

J&J CAPSTONE PROJECT

AutoML Prediction Machine of Adverse
Outcomes Following Hip Fracture Surgery

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Project Introduction

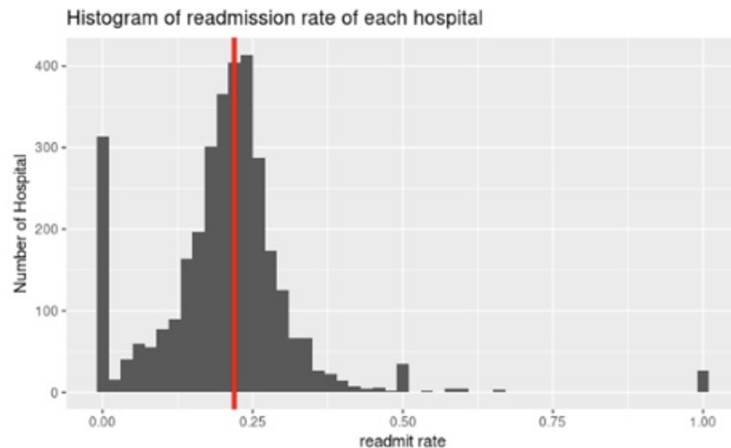
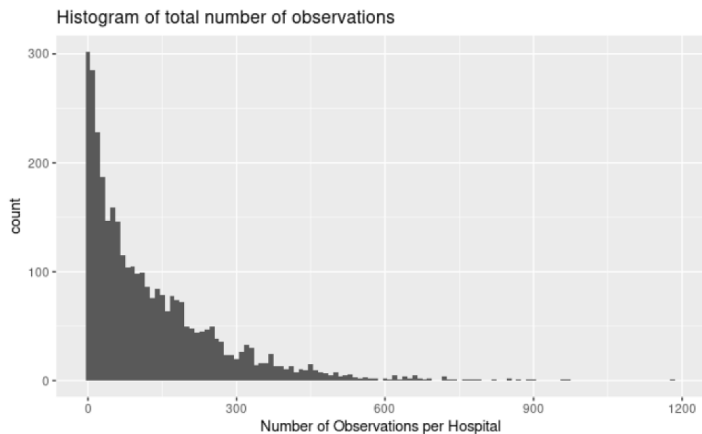
- Objective:
Build a reusable, flexible platform for rapid prediction at the hospital level on hip fracture patients.
- Why?
 - Hip fractures are a major public health burden
 - J&J works with hospitals to reduce complications after hip fracture surgeries
- ❖ Data source: Medicare + other public data (census) - 400K+ patient records.
- ❖ Outcome: 90-Day Risk of Readmission

Data Exploratory Analysis

- Over 430,000 observations, 247 features
- Feature types
 - hospital information
 - personal information
 - medical record
 - diagnosis and procedure of surgery
 - follow-up information

Data Exploratory Analysis

- Over 3,000 hospitals
- Imbalanced classes for target variable: 23% positive



Data Preprocessing

- Removed features with leaking info, with collinearity
- Added time related features: month, day of week...
- 137 features left

Categorical Features Processing

- Regrouping: group by type, keep the top classes and drop repeating information
- An encoding approach that combines both encoders: One-Hot encoder with classes ≤ 5 , target encoder with classes > 5

Approaches

- Develop model that can accurately predict individual patient's risk of readmission.
 - Population Model
 - Hospital Model
 - Ensemble Method
- Then use the best approach from above to generate readmission rate for each hospital.

Population Model

- Goals: build one model for all hospitals
- Sampling Method
 - We only keep hospital which has >10 positive/ negative observations to exclude extreme cases, which also meet the Medicare data policy
 - Remove hospital which has less than 100 observations
- Train/ Test Split by chronological order
 - Train/ validation/ Test Ratio: 0.7: 0.15: 0.15

Population Model

- Three model types: regularized logistic regression, random forest, Xgboost
- Four feature sets: Base, Base with time features, Boruta features, Boruta with time features
- Metrics (F-1 score):
 - F-1 score can help balance metric when there is an imbalance dataset
 - F-1 score summarise Recall, Precision, True Positive, False Positive, False Negatives into one

Population Model

- Random Forest with base + time feature group as our final population model (train with 100% data)

Trail	Model	Feature set	Cross Validation F1	Validation F1 Score	Log Loss	AUC	Accuracy
1	Random Forest	Base + Time	0.6073	0.3670	0.8200	0.5300	0.3200
2	Random Forest	Base + Time	0.6085	0.4066	0.6850	0.6379	0.5544
3	Random Forest	Base + Time	0.6058	0.3714	0.7868	0.5620	0.3585
4	Random Forest	Base + Time	0.6062	0.4075	0.6798	0.6398	0.5568
5	Random Forest	Base + Time	0.6063	0.4068	0.6879	0.6377	0.5537
6	Random Forest	Base + Time	0.6058	0.4038	0.6907	0.6339	0.5459

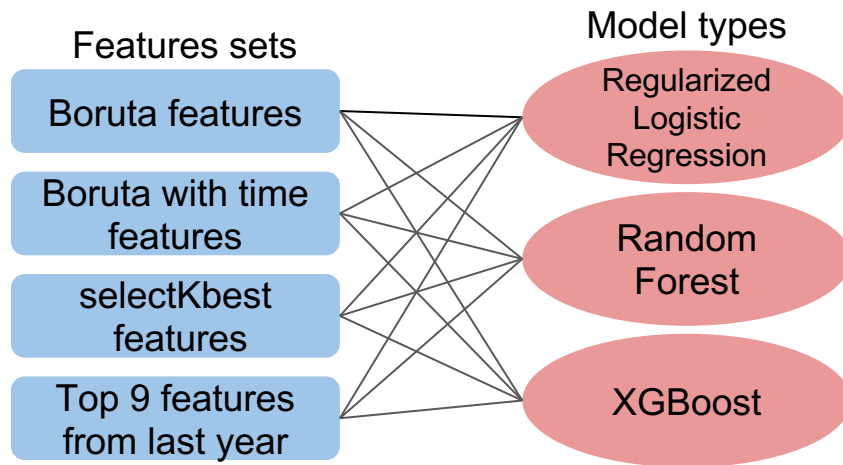
Hospital Level Models

Goal: Build different models for each hospital.

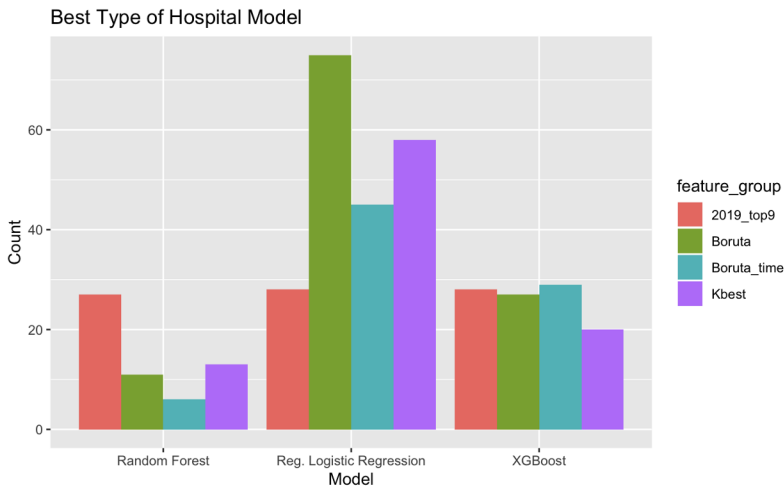
- Data Preprocessing
 - Grouped by hospitals, 3378 hospitals in total
 - Removed features with 0 variance within groups, 80 features left
- Sampling and Train Test Split by chronological order
 - Removed hospitals with less than 66 positive/negative cases, 367 hospitals left
 - 70% train, 15% validation and 15% test
 - Upsampled train dataset for each hospital

Hospital Level Models

- **Model Process**
 - 4 types of feature sets and 3 types of models, 12 combinations in total
 - Selected the best model from 12 models based on the F1 score on validation set



Hospital Level Models - Results



Ensemble Model Result

- $\text{Alpha} * \text{Population Model} + (1 - \text{Alpha}) * \text{Hospital Model}$
- Selected best alpha based on validation F1 Scores

Comparison - Validation Set



Accumulative Validation and Test Score

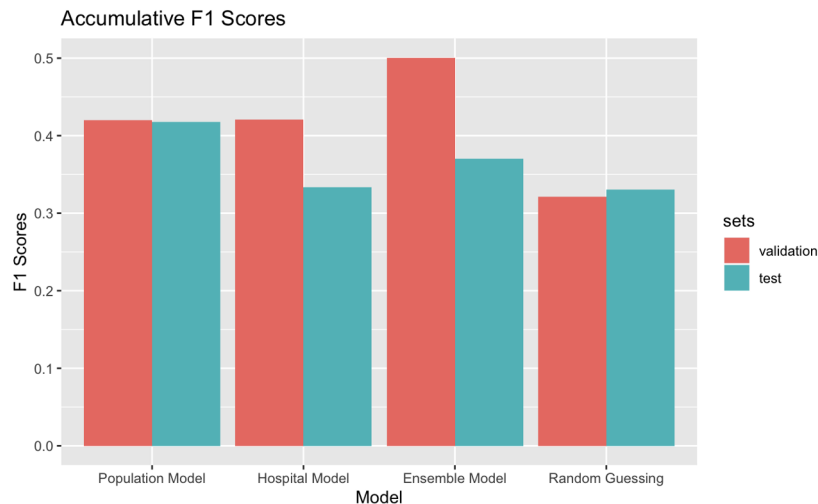
- Gather all 367 hospitals' validation sets into one big validation sets, same thing for the test set
- Random Guessing: 0 or 1 based on uniform distribution

Validation Scores				
Model	Val F1	Log Loss	AUC	Accuracy
Population Model	0.4196	0.6822	0.6404	0.5623
Hospital Model	0.4211	0.8201	0.6074	0.6442
Ensemble Model	0.5007	0.6497	0.6603	0.6900
Random Guessing	0.3210	0.9915	0.5504	0.5037

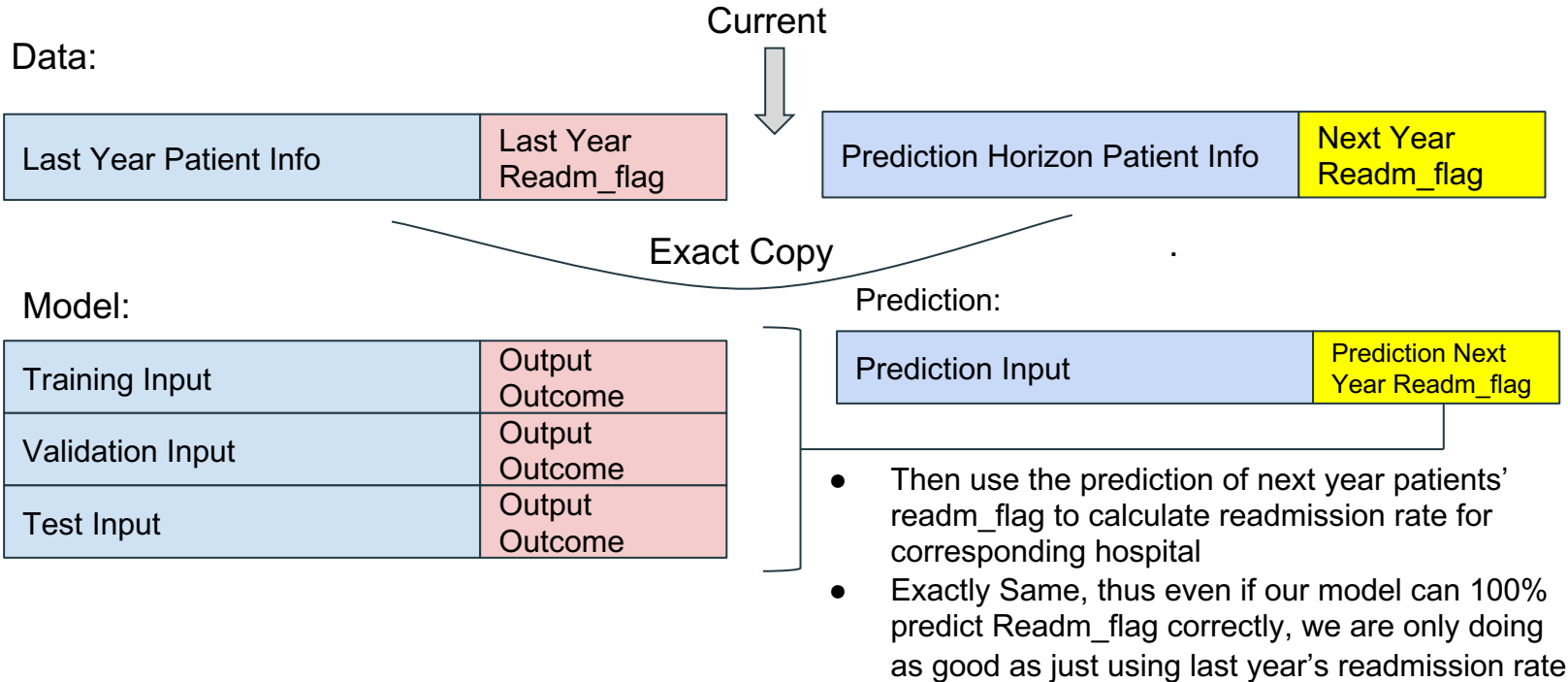
Test Scores				
Model	Test F1	Log Loss	AUC	Accuracy
Population Model	0.4179	0.6891	0.6326	0.5543
Hospital Model	0.3331	0.8905	0.5479	0.5894
Ensemble Model	0.3705	0.6784	0.5945	0.6079
Random Guessing	0.3307	0.9892	0.5073	0.5760

Accumulative F1 Scores

- Hospital model and ensemble model results are biased and not generative
- Does population model works for predicting the hospital's future readmission rate?

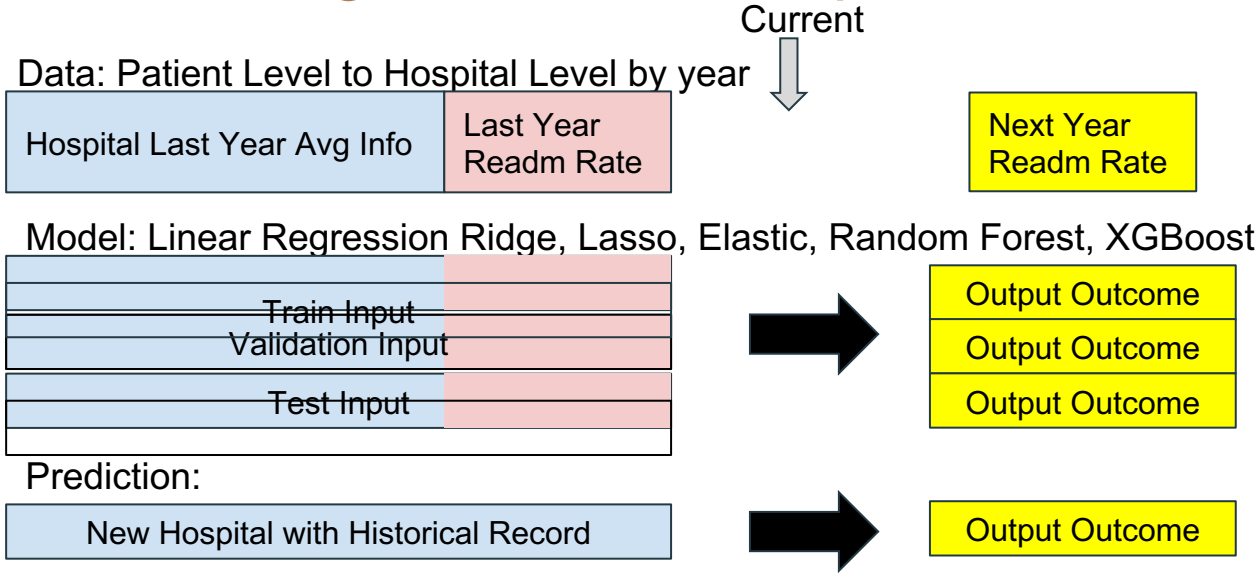


Population Model (Classification) Logic



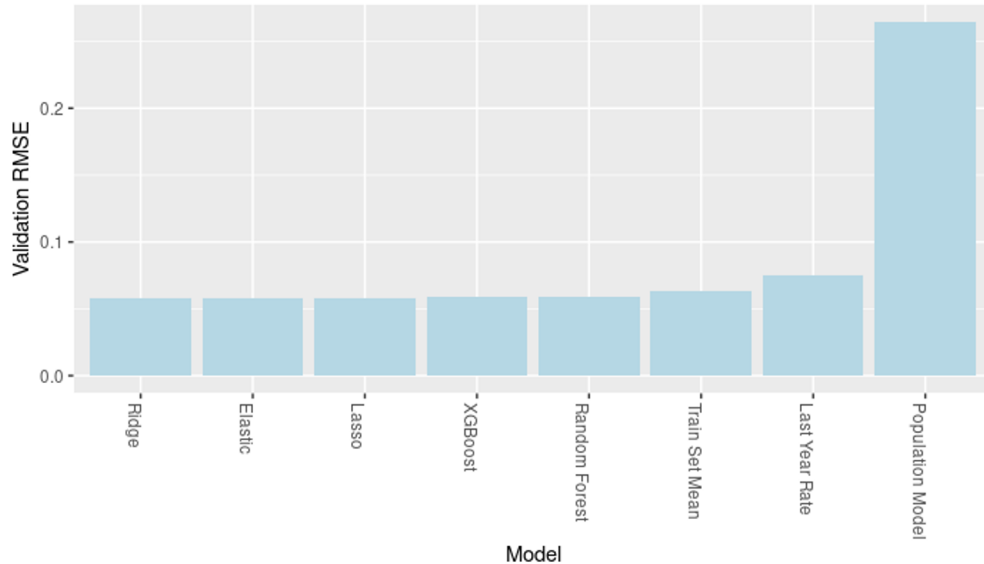
Other Approach

Regression on Hospital Level Data



Result - RMSE

Score for Predicting Next Year Readmission Rate



- Population Model (Classification): 0.27
- Regression Model: 0.06
- Last Year Rate: 0.07
- Train Mean: 0.65

Conclusion

- The classification on patient level data does not help to predict future hospital readmission rate if using exactly same past data as prediction horizon data
- Regression to directly predict hospital's future readmission rate might be a better approach
- Future step: better model and feature set for the regression method



Thank You

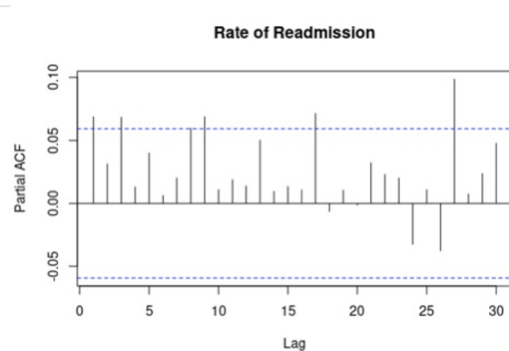
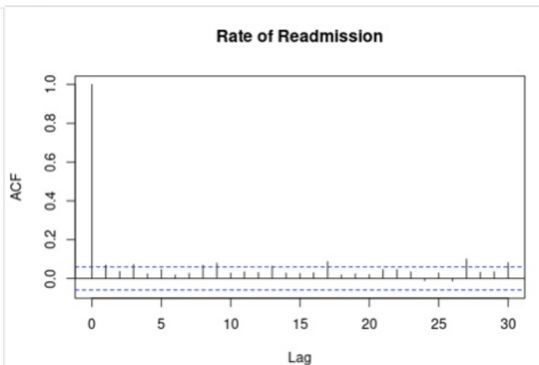
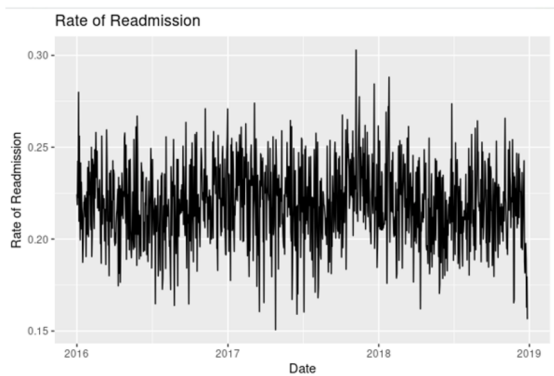
Presenters: MIKE WANG, ZINING FAN,
QIANG ZHAO, SIYUAN WANG



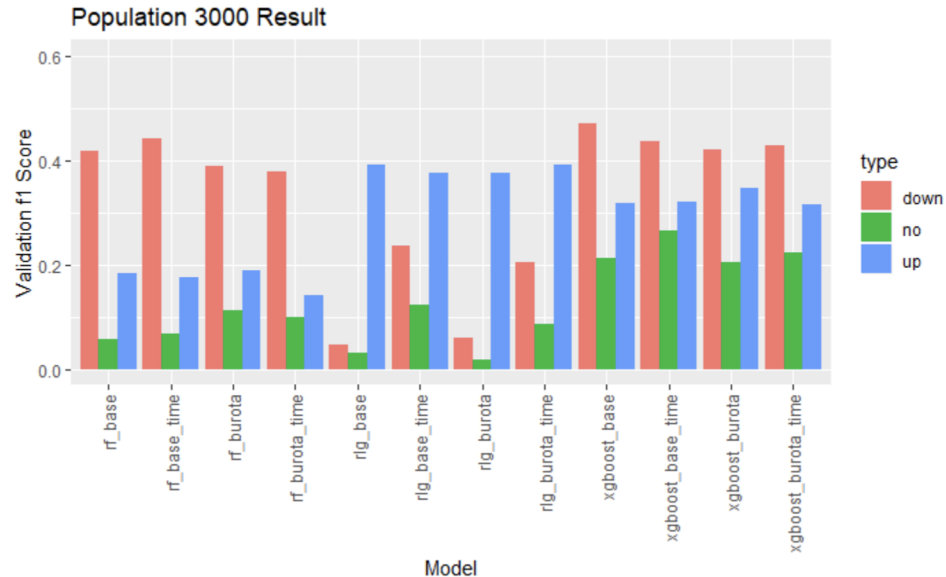
Appendix

Appendix- Temporal Dependency

- No significant temporal dependency for target variable
- Generated feature set combinations for further testing

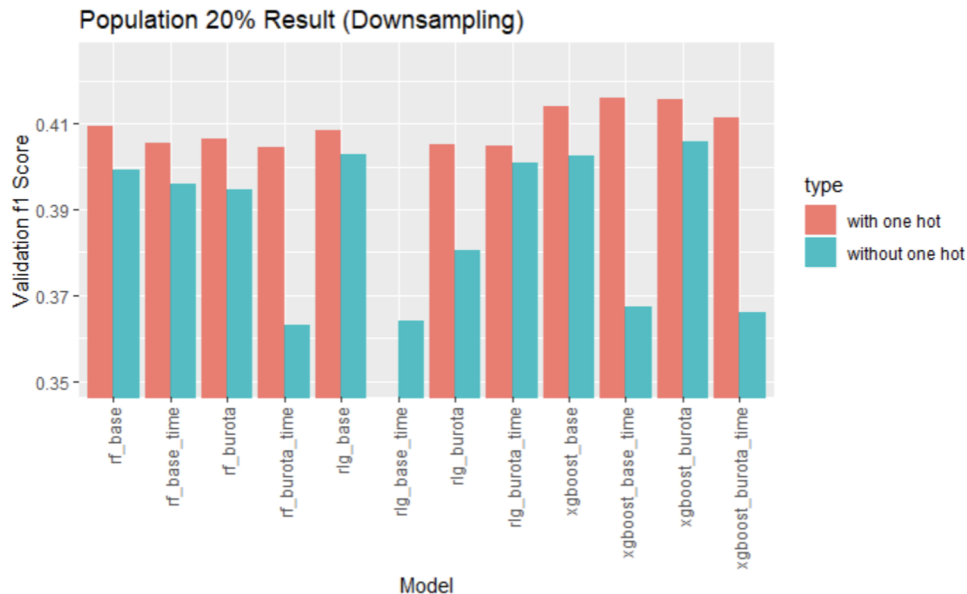


Appendix- Population Model - Without Categorical Regrouping

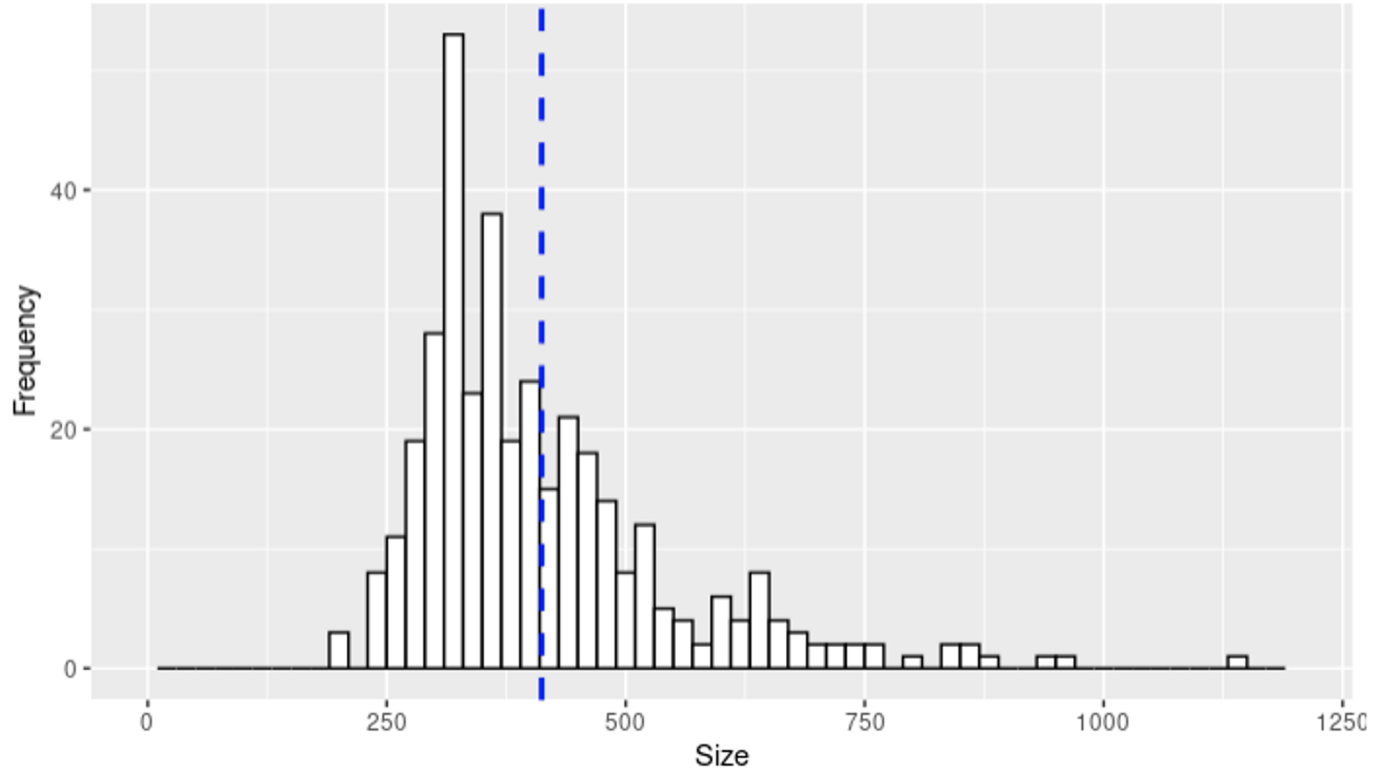


- Downsampling perform better in random forest and XGboost models
- Upsampling perform better in regularized logistic regression
- Considering about the large size of data, we decide to use downsampling approach to fasten our running time

Appendix- Population Model - Compare Encoding method



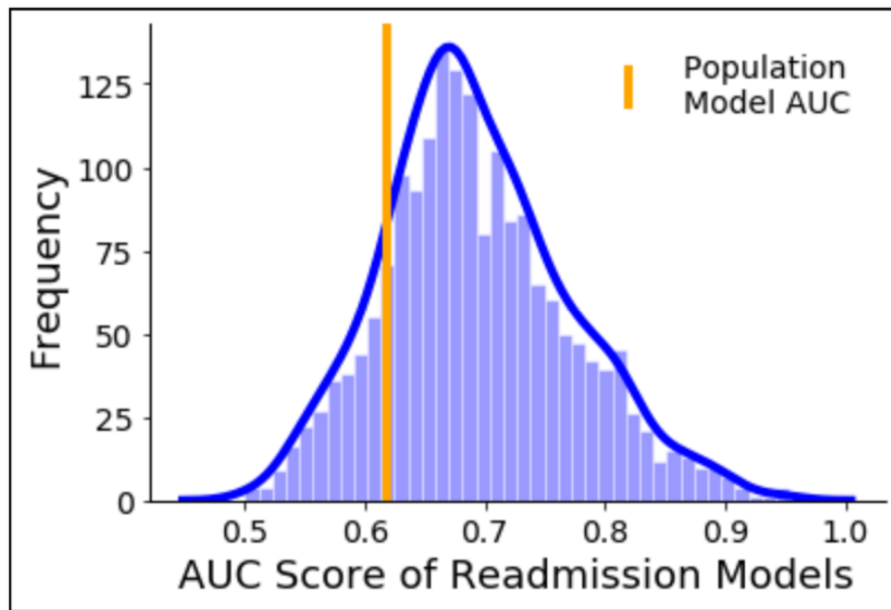
Selected Hospitals' Size Distribution



Appendix - Comparison - Hospital Level (order by size)

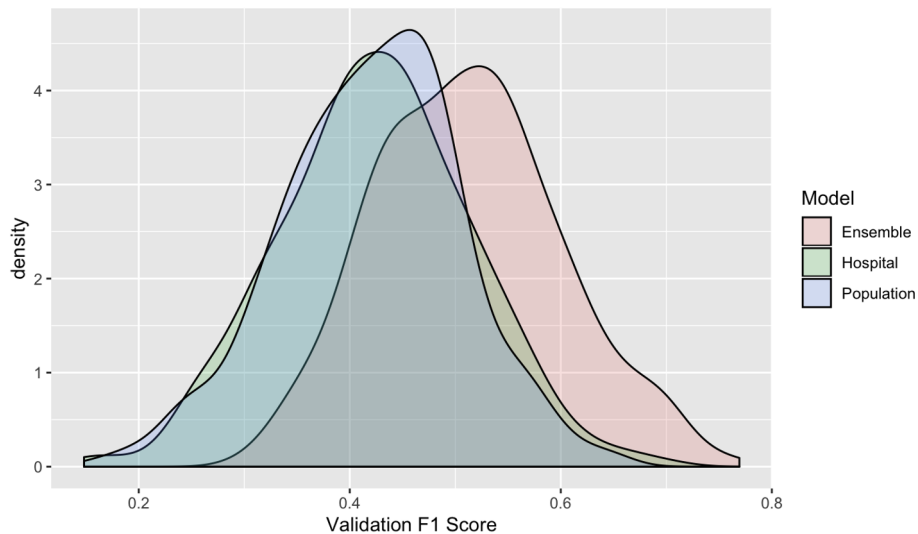


Appendix - AUC Last Year

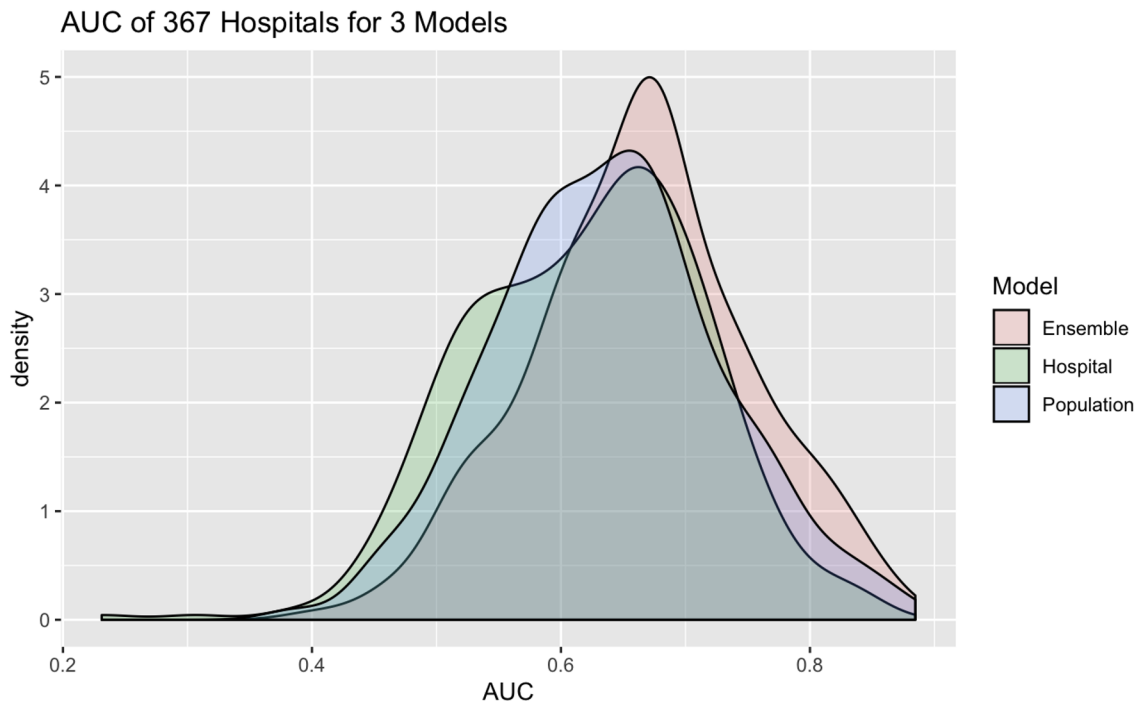


Appendix - F1 All Three

Validation F1-Score of 367 Hospitals for 3 Models

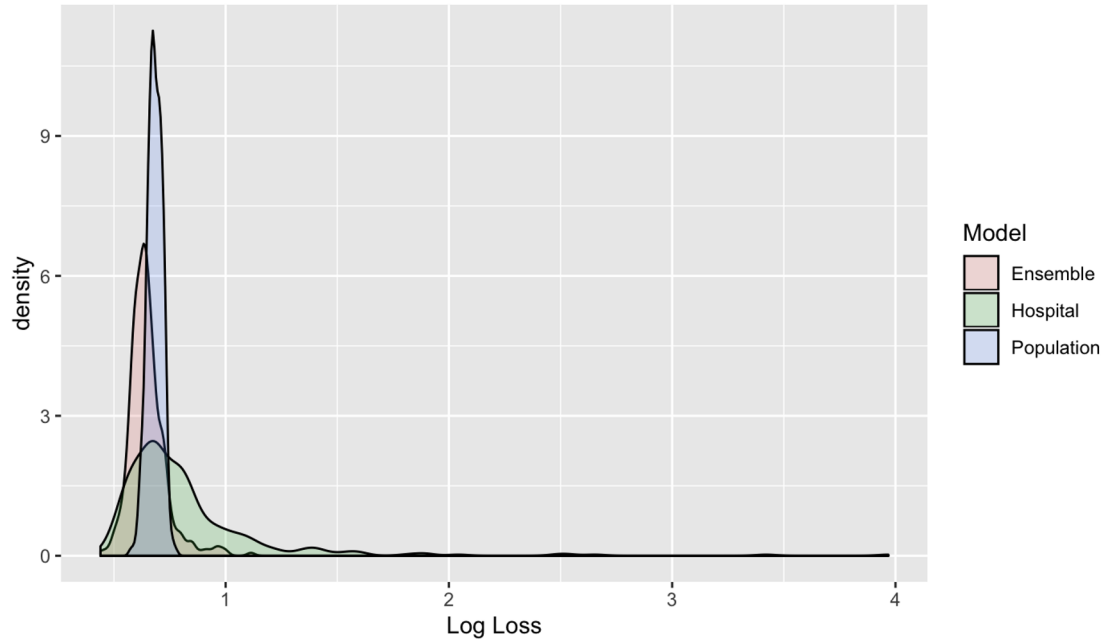


Appendix - AUC All Three



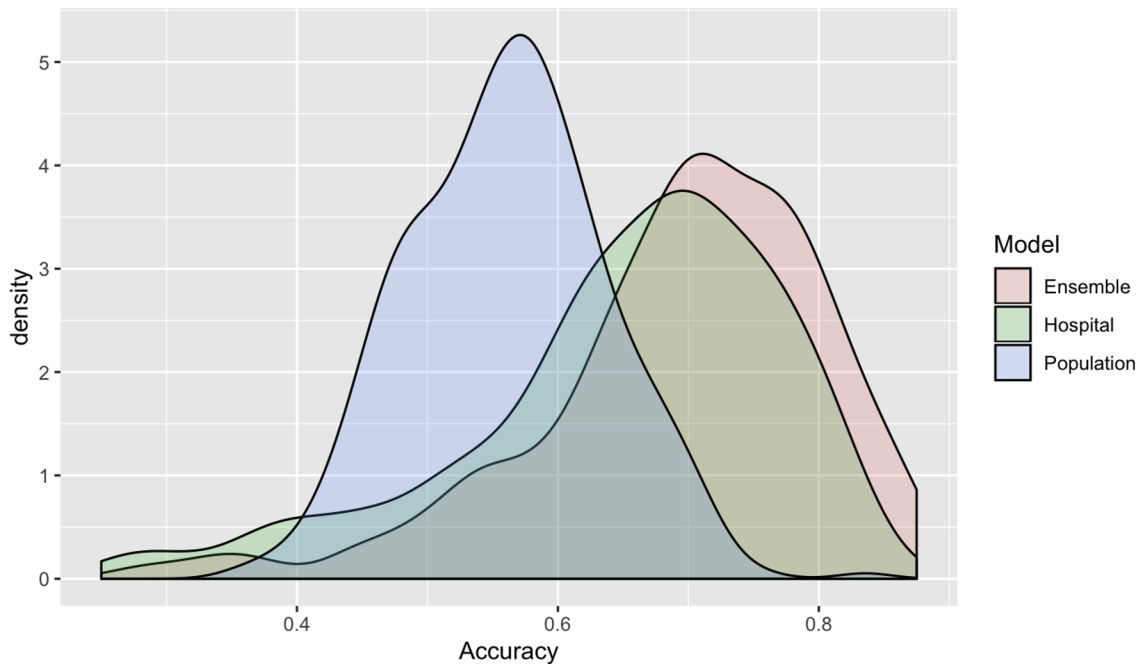
Appendix - Log Loss All three

Log Loss of 367 Hospitals for 3 Models



Appendix - Accuracy

Accuracy of 367 Hospitals for 3 Models



Appendix - Validation Results

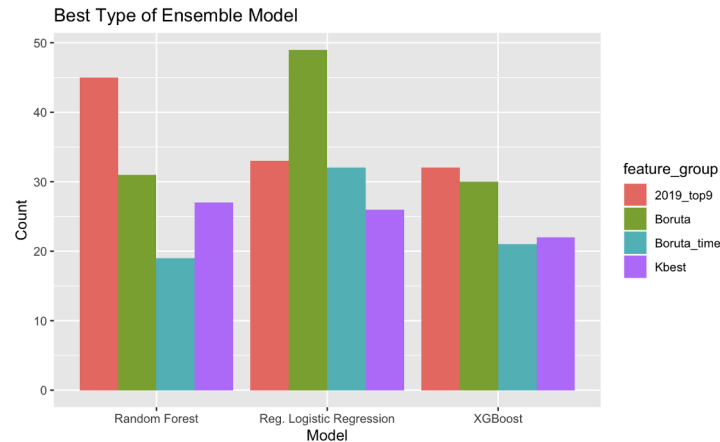
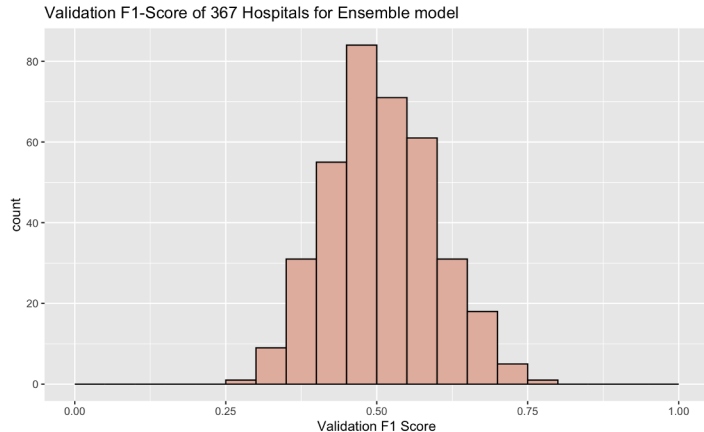
Validation Scores							
	validation F1 Score	Log Loss	AUC	Accuracy	PRAUC	Precision	Recall
Population Model	0.4196	0.6822	0.6404	0.5623	0.3503	0.3054	0.6704
Hospital Model	0.4211	0.8201	0.6074	0.6442	0.3100	0.3418	0.5483
Ensemble Model	0.5007	0.6497	0.6603	0.6900	0.3499	0.4039	0.6585
Random Guessing	0.3149	1.0044	0.4929	0.4975	0.2311	0.2321	0.4893

Appendix - Test Results

Test Scores							
	test F1 Score	Log Loss	AUC	Accuracy	PRAUC	Precision	Recall
Population Model	0.4179	0.6891	0.6326	0.5543	0.3389	0.3029	0.6737
Hospital Model	0.3331	0.8905	0.5479	0.5894	0.2685	0.2711	0.4319
Ensemble Model	0.3705	0.6784	0.5945	0.6079	0.2996	0.2994	0.4859
Random Guessing	0.3307	0.9892	0.5073	0.5076	0.2398	0.2441	0.5122

Appendix- Ensemble Model Result

- $\text{Alpha} * \text{Population Model} + (1 - \text{Alpha}) * \text{Hospital Model}$
- Selected best based on validation F1 Scores



Appendix -Patient Level Data to Hospital Level Data

Patient Level Data												
Patient ID	prvdr_num	age	sex	M_onehot	state	State target encoder	dgns_cd	dgns_cd.S	dgns_cd.M	dgns_cd.T	Readmission	Year
1	A	50	M	1	NY	0.7	S	1	0	0	1	2016
2	A	60	M	1	NY	0.7	T	0	0	1	0	2016
3	A	70	F	0	NY	0.7	M	0	1	0	0	2016
4	A	80	F	0	NY	0.7	S	1	0	0	0	2016
5	A	55	M	1	NY	0.7	S	1	0	0	1	2016
6	A	60	F	0	NY	0.7	T	0	0	1	1	2016
7	A	65	F	0	NY	0.7	S	1	0	0	0	2016
8	A	50	M	1	NY	0.7	S	1	0	0	1	2017
9	A	60	M	1	NY	0.7	M	0	1	0	0	2017
10	A	70	F	0	NY	0.7	M	0	1	0	0	2017

Hospital Level Data									Current Readmission Rate	Next Year Readmission rate
prvdr_num	age	Male Ratio	State	dgns_cd.S ratio	dgns_cd.M ratio	dgns_cd.T ratio	Year			
A	62.86	0.43	NY	0.57	0.14	0.29	2016	0.43	0.33	
A	60.00	0.67	NY	0.33	0.67	0.00	2017	0.33		