be used to predict the demand for hospital beds related to Covid



#### **Data**

37.5M rows of patient-level data for all Covid-19 cases reported in the US gathered by CDC

- Case month (recent 3 months is picked)
- State, county
- Age group
- Sex
- Race
- Known exposure
- Symptom status
- Hospitalized





## **Training Workflow**

**1** Feature Engineering

- Grouping categories
- One Hot Encoder for categorical features



**Establish Baseline** 

• Train on Logistic Regression model

3 Try Different Models

- Tree Classifier
- Random Forest
- Gradient Boosted Trees (XGBoost)
- Naive Bayes

Class Imbalance

- Resampling (over, **under**, SMOTE)
- Class Weight
- **5** Hyperparameter Tuning
- # of estimators
- Max depth
- Min samples split
- Min samples leaf





## **Feature Engineering**



#### **Exposure**

- Yes
- Missing
- Unknown
- NaN



#### Race

- White
- Black
- Asian
- Other
- American Indian/Alaska Native
  - And more...



#### Location

Group states/territories into four regions based on the official FIPS code





## **Result - Preliminary Training**

	Logistic	Tree	Random Forest	XGBoost
Precision	0.6101	0.6472	0.6362	0.6526
Recall	0.1161	0.1306	0.1328	0.1216
F1	0.1950	0.2174	0.2197	0.2050





## **Result - Confusion Matrix**



Predicted hospitalization



## **Result - Class Imbalance Solution**

	Oversampling	Undersampling	SMOTE	Class Weight (1:5)
Precision	0.3193	0.3135	0.3151	0.3197
Recall	0.6681	0.6785	0.6754	0.6685
F1	0.4321	0.4288	0.4297	0.4325

Best from 1:1 to 1:10





## **Recall = 0.6783**

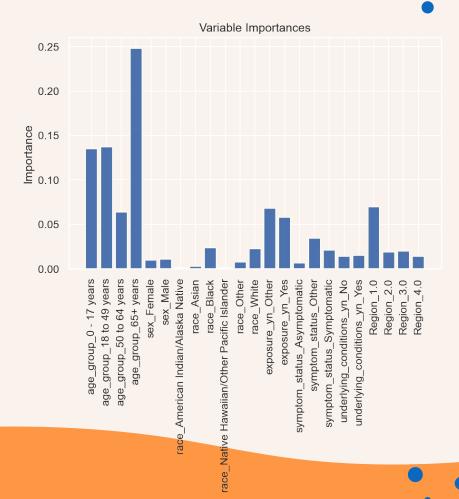
## Final Model

- Random Forest
- Undersampling (% of 0)
  - n\_estimators = 100
- min\_samples\_split = 5
- min\_samples\_leaf = 4
  - And more...



## Feature Importances

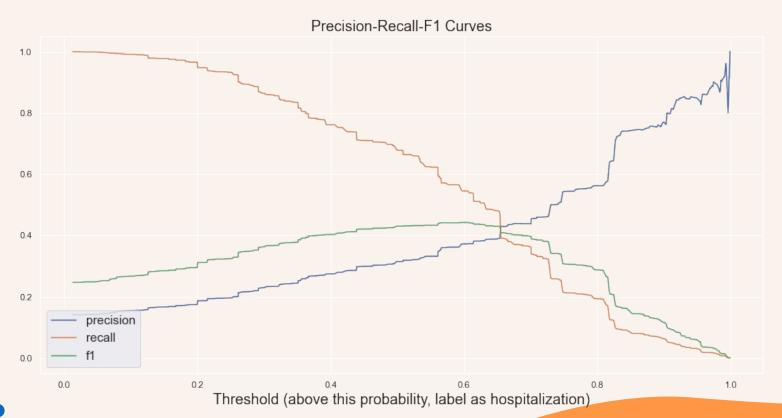
"Age group" appears to be the most important feature, followed by "Known Exposure."







## **Result - Precision vs Recall**



## Conclusion

#### **Predictability**

The model can identify 68% of people who will likely get hospitalized later

#### **Adaptability**

The model can be adjusted for an ideal true positive rate based on the current capacity of the healthcare system



## Thanks!

Do you have any questions?

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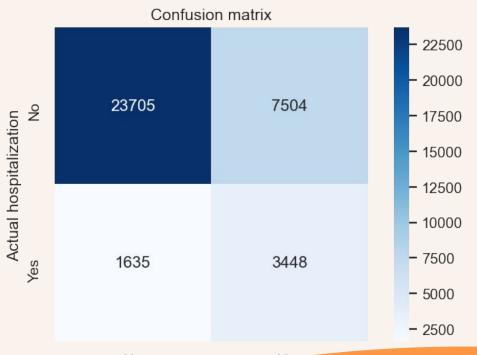
# Appendix







## **Confusion Matrix - Final Model**



No Yes Predicted hospitalization



## **Result - ROC Curve**

