Exploring and Predicting Readmissions:

A Retrospective Review of Intensive Care Unit Admissions, Discharges, and Hospital Readmissions

By

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Intensive Care Unit: Readmissions

- Intensive Care Units [ICU] treat patients with the most acute medical needs
- Unknown if readmissions within a specified period of time is actually a reliable indicator of quality, but…
- Remains a common quality metric followed by hospitals (Brown, Ratcliffe, & Halpern, 2013)
- CMS now adjusts payment according to readmission rates
- Hospitals have a financial incentive to improve readmission rates

Literature Review

- ICU readmission timeframe as a quality indicator has been empirically derived at two calendar days, as opposed to 24 hours.
(Brown, Ratcliffe, & Halpern, 2013)
  - After 2 calendar days, ICU interventions showed diminished influence on readmissions, compared with patient characteristics.
  - 1.0% (2242) were readmitted to the ICU within 24 hours and only 4.2% (9062) within 7 days, in this study of over 200,000 patients.
  - Interval defined by 2 full calendar days produced more valid results than fixed numbers of hours, due to the predominance of afternoon ICU readmissions.

- Advanced modeling techniques have seldom been demonstrated to have sufficient sample sizes or reproducibility to generalize specific prediction tools. (Alba, Agoritsas, Jankowski, Courvoisier, Walter, Guyatt, & Ross, 2013)

Principal Research Question

- What is the best statistical method to predict hospital readmissions after an ICU stay, and what identifying characteristics of local clients best differentiate patients who are readmitted within 30 days from those who are not?

Study Aims

- Global Aim: To predict hospital readmissions after an ICU stay
- Specific Aims:
  - To develop multiple, multivariable statistical models to predict ICU and hospital readmissions, after a patient has been treated in the ICU.
  - To compare and contrast the multiple models, thereby discovering the best model to predict 30-day readmissions.
  - To discover factors that best differentiate patients who are likely to be readmitted within 30 days of discharge after an ICU stay from those who are not

Hospital Setting & Payer Mix

- Urban, non-teaching Hospital in mid-sized American city
- 20-bed Intensive Care Unit, with 3 sub-units, sometimes filled to capacity
- A large proportion of patients are covered by Medicare or Medicaid (approximately 2/3)

Medical Coding

- CMS pays for each admission, based on the specific Diagnostic Related Group [DRG] code assigned for that admission, and a *per diem* rate that is weighted according to the hospital's basic characteristics. (Green & Rowell, 2010)
- DRG codes are based on the summary of ICD9 codes assigned to a patient for that visit
- Thousands of ICD9 codes exist to describe the complex states of patients' health and illness.
- Therefore, a great deal of variability exists among patients, based on their comorbidities.

Medical Documentation & Effect on Prediction

- It follows that medical documentation requirements also vary, based on patient conditions, procedures, and diagnostics
- Traditional prediction techniques, such as logistic regression, do not tolerate missing data
- However, many newer, computationally-intensive techniques are robust to missing data: specifically, the multiple forms of recursive partitioning: decision trees, gradient boosted trees, and bootstrap forests.

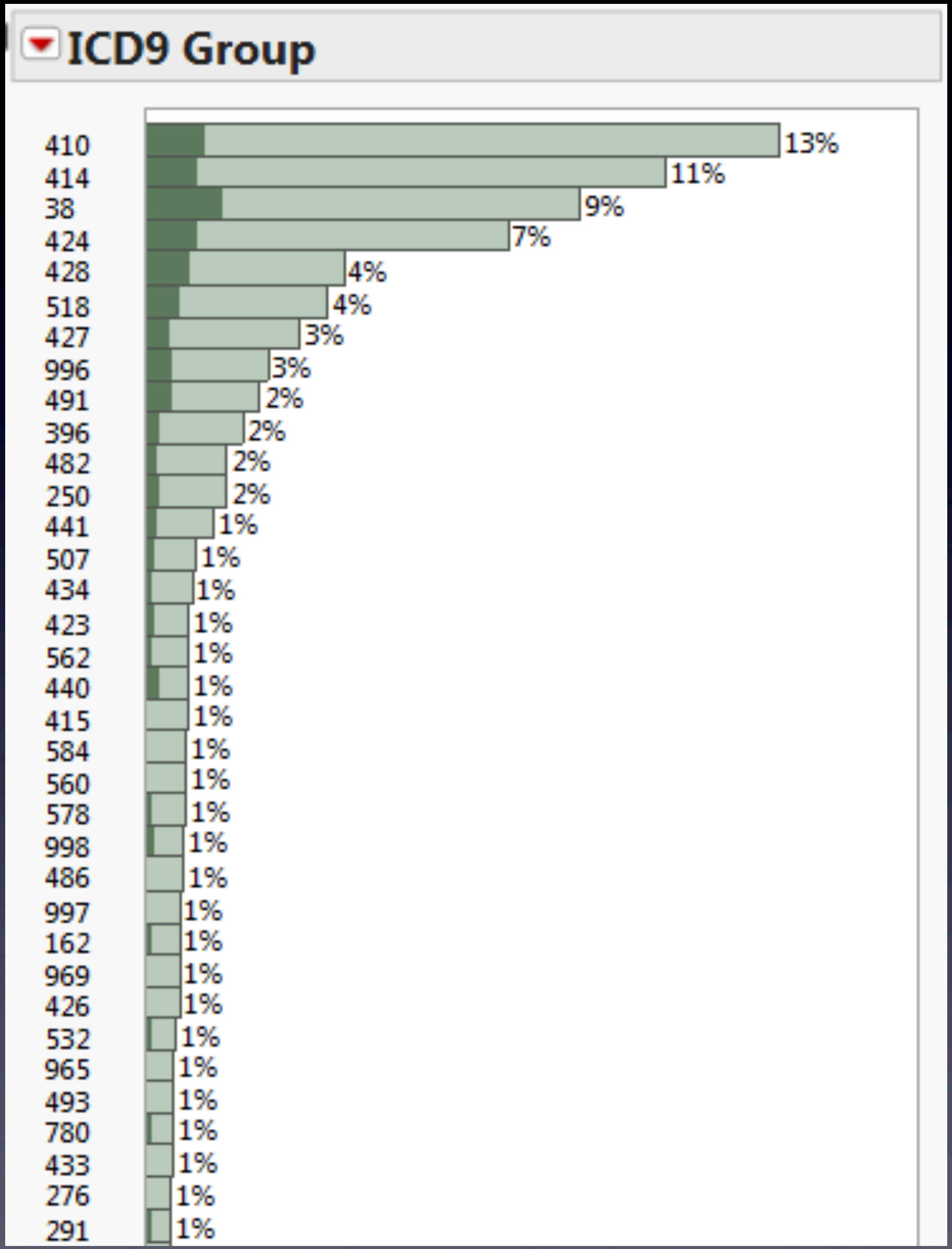
Data Tabulation & Exploration

- A comparative analysis of 30 variables was performed through dynamic visualization techniques:
  - Interactive histograms with summary statistics
  - Scatterplot matrices, mosaic plots, 3D plots & more…
- Multiple Correspondence Analysis (a dimension reduction technique) was performed to depict natural groupings in the data of ICD9 codes, which represent comorbid conditions.

Summary Statistics for ICU Admissions

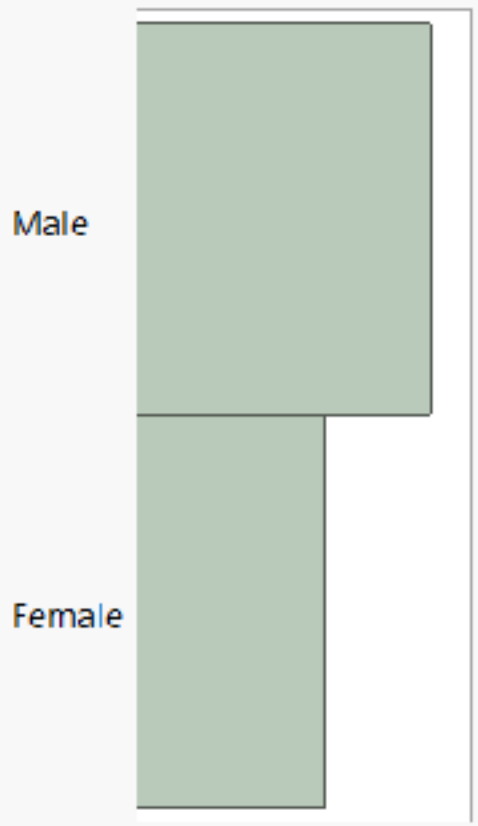
- Total ICU patients in Study: 4134
- Total ICU Visits in Study: 4785
- Readmission applicable after visit: 89.7% (4290/4785) of cases.
- 17% (720/4290) of visits resulted in readmission to a hospital (any unit) within 30 days of discharge. Only about 5% actually required readmission to the ICU within 30 days of hospital discharge.
- 83% (3570/4290) of visits did not result in hospital readmission within 30 days of discharge.
- 15% (648/4290) of visits led to an ICU Readmission within the 3 year (1095 days) study window.
- 85% (3642/4290) of visits did not lead to an ICU Readmission within the study window.

ICU Admissions by ICD9 Group



Gender and Expiration by Visit

Gender

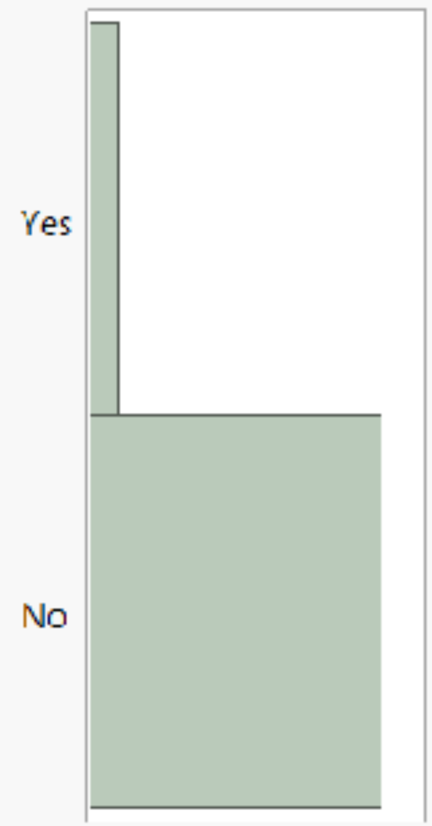


Frequencies

Level	Count	Prob
Female	1871	0.39101
Male	2914	0.60899
Total	4785	1.00000

N Missing 0
2 Levels

Expired

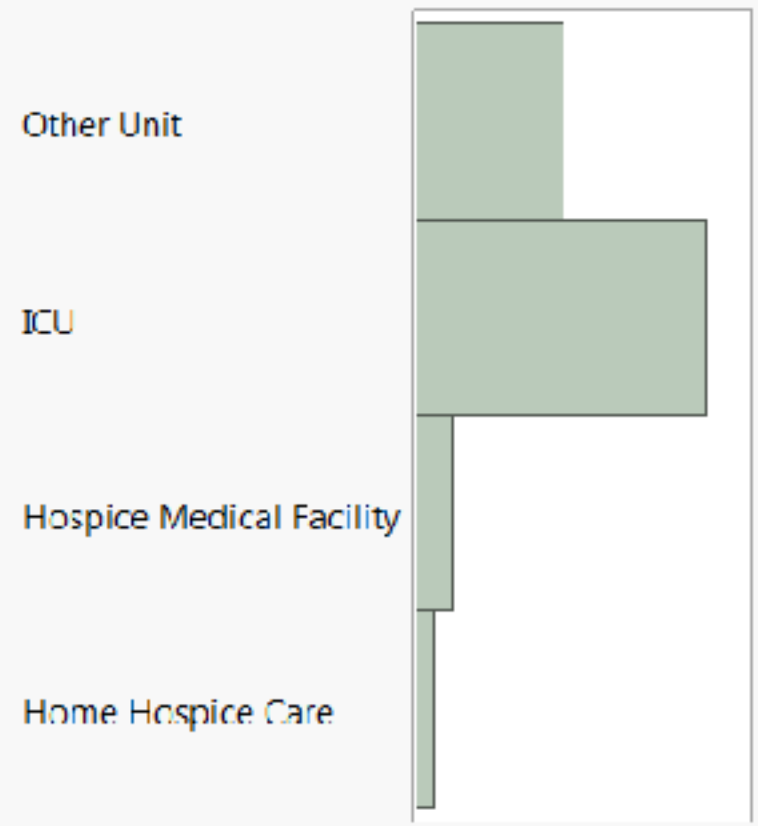


Frequencies

Level	Count	Prob
No	4347	0.90846
Yes	438	0.09154
Total	4785	1.00000

N Missing 0
2 Levels

Place Died



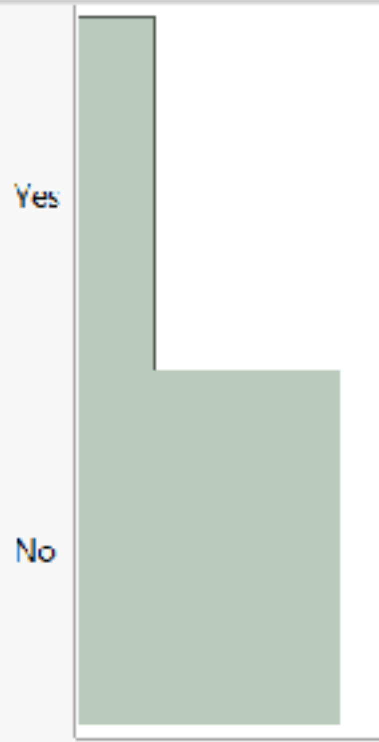
Frequencies

Level	Count	Prob
Home Hospice Care	19	0.03838
Hospice Medical Facility	38	0.07677
ICU	291	0.58788
Other Unit	147	0.29697
Total	495	1.00000

N Missing 4290
4 Levels

Proportion of Visits by Patients with Multiple ICU Admissions (23%)

Multiple ICU Admissions



Frequencies

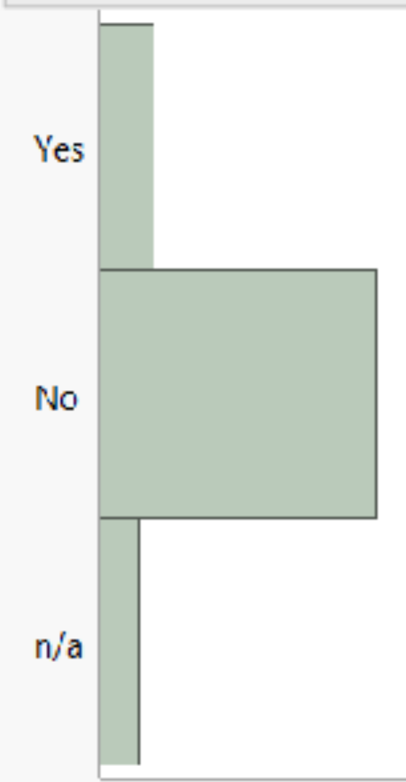
Level	Count	Prob
No	3675	0.76803
Yes	1110	0.23197
Total	4785	1.00000

N Missing 0

2 Levels

Proportion of Visits with Readmission < 30 Days (17%, 720 of 4290 patients)

Readmitted<30 Days



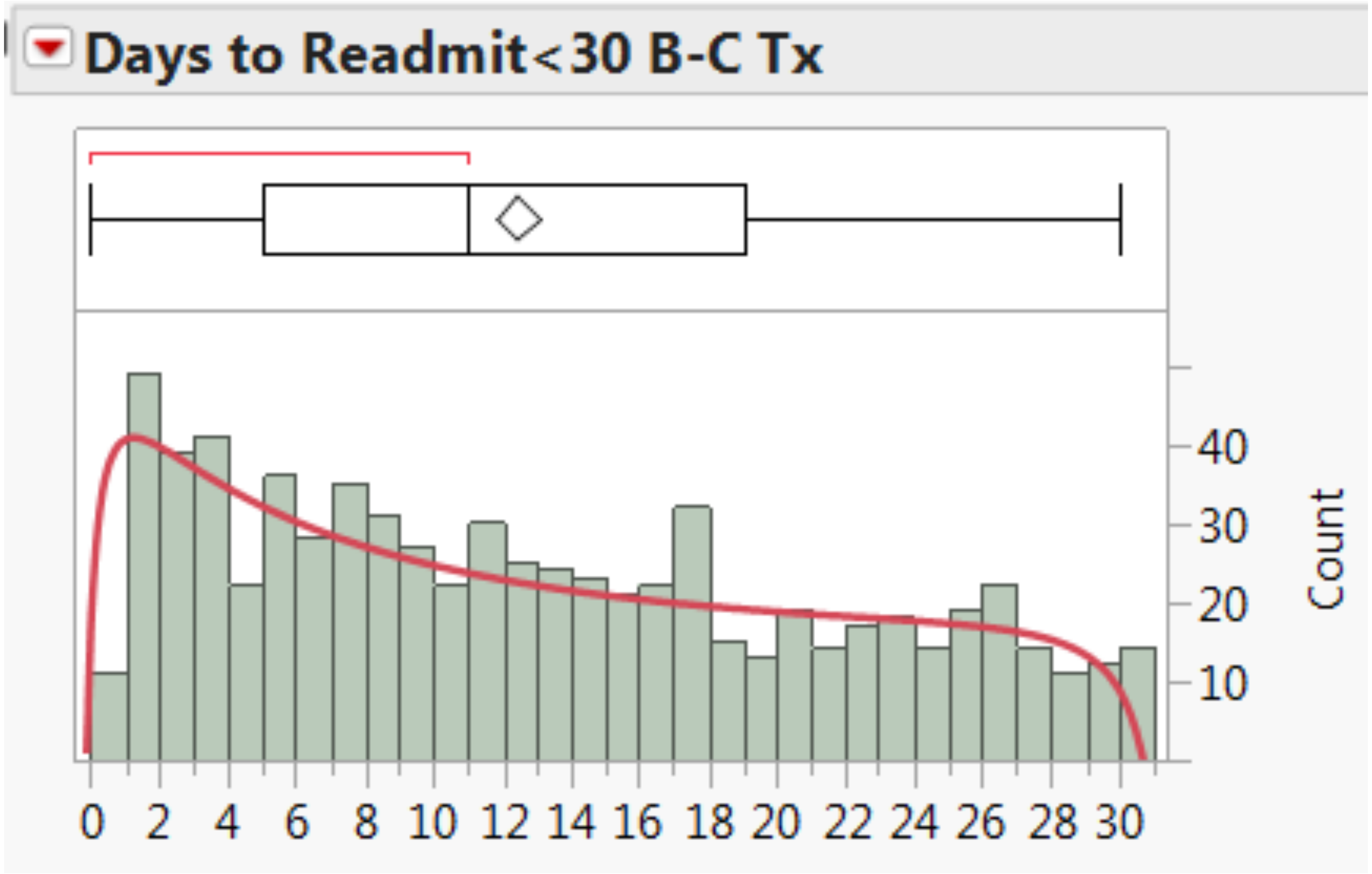
Frequencies

Level	Count	Prob
n/a	495	0.10345
No	3570	0.74608
Yes	720	0.15047
Total	4785	1.00000

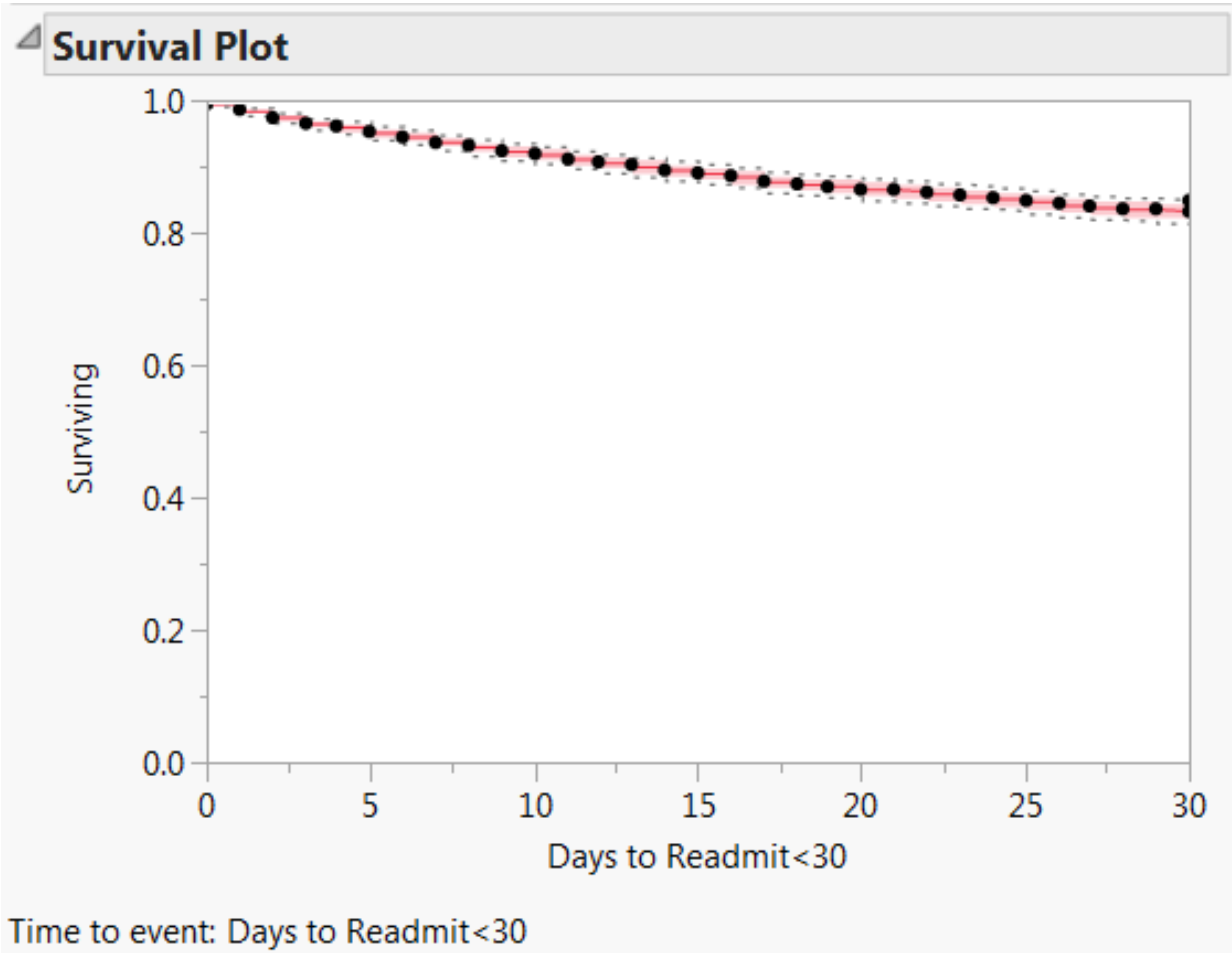
N Missing 0

3 Levels

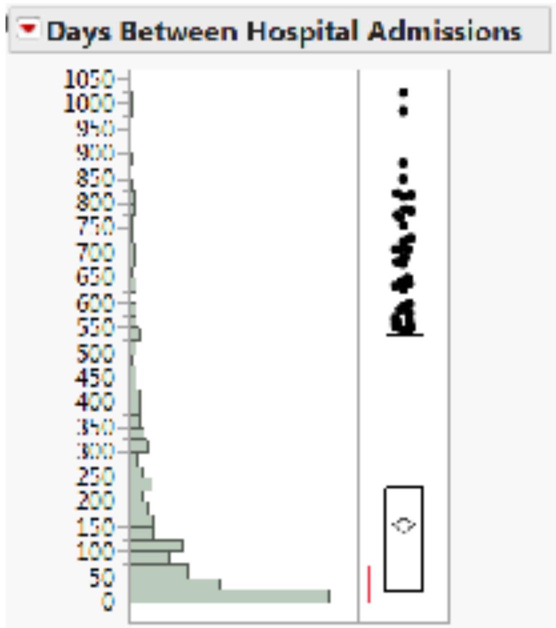
Readmission Counts per Day
Within 30 Days of Hospital Discharge



30-Day Readmission Estimates



Days Between ICU Admissions

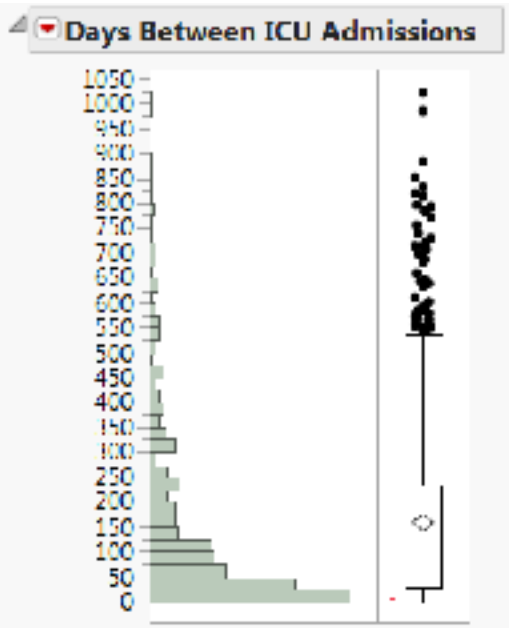


Quantiles

100.0%	maximum	1022.44
99.5%		872.303
97.5%		708.028
90.0%		444.208
75.0%	quartile	227.645
50.0%	median	72.0028
25.0%	quartile	20.584
10.0%		5.85764
2.5%		1.19427
0.5%		0.4309
0.0%	minimum	0.00069

Summary Statistics

Mean	155.01966
Std Dev	193.13786
Std Err Mean	7.581128
Upper 95% Mean	169.90571
Lower 95% Mean	140.13312
N	649



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100.0%	maximum	1022.57
99.5%		875.969
97.5%		714.448
90.0%		450.439
75.0%	quartile	232.383
50.0%	median	80.1311
25.0%	quartile	27.2225
10.0%		10.7774
2.5%		5.22102
0.5%		1.93728
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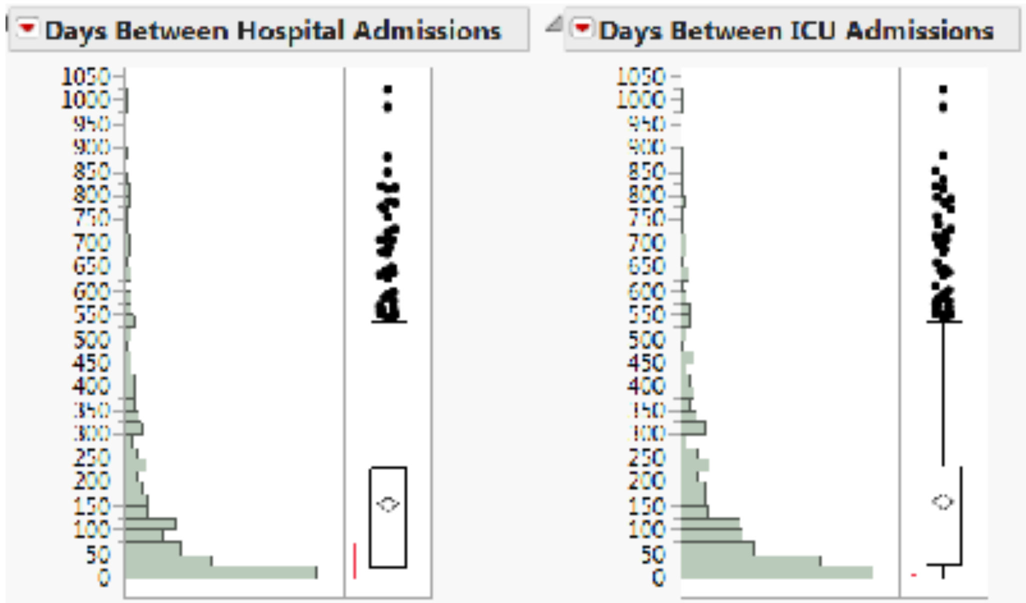
Summary Statistics

Mean	160.40878
Std Dev	192.91011
Std Err Mean	7.5723843
Upper 95% Mean	175.27815
Lower 95% Mean	145.5394
N	649

- 4% (177/4290) were discharged from ICU and readmitted to ICU within 30 days.
- 3% (128/4290) were discharged from ICU and readmitted to ICU within 21 days.
- 2% (94/4290) were discharged from ICU and readmitted to ICU within 14 days.
- 1.4% (58/4290) were discharged from ICU and readmitted to ICU within 10 days.
- 0.7% (30/4290) were discharged from ICU and readmitted to ICU within 7 days.
- 0.1% (5/4290) were discharged from ICU and readmitted to ICU within 3 days (72 hours).
- No patients readmitted within 72 hours died on readmission: 3 had respiratory arrest, one had a saddle embolus of the pulmonary artery, and one had malignant hypertension.
- 13.6% of all readmissions to the ICU within 30 days of discharge ended with the patient's death.

Days to Hospital Readmission with Eventual ICU stay



Quantiles (Days Between Hospital Admissions)

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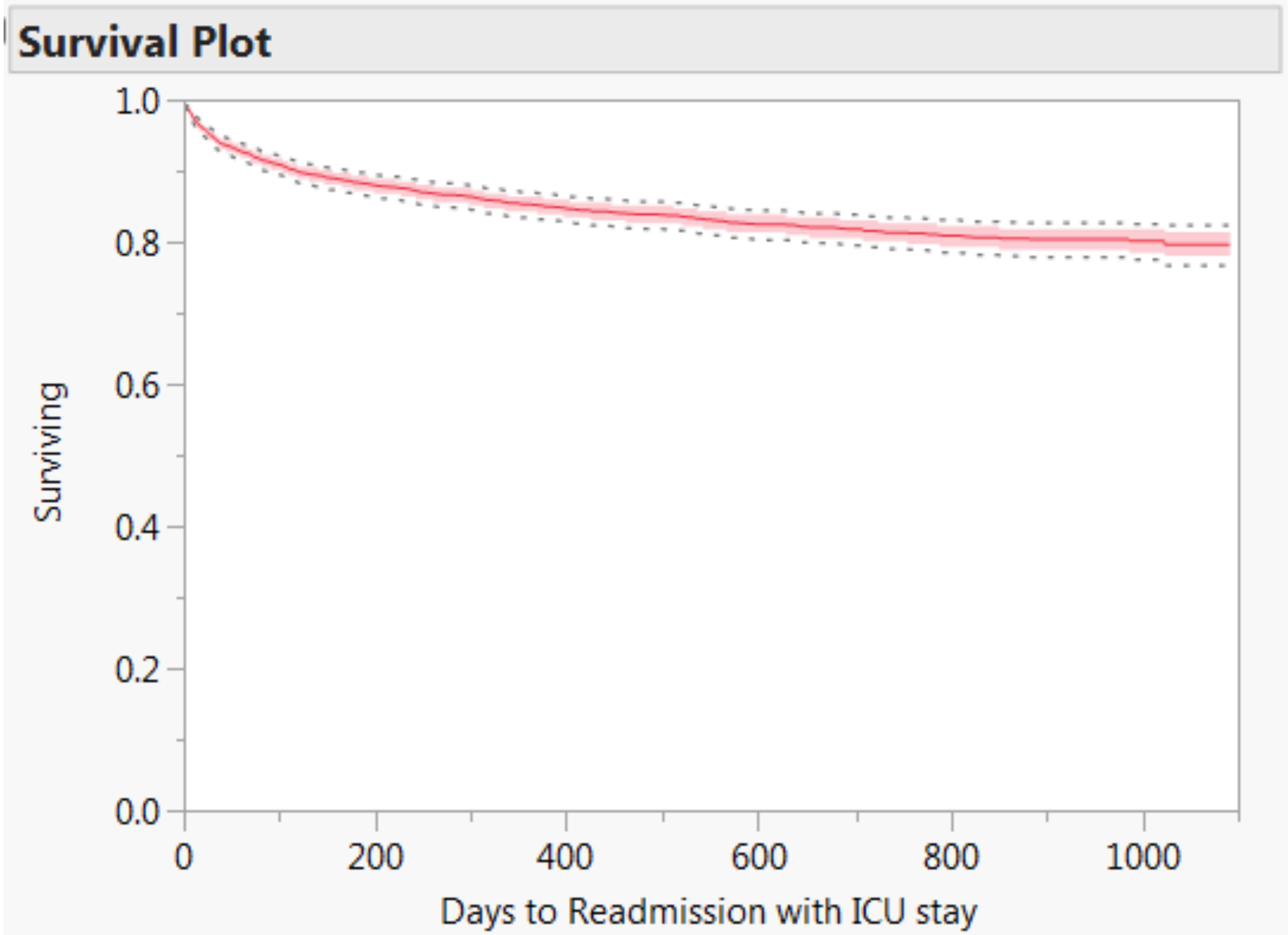
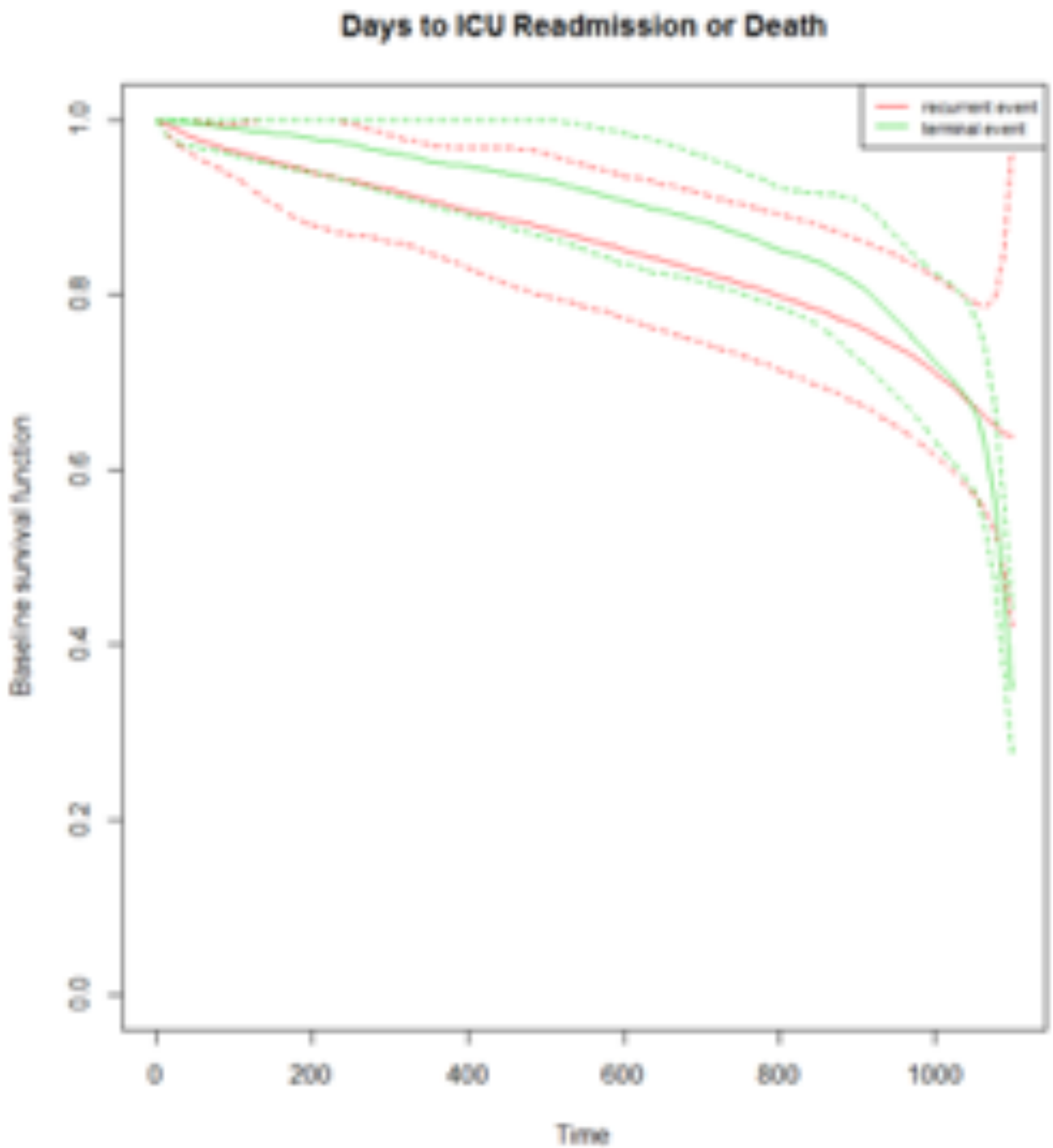
- Time to Hospital Readmission with ICU stay, after Hospital Discharge with ICU stay:
- 5% (211/4290) were readmitted to hospital within 30 days, with eventual stay in ICU.
- 4% (160/4290) were readmitted to hospital within 21 days, with eventual stay in ICU.
- 3% (131/4290) were readmitted to hospital within 14 days, with eventual stay in ICU.
- 2.5% (106/4290) were readmitted to hospital within 10 days, with eventual stay in ICU.
- 2% (77/4290) were readmitted to hospital within 7 days, with eventual stay in ICU.
- 1% (41/4290) were readmitted to hospital within 3 days, with eventual stay in ICU.
- 0.6% (26/4290) were readmitted to hospital within 2 days, with eventual stay in ICU.
- Note: many were readmitted, but did not return to the ICU during the subsequent hospitalization, and were not included here.

Time to Hospital Readmission with ICU Stay



Joint Frailty Model

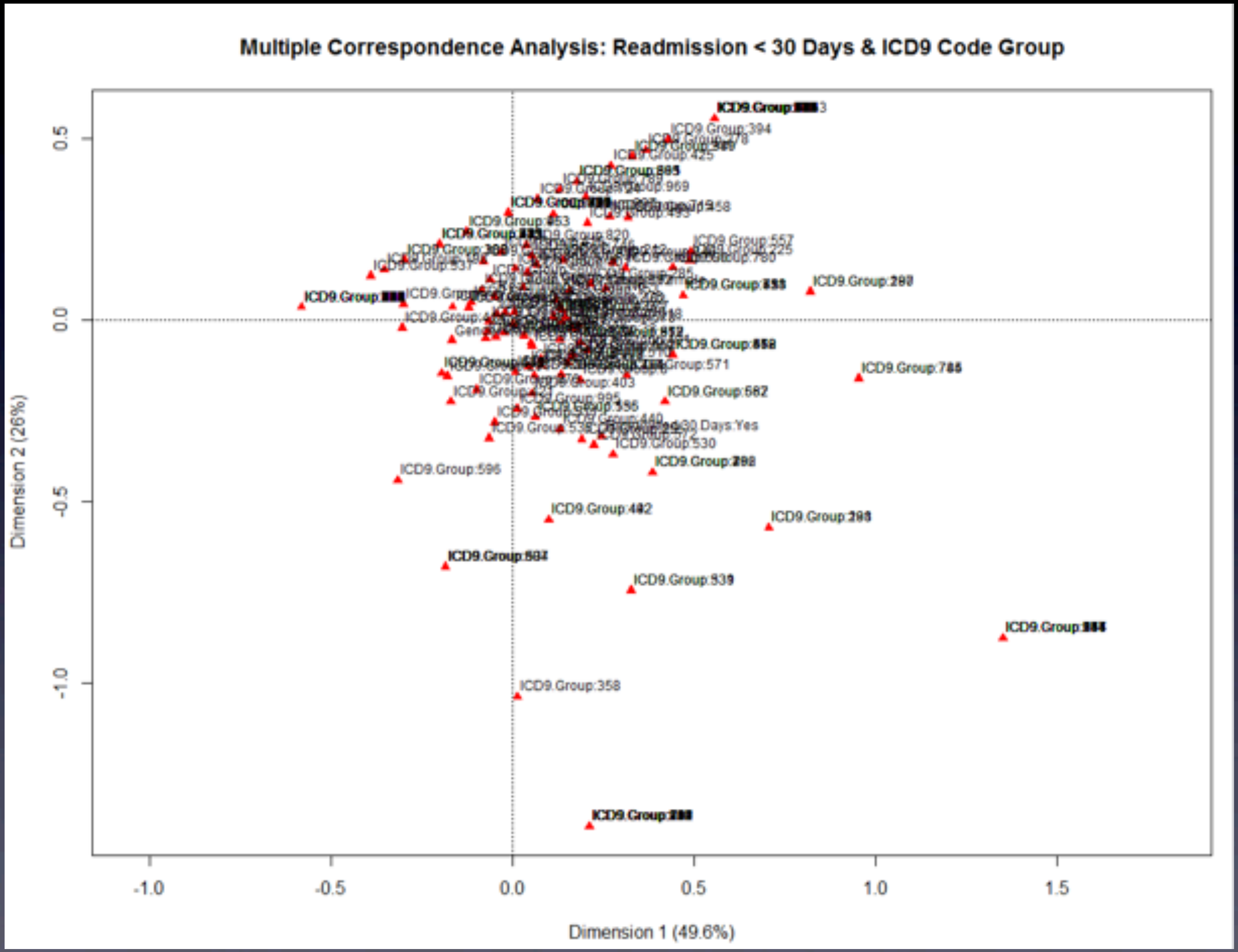
Readmission & Expiration



Joint Frailty Models simultaneously estimate the proportion of patients that are expected to be alive over time (green), contingent on the number of times they have been readmitted, and the proportion of patients that not expected to have been readmitted (red), contingent on survival over time.

Confidence Bands are dotted.

Exploratory Data Analysis



Predictive Models

- Prior to training the models with separate sampling and optimization with a profit matrix, negative predictions overwhelmed each model.
  - Optimal prediction was offered by any model predicting absolutely no readmissions (83.3% correct), however…
  - These models are useless, because they are totally insensitive to predicting readmissions.
- Boosted Tree Model
  - Small positive predictive value
- Bootstrap Forest Model
  - Offered optimal prediction (71% correct, pooled) for all causes of readmission within 30 days of hospital discharge after an ICU stay.

Most Influential Predictors

Column Contributions

Term	Number of Splits	G^2	Portion
Principal ICD9 Code	346	27628.1135	0.1978
ICD9 Group	190	3570.50873	0.0256
ICD9 Sum	236	2452.11968	0.0176
Hemoglobin	227	2384.69181	0.0171
Admited To ICU Via	205	1761.93336	0.0126
First Admitted To Unit	184	1718.27872	0.0123
Age at Discharge	211	1521.46719	0.0109
RangeDiastolicBloodPressure	169	1512.72944	0.0108
Discharge Disposition	197	1483.45741	0.0106
MaximumSystolicBloodPressure	186	1439.74808	0.0103
Final Recorded HeartRate	196	1386.94494	0.0099
MinimumDiastolicBloodPressure	188	1359.73942	0.0097
Hematocrit	165	1349.12335	0.0097
AverageSystolicBloodPressure	180	1313.91317	0.0094
AverageDiastolicBloodPressure	188	1302.58787	0.0093
O2Saturation	186	1245.14979	0.0089
Creatinine	179	1235.20101	0.0088
Discharge Height m	177	1219.87898	0.0087
Drip Sum	139	1209.99876	0.0087
GFR	122	1197.94169	0.0086
MaximumDiastolicBloodPressure	158	1191.31054	0.0085
RangeSystolicBloodPressure	160	1166.23548	0.0083
PaCO2	146	1157.75856	0.0083
Total Length of Stay seconds	157	1154.60442	0.0083
Final Drip Stop Time to DC fxd	167	1153.34944	0.0083

Profit Matrix

Specify Profit Matrix

Enter positive numbers as profits for correct decisions on the diagonal.
Enter negative numbers as costs for incorrect decisions off the diagonal.
An extra decision row can be used to indicate an alternative to prediction.

Reading across a row shows the consequences if you predict this response.
Reading down a column shows the consequences if the actual response is this.

When you save prediction formulas, these values will be used to create best decision columns.
The best decision is the one with greatest expected profit.

Decision or Prediction	Actual: No	Actual: Yes
No	0	-1
Yes	-0.2	0.2
Undecided	.	.

☑ Save to column as property.

Bootstrap Forest Details

Bootstrap Forest for Readmitted<30 Days

Specifications

Target Column:	Readmitted<30 Days	Training rows:	898
		Validation rows:	409
Number of trees in the forest:	44	Test rows:	0
Number of terms sampled per split:	814	Number of terms:	3259
		Bootstrap samples:	898
		Minimum Splits Per Tree:	10
		Minimum Size Split:	5

Overall Statistics

Measure	Training	Validation	Definition
Entropy RSquare	0.4859	0.0226	1-Loglike(model)/Loglike(0)
Generalized RSquare	0.6526	0.0407	(1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n))
Mean -Log p	0.3541	0.6643	$\sum$ -Log(ρ[j])/n
RMSE	0.3066	0.4854	$\sqrt{\sum(y[j]-\rho[j])^2/n}$
Mean Abs Dev	0.2913	0.4654	$\sum$ |y[j]-ρ[j]|/n
Misclassification Rate	0.0267	0.3741	$\sum$ (ρ[j]≠ρMax)/n
N	898	409	n

Confusion Matrix

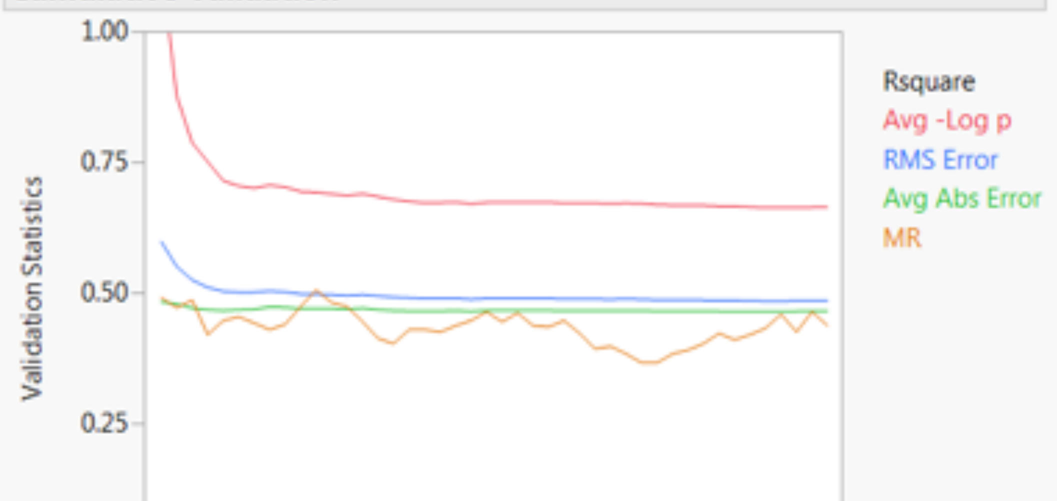
Actual / Predicted

Training	No	Yes
No	487	4
Yes	20	387

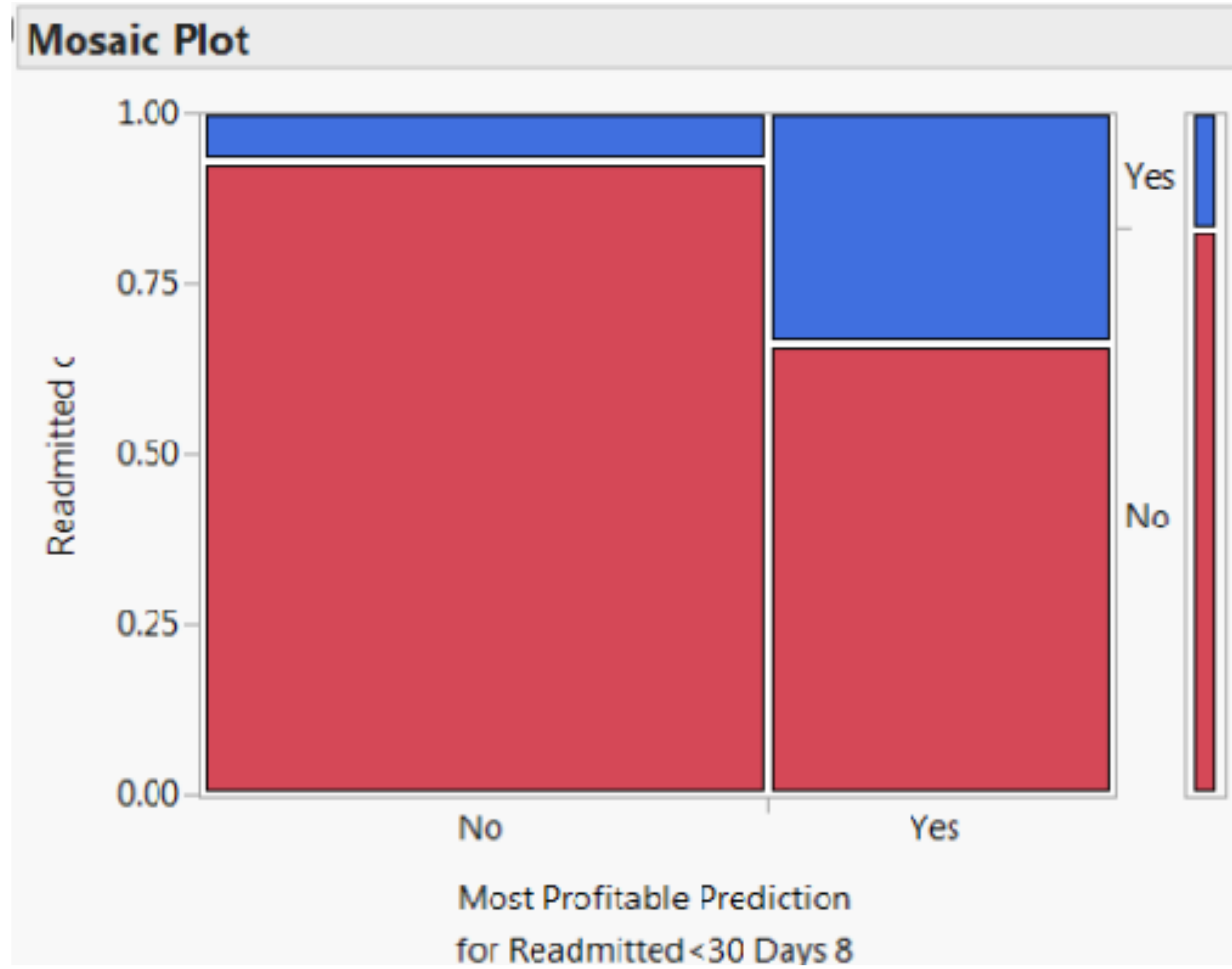
Actual / Predicted

Validation	No	Yes
No	167	71
Yes	82	89

Cumulative Validation



Mosaic Plot for Bootstrap Forest Model

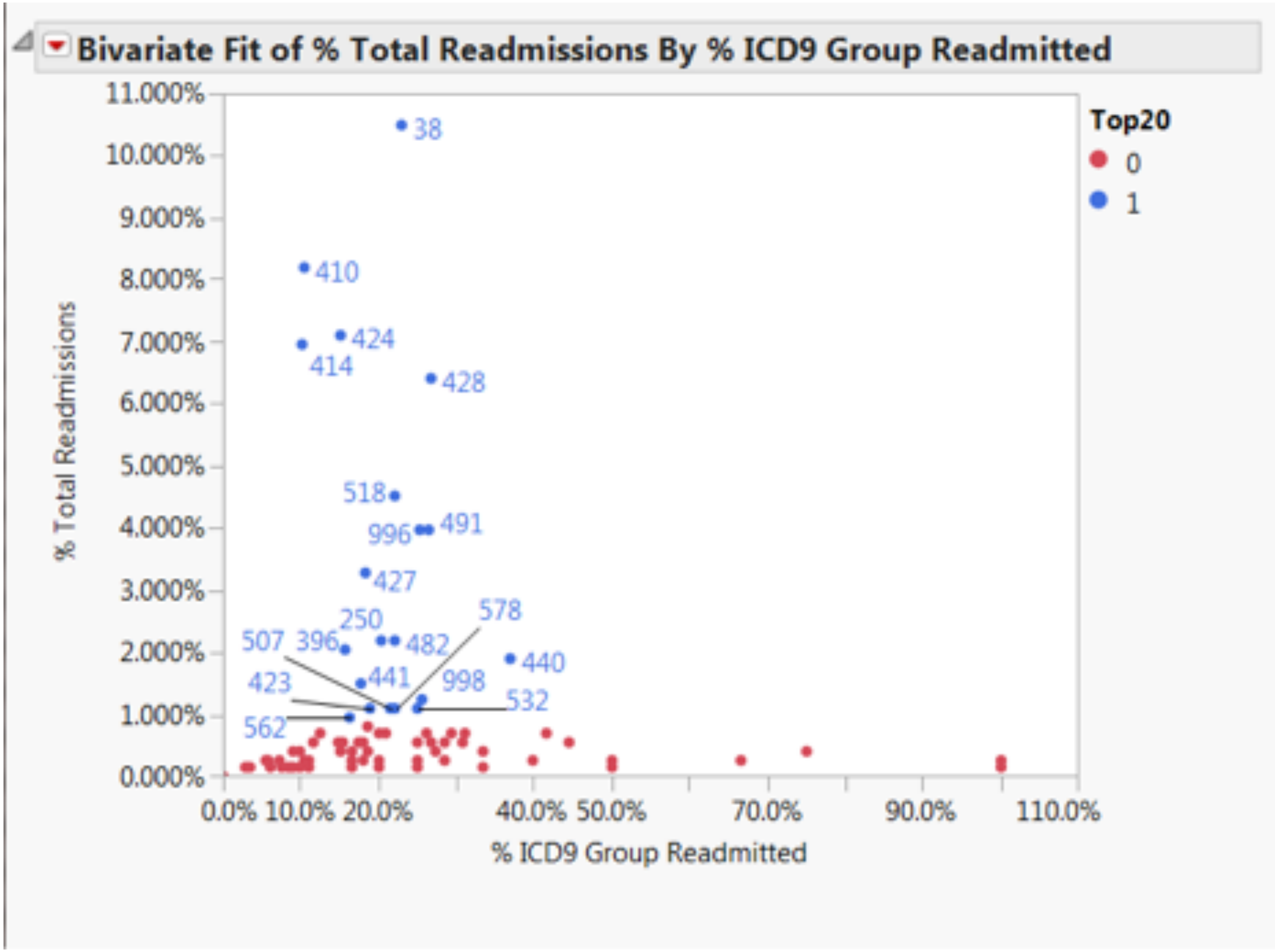


Blue = Readmitted

Red =
Not Readmitted

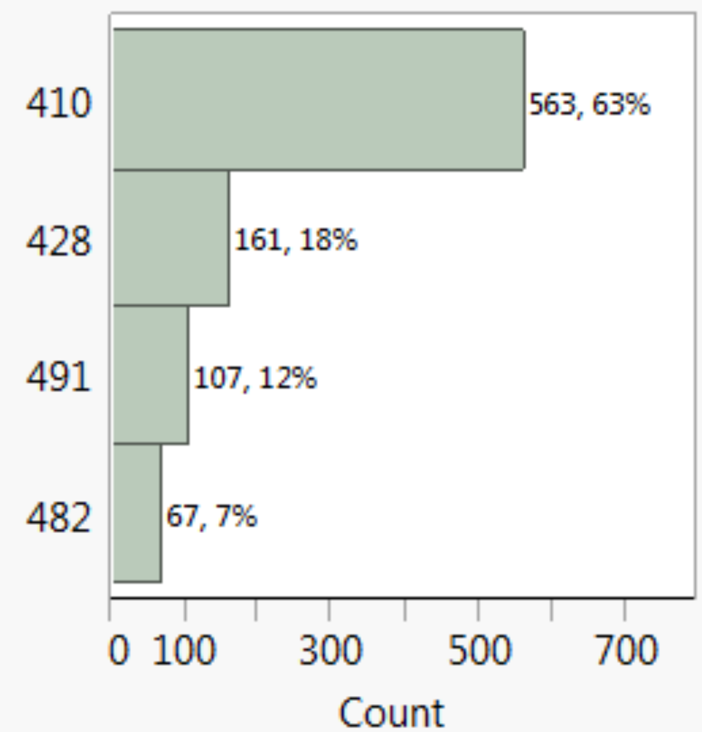
Bootstrap Forest Model optimized with separate sampling and profit matrix

Primary Diagnoses with Highest Volume of Readmissions



Demographics for Reduced Models

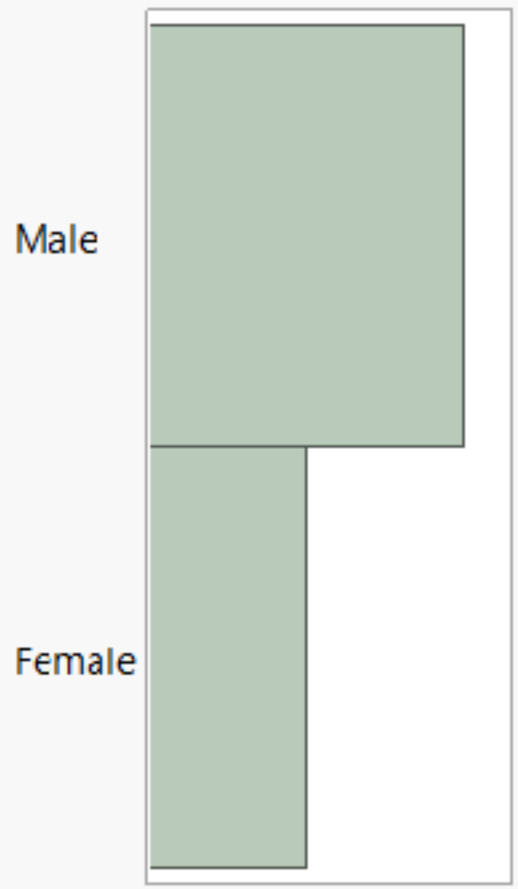
ICD9 Group



Frequencies

Level	Count	Prob
482	67	0.07461
491	107	0.11915
428	161	0.17929
410	563	0.62695
Total	898	1.00000

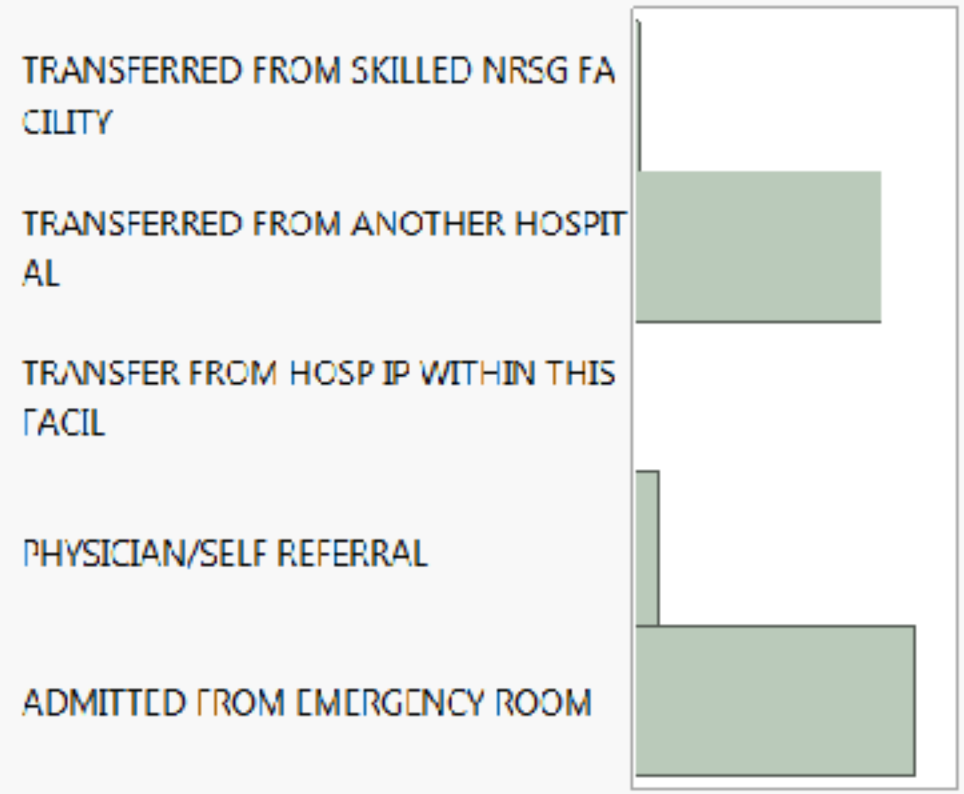
Gender



Frequencies

Level	Count	Prob
Female	299	0.33296
Male	599	0.66704
Total	898	1.00000

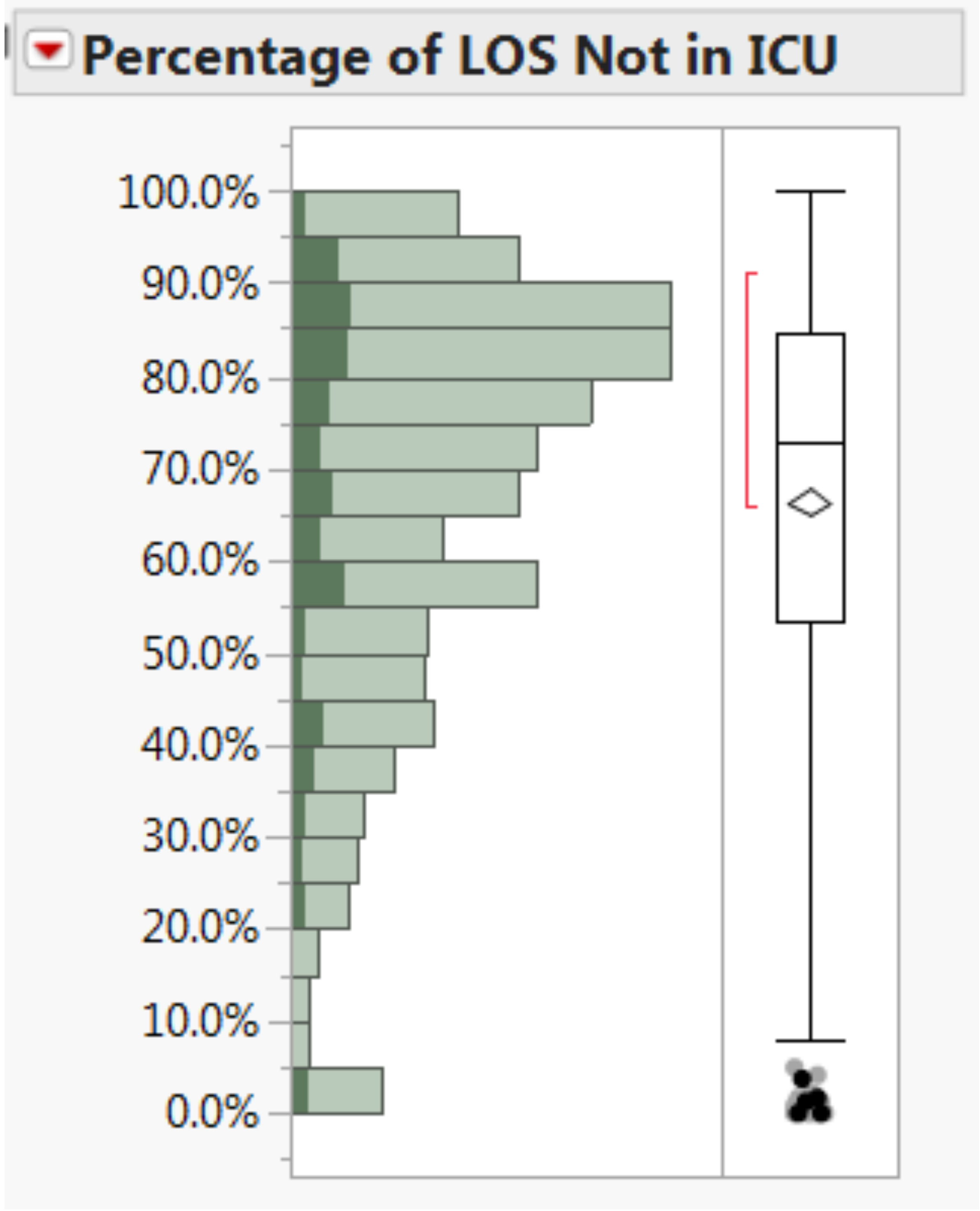
Admited To ICU Via



Frequencies

Level	Count	Prob
ADMITTED FROM EMERGENCY ROOM	447	0.49777
PHYSICIAN/SELF REFERRAL	42	0.04677
TRANSFER FROM HOSP IP WITHIN THIS FACIL	5	0.00557
TRANSFERRED FROM ANOTHER HOSPITAL	395	0.43987
TRANSFERRED FROM SKILLED NRSG FACILITY	9	0.01002
Total	898	1.00000

Proportion of ICU Time: Reduced Models



Predictive Models: Reduced

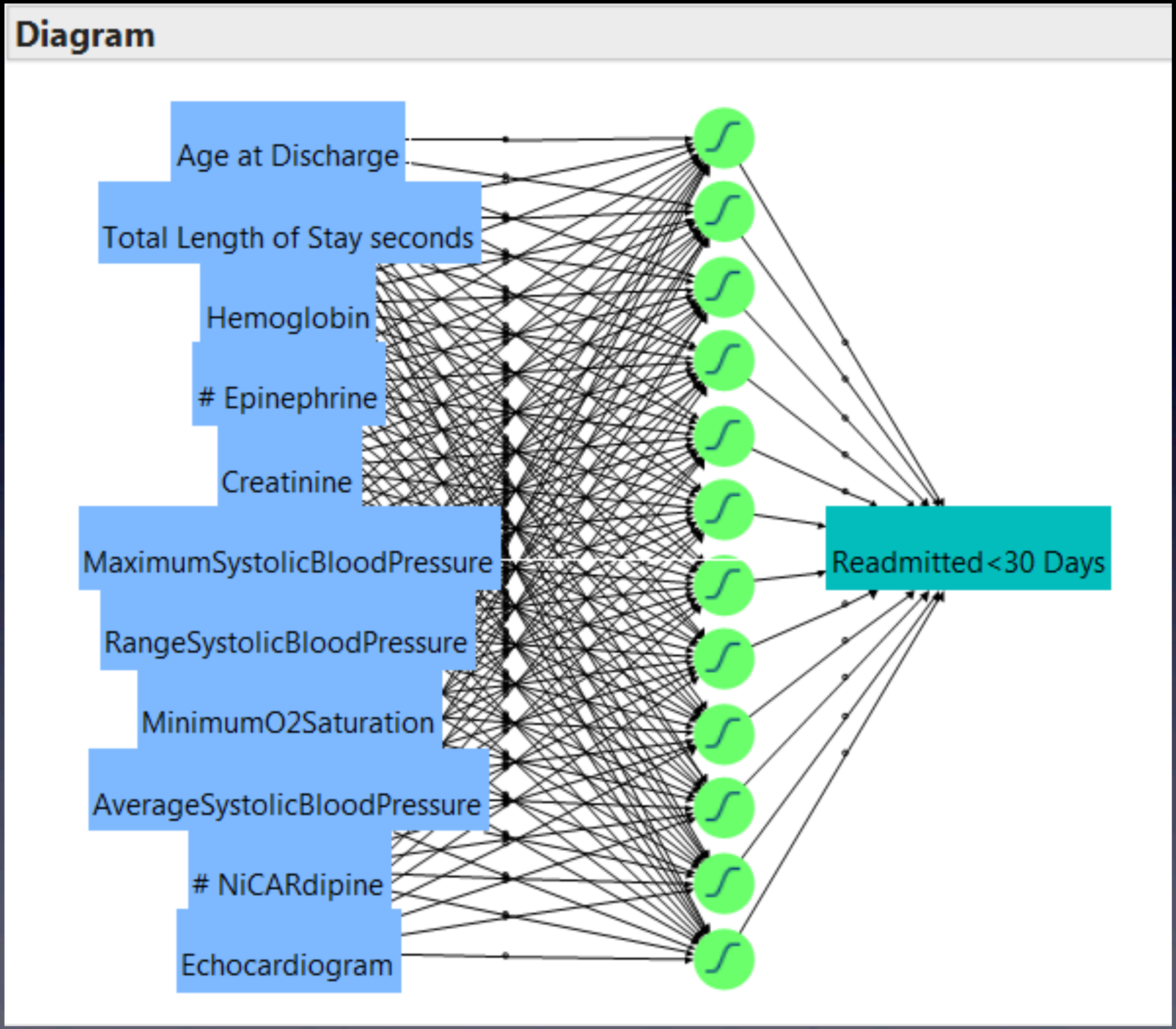
- Prior to training the models with separate sampling and optimization with a profit matrix, negative predictions overwhelmed each model, as before.
  - Again, optimal prediction was offered by any model predicting absolutely no readmissions (83% correct), however,
  - With separate sampling and another profit matrix…
- Neural Net Model
  - Worked quite well (70%) – interesting relationships discovered
- Bootstrap Forest Model
  - Again, offered optimal prediction (85% correct, pooled) for 4 causes of readmission (AMI, HF, COPD, PN) within 30 days of hospital discharge after an ICU stay.

Most Influential Predictors: Reduced Model

Column Contributions

Term	Number of Splits	G^2	Portion
# Epinephrine	4	70.6686575	0.0744
Hemoglobin	6	50.7956379	0.0535
MaximumSystolicBloodPressure	3	35.2124373	0.0371
Age at Discharge	4	32.5950829	0.0343
Admited To ICU Via	3	30.640856	0.0323
Principal ICD9 Code	2	29.0795113	0.0306
Total Length of Stay seconds	3	28.7571269	0.0303
Admit BMI	3	24.9794157	0.0263
RangeSystolicBloodPressure	4	23.6763066	0.0249
Echocardiogram	5	20.4988341	0.0216
990	3	19.633508	0.0207
496	3	19.1565084	0.0202
MinimumO2Saturation	2	17.8125154	0.0188
5990	2	17.3076678	0.0182
2500	2	15.6921179	0.0165
AverageSystolicBloodPressure	1	15.1860969	0.0160
Creatinine	2	14.2486721	0.0150
# NiCARdipine	2	13.937239	0.0147
1881	3	13.7248957	0.0145
Airway Removal <12 Hours	1	13.4807553	0.0142
414	2	12.5235148	0.0132
V5866	2	12.3052469	0.0130
Admit Height cm	3	12.0912377	0.0127
Arterial Line Removal <12 Hours	2	11.9746777	0.0126
4107	1	11.4556727	0.0121
Final Drip Stop Time to DC fxd	1	11.4550831	0.0121
Arterial Line	2	11.3771607	0.0120
2724	2	11.1910091	0.0118
Gender	2	11.053783	0.0116
# EPINEPHrine	1	10.7135454	0.0113
4019	4	10.5784077	0.0111
Ectopy <12 Hours	2	10.5254337	0.0111
Phenylephrine	2	10.2084852	0.0107
412	2	10.0169534	0.0105
Final Drip Stop Time to ICU DC fxd	1	9.8309567	0.0104
# Furosemide	1	9.50254374	0.0100
3051	3	9.36067343	0.0099

Neural Net: Reduced Model



Neural Net Details: Reduced Model

Variable Importance: Independent Resampled Inputs

Summary Report

P(Readmitted<30 Days=Yes)

Column	Main Effect	Total Effect
MinimumO2Saturation	0.325	0.388
MaximumSystolicBloodPressure	0.122	0.155
Age at Discharge	0.061	0.14
# NiCARdipine	0.119	0.129
Hemoglobin	0.081	0.102
AverageSystolicBloodPressure	0.073	0.092
Echocardiogram	0.063	0.087
Creatinine	0.014	0.043
# Epinephrine	0.019	0.038
Total Length of Stay seconds	0.012	0.013
RangeSystolicBloodPressure	0.01	0.013

Neural Net Details: Reduced Model

Neural

Missing Value Coding

Model Launch

Validation Method

Holdback

Holdback Proportion: 0.3

Hidden Layer Structure

Number of nodes of each activation type

Activation	Sigmoid TanH	Identity Linear	Radial Gaussian
First	3	0	0
Second	0	0	0

Second layer is closer to X's in two layer models.

Boosting

Fit an additive sequence of models scaled by the learning rate.

Number of Models: 10

Learning Rate: 0.1

Fitting Options

- [ ] Transform Covariates

Penalty Method: Squared

Number of Tours: 1

Neural

Validation: Random Holdback

Missing Value Coding

Model Launch

Model NTanH(3)NBoost(4)

Training

Readmitted<30 Days

Measures	Value
Generalized RSquare	0.1325356
Entropy RSquare	0.0761936
RMSE	0.4686377
Mean Abs Dev	0.4460063
Misclassification Rate	0.3432836
-LogLikelihood	126.48985
Sum Freq	201

Confusion Matrix

Actual Readmitted<30 Days	Predicted n/a	No	Yes
n/a	0	0	0
No	0	93	23
Yes	0	46	39

Confusion Rates

Actual Readmitted<30 Days	Predicted n/a	No	Yes
n/a	.	.	.
No	0.00000	0.80172	0.19828
Yes	0.00000	0.54118	0.45882

Validation

Readmitted<30 Days

Measures	Value
Generalized RSquare	0.1131791
Entropy RSquare	0.0645248
RMSE	0.4720268
Mean Abs Dev	0.4465955
Misclassification Rate	0.3218391
-LogLikelihood	55.500708
Sum Freq	87

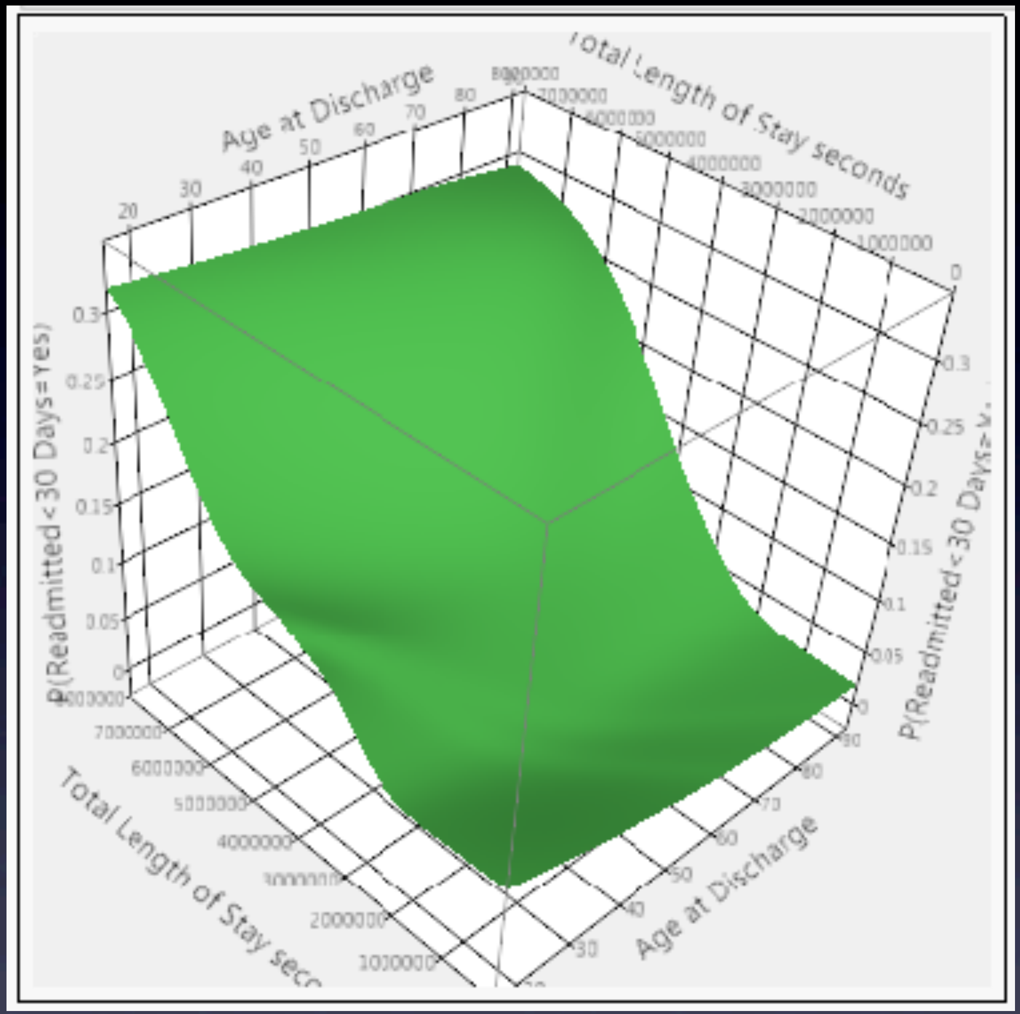
Confusion Matrix

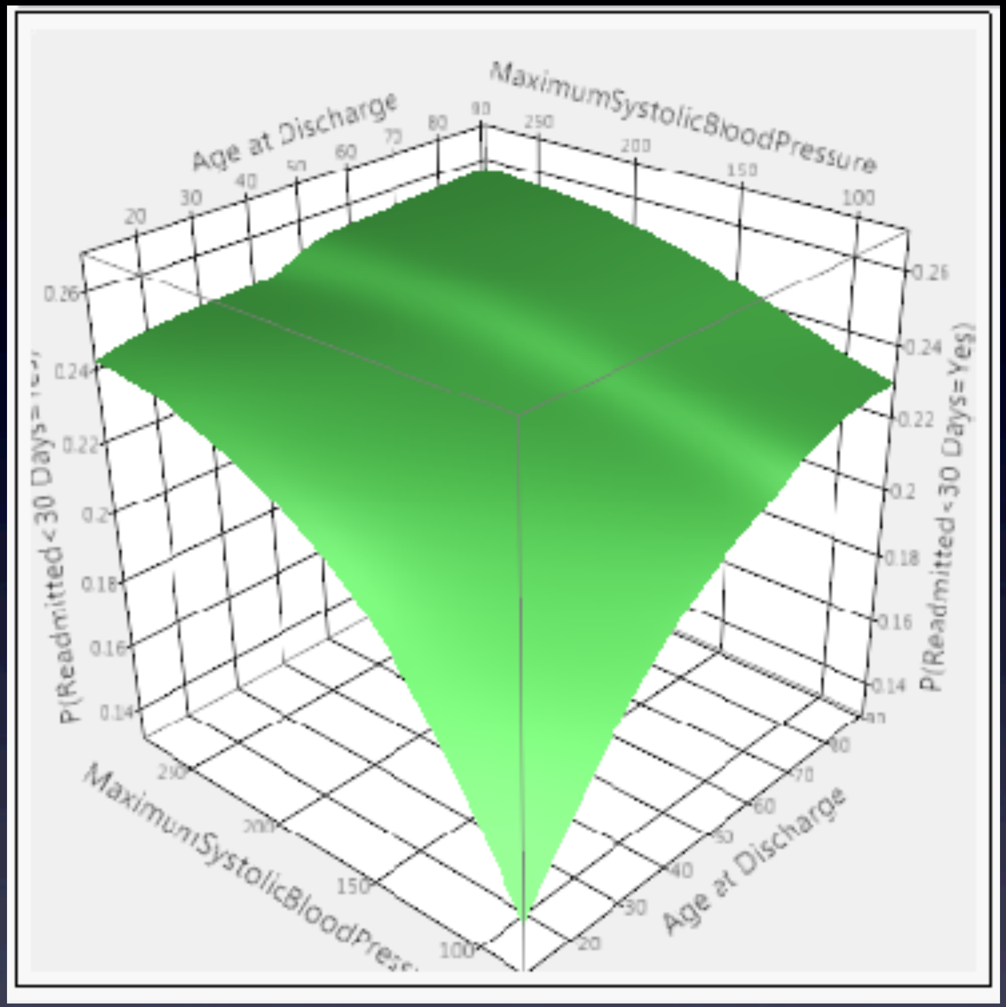
Actual Readmitted<30 Days	Predicted n/a	No	Yes
n/a	0	0	0
No	0	38	12
Yes	0	16	21

Confusion Rates

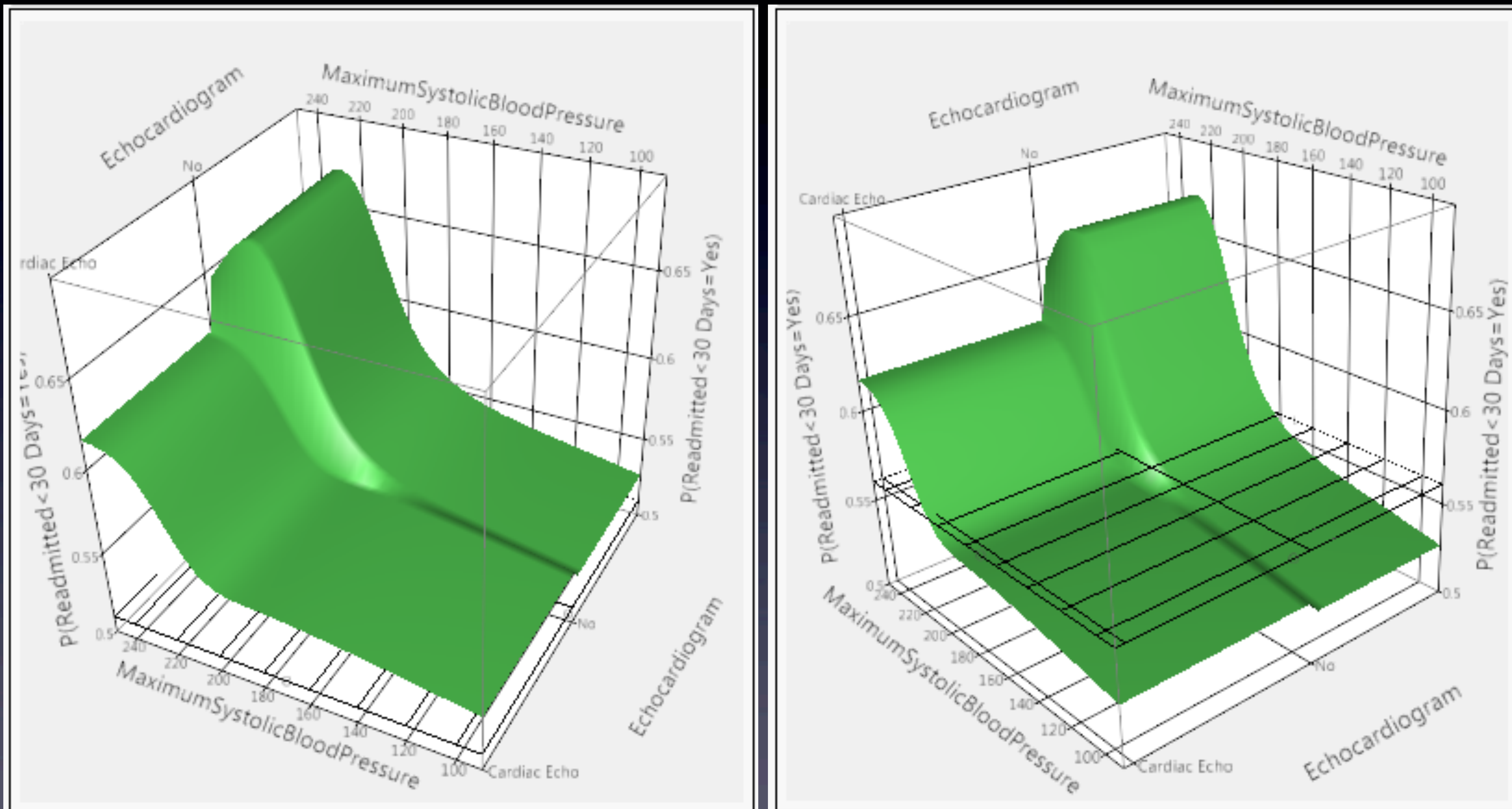
Actual Readmitted<30 Days	Predicted n/a	No	Yes
n/a	.	.	.
No	0.00000	0.76000	0.24000
Yes	0.00000	0.43243	0.56757

Neural Net Details: Reduced Model

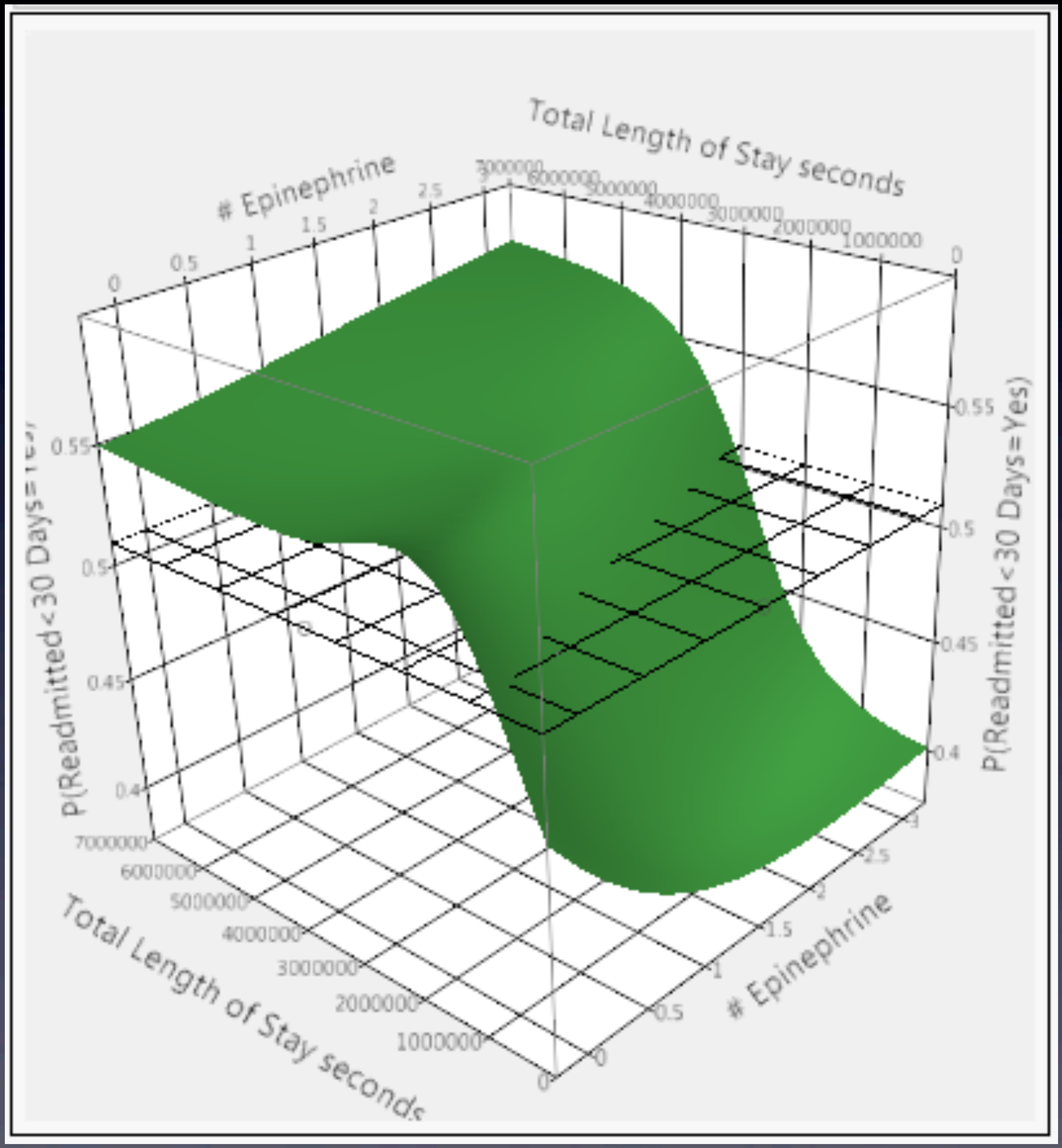


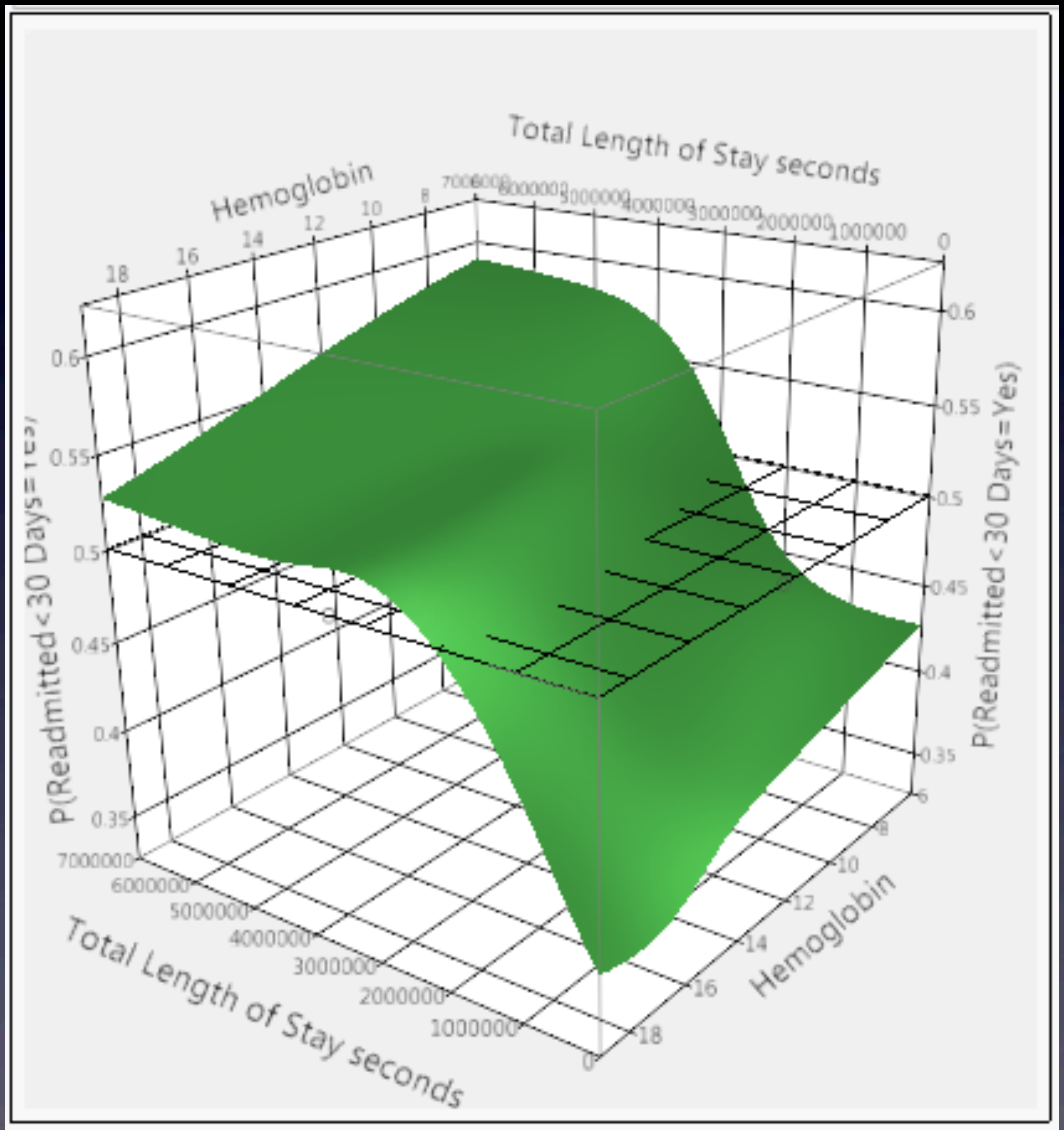


Neural Net Details: Reduced Model

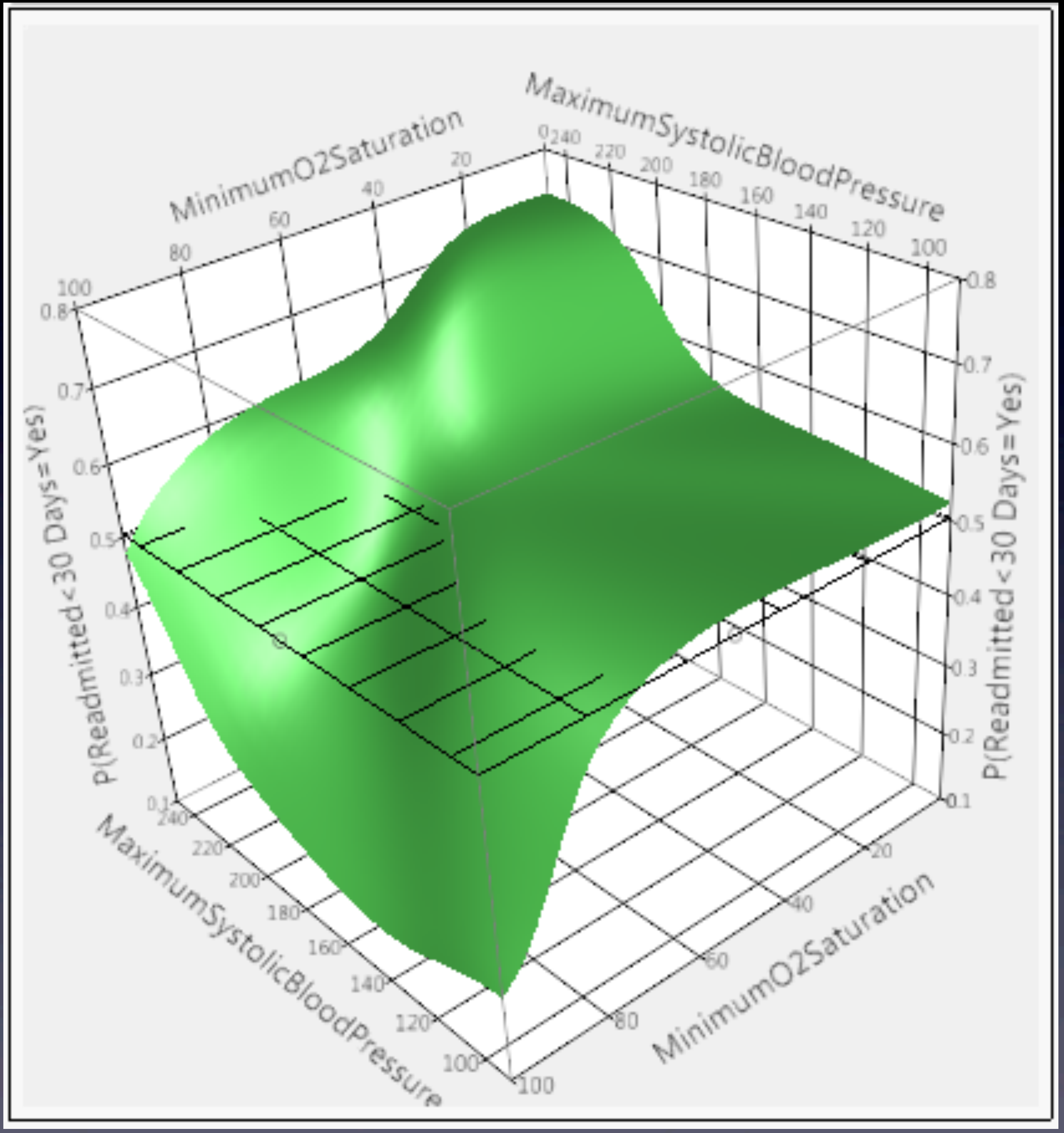


Neural Net Details: Reduced Model

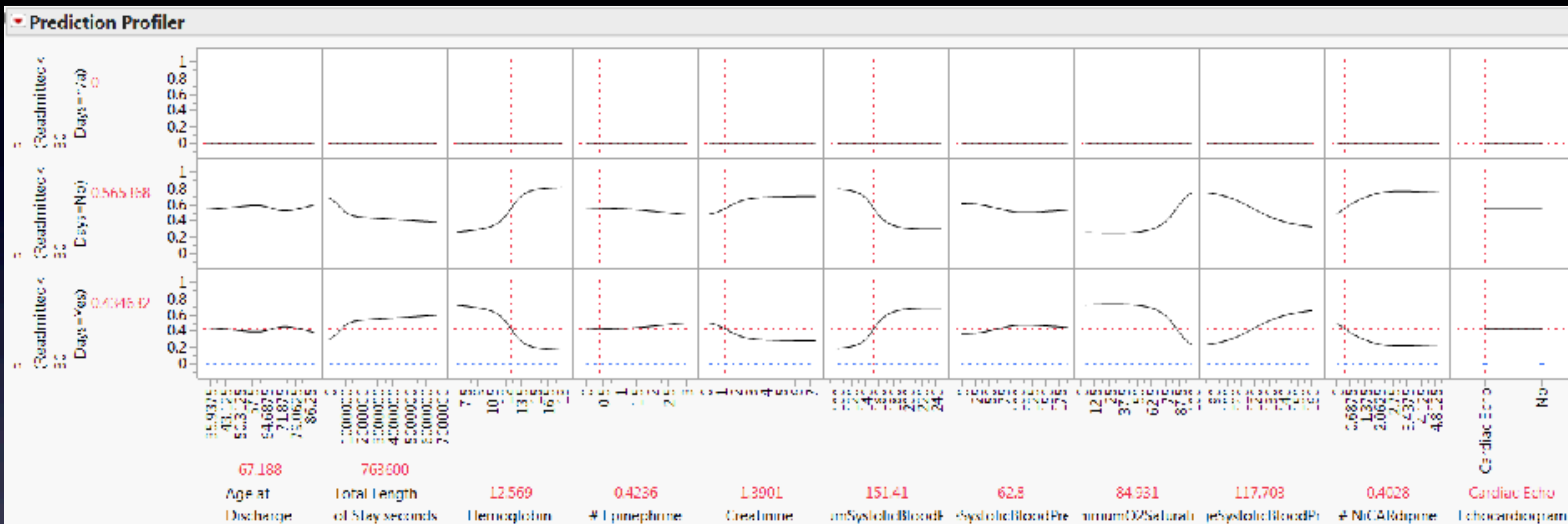




Neural Net Details: Reduced



Neural Net Details: Reduced Model



Prediction Profiler– allows one to see how the
Outcome changes as one manipulates the input values

Bootstrap Forest Details: Reduced Model

Bootstrap Forest for Readmitted<30 Days

Specifications

Target Column:	Readmitted<30 Days	Training rows:	188
		Validation rows:	100
Number of trees in the forest:	9	Test rows:	0
Number of terms sampled per split:	814	Number of terms:	3259
		Bootstrap samples:	188
		Minimum Splits Per Tree:	10
		Minimum Size Split:	5

Overall Statistics

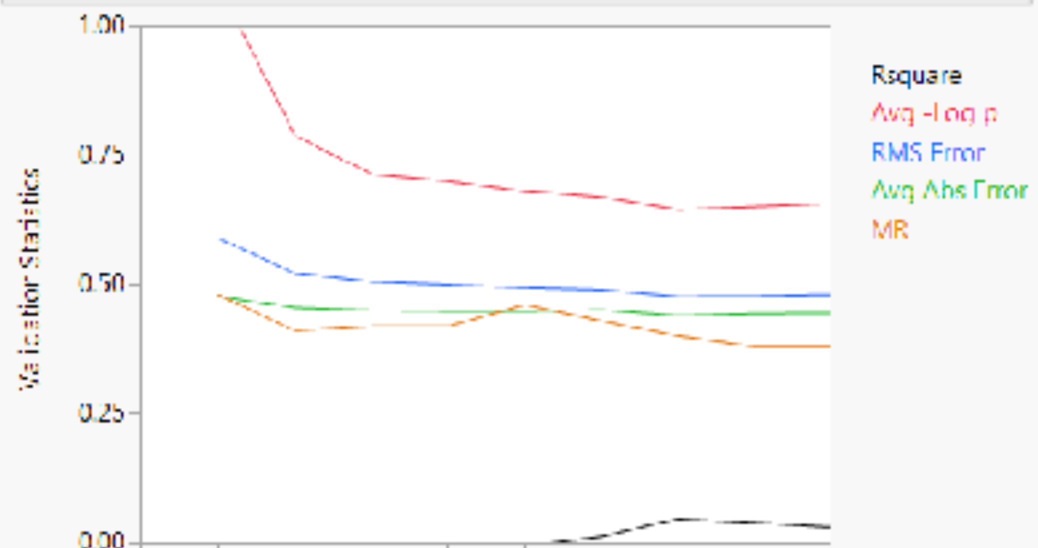
Measure	Training	Validation	Definition
Entropy RSquare	0.4626	0.0298	1-Loglike(model)/Loglike(0)
Generalized RSquare	0.6290	0.0533	$(1-(L(0)/L(model))^{(2/n)})/(1-L(0)^{(2/n)})$
Mean -Log p	0.3674	0.6567	$\sum -Log(\rho[j])/n$
RMSE	0.3226	0.4809	$\sqrt{\sum(y[j]-\rho[j])^2/n}$
Mean Abs Dev	0.2928	0.4449	$\sum \lvert y[j]-\rho[j]\rvert/n$
Misclassification Rate	0.0691	0.3600	$\sum(\rho[j] \neq \rho Max)/n$
N	188	100	n

Confusion Matrix

Actual Training	Predicted No	Predicted Yes
No	100	7
Yes	6	75

Actual Validation	Predicted No	Predicted Yes
No	40	19
Yes	17	24

Cumulative Validation



Profit Matrix: Reduced Model

Specify Profit Matrix

Enter positive numbers as profits for correct decisions on the diagonal.
Enter negative numbers as costs for incorrect decisions off the diagonal.
An extra decision row can be used to indicate an alternative to prediction.

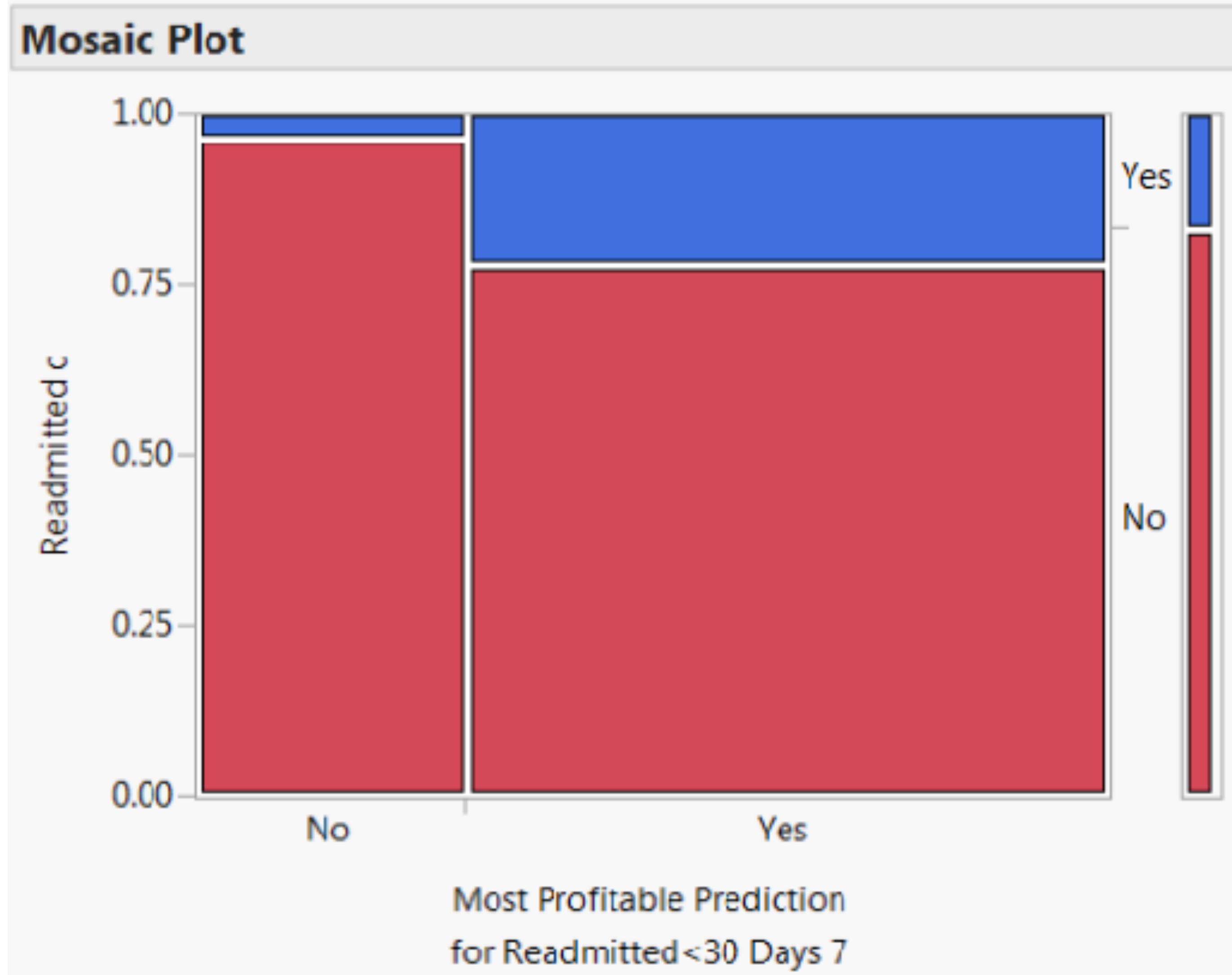
Reading across a row shows the consequences if you predict this response.
Reading down a column shows the consequences if the actual response is this.

When you save prediction formulas, these values will be used to create best decision columns.
The best decision is the one with greatest expected profit.

Decision or Prediction	Actual: No	Actual: Yes
No	0	-1
Yes	-0.2	0.2
Undecided	.	.

☑ Save to column as property.

Mosaic Plot for Reduced Bootstrap Forest Model



Blue = Readmitted

Red =
Not Readmitted

Bootstrap Forest Model optimized with separate sampling and profit matrix

Reduced Bootstrap Forest Model

Adjusted Confusion Matrix

Confusion Matrix for Cut-off = 0.2

Target: Readmitted<30 Days
Predictor: Bootstrap Forest

	Predicted	
Readmitted c	**No**	**Yes**
No	125	627
Yes	4	141

101 rows have been excluded.

Confusion Rates (0.2)

	Predicted	
	No	**Yes**
Readmitted c	**Row %**	**Row %**
No	16.62%	83.38%
Yes	2.76%	97.24%

For future experiments or quality projects, an adjusted confusion matrix can be employed to screen patients

This would ensure nearly all of the patients that are at high risk for readmission are screened into the study

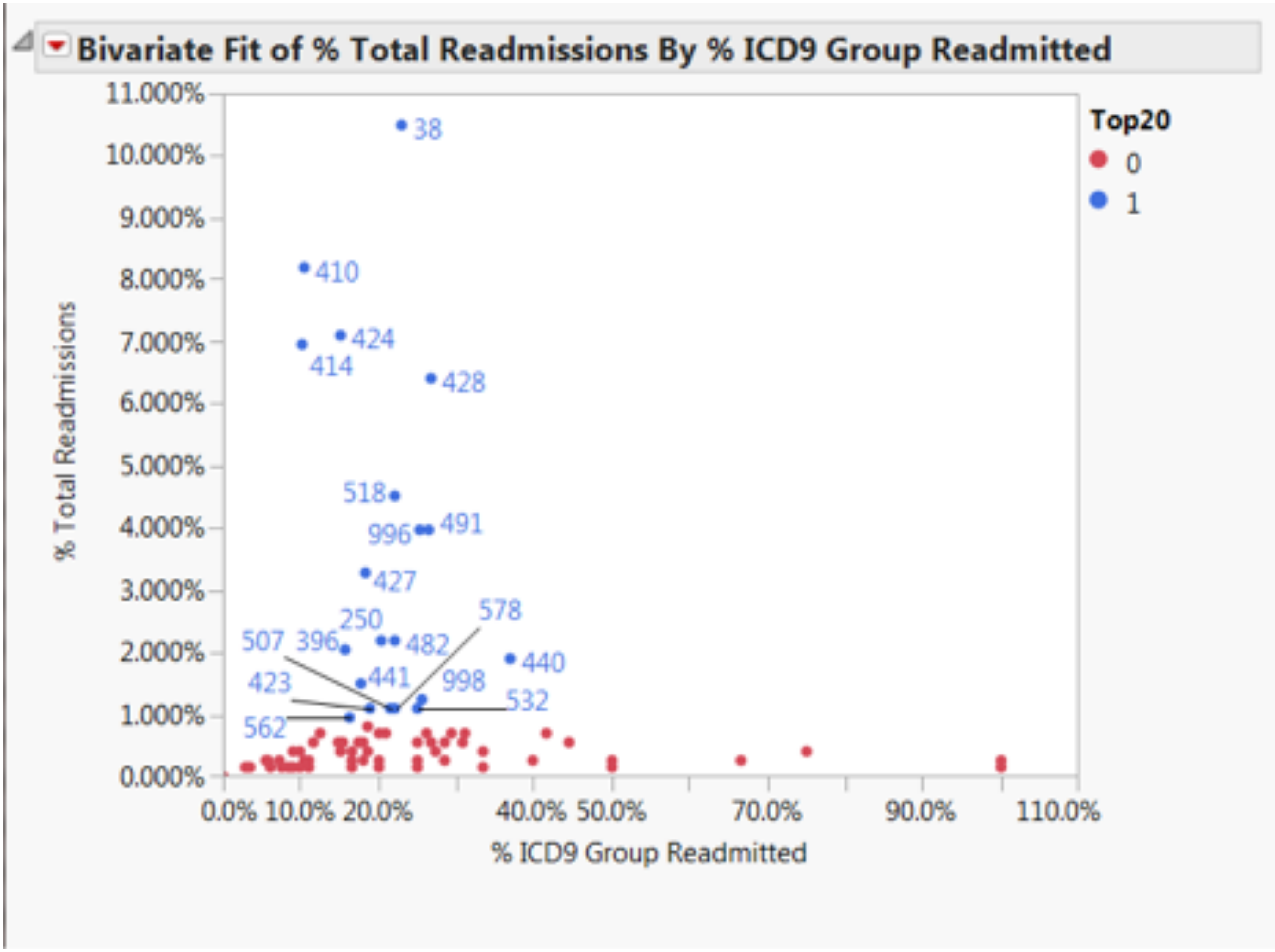
Ruling out readmission is the best way to use this type of risk-based screening tool

The screening tool can also be used to stratify risk for those treated or followed in the intervention group

List of Top 20 Primary Diagnosis Groups, Ranked according to Highest Volume of Readmissions

Dx1 038 - Septicemia
Dx2 410 - Acute Myocardial Infarction
Dx3 424 - Endocarditis & Valve Disorders
Dx4 414 - Chronic Ischemic Heart Disease
Dx5 428 - Heart Failure
Dx6 518 - Lung Disease with Edema
Dx7 491 - COPD
Dx8 996 - Complications of Implanted Objects
Dx9 427 - Cardiac Dysrhythmias
Dx10 482 - Bacterial Pneumonia
Dx11 250 - Diabetes Mellitus
Dx12 396 - Mitral & Aortic Valve Disorders
Dx13 440 - Atherosclerosis & PVD
Dx14 441 - Aortic Aneurism & Dissection
Dx15 998 - Complications of Procedures
Dx16 532 - Duodenal Ulcer
Dx17 578 - Gastrointestinal Hemorrhage
Dx18 507 - Solid Aspiration Pneumonitis
Dx19 423 - Pericardial Disease
Dx20 562 - Diverticula of Intestine

Primary Diagnoses with Highest Volume of Readmissions

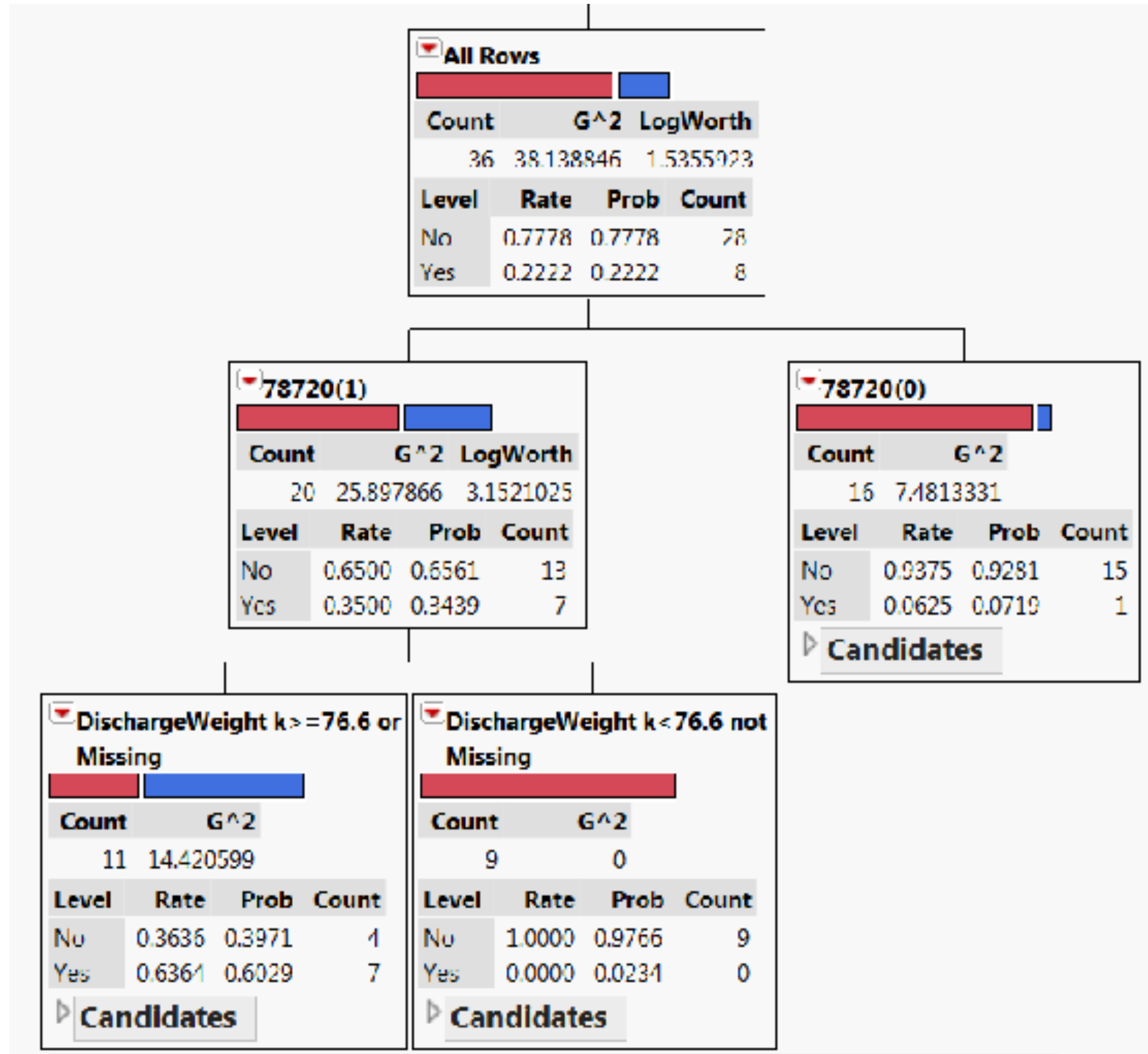


Decision Tree for Recursive Partitioning Model
Example for One Diagnosis

Clients Readmitted <30 Days for:

Solid Aspiration Pneumonitis, ICD9 507

ICD9 787.20 = Dysphagia



Most were readmitted

None were readmitted

Few were readmitted

Sample & Effect Size

- The sample of visits (n=4785) was of moderate size, enabling some predictive power for holdback validation in the boosted tree and boosted forest models, as well as k-fold cross-validation for the subsamples of varying size.
- Clinically significant relationships were detected for each subsample. Splits at the tops of decision trees are typically more powerful and more stable than subordinate splits.
- The recursive partitioning models [of subsamples] based on individual Primary ICD9 Diagnosis Codes should be considered more descriptive in nature than predictive.
- Strong effects may be difficult to change.
- Prediction does not imply causation, nor explanation.

Limitations

- Holdback validation should be performed on the decision tree models developed for individual ICD9 groups, once additional data is collected, prior to use for predicting readmissions. (Cox, Guadard, Ramsey, Stephens, & Wright, 2010)
- The specific elements and cut-off scores of recursive partitioning models for ICU readmissions are not easily generalizable across settings, due to differences in patient populations and local scope of practice.
- However, the techniques themselves are useful for quality improvement and classification purposes.
- The data collected in retrospective analyses are typically not as reliable as those collected from prospective experiments, which should be performed to identify interventions that decrease readmissions. (Cox, Guadard, Ramsey, Stephens, & Wright, 2010)

Disease Management Programs

- Nurse-led Disease Management Programs [DMP] have:
    - Reduced length of stay [LOS] for some types of patients (Thomas, 2007)
    - Improved clients' quality of life [QOL].
      (Williams, 2003; Daly, Genet-Kelley, Douglas, O'Toole, & Montenegro, 2007)
- RN-led DMPs have not been shown to reduce readmission rates
    - Including those with Visiting Nurses Services [VNS]
      (McCoy, Davidhizar, & Gillum, 2007)
- Nurse Practitioner-led DMPs have led to improved outcomes.
  (Griffiths, 2004; Naylor, Brooten, & Campbell, 2004)
- Nurse Practitioners able to bill for teleconference visits, once every 3 days
- Screening clients for readmission risk with predictive modeling serves to improve the cost-effectiveness of DMPs, by limiting enrollment, somewhat.

Implications for Practice

- Disease Management Programs should employ Statistical Analysts
  - Can screen clients for readmission risk using a bootstrap forest model with profit matrix / adjusted confusion matrix.
  - Ensure interventions are both effective and cost-effective
- Nurse-Practitioners and Physician Assistants:
  - Make the business case for DMPs:
    - NPs can alter medication regimens and order treatments
    - NPs can bill for outpatient and rural telecommunication visits
    - In 2016, may also be able to bill for counseling regarding end of life care

Conclusions

- The ICU is doing a terrific job: few are readmitted in 30 days
  - Fewer Readmissions than national average
  - Even these readmissions are unlikely related to ICU care
- Bootstrap Forest models proved optimal for this data set.
  - Robust to missing data and the effects of multicollinearity
- Predictive models can serve as useful tools for:
  - Targeting high-risk client populations,
  - Optimizing resource allocation, and
  - Improving both health outcomes, while using resources judiciously.

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