Improving the Prediction of Readmissions Amongst Medicare Patients in a California Hospital

Nhan Huynh, Dylan Robbins-Kelley, Holly Fallah

Faculty Advisors: Ian Duncan, Janet Duncan, Wade Herndon

Dept. of Statistics and Applied Probability, University of California Santa Barbara

Introduction

Purpose and Motivation

- Centers for Medicare and Medicaid Services (CMS) reduced Medicare payments for hospitals with excess readmissions (within 30 days of discharge) for following health conditions:
  - Heart Attack, Heart Failure, Pneumonia, Hip/Knee Replacement, Chronic Obstructive Pulmonary Disease.
- Readmissions can lead to longer stays, and put patients at additional risk of hospital-acquired infections and complications.

Development of LACE

- Currently the LACE index is a widely used readmission model in the United States, due to its simplicity and moderate predictive power.
- LACE scores every patient on the risk of readmission upon discharge based on the following parameters:
  - **L**ength of stay
  - **A**cuity of admission
  - **C**omorbidity
  - **E**mergency department visits in the previous 6 months.
- LACE scores range from 0-19
  - Low Risk 0-4
  - Moderate Risk 5-9
  - High Risk 10-19

Data Summary

- Data aquired from single hospital consisting of 76,538 patients in five years

N=76538		Year 2010 (n=15516)	Year 2011 (n=15072)	Year 2012 (n=15566)	Year 2013 (n=15176)	Year 2014 (n=14937)
Variable	Factors					
Race	White	.71	.70	.71	.71	.94
	Hispanic	.23	.24	.23	.24	
	Asian	.02	.02	.02	.02	.02
	Black	.02	.02	.02	.02	.02
	Other	.02	.02	.02	.02	.02
DRG	Medical	.48	.48	.51	.51	.53
	Surgical	.46	.46	.43	.42	.40
	Ungroup	.06	.06	.06	.07	.07
Admitted from Type	Emergency	.40	.40	.42	.46	.45
	Pre Admit	.40	.38	.37	.34	.33
	Observation	.14	.15	.15	.15	.16
	Other	.06	.07	.06	.05	.06
Readmission	Yes	.072	.074	.075	.068	.064
	No	.928	.926	.925	.932	.936
Age	Min	15	15	15	15	15
	Mean	57.89	57.75	57.74	57.92	57.84
	Max	104	110	111	112	106
LACE	Min	1	1	1	1	1
	Mean	5.6	5.78	5.65	6.01	6.30
	Max	19	19	17	19	19
CDPS	Min	.14	.14	.14	.14	.14
	Mean	3.008	3.095	3.207	3.359	3.538
	Max	29	22.14	20.44	29.850	25.870
Length of Stay	Min	0	0	0	0	0
	Median	3	3	3	3	3
	Mean	3.820	4.154	4.309	3.977	4.029
	Max	79	239	143	98	122

Methodology

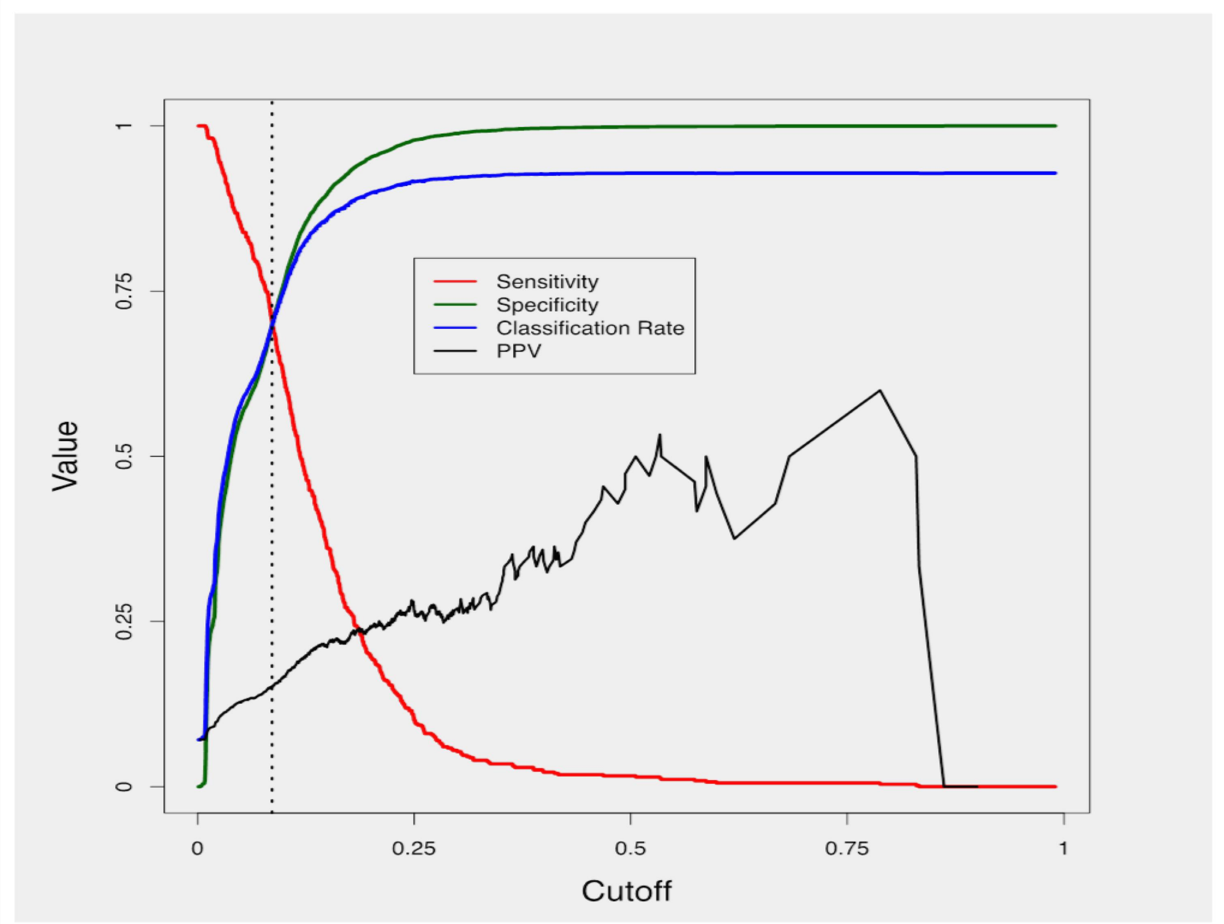
Logistic Regression

- A regression model where the data set has a binary response or a multinomial response and several predictors
- We are interested in predicting the probability a patient is readmitted to the hospitals within 30 days after discharge based on characteristics such as:
  - age, gender, length of stay during admission, diagnoses, admission from emergency department, number of emergency visits, etc…
- Logistic regression links the binary outcomes of readmission status with a combination of the linear predictors.
- Let p=probability the patient is readmitted within 30 days after discharge
  Let b_0=intercept
  Let b_p=coefficient of variable
  Let X_p=variable

$$\hat{p} = \frac{\exp(b_0 + b_1X_1 + b_2X_2 + \ldots + b_pX_p)}{1 + \exp(b_0 + b_1X_1 + b_2X_2 + \ldots + b_pX_p)}$$

Validation

- Logistic regression is built on 80% of the data set. The remaining 20% of the data set is used for internal validation.
- A confusion matrix was examined to compare the sensitivity (true positive rate), specificity (false negative rate), positive predicted value, and c-statistic.
- A new cutoff value was created to compromise the tradeoff between the true positive rate and false negative rate.



Results

Models

- Three models were created:
  - LACE model
  - General Model
  - Age 65+ model with CMS penalty conditions

Criteria	LACE	General Model	Age 65+ and Penalty Conditions Model
Cutoff Values	HIGH	.086	.124
Sensitivity	.43	.7	.66
Specificity	.88	.7	.66
PPV	.17	.15	.21
AUC	N/A	.78	.71

- Table to compare predicted and actual re-admissions using the age 65+ model:

Decile	Number in decile	Mean Prediction within Quantile	Actual Readmissions	Predicted Readmission
0-10	666	0.0092	6.0	6.1
10-20	666	0.0114	4.0	7.6
20-30	666	0.0185	15.0	12.3
30-40	666	0.0255	15.0	17.0
40-50	666	0.0364	22.0	24.2
50-60	666	0.0568	48.0	37.8
60-70	666	0.0821	60.0	54.7
70-80	666	0.1032	61.0	68.7
80-90	666	0.1366	98.0	91.0
90-100	666	0.2319	157.0	154.4
Sum	**6,660**		**486.0**	**473.9**

Conclusions

- Sensitivity values in logistic regression models are higher than the value in the LACE model.
- Specificity is higher in LACE, however the slightly lower specificity values in the regression models are worth the compensation to gain sensitivity.
- This indicates an improvement in predictive power of regression models compared to the LACE model.
- When comparing both regression models, the general model is preferred because of its higher sensitivity, specificity, and AUC vales compares to the age and penalty specific model.

References

1. Van Walraven C, Dhalla IA, Bell C, et al. Derivation and Validation of an Index to Predict Early Death or Unplanned Readmission After Discharge From Hospital to the Community. CMAJ 2010; 182: 551-557.

2. Spiva L, Hand M, VanBrackle L, et al. Validation of a Predictive Model to Identify Patients at High Risk for Hospital Readmission. JHQ 2014; 00(0): 1-7.

3. S, Farooq F, van Esbroeck A, et al. Predicting Readmission Risk with Institution-Specific Prediction Models. Artificial Intelligence in Medicine 2015; 65(2): 89-96.

4. Billings J, Dixon J, Mijanovich T, et al. Case finding for patients at risk of readmission to hospital: development of algorithm to identify high risk patients. BMJ 2006, doi:10.1136/bmj.38870.657917.AE.