

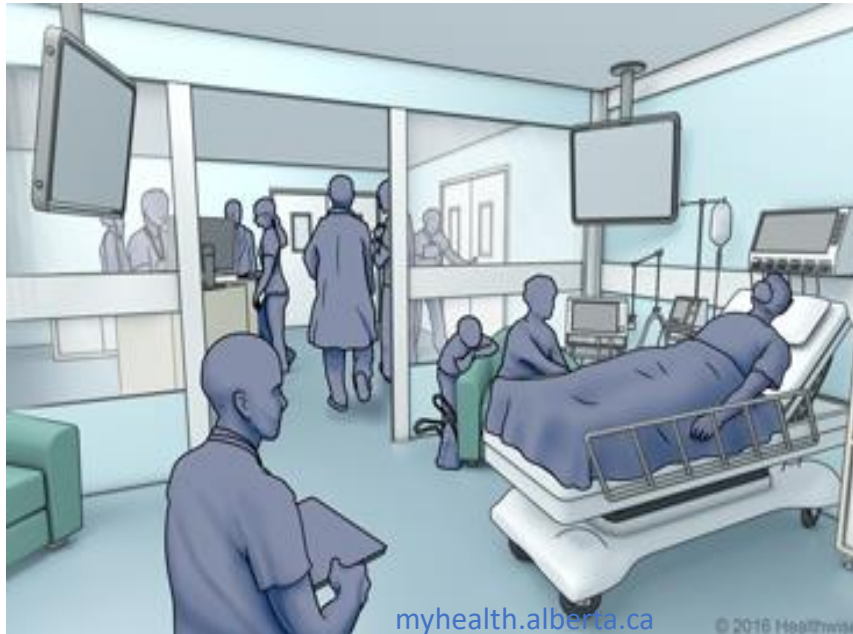
# Predicting mortality of ICU patients

Sricharan Bandhakavi

Insight Health Data Science Fellow

Sep 2019

# Mortality Prediction of ICU Patients - PhysioNet Computing in Cardiology Challenge 2012\*



[\\*https://physionet.org/challenge/2012](https://physionet.org/challenge/2012)

## QUESTION

Can information collected during the first two days of an ICU stay predict in-hospital mortality?

## OUTCOME

Logistic regression model based on ICU data predicts in-hospital mortality with

- 83% AUC
- 76% sensitivity, 74% specificity
- 32% precision

Model performs significantly better than current measures of mortality (SOFA/SAPS-I based models)

# Data description

- Predictors (acute physiological measures as time-series data + general descriptors as non-time series data) along with survival outcomes on 4000 patients data

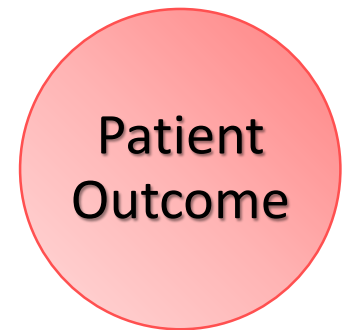
Acute physiological measures on up to 37 features over 48 hours ICU stay such as:

- Respiratory rate
- Heart rate
- Glucose level
- Blood urea nitrogen
- Coma score
- Additional health/physiological measures



General patient level descriptors collected at time of ICU admission such as:

- Record ID
- Age (years)
- Gender (0: female, 1: male)
- Height (cm)
- ICU type (1: Coronary care, 2: Cardiac surgery recovery, 3: Medical ICU, 4: Surgical ICU)

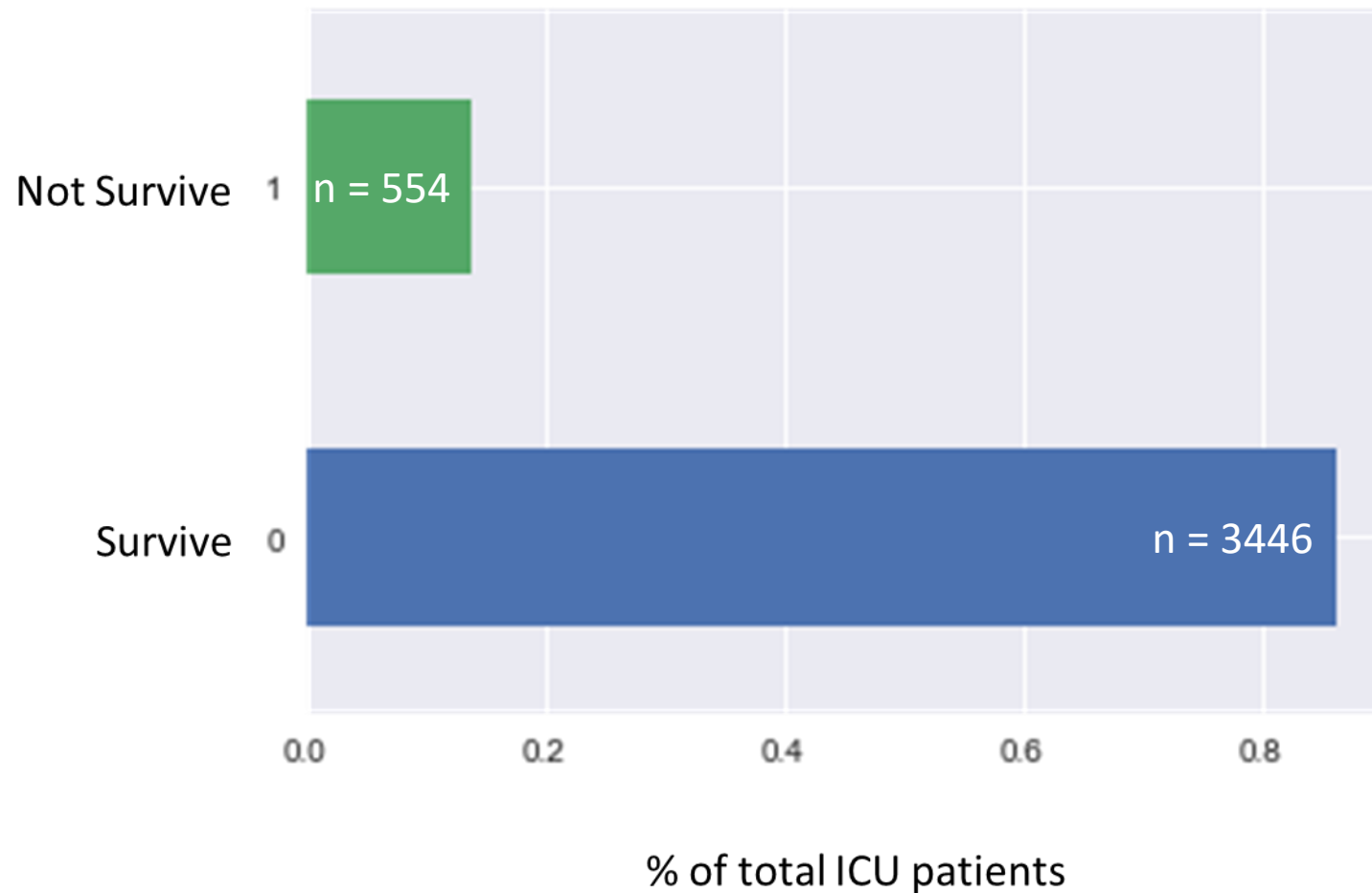


**Survived or Not**

Predictors

Outcome

# Distribution of patient outcomes



Imbalanced outcomes in dataset

(addressed during modeling  
via class\_weights “balancing”)

# Feature extraction

## Non-time-series data

- One-hot encoding of categorical features (Gender, ICU-type)
- Address missing values (eg: for gender created a new category of “missing”)
- Cap “outliers”

## Time-series data

- For numeric features, extract minimum, maximum, median value, change (max-min)
- For categorical features, generate counts/patient
- Address missing values and cap “outliers”

Predictor Matrix

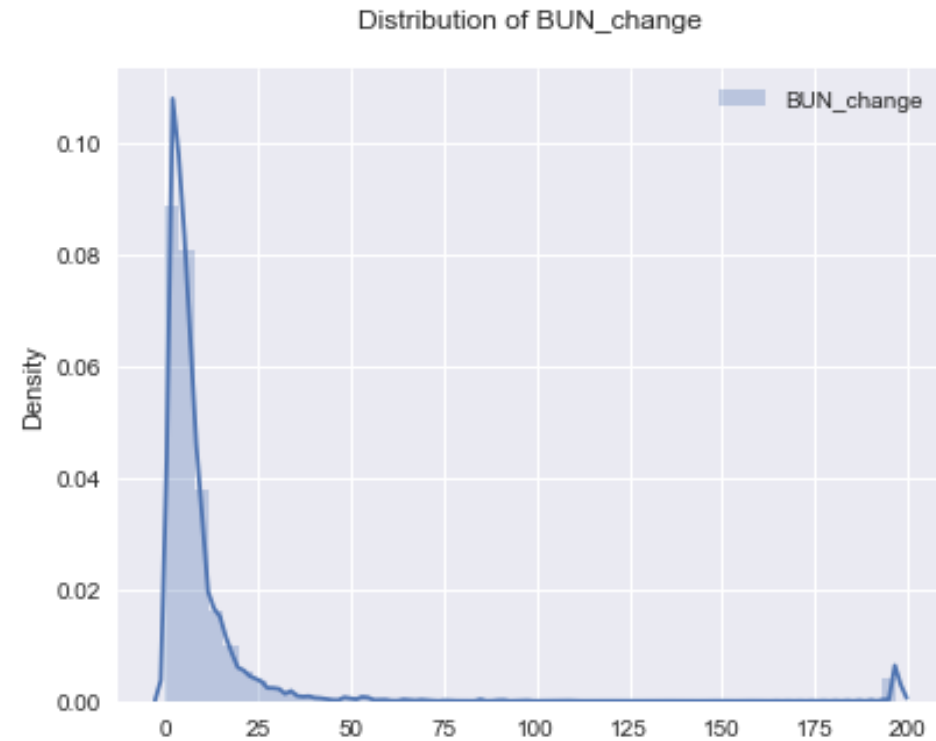
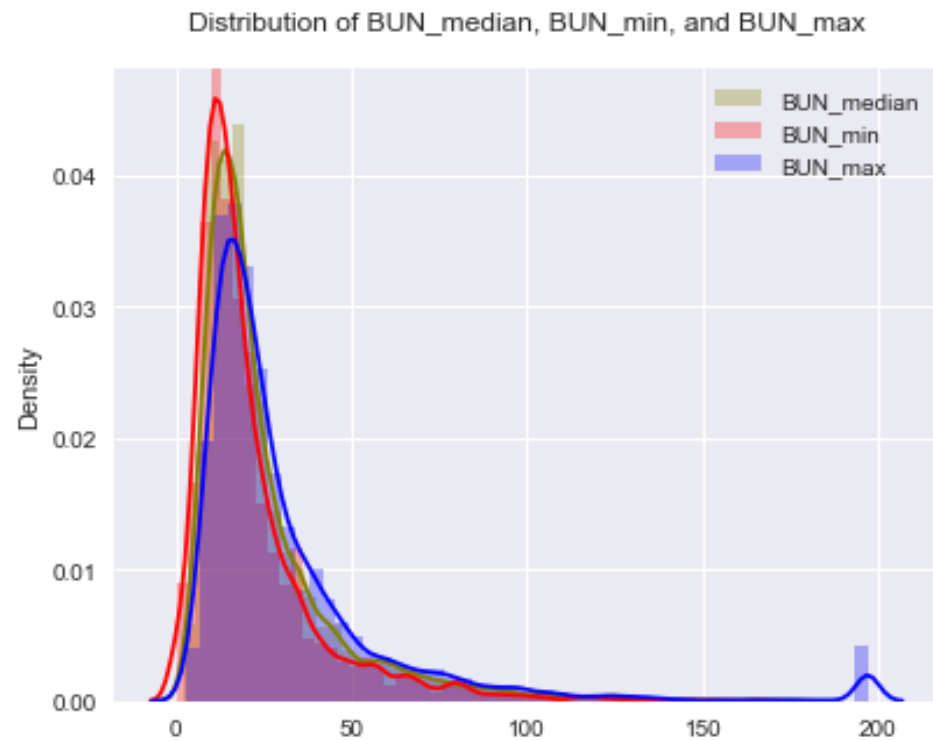
9 features



145 features

# Example feature distributions/exploratory analysis

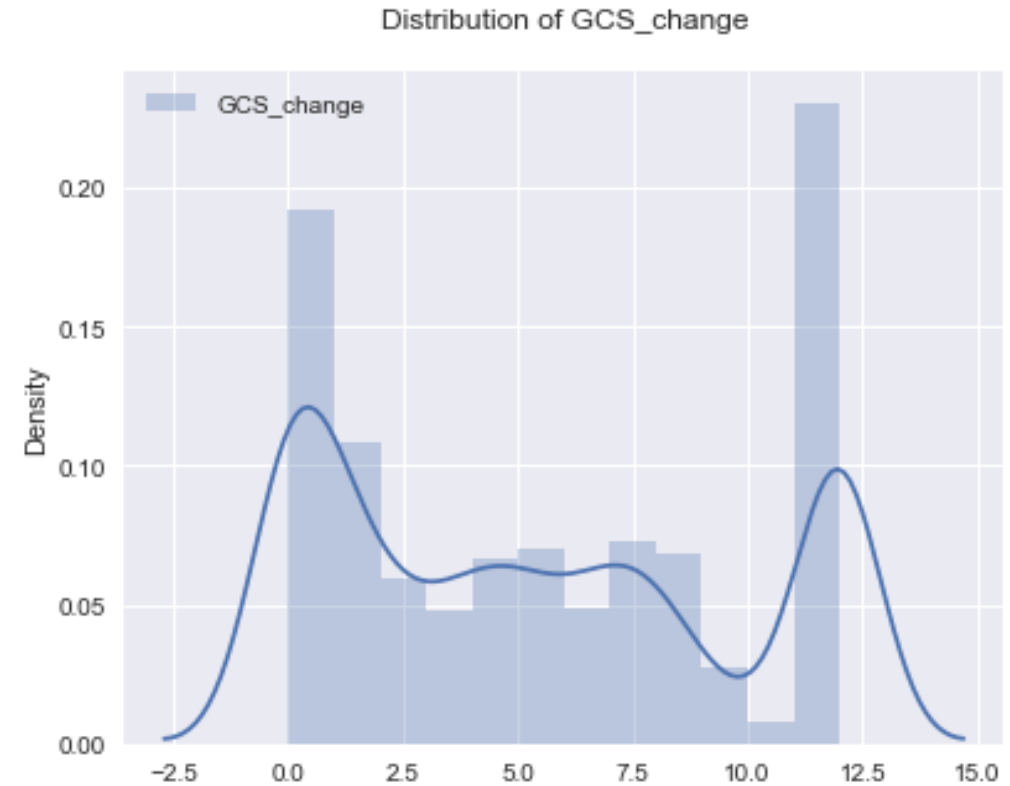
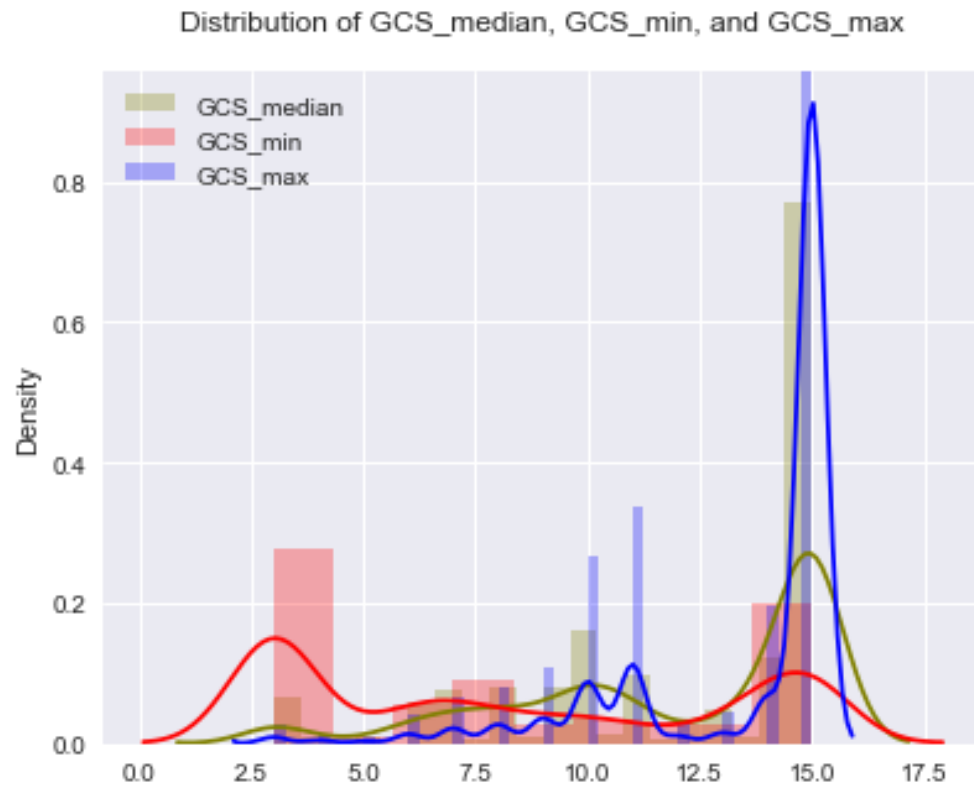
- Patient distributions of Blood Urea Nitrogen extracted features



- Nearly overlapping distributions of BUN across median, min, and max.
- Small % of patients show large BUN\_change

# Example feature distributions/exploratory analysis

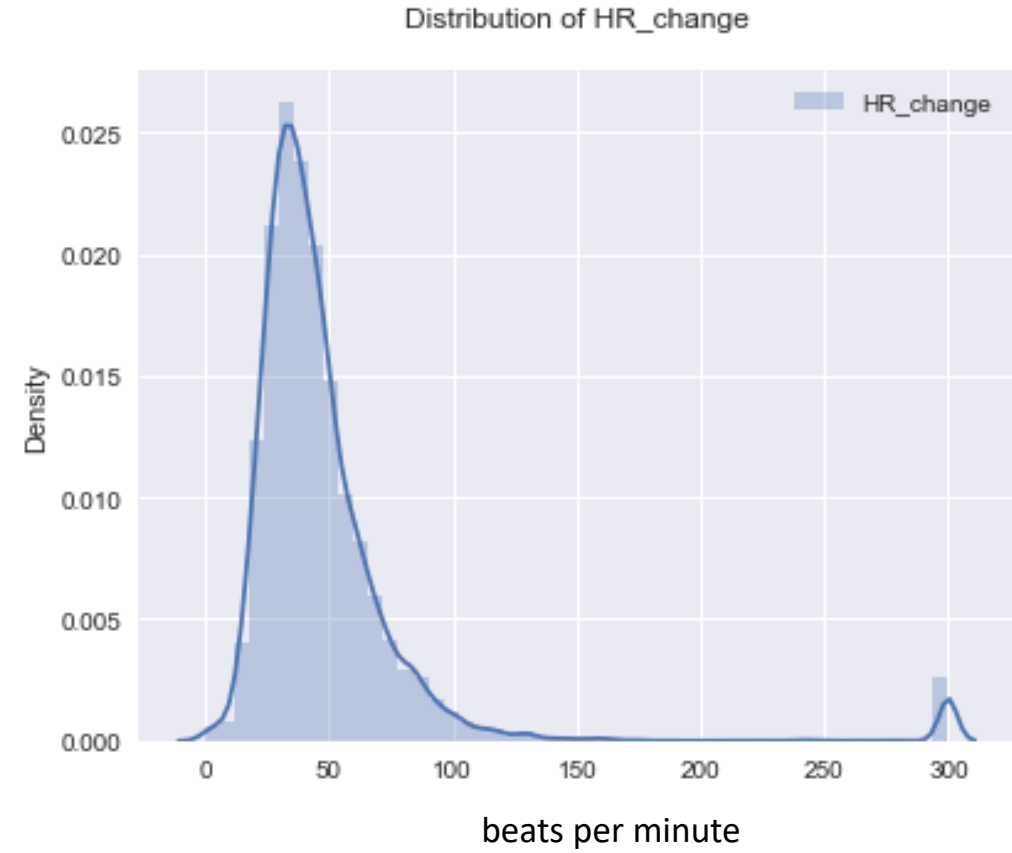
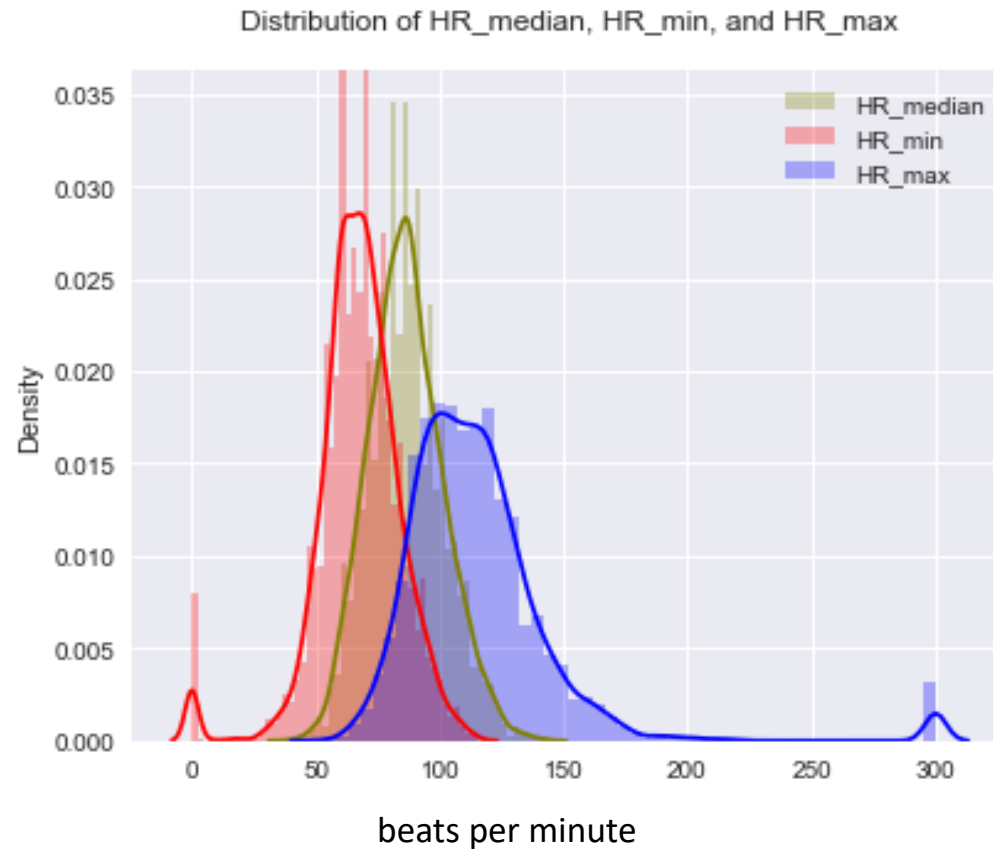
## - Distribution of extracted Gleason Coma Scores



- Relatively different distributions of GCS\_min vs GCS\_max.

# Example feature distributions/exploratory analysis

- Distribution of extracted heart rate features (unadjusted)

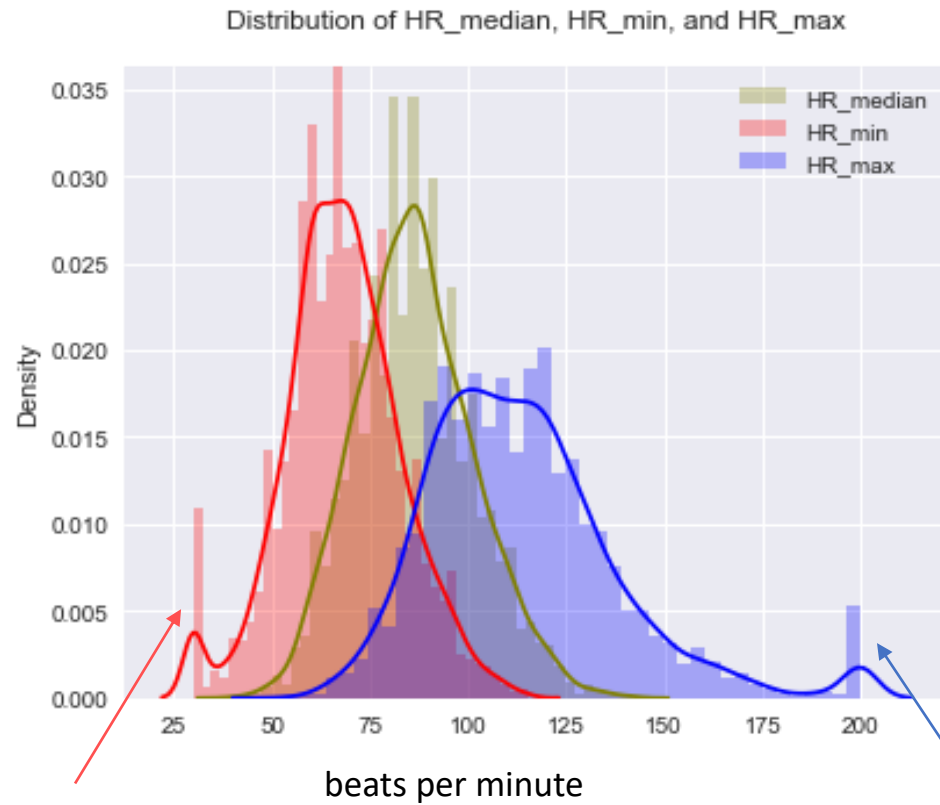


- Relatively different distributions of HR\_min vs HR\_max.
- Small % of patients show large change in heart rate during ICU stay

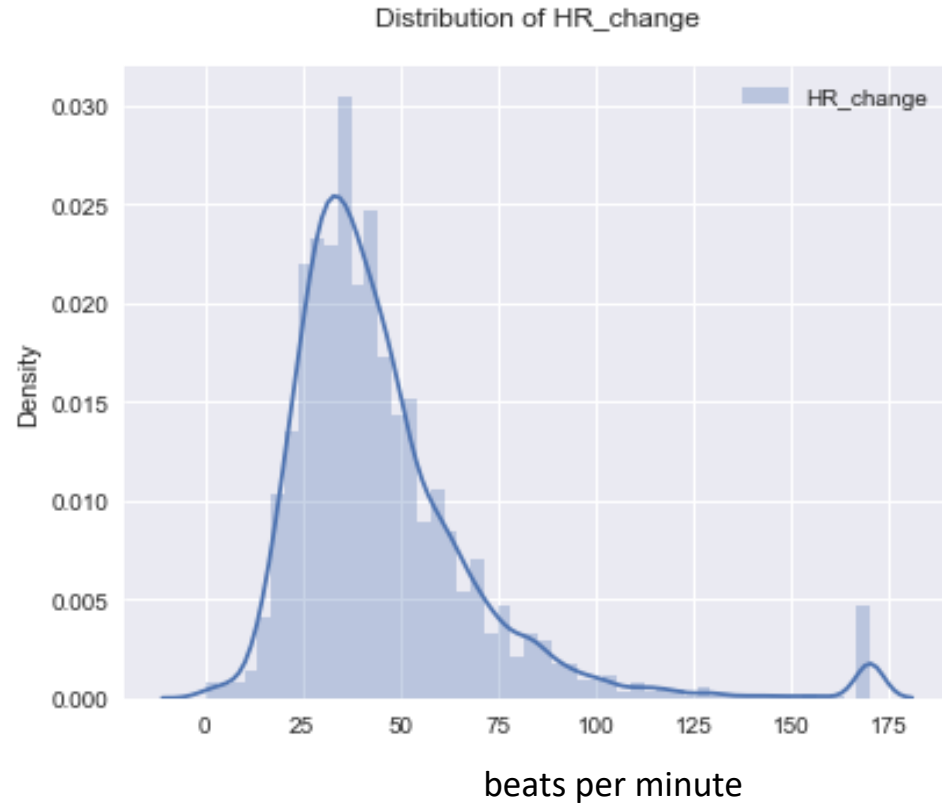


# Example feature distributions/exploratory analysis

- Distribution of extracted heart rate features (with outlier “capping”)

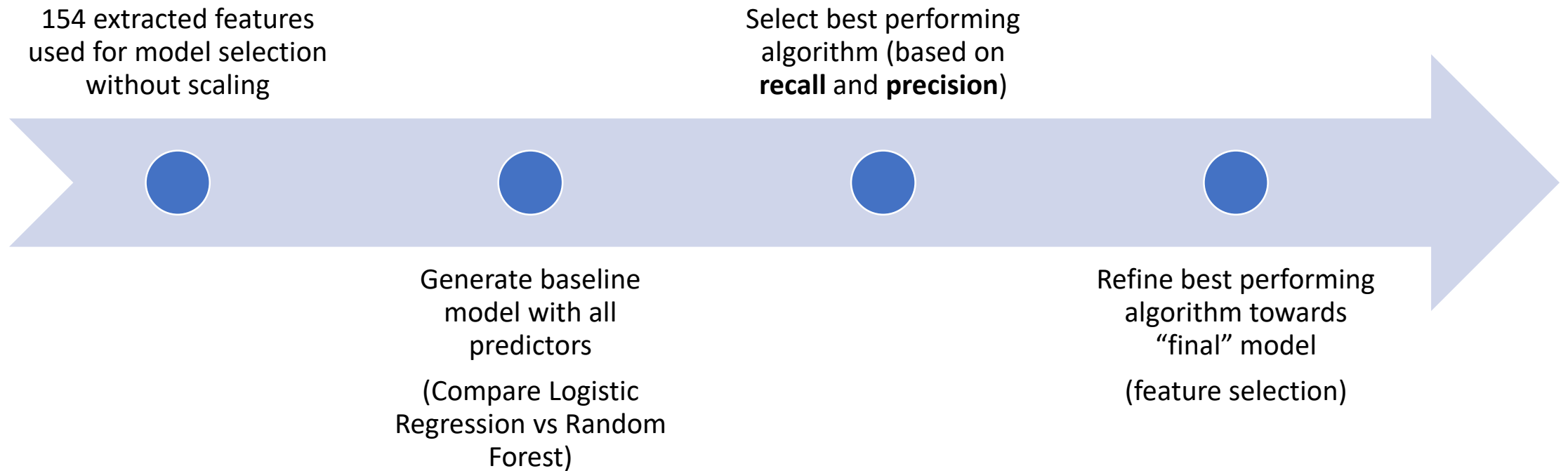


Outliers capped at  
<2.5%ile  
of distribution



Outliers capped at  
>97.5%ile  
of distribution

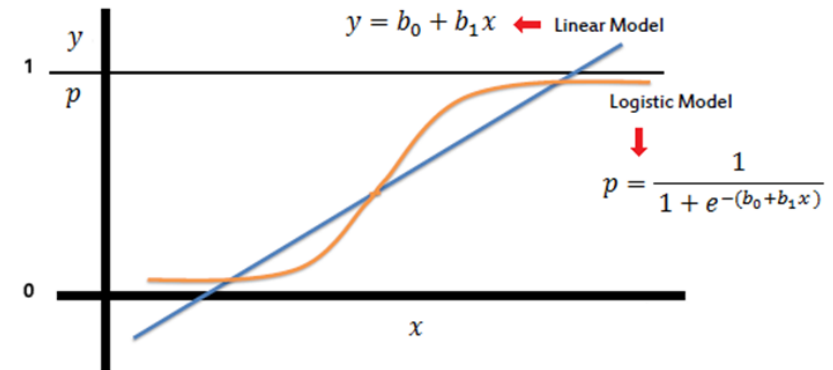
# Predictive modeling – high level schema



# Logistic Regression vs Random Forest

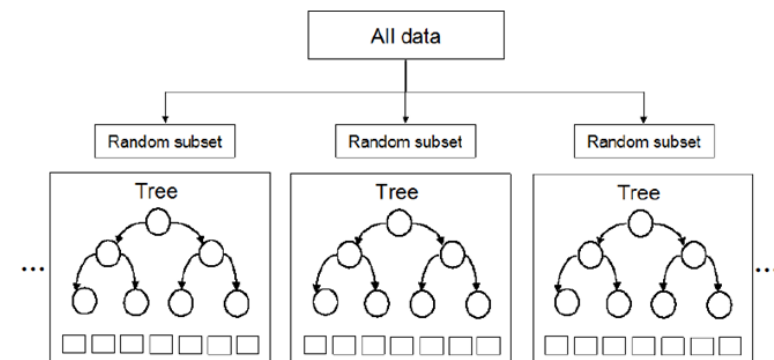
## Logistic Regression

- Classification based on the probability of odds given a combination of predictor variables

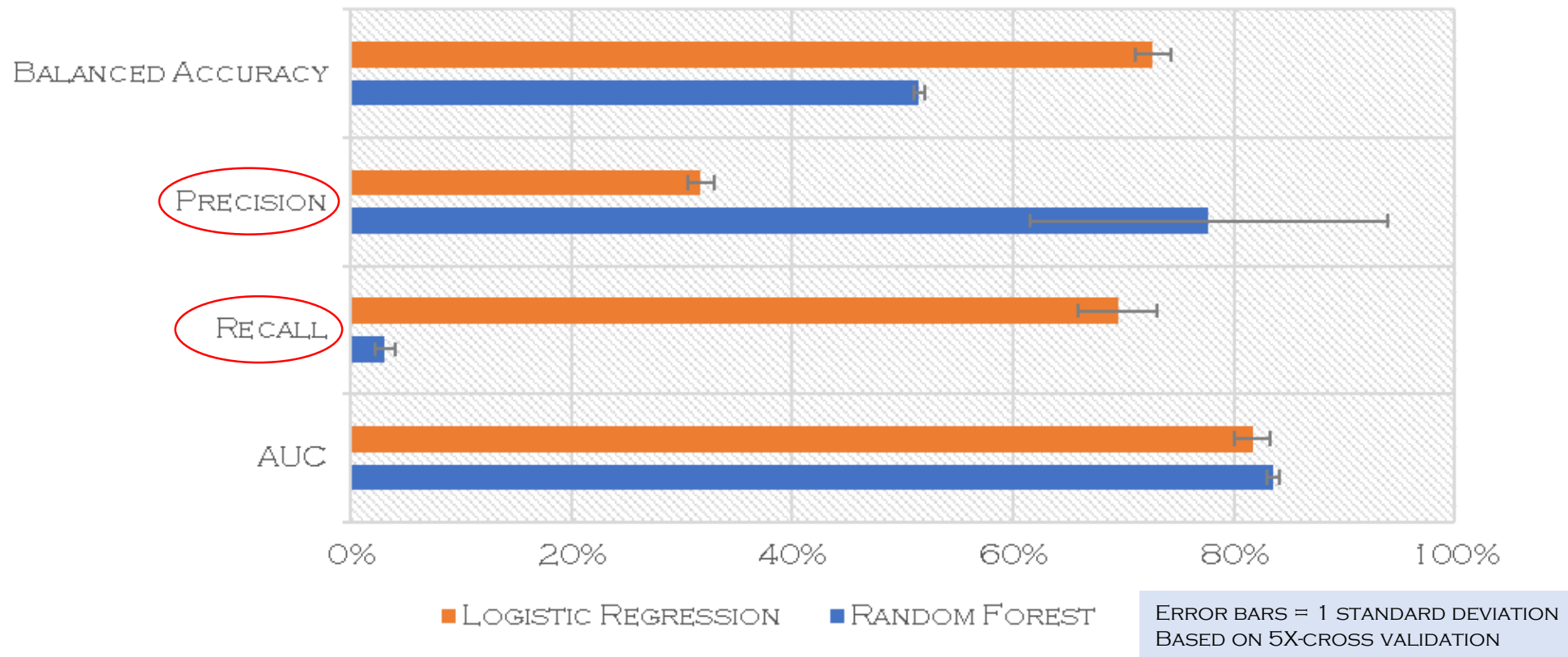


## Random Forest

- Classification based on an ensemble of decision trees trained on different subsets of features and observations

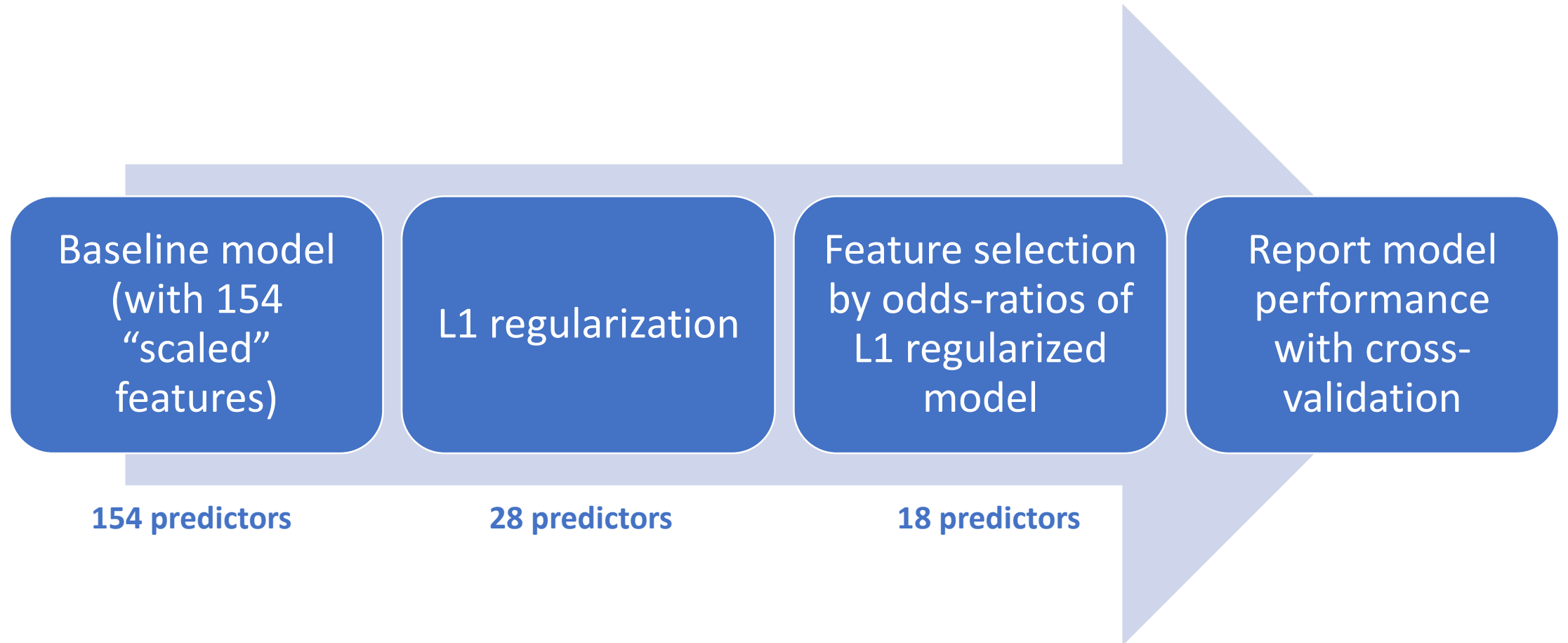


# Poor recall with out-of-the-box Random Forest compared to Logistic Regression

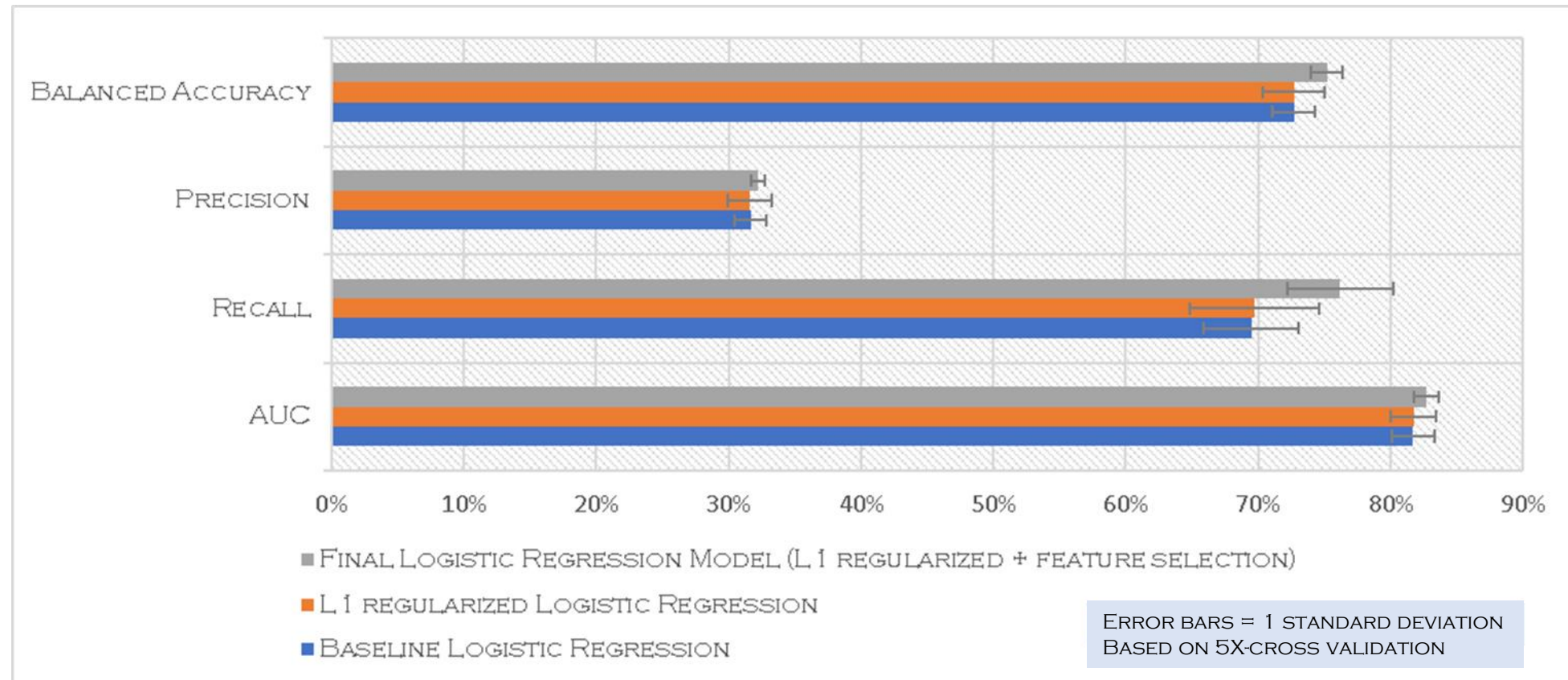


→ Logistic regression algorithm chosen for further refinement towards “final” model

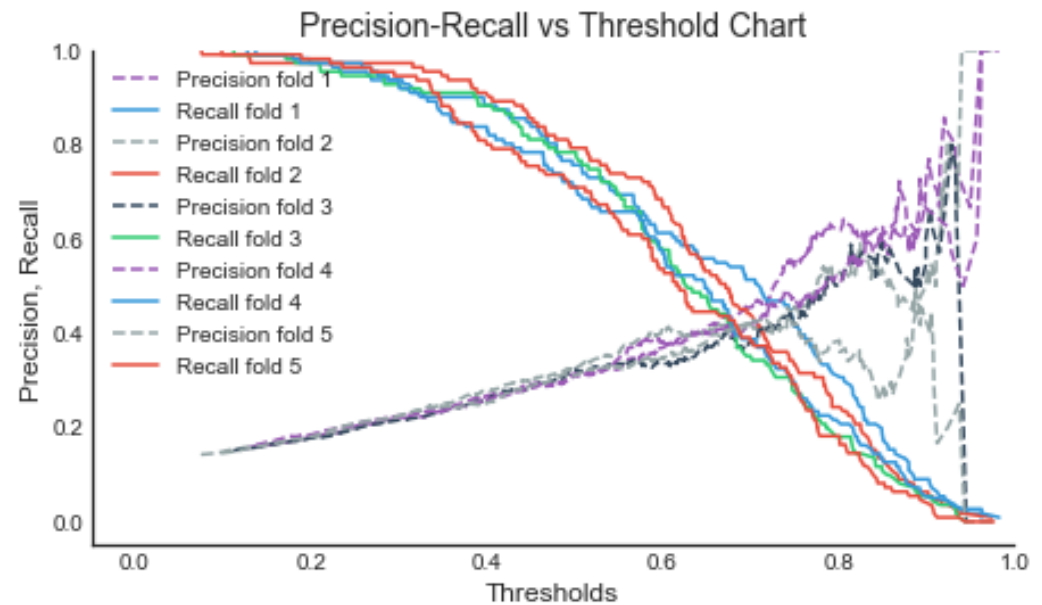
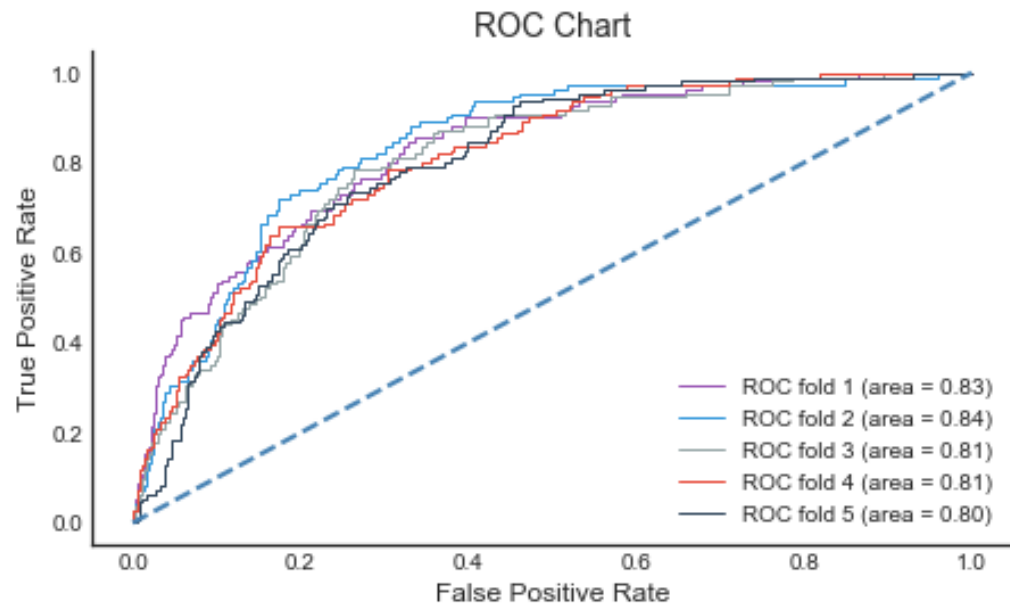
# Logistic regression model refinement schema



# Comparison of performance metrics for all (logistic regression) models

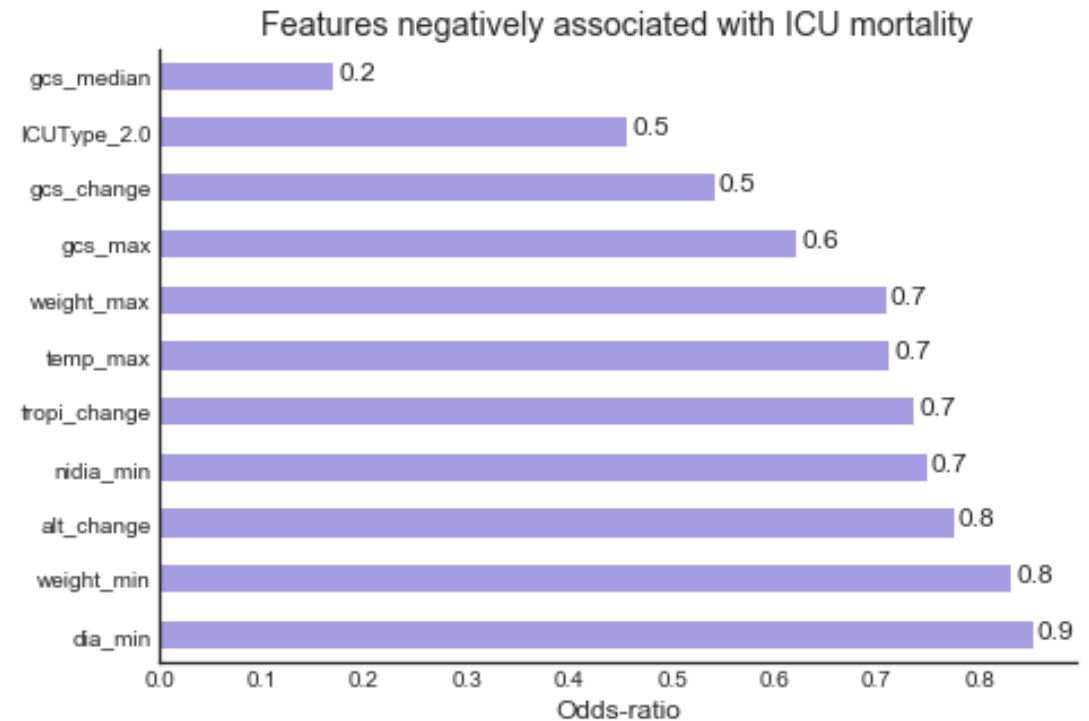
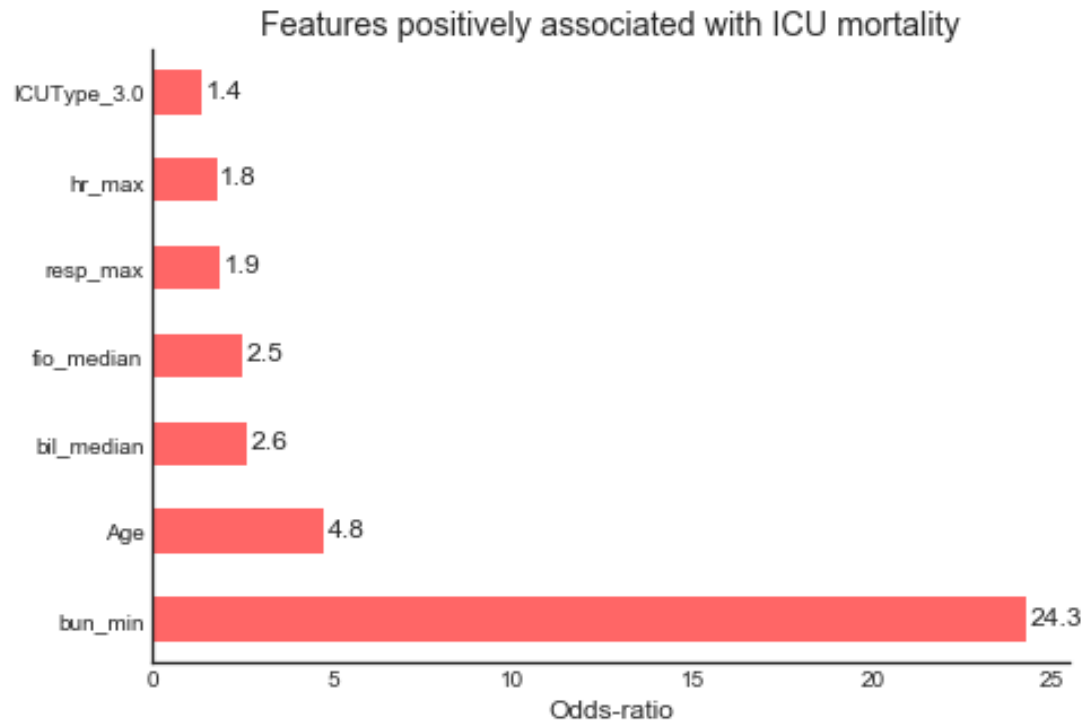


# ROC and Precision-Recall vs Threshold Chart



→ Opportunity exists to improve model sensitivity via reducing probability threshold  $< 0.5$  (at cost of precision)

# “Final” model predictors of in-hospital mortality for ICU patients and odds-ratios\*

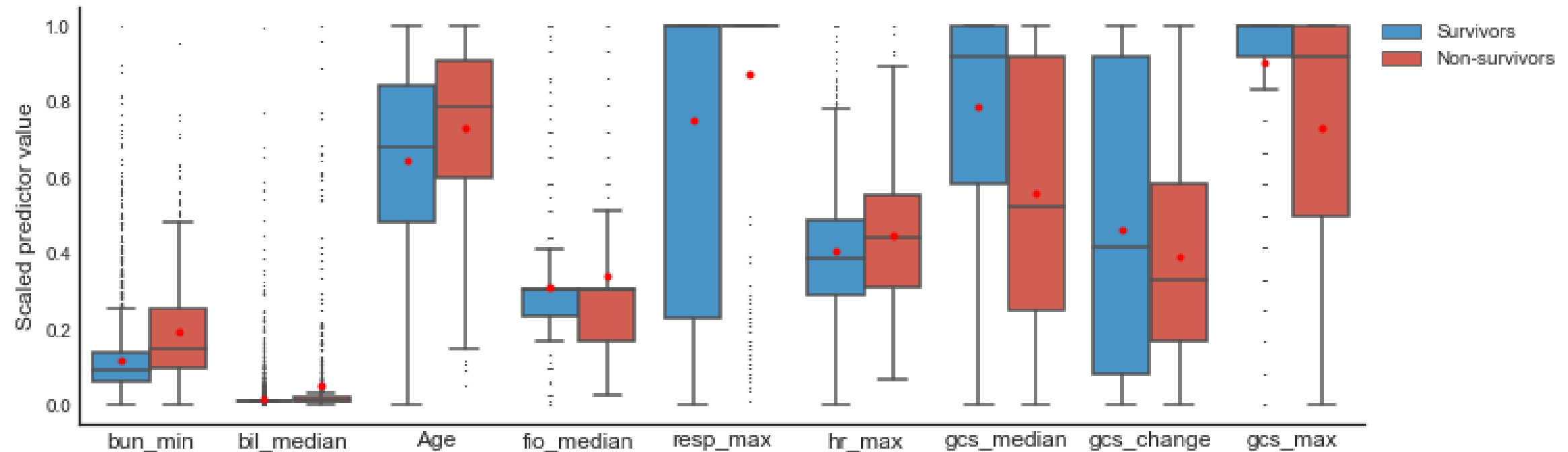


\*for predictors scaled between 0 – 1.

→ \*Thus, an odds-ratio of 24.3 for BUN\_min (Blood Urea Nitrogen minimum) indicates increase in odds of on-hospital mortality as BUN\_min increases from lowest to highest value of its measured range.

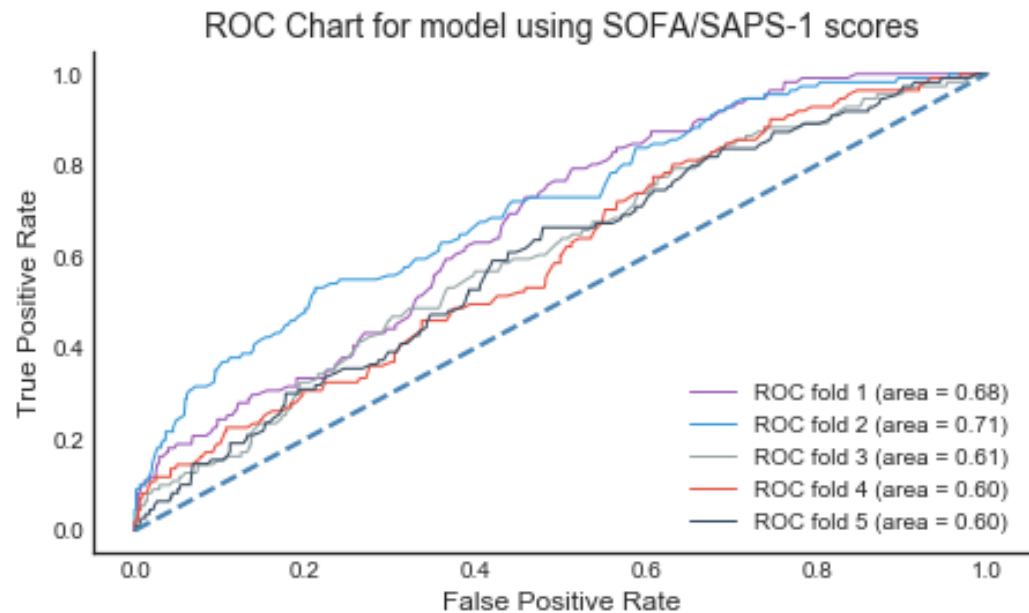
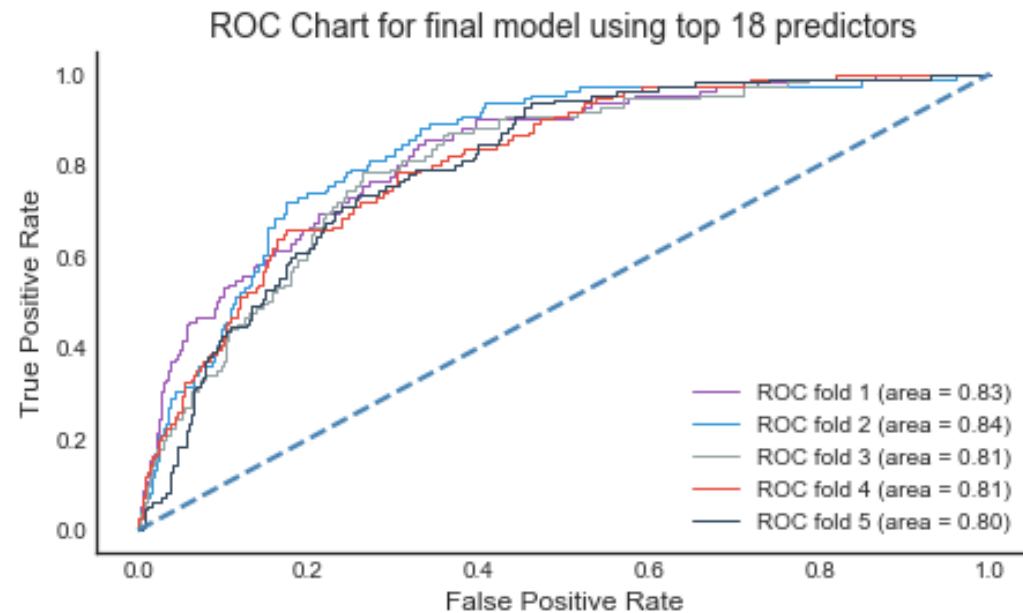


# Distributions of top predictors in survivors vs non-survivors



→ Positive predictors of mortality have generally higher values in non-survivors (bun\_min, bil\_median, age, fio\_median) and negative predictors have mortality have generally lower values in non-survivors.

# Comparison of “final” model to “benchmark” model using SOFA/SAPS-1 scores



→ Across multiple test-train subsets, “final” model generated in this study outperforms models developed using SOFA/SAPS-1 scores

# Summary/Conclusions

A parsimonious logistic regression model based on 18/154 total features was developed to predict in-house mortality of ICU patients. Most important predictors are:

- Blood urea nitrogen levels
- Gleason Coma Score level
- Age
- Bilirubin levels

Model shows superior performance to benchmark models using current measures of mortality. It may be possible to further improve model performance by:

- Addition of more features (eg: past medical history)
- Addition of more data
- Increase of model sensitivity (at cost of precision) via lowering of probability thresholds