20 PREDICTING HOSPITAL READMISSIONS

20.1 WHY ARE HOSPITAL READMISSIONS IMPORTANT?

Many hospitals have decided to prioritize reducing readmission rates across the United States due to the Hospital Readmissions Reduction Program (HRRP), which was established in 2012 by the Centers for Medicare & Medicaid Services (CMS) [1]. CMS provides considerable information about the program on its website, [2]. Hospital readmissions are disruptive for both patients and hospital administration. Readmissions can lead to longer stays, and put patients at additional risk of hospital-acquired infections and complications. Meanwhile, hospital readmissions are often costly to the nation's healthcare system. An analysis of 2005 Medicare claims by the Medicare Payment Advisory Commission (MedPAC) concluded that avoidable readmissions within 30 days of discharge resulted in an estimated $12 billion in Medicare spending [3]. According to the Agency for Healthcare Research and Quality between January and November 2011 (before HRRP became affective), hospitals spent $41.3 billion to treat patients readmitted within 30 days of discharge [4]. Thus, in order to promote better quality of care, increase hospital efficiency and to reduce healthcare costs, HRRP was put into effect in November 2012. Section 3025 of the Affordable Care Act added section 1886(q) to the Social Security Act establishing the Hospital Readmissions Reduction Program, which required CMS to reduce payments to IPPS hospitals with excess readmissions, effective for discharges beginning on October 1, 2012.

HRRP places penalties on hospitals with high readmission rates. Hospitals with readmission rates exceeding the national average for certain conditions (initially heart failure, pneumonia, and acute myocardial infarction) will have their total Medicare reimbursement (all discharges, not just the target conditions) reduced. Initially the reduction in funding was capped at 1% of the reimbursement, but this has risen to 3% as of 2015. Under this financial pressure, hospitals are making significant progress with different strategies to reduce their readmission rates. According to CMS, the national readmission rate fell to 17.5 percent in 2013, whereas for many years before HRRP the readmission rate was steady at 19.5 percent [2].

In the FY 2012 Inpatient Prospective Payment System (IPPS) final rule, CMS finalized the following policies with regard to the readmission measures under the Hospital Readmissions Reduction Program:

- Defined readmission as an admission to a subsection (d) hospital within 30 days of a discharge from the same or another subsection (d) hospital;
- Adopted readmission measures for the applicable conditions of acute myocardial infarction (AMI), heart failure (HF), and pneumonia (PN);

- Established a methodology to calculate the excess readmission ratio for each applicable condition, which is used, in part, to calculate the readmission payment adjustment. A hospital's excess readmission ratio is a measure of a hospital's readmission performance compared to the national average for the hospital's set of patients with that applicable condition.
- Established a policy of using the risk adjustment methodology endorsed by the National Quality Forum (NQF) for the readmissions measures to calculate the excess readmission ratios, which includes adjustment for factors that are clinically relevant including certain patient demographic characteristics, comorbidities, and patient frailty.
- Established an applicable period of three years of discharge data and the use of a minimum of 25 cases to calculate a hospital's excess readmission ratio for each applicable condition.

CMS has been updating the definitions of target conditions since the program was introduced. In the FY 2014 IPPS final rule, CMS finalized the expansion of the applicable conditions beginning with the FY 2015 program to include: (1) patients admitted for an acute exacerbation of chronic obstructive pulmonary disease (COPD); and (2) patients admitted for elective total hip arthroplasty (THA) and total knee arthroplasty (TKA). In the FY 2015 IPPS final rule, CMS finalized the expansion of the applicable conditions beginning with the FY2017 program to include patients admitted for coronary artery bypass graft (CABG) surgery in the calculation of a hospital's readmission payment adjustment factor.
In the FY 2016 IPPS final rule, CMS finalized an update to the pneumonia readmission measure by expanding the measure cohort to include additional pneumonia diagnoses: (i) patients with aspiration pneumonia; and (ii) sepsis patients coded with pneumonia present on admission (but not including severe sepsis).

This chapter focuses on creating practical models that aid in the prediction of the risk of readmission to a specific hospital within 30 days of discharge for Medicare patients, to aid in the identification and stratification of at-risk patients for hospitals considering building an intervention program in a cost-effective manner.

For readers who wish to develop their own predictive model, a dataset is provided on the Actexmadriver.com website, and R code is provided in the appendix to this chapter.

20.2 READMISSION ADJUSTMENT PENALTY CALCULATION

Calculating the Readmission Adjustment Factor

$$\textbf{Excess readmission ratio} = \frac{\text{risk-adjusted predicted readmissions}}{\text{risk-adjusted expected readmissions}}$$

Aggregate payments for excess readmissions = [sum of base operating DRG payments for AMI x (excess readmission ratio for AMI-1)] + [sum of base operating DRG payments for HF x (excess readmission ratio for HF-1)] + [sum of base operating DRG payments for PN x (excess readmission ratio for PN-1)] + [sum of base operating DRG payments for COPD x (excess readmission ratio for COPD-1)] + [sum of base operating payments for THA/TKA x (excess readmission ratio for THA/TKA -1)]

Note: if a hospital's excess readmission ratio for a condition is less than/equal to 1, then there are no aggregate payments for excess readmissions for that condition included in this calculation.

Aggregate payments for all discharges = sum of base operating DRG payments for all discharges

Ratio = 1 - (Aggregate payments for excess readmissions/ Aggregate payments for all discharges)

Readmissions Adjustment Factor = the higher of the Ratio or 0.97 (3% reduction). (During the phase-in years these penalties were higher: for FY 2013, the higher of the Ratio or 0.99% (1% reduction), and for FY 2014, the higher of the Ratio or 0.98% (2% reduction).)

Formulas to Compute the Readmission Payment Adjustment Amount

Wage-adjusted DRG operating amount = DRG weight x [(labor share x wage index) + (non-labor share x cola, if applicable)]

Base Operating DRG Payment Amount = Wage-adjusted DRG operating amount + new technology payment, if applicable.

Readmissions Payment Adjustment Amount = [Base operating DRG payment amount x readmissions adjustment factor] - base operating DRG payment amount.

The readmissions adjustment factor is always less than 1.0000. Therefore, the readmissions payment adjustment amount will always be a negative amount (i.e., a payment reduction).

Example of Penalty Calculation

Assume:

- 125-bed hospital. For simplicity, assume all admissions are Medicare.
- Average length of stay for a Medicare admission: 5.5 days.
- 85% occupancy.
- Admissions = Discharges.

- Total discharges = 7,000 per year. (Discharges are calculated as: 125*0.85*365/5.5).
- Revenue (Base DRG payment): 7,000 * $10,000 = $70,000,000 per year.
- Hospital has only one admission type (of the penalty admissions): Heart Failure (CHF).
- Heart Failure admissions: 3.66 % of all admissions = 256.0 per year.
- Average reimbursement per CHF admission: $8,651.
- CHF Revenue: $8,651 * 256.0 = $2,216,000 per year.
- CHF Readmissions expected: 25% * 256.0 = 64.0 per year.
- Actual CHF Readmissions: 110% of expected = 70.4.
- Excess Revenue: (110% -100%) * $2,216,000 = $221,600.
- Ratio of Excess Readmission Payments: 1- (221,600/70,000,000) = (1-0.0032) = 0.9968.

0.9968 is higher than the 0.99 floor so adjustment factor is 0.9968. Hospital DRG payment is reduced by 0.32% in FY 2013 ($221,000).

Maximum Hospital payment reduction going forward is 3% from FY 2015. In the case of the example, however, the penalty is limited to the hospital's own ratio, which is lower than the maximum penalty.

20.3 EXISTING READMISSION PREDICTIVE MODELS

The LACE index is a widely used readmission model in the United States, due to its simplicity and moderate predictive power. The acronym LACE is taken from the initial letters of the four components on which the model is based:

- Length of stay
- Acuity of admission
- Comorbidity
- Emergency department visits in the previous 6 months. [5]

LACE scores every patient on the risk of readmission upon discharge based on the four parameters. LACE scores range from 0-19. If a score is between 0-4, the patient is at low risk of readmission. If a LACE score is between 5 and 9, the patient is at moderate risk of readmission. LACE scores above 10 are considered high risk of readmission to the hospital. In order to achieve better outcomes for patients, a simple and practical predictive tool such as the LACE index can prove helpful. An article published by the first hospital to use the LACE index in the U.S. suggested that the LACE index should be combined with additional patient-level risk factors (age, living situation, discharge status, etc.) to increase the discrimination and accuracy level of prediction [6]. Results were shown to be slightly better than those of the LACE index alone. Developing a more specific readmission risk prediction model could

further explain causes of readmissions, as well as more accurately identify and stratify a population at risk of re-admission for intervention. A study comparing an institution-specific model to the generic LACE model on three conditions: heart failure (HF), acute myocardial infarction (AMI), and pneumonia (PN) (as well as a combined model), for three institutions found the c-statistic for the area under the curve (AUC) to be higher for the specific models compared to LACE [6].

As lowering readmission rates is in part a monetary issue, a complete evaluation of a model to predict re-admissions would take into the account the cost of intervening on a patient identified with higher risk of readmission, together with the effectiveness of the intervention. In addition the "competing" financial forces (a reduction in the hospital's revenue as a result of the avoided readmission, and the offsetting effect of the reduction in any penalties applied by CMS) need to be considered. CMS's penalty formula makes this a particularly difficult calculation, and one that is hospital-specific. The "business case" of a model has proven to be an important factor in judging its effectiveness [7].

20.4 DATA

The data for this study focuses on Medicare patients from around the United States. The dataset was developed specifically for this study from the Medicare Synthetic Public Use Files, a sample file of Medicare data made available for research by CMS. These files may be found at https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/SynPUFs/DE_Syn_PUF.html. The data are more limited than those available in other Medicare files (lacking all the fields discussed, for example, in Chapter 3). The database available for modeling consisted of admission, re-admission, and emergency room visits for 66,782 patients collected from 2007 to 2010. The number of emergency visits represents only the number of visits within the same year as admission to the hospital. The following are explanatory variables that were provided in the data: admission and discharge date, birthday, race, sex, state and county codes, diagnosis related group (DRG), and emergency room visits. (Other variables were calculated as necessary.)

From the original dataset we have derived the following additional variables: age, length of stay, DRG classification into Medical or Surgical (see Appendix to Chapter 3), and HCC Risk Score.

- **Age** was calculated from the patients' birthdates and the year of admission.
- **Length of stay** was calculated as the difference between the discharge and admission dates.
- **Diagnosis-Related Group (DRG)** is a statistical system of classifying inpatient into groups for the purposes of payment using the following information: diagnoses, age and sex of the patients and the presence of co-morbidities and complications (see Chapter 6). Additionally, DRG classification is divided into subcategories based on whether or not the patient experienced major complications. For example, the diagnostic group for Chronic Obstructive Pulmonary Disease (COPD) admissions (medical) consists of three different DRG codes: 190: Chronic obstructive pulmonary disease with mcc; 191: COPD with cc and 192: Chronic obstructive pulmonary disease without cc/mcc. ("With mcc" means "with major complications and

comorbidities" (most expensive case); "with cc" means "complications and comorbidities" (moderately expensive case) and "without cc/mcc" means "no complications and comorbidities" (least expensive case).

- **Hierarchical Condition Category (HCC) Risk Score** is the relative risk score based on the enrollee health status and their demographic characteristics (age, and gender). Raw HCC Risk Score = Demographic score + Health Status scores. The system of risk scores measures the disease burden that includes 189 HCC categories, which are determined based on ICD-9 Codes. In this study, we used the 2011 CMS-HCC preliminary community factors. Each patient could have more than one HCC category assigned to them; the final HCC risk score represents the cumulative risk of all the diseases. Higher HCC Risk Scores indicate a riskier patient. For an example, assume we have a male patient who is 50 years old. He was diagnosed with diabetes with acute complications (HCC17) and dementia without complication (HCC52). The HCC risk score for this patient is: HCC risk score =demographic score + health status scores= 0.165+ 0.344 +0.343 =0.852. A SAS program is available from CMS to generate binary HCC flags (1/0 depending on whether the patient has a diagnosis within the particular HCC). In the Appendix to this chapter we provide R code that allows analysts without access to SAS to run HCCs and risk scores.

Table 20.1 summarizes the available data.

Table 20.1 Summary of Available Data

N = 66,782		Year 2007 (n=226)	Year 2008 (n=27,662)	Year 2009 (n=25,170)	Year 2010 (n=13,724)
Variable	Factors				
Length of Stay	Min	1	0	0	0
	Median	10	4	4	4
	Mean	12.46	5.768	5.672	5.554
	Max	35	35	35	35
Age	Min	24	25	26	27
	Median	74.5	75	75	75
	Mean	73.27	73.42	73.55	74.24
	Max	98	99	100	101
Sex	Male	0.47	0.43	0.43	0.43
	Female	0.53	0.57	0.57	0.57
Race	White	0.82	0.84	0.84	0.84
	Black	0.12	0.11	0.11	0.1
	Hispanic	0.03	0.02	0.02	0.02
	Other	0.03	0.03	0.04	0.04
DRG	Medical	0.57	0.54	0.53	0.53
	Surgical	0.42	0.45	0.46	0.46
	Ungroup	0.01	0.01	0.01	0.01
HCC Risk Score	Min	0.079	0.079	0.079	0.079
	Median	3.036	2.232	1.749	1.517
	Mean	3.186	2.748	2.162	1.856
	Max	9.101	11.37	12.31	10.57
Readmission	Yes	0.053	0.186	0.098	0.057
	No	0.947	0.814	0.902	0.943
ER Visits	Min	0	0	0	0
	Median	0	0	0	0
	Mean	0.5088	0.5166	0.504	0.4993
	Max	5	9	7	7

20.5 THE MODEL

The response variable for our model is readmissions. In total the data contain 8,409 readmissions, while 58,373 patients have not experienced a readmission, implying a readmission rate of 12.59%. Because we are dealing with a binary response of either readmission or non-readmission, we chose to fit a logistic regression model for the purpose of this study.

20.5.1 METHODOLOGY

Notation

Let **P** be the probability that the patient is readmitted within 30 days after discharge, and **(1-P)** the probability that the patient is not readmitted within 30 days after discharge.
Log is the natural logarithm.
Odds: the ratio of the number of ways something can occur to the number of ways it cannot occur (i.e. P/(1-P)).
logit: denotes the log of the odds (i.e. log (P/(1-P))); and
Y is the response variable (readmission); Y=1 implies readmission; Y=0 implies no readmission.

Logistic regression

Logistic regression (logit model/logit regression) is a regression model that applies where the data set has a binary or a multinomial response and several predictors. In our case we have a binary response (re-admitted/not re-admitted), and a number of possible predictors.

- The response variable (Y|X) follows a Bernoulli distribution with (Y=1|X) occurring with unknown probability P, and (Y=0|X) occurring with unknown probability (1-P).
- The predicted value for the response variable must be either 0 or 1, according to the logistic distribution function. The model is a special case of a generalized linear model, in which the link function component is the logit function. In the context of our research, we are interested in predicting the probability that a patient is readmitted to the hospital within 30 days after discharge based on characteristics such as: age, gender, race, length of stay during admission, diagnoses, number of emergency visits, etc. Logistic regression links the binary outcome (readmission status) with a combination of the linear predictors. The statistical model of logistic regression may be simplified as follows:

$$P\,\mathrm{X}\frac{e^{(\sim\Gamma\ {}_1X_1....\Gamma\ {}_nX_n)}}{1\Gamma e^{(\sim\Gamma\ {}_1X_1....\Gamma\ {}_nX_n)}}$$

Alpha and Beta are estimated using maximum likelihood based on iterative methods such as Fisher Scoring.

20.5.2 MODEL BUILDING

We built a logistic regression model using 70% (46,747 observations) of the data set. The remaining 30% (20,035) of the data set is used for internal validation.

Table 20.2: Results from training data
(Bolded variables indicate those that are significant at an alpha value of .05)

Variable	Coefficient	Odds Ratio	Confidence Interval
Intercept	**-2.8720**	**0.0566**	**(0.047 0.068)**
Age	**-0.0044**	**0.9956**	**(0.994 0.998)**
Male (vs. Female)	-0.0010	0.9990	(0.944 1.061)
Length of Stay	**0.0070**	**1.0070**	**(1.010 1.019)**
HCC Risk Score	**0.4118**	**1.5095**	**(1.487 1.532)**
Number of previous ER visits	0.0235	1.0238	(0.989 1.059)
White (vs Black)	0.0052	1.0052	(0.916 1.105)
Others (vs Black)	0.0056	1.0056	(0.839 1.201)
Hispanic (vs Black)	0.0861	1.0899	(0.871 1.354)
DRG Class Ungroupable (vs. Medical)	-0.0070	0.9930	(0.774 1.384)
DRG Class Surgical (vs. Medical)	0.0422	1.0431	(0.937 1.052)

The predictive power of the model can be assessed using the Receiver Operating Curve (ROC; see chapter 7). Figure 20.1 shows the ROC curve for this model.

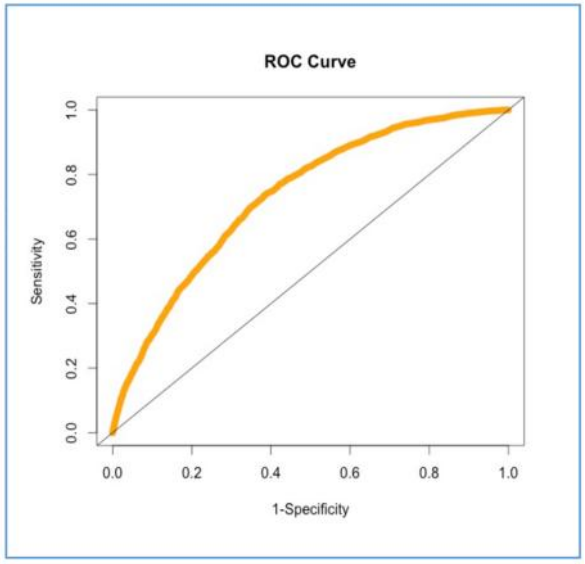

Figure 20.1: ROC Curve for Readmission Model

The ROC value for the model is 0.73, which indicates a moderate predictive value. The moderate predictive value is in part due to the limitations of the dataset. In a test of the model on actual hospital data the model performed better, and outperformed the LACE model.

20.5.3 MODEL SELECTION

The full model includes 7 variables. Only 3 of these variables (age, HCC risk- score, and length of stay) were significant. We want to test whether the reduced model (with only 3 significant variables) performs better than the full model by using deviance analysis. In GLM, we cannot use residual sums of squares; instead deviance is a measure of "badness of fit." A large value of deviance indicates that the logistic model does not fit the data well. The residual deviance shows how well the response variable is predicted by the current model. In this data set, the response variable follows a Bernoulli distribution. Therefore, deviance analysis is performed using the chi-square test. From our R output, we have the following deviance summary:

Table 20.3: Deviance Summary, Full and Reduced Models

Model	Residual Degrees of Freedom	Residual Deviance
Reduced Model (3 significant variables)	46743	32023
Full Model (7 variables)	46736	32021

In the case of a model with more variables, we would expect the model to explain more of the variance, and therefore to have less residual deviance than a model with fewer variables. We apply a test to determine whether the addition of further variables has a significant effect on the accuracy of the model.

We test the hypothesis H_0 that the reduced (3 variable) model is preferred over the full model (7 variables) $H_{\sim}$. If H_0 is correct, the difference in deviance between the two models:

$$W \text{ X } \frac{\text{Residual Deviance }_{reduced} \text{ Z Residual Deviance }_{full}}{\text{¤}} \text{ under } H_0 \sim \text{¡}^2_{resid\ d.f.reduced \text{ Z } resid\ d.f.full}$$

$$\text{X ¡}^2_{7d.f.}$$

W_{obs} X$\frac{32023\,Z32021}{¤\ X1}$ (When the response variable follows a Bernoulli distribution, the over-dispersion variable, ¤ X1.)

W_{obs} X2; <i $^{2}_{7d.f.;\sim X0.05}$ X2.167

Conclusion: we cannot reject the null hypothesis H_0 that the reduced model is preferred over the full model.

We also considered interaction terms, but did not find any that improved the fit of the model.

20.5.4 INTERPRETING COEFFICIENTS

A problem with the logistic regression model is that (unlike in the case of linear regression) coefficients cannot be directly interpreted, and require exponentiation and comparison with a baseline case.

Age is a significant variable: the odds ratio for age is close to 1.00, which implies that an increase of 1 year in age is unlikely to have much effect on readmission. However, a more significant difference in age will have an effect on the likelihood of readmission (although the effect of increased age is counter-intuitive: our result suggests that odds decrease with increased age).
Gender: interestingly, gender is not a significant predictor of readmission: males and females have about the same likelihood of being readmitted.
Length of stay: an increase of a day in length of stay increases the likelihood of a readmission by slightly less than 1%.
HCC Risk Score: Risk Scores (as a measure of disease burden) have a significant effect on the probability of readmission. With a value of 1.51, an increase of 1 point in the patient's risk score increases the likelihood of a readmission by 50%.

Other variables: are not significant.

20.5.5 THE CUT-OFF VALUE

The output of the model is probabilities of being readmitted. There are different ways for determining whether a patient is likely to be readmitted or not. One method is to determine *a priori* a "cutoff value." This cutoff value is a probability such that it represents a threshold value for the likelihood of being readmitted; if the patient is more likely to be readmitted than the cutoff value, the patient will be classified likely to be readmitted. We will use 50% probability as the baseline cutoff value. At a 50% cutoff value, the sensitivity of the model is very low, meaning that we misclassify most readmissions as non-readmissions. In order to increase sensitivity, we pick the point where specificity is equal to sensitivity. We find that this occurs at a cutoff value of 11%. If a patient has a probability in excess of 11% of being readmitted, we will classify that patient as likely to be readmitted.

Figure 20.2 illustrates the selection of a cut-off value.

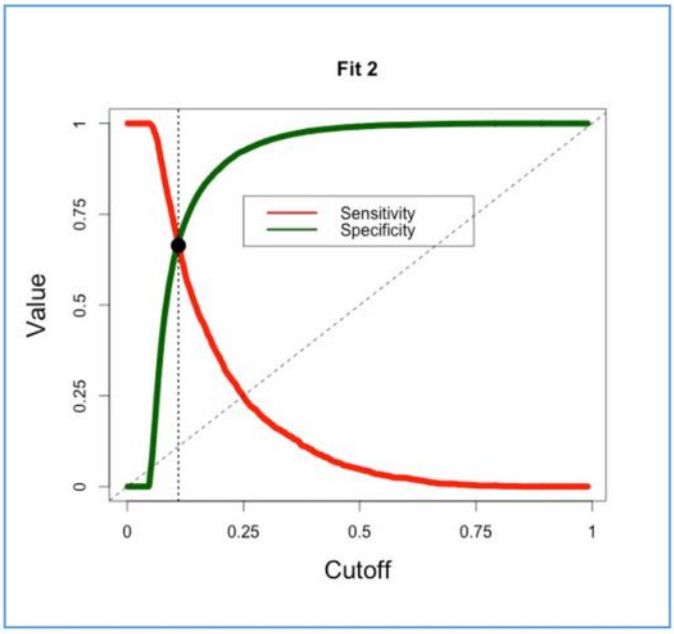

Figure 20.2: Sensitivity/Specificity Trade-off

At a cut-off value (probability of readmission) of 0.5 the sensitivity line has a very low value, implying that few patients will be identified. At this value the specificity of the model is very high, implying that, although few patients are identified, those that are identified have a very high likelihood of readmission. At the intersection of Sensitivity and Specificity (11%) we identify more patients than at 0.5, but at the cost of more false positives (lower specificity).

The false positive (incorrectly identifying a patient who does not have a readmission) and false negative rates (incorrectly missing a patient who does have an admission) are related to Type 1 and Type 2 errors:

The false positive (incorrectly identifying a patient who does not have a readmission) and false negative rates (incorrectly missing a patient who does have an admission) are related to Type 1 and Type 2 errors:

- Sensitivity = 1 - Type II Error = true positive rate à the ability to correctly detect re- admissions.
- Specificity = 1- Type I Error = true negative rate à the ability to correctly detect non re- admissions.

The Sensitivity and Specificity for cut-off values of 0.5 and 0.11 can be seen in Table 20.3.

Cutoff Value	Type 1 Error	Type 2 Error	Sensitivity	Specificity
50%	0.85%	95.17%	4.83%	99.15%
11%	32.82%	33.62%	66.38%	67.18%

Table 20.3 Sensitivity and Specificity for two cut-off values

20.6 PRACTICAL APPLICATION

If this type of model is to be useful in healthcare, it must have practical application. The discussion above (cut-off values; model selection) is important but the ultimate test of a model is whether it can be implemented in practical situations, and helps a healthcare organization to distinguish those patients likely to be re-admitted from those that are not. For this purpose, an evaluation of quantile outcomes is very useful.

Table 20.4 shows an application of this method to the hold-back population. We first "score" the population by applying the model and calculating each patient's risk score. We then segment the population according to their predicted risk of readmission. Thus the 10% of the population with the lowest predicted risk score is mapped to the lowest decile, etc. We then test these patients' outcomes in the hold-back data, looking to see how many of the patients had the predicted outcome (readmission). Essentially we are looking to test model performance in terms of predicting high and low risk. Overall (2,528 predicted; 2,549 actual) the model is reasonably good at predicting readmissions in total. But is it good at discriminating between those patients that require additional resources to *prevent* the

readmission? Operationally we could apply additional resources to those patients with a cut-off value of 0.11 (as discussed above). This cut-off value implies xxx patients to manage. Our alternative is to manage the highest risk-score deciles. The issue becomes one of finances: what is the return on managing the highest decile patients, given the ability of the model to discriminate between high and low opportunity patients?

Decile	Count	Mean% Readmission	Predicted Readmissions	Actual Readmissions	Error Rate
0-9	2,004	0.0513	103	32	222%
10-19	2,003	0.0588	118	62	90%
20-29	2,004	0.0655	131	104	26%
30-39	2,003	0.0729	146	136	7%
40-49	2,004	0.0825	165	189	-13%
50-59	2,003	0.0956	192	228	-16%
60-69	2,004	0.1148	230	348	-34%
70-79	2,003	0.1458	292	335	-13%
80-89	2,004	0.2025	406	466	-13%
90-99	2,003	0.3699	745	649	15%
TOTAL	20,035		2,528	2,549	-1%

Table 20.4: Predictive Accuracy by Decile

Table 20.4 shows that the model is relatively inaccurate at the extremes (something that is true of most models). In the highest decile (most risky patients) the model "over-predicts" the readmissions by 15%. In the next decile, the model under-predicts by a similar percentage, so perhaps if we intervened on all 4,007 patients we would be rather accurate in our predictions? If we add these 2 deciles, the over-prediction amounts to only 3%, which is good for business purposes. The overall frequency in these two deciles is 29%, implying that we expect slightly fewer than one in three of the patients assigned to the top two deciles to experience the predicted event (readmissions). Overall, the model appears to be good at discriminating between those patients likely to experience a readmission, compared with those that are not likely.

20.7 AN ECONOMIC MODEL FOR READMISSION INTERVENTION

To see how the model is implemented in practice, we assume that we are developing a case management program in the hospital to reduce readmissions. We wish to apply the intervention to all 2,003 patients in the highest-risk decile, and that these patients are assigned to nurse case-managers. In Table 20.5, the nurse case manager is assumed to follow the patient in the hospital and for 10 days following discharge. Given that the average Medicare

length of stay is 5.5 days, in total patients are managed by the nurses for 15.5 days, implying that these patients represent 31,047 days of care.

We need to estimate how many nurses are required to manage the 2,003 patients who generate 31,047 days of care. We assume that a nurse case-load is 50 patients and that the nurse works a 200-day work year. Given this level of productivity, 3.10 nurses are required to manage the highest-risk decile in the course of the year. We assume a loaded nurse cost of $150,000 annually (here, the load includes incidental expenses such as IT, reporting, management, etc.) and an average per admission reimbursement of $10,000. Hence, management of the top decile of the population is expected to cost $465,698. We assume that the program is able to engage 40% of all targeted patients in the top decile, and to change the outcome (reduce the re-admissions) on 50% of the engaged patients. Assuming a cost of $10,000 per admission, the reduction in revenue from reduced readmissions is $1.5 million. Continuing the estimation for other deciles we see a positive return in the two top deciles (80% and above), a marginal return in the third decile and negative returns below 70%.

Focusing for the moment just on the top decile, we see that the hospital experiences a revenue reduction of $1.5 million, and a cost in terms of nurse and other resources of $465,698. This revenue reduction has to be compared with the reduction in penalty that the hospital experiences from CMS as a result of its performance on readmissions. This penalty will depend on the specific circumstances of the hospital and its performance in terms of readmissions; however, if we assume that it has performed poorly and is experiencing the maximum penalty (3% of Medicare revenue) we can calculate the hospital's penalty by estimating Medicare revenue. In Table 20.4 we reported 20,035 admissions annually; at an average reimbursement of $10,000, Medicare revenue would amount to $200 million annually. The penalty would therefore be $6 million. If we assume that the hospital experiences 10% excess readmissions, this implies an excess of 230 (2,528-2,298). Intervening on the top 3 deciles in Table 20.5 is expected to reduce readmissions by 287, or sufficient reduction to eliminate the 10% excess that has led to the penalty. However, this reduction comes at the cost of reduced revenue of $2.87 million. Overall, intervening on the top 3 deciles costs $4.3 million. By intervening on the top 3 deciles, the hospital has avoided a penalty of $6 million, but at a cost (in terms of resources and lost revenue) of $4.3 million.

Decile	Count	Mean% Readmission	Predicted Readmissions	Managed Days	Mgd. Days/case-load	No. Nurses	Nurse Cost (+overhead)	Engagement (0.4)	Behavior change (0.5)	Avoided Admissions	Cost Avoided	Savings/ Patient	ROI
0-9	2,004	0.0513	103	31,062	621	3.11	$ 465,930	802	401	21	$ 205,610	$ (130)	0.44
10-19	2,003	0.0588	118	31,047	621	3.10	$ 465,698	801	401	24	$ 235,553	$ (115)	0.51
20-29	2,004	0.0655	131	31,062	621	3.11	$ 465,930	802	401	26	$ 262,524	$ (102)	0.56
30-39	2,003	0.0729	146	31,047	621	3.10	$ 465,698	801	401	29	$ 292,037	$ (87)	0.63
40-49	2,004	0.0825	165	31,062	621	3.11	$ 465,930	802	401	33	$ 330,660	$ (68)	0.71
50-59	2,003	0.0956	192	31,047	621	3.10	$ 465,698	801	401	38	$ 382,974	$ (41)	0.82
60-69	2,004	0.1148	230	31,062	621	3.11	$ 465,930	802	401	46	$ 460,118	$ (3)	0.99
70-79	2,003	0.1458	292	31,047	621	3.10	$ 465,698	801	401	58	$ 584,075	$ 59	1.25
80-89	2,004	0.2025	406	31,062	621	3.11	$ 465,930	802	401	81	$ 811,620	$ 173	1.74
90-99	2,003	0.3699	745	31,047	621	3.10	$ 465,698	801	401	148	$ 1,481,819	$ 507	3.18
TOTAL	20,035		2,528										

Table 20.5 Economic Model for Interventions and Savings from Readmission Reduction

Whether this intervention program results in an overall net gain or loss to the hospital depends on other factors:

- The hospital experiences a reduction of 1.4% in its overall admission volume. How it addresses this reduction will be a factor in determining whether, in total, the readmission reduction program is financially successful. Although admission volume has only been reduced by 1.4% the hospital will need to make decisions about staffing and possibly closing beds.
- The decision will depend in part on whether there is excess demand for hospital services. With excess demand the empty beds are likely to be filled, and the lost revenue replaced.
- The reduction in admissions comes from Medicare patients. Are Medicare patients a source of gains for the hospital? Some hospitals experience losses on their Medicare business implying that a reduction in Medicare patients can be negative to the top line but positive to the bottom line.

The economic viability of the program in this model depended, among other things, on the assumption that the hospital pays the maximum penalty. With a lesser penalty, for example 1%, readmission reductions will avoid only $2 million in penalties. In this case the cost of intervening on the top 3 deciles ($1.4 million) together with the reduction in revenue from avoided readmissions ($2.87 million) is significantly greater than the avoided penalty.

In planning a readmission reduction program, there may be other factors relevant to a specific hospital. However, as this model shows, in some circumstances a readmission reduction program may be economically viable for a hospital, in which case a predictive model, such as that developed here can be helpful in identifying patients for intervention.

References

1. Health Affairs and Robert Wood Johnson Foundation, *Medicare Hospital Readmissions Reduction Program. To improve care and lower costs, Medicare imposes a financial penalty on hospitals with excess readmissions.*, in *Health Affairs*. 2012: Washington D.C.
2. Centers for Medicare and Medicaid Services. *Medicare Fee for Service payment Acute inpatient re-admission reduction program*. 2016 [cited 2016 2016-04-25]; Available from: https://www.cms.gov/medicare/medicare-fee-for-service-payment/acuteinpatientpps/readmissions-reduction-program.html.
3. Medicare Payment Advisory Commission, *Report to the Congress: Promoting Greater Efficiency in Medicare*. 2007: Washington D.C.
4. Anika L. Hines Marguerite L. Barrett H. Joanna Jiang and Claudia A. Steiner, *Conditions With the Largest Number of Adult Hospital Readmissions by Payer, 2011*, in *Statistical Brief*. 2014, Agency for Healthcare Quality and Research: Baltimore MD.
5. Carl van Walraven MD Irfan A. Dhalla MD Chaim Bell MD Edward Etchells MD Ian G. Stiell MD Kelly Zarnke MD Peter C. Austin PhD Alan J. Forster MD, *Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community.* Canadian Medical Assoc. Journal, 2010. **182**(6): p. 551-7.
6. Yu S. Farooq F. Van Esbroek A. Fung G. Anand V. and Krishnapuram B, *Predicting Readmission Risk with Institution-specific prediction models.* Artificial Intelligence in Medicine, 2015. **65**(2): p. 89-96.
7. Billings J. Dixon J. Mijanovich T. and Wennberg D., *Case finding for patients at risk of readmission to hospital: development of algorithm to identify high risk patients.* British Medical Journal, 2006: p. doi:10.1136/bmj.38870.657917.AE.

APPENDIX 20.1: R code for running the model

```
# import the data set
setwd("~/Dropbox/196 package")
library("data.table")
data<- as.data.table(read.csv("Dataset196.csv",header=T))

# 1.DRG Classification ----------------------------------------------------
# Classify DRG into 2 groups: DRG medical/surgical.Link of classification is below:
# Https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-
Reports/MedicareFeeforSvcPartsAB/downloads/DRGdesc08.pdf

# valid codes for DRG surgical
surgicalG<-
c(1:42,113:117,129:139,163:168,215:264,326:358,405:425,453:517,573:585,614:630,652:67
5,707:718,734:750,765:770,799:804,820:830,853:858,876,901:909,927:929,939:941,955:959
,969:970,981:989)
# valid codes for DRG medical
medicalG<-
c(52:103,121:125,146:159,175:208,280:316,368:395,432:446,533:566,592:607,637:645,682:
700,722:730,754:761,774:795,808:816,834:849,862:872,880:897,913:923,933:935,945:951,9
63:965,974:977)
# create DRG.Class variable
data[DRG %in% surgicalG,DRG.Class:=as.factor("SURG")]
data[DRG %in% medicalG,DRG.Class:=as.factor("MED")]
data[is.na(DRG.Class),DRG.Class:=as.factor("UNGROUP")]

# 2.Determine length of stay ----------------------------------------------
data[,LOS:=as.Date(as.character(Discharge.Date),'%m/%d/%Y')-
as.Date(as.character(Admit.Date),"%m/%d/%Y") +1]

# 3.Determine age (up to the date of admission) ---------------------------------------
data[,Age:=year(as.Date(as.character(Admit.Date),"%m/%d/%y"))-
year(as.Date(as.character(Birthday),'%Y%m%d'))]

# 4.Changing labels for Gender ---------------------------------------------------------
data[,Gender:=as.factor(Gender)]
levels(data$Gender)<- c("M","F")

# 5. Changing labels for Race ----------------------------------------------
data[,Race:=as.factor(Race)]
levels(data$Race)<- c("White","Black","Others","Hispanic")

# 6.Calculate HCC riskscore ------------------------------------------------
```

```
# A. Calculate demographic riskscore
# a) Subset important information to calculate riskscore: need age,gender,and HCCs
demo.get<- data[,.(ID.Codes,Age,Gender)]
# b) create a data table that contains risk-score for each demographic group
Age<-rep(seq(0,120),2)
Gender<- c(rep("F",121),rep("M",121))
demo.score<-
c(rep(0.198,35),rep(0.212,10),rep(.274,10),rep(.359,5),rep(.416,5),rep(.283,5),rep(.346,5),rep
(.428,5),rep(.517,5),rep(.632,5),rep(.755,5),rep(.775,26),rep(.079,35),rep(.119,10),rep(.165,1
0),rep(.292,5),rep(.332,5),rep(.309,5),rep(.378,5),rep(.464,5),rep(.565,5),rep(.647,5),rep(.776,
5),rep(.963,26))
demo<- as.data.table(cbind(Age,Gender,demo.score))
# convert age and demo.score into numerics:
cols<- c("Age","demo.score")
demo[,(cols):=lapply(.SD,as.numeric),.SDcols=cols]
# convert Gender into categorical:
demo[,Gender:=as.factor(Gender)]
# c) Merge demo into demo.get, using Age and Gender columns to merge:
demo.get<- merge(demo.get,demo,by=c("Age","Gender"))
demo.get<- demo.get[order(ID.Codes)]
rm(demo)
# B. Calculate disease riskscore:
# a) Subset important information to calculate riskscore:
hcc.get<- data[,c(22:100),with=FALSE]
hcc.get<- matrix(sapply(hcc.get,as.numeric),nrow=66782,ncol=79)

# b) Input Disease Coefficients (Community Factor):
# Use data in Table 1:Preliminary Community and Institutional Relative Factors for the
CMS-HCC Risk Adjustment Model
# this data set doesn't have HCC51, HCC52, HCC138, HCC139, HCC140, HCC141,
HCC159, HCC160
diseaseC<-
as.matrix(c(.492,.520,.557,2.425,1.006,0.695,.330,.180,0.334,.334,.124,.653,.342,.240,1.003,.
425,.313,.337,.257,.279,.423,.376,1.078,.306,.258,.358,.358,.471,.318,1.075,.868,.441,1.016,.
036,.281,.460,.482,.555,.252,.533,1.732,.769,.326,.361,.283,.283,.210,.276,.371,.333,.481,.21
2,1.313,.417,.288,.388,.388,.294,.691,.212,.223,.248,.617,.617,.227,.277,1.071,1.071,.473,.45
8,.533,.141,.441,.363,.379,.555,1.032,.609,0.804),nrow=79,ncol=1)
# c) the riskscore vector is the multiplication between hcc.get and diseaseC:
hcc.get<- as.data.table(hcc.get %*% diseaseC)
hcc.get<- cbind(data$ID.Codes,hcc.get)
names(hcc.get)<- c("ID.Codes","hcc.score")
hcc.get<- hcc.get[order(ID.Codes)]
# C. Calculate the total HCC riskscore and add it into the big data set:
```

```
data<- data[order(ID.Codes)]
data$HCC.Riskscore<- demo.get$demo.score+hcc.get$hcc.score

# 7. Mapping DRG Complication ----------------------------------------
SurgMCC.CC<-
c(1,5,11,20,23,25,28,31,34,37,40,163,166,216,219,222,224,226,228,231,233,235,237,239,24
2,246,248,250,252,255,258,260,326,329,332,335,338,341,347,420,423,453,456,459,461,463,
466,469,471,474,477,480,485,492,495,500,503,510,515,573,576,579,616,619,622,625,628,6
53,656,659,662,665,668,673,736,739,799,802,820,
823,826,856,901,907,939,957,969,981,984,987,12,21,26,29,32,35,38,41,113,116,129,131,13
3,135,137,164,167,217,220,229,240,243,253,256,261,327,330,333,336,339,342,345,348,351,
354,357,464,467,472,475,478,481,483,486,488,490,493,496,498,501,504,507,511,513,516,5
74,577,580,582,584,614,617,620,623,626,629,654,657,660,663,666,669,671,674,707,709,71
1,713,715,717,734,737,740,742,744,746,749,800,803,821,824,827,829,854,857,902,908,928,
940,958,982,985,988)

SurgNoC<-
c(2,6,13,22,24,27,30,33,36,39,42,114,117,130,132,134,136,138,165,168,218,219,220,221,22
3,224,225,226,227,230,232,234:236,238,241,244,247,249,250,251,254,257,259,262,328,331,
334,337,340:343,349,352,355,358,407:410,413:419,422,425,455,459,460,462,465,468,470,4
73,476,479,482,484,487,489,491,494,497,499,502,505,508,512,514,517,575,578,581,583,66
1,664,667,670,672,675,708,710,712,714,716,718,735,738,741,743,745,747,750,766,801,804,
822,825,828,830,855,858,903,905,909,929,941,959,970,983,986,989)

MedicalMCC.CC<-
c(54,56,58,61,64,67,70,73,77,80,82,85,88,91,94,97,100,102,124,146,150,152,154,157,175,17
7,180,183,186,190,193,196,199,205,280,283,286,288,291,296,299,302,304,306,308,314,368,
371,374,377,380,383,385,388,391,393,432,435,438,441,444,533,535,539,542,545,548,551,5
53,555,557,559,562,564,592,595,597,602,604,606,637,640,643,682,686,689,693,698,722,72
5,727,754,757,808,811,814,834,837,840,843,846,862,865,867,871,896,913,915,917,922,947,
963,974,52,59,62,65,71,75,78,83,86,89,92,95,98,121,147,155,158,178,181,184,187,191,194,
197,200,202,281,284,289,292,294,297,300,309,315,369,372,375,378,381,386,389,394,433,4
36,439,442,537,540,543,546,549,560,565,593,598,600,638,644,687,691,699,723,729,755,75
8,760,765,809,815,835,838,841,844,847,868,920,945,949,964,975)

MedicalNoC<-
c(53,55,60,63,66,67,68,72,74,76,79,81,84,87,90,96,99,101,103,122,125,148,151,156,159,176
,179,182,185,188,192,195,198,201,203,206,282,285,287,290,293,295,298,301,303,305,307,3
10,316,370,373,376,379,382,384,387,390,392,395,434,437,440,443,446,534,536,538,541,54
4,547,550,552,554,556,558,561,563,566,594,596,599,601,603,605,607,639,641,645,684,688,
690,692,693,694,696,700,724,728,730,756,759,761,775,810,812,816,834,835,836,839,842,8
45:848,866,869,871,872,897,914,916,918,921,923,933,946,948,950,965,976,977)

data[DRG %in% SurgMCC.CC, DRG.Complication:=as.factor("SurgMCC.CC")]
```

```
data[DRG %in% SurgNoC, DRG.Complication:=as.factor("SurgNoC")]
data[DRG %in% MedicalMCC.CC, DRG.Complication:=as.factor("MedicalMCC.CC")]
data[DRG %in% MedicalNoC, DRG.Complication:=as.factor("MedicalNoC")]
data[is.na(DRG.Complication),DRG.Complication:=as.factor("Other")]

# 8. Budilding Logistic Regression ----------------------------------------
# subset important variables to build the model
final<- data[,c(1,4,7:8,101:106)]
# make sure the response variable is categorical
final$Readmission.Status<-as.factor(final$Readmission.Status)

# split data into training and test set, using training set to build model and test set to validate
the model
set.seed(1)
# 70% of data as training set
train <- sample(1:nrow(final),46747)
final.train<-final[train,]
final.test<- final[-train,]

# proportional binomial/logit model:
fit.train<-glm(Readmission.Status~ Age + Gender + LOS + HCC.Riskscore + Race +
DRG.Class + ER,family="binomial",data=final.train)
summary(fit.train)
# this model is built on the training set

# Variable selection and model selection:

# stepwise regression using backward elimination method (without any interaction terms)
fit2<- step(fit.train,direction="backward")
# investigate interaction terms in the model
library("MASS")
fit3<- update(fit2,.~.^2)
summary(fit3)

# Using chi-square test to perform deviance analysis:
anova(fit2,fit3,test="Chi") #--> prefer the reduced model: fit2
anova(fit2,fit.train,test="Chi") #--> prefer the reduced model: fit3

# fit this model on the test set:
fitpreds = predict(fit2,newdata=final.test,type="response")

# 9. Cutoff value and related plots ---------------------------------------
# determine the optimal cutoff value (where sensitivity==specificity):
library("ROCR")
```

```
fitpredsk<- prediction(fitpreds,final.test$Readmission.Status)
t<- performance(fitpredsk,"ppv")
k<-unlist(t@x.values)
k2<-unlist(t@y.values)

y<- as.numeric(final.test$Readmission)-1
perf = function(cut, fitpreds,y)
{
  yhat = (fitpreds>cut) ## logical value: TRUE or FALSE if predicted prob. >cutoff
  w = which(y==1) #index of true population of readmission cases
  sensitivity = mean( yhat[w] == 1 ) # probability of readmission given that the patient is
readmitted
  specificity = mean( yhat[-w] == 0 ) # probability of no readmission given that the patient is
not readmitted
  c.rate = mean( y==yhat )
  d = cbind(sensitivity,specificity)-c(1,1)
  d = sqrt( d[1]^2 + d[2]^2 )
  out = t(as.matrix(c(sensitivity, specificity, c.rate,d)))
  colnames(out) = c("sensitivity", "specificity", "c.rate", "distance")
  return(out)
}

s = seq(.001,.99,length=1000)
OUT = matrix(0,1000,4)
for(i in 1:1000) OUT[i,]=perf(s[i],fitpreds,y)
plot(s,OUT[,1],xlab="Cutoff",ylab="Value",cex.lab=1.5,cex.axis=1.5,ylim=c(0,1),type="l",l
wd=8,axes=FALSE,col=2,
    main="Fit 2")
axis(1,seq(0,1,length=5),seq(0,1,length=5),cex.lab=2)
axis(2,seq(0,1,length=5),seq(0,1,length=5),cex.lab=2)
lines(s,OUT[,2],col="darkgreen",lwd=8)
# lines(k,k2,lwd=2,col="black")
box()
legend(.25,.8,col=c(2,"darkgreen"),cex=1,lwd=c(3,3,3,3),c("Sensitivity","Specificity"))
abline(v=0.11,lty=3,lwd=2)
abline(0,1,lty=2)
points(.11,0.6638,pch=19,lwd=10)
## The intersection between sensitivity and specificity curves is 0.11

# obtain ROC curve for this model:
plot(1-OUT[,2],OUT[,1],main="ROC Curve",
    xlab=c("1-Specificity"), ylab="Sensitivity",
    type="l",lwd=10,col="orange")
abline(0,1)
```

```
# obtain c-statistic or area under the curve:
(c.stat<- performance(fitpredsk,measure="auc")@y.values)

# 10. Model performance by quantiles ----------------------------------
# Find the quantiles and the mean of prediction within each quantile:
quan<- quantile(fitpreds,c(0,.1,.2,.3,.4,.5,.6,.7,.8,.9,1))
# mean prediction within each quantile:
mean<- c()
for (i in 2:11){
  mean[i-1]<- mean(fitpreds[(fitpreds>= quan[i-1])&(fitpreds<= quan[i])])
}

# actual cases of readmission within each quantiles:
actualOut<- c()
for (i in 2:11){
  actualOut[i-1]<- length(which((fitpreds>= quan[i-1]) & (fitpreds<= quan[i]) & actual==1))
}

# number of observations in each quantile:
num<- c()
for (i in 2:11){
  num[i-1]<- length(fitpreds[(fitpreds>= quan[i-1])&(fitpreds<= quan[i])])
}

# predicted outcomes:
predictedOut<- mean*num

## Model Performance by Quantiles Plot:
actual<- c(32,62,104,136,189,228,348,335,466,649)
predicted<- c(103,118,131,146,165,192,230,292,406,745)
plot(actual,type="l",lwd=6,col="orange",
     xlim=c(0,10),xaxt = "n",xlab="Quantiles",
     ylim=c(0,800),ylab="Number of outcomes",
     cex.lab=1)
grid()
points(predicted,type="l",lwd=6,col="darkturquoise")
axis(1, at=1:10, labels=c(0.1,.2,.3,.4,.5,.6,.7,.8,.9,1),lwd=4)
axis(2,lwd=4)
title("Model Performance by Quantiles")
box()
legend(1,400,col=c("orange","darkturquoise"),cex=1,lwd=c(2,2,2,2),c("Actual","Predicted"))
```