Developing Risk Adjustment Techniques Using the SAS® System for Assessing Health Care Quality in the IMSystem®

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Abstract

Risk adjustment is a statistical technique that is used to overcome the effect of differences between health care organizations that can influence indicator rates and distort comparisons. In order to provide valid comparative information to hospitals participating in the Joint Commission IMSystem, the data are adjusted for certain characteristics which patients bring to the health care encounter. The objective of risk adjustment is to identify a model which can accurately predict the outcome while controlling for an array of statistically and clinically significant patient risk factors. Logistic regression is used to ascertain the influence of specific patient confounding variables on the binary outcome. This paper will discuss the process for developing IMSystem risk adjustment models using the SAS system from variable selection, model building, model evaluation through applying the risk adjustment model. The SAS/BASE®, SAS/STAT® and SAS/GRAPH® products are used to achieve the objectives of risk adjustment.

Introduction

How is it possible to evaluate a hospital's performance on patient outcomes more fairly? How is it possible to compare one hospital's performance on patient outcomes to another more fairly? Since one hospital patient population may differ from the total patient population or from another hospital patient population in a number of patient characteristics, comparisons are meaningless without considering disparities of patient mix among hospitals. Risk adjustment is a statistical technique that is used to overcome the effect of differences among hospitals so that comparisons of health care quality provided are more fair.

The Joint Commission's Indicator Measurement System (IMSystem) is an indicator-based performance measurement system designed to help health care organizations measure and improve their performance and also to assist the Joint Commission in integrating the performance measurement into the survey and accreditation process. An indicator in the IMSystem is defined as a quantitative measure that can be used as a guide to monitor and evaluate the performance of activities important to patient care. Two types of Indicators exist in the IMSystem: binary (occurrence or nonoccurrence) and continuous (length of stay) variables. In the past two years, the IMSystem has developed six risk adjustment models for perioperative and obstetrical care binary outcome indicators. This paper will discuss the processes for developing risk adjustment models for binary outcome indicators using SAS system.

The IMSystem accepts patient level data for every episode of care (EOC) from participating IMSystem hospitals and provides a quarterly comparative report. The IMSystem uses a logistic regression model to ascertain the influence of specific patient risk factors on the binary outcome. The objective of risk adjustment is to identify a model which can accurately predict the outcome while controlling for an array of statistically significant patient risk factors. Applying the risk adjustment models to a hospital's data helps 'level the playing field', so that a hospital can compare it's indicator rates to other hospitals more fairly.

The risk factors considered for assessing health care quality include patient clinical and demographic variables such as gender, age, primary payment source, co-morbidities, ASA-PS scores, and a wide range of other preexisting conditions and associated diagnoses. The IMSystem does not consider hospital level information for risk adjustment because of the possibility that these factors may be the very factors explaining variance in performance between organizations. Every quarter all IMSystem risk adjustment models are re-evaluated and updated to reflect the current indicator population.

The following describes using the SAS System to develop risk adjustment models for assessing health care quality in the IMSystem. IMSystem indicator 6 (patients delivered by C-Section) will be used in the sample SAS output.

Risk Factor Preparation

After clinicians identify the potential patient risk factors for each indicator, each potential risk factor is recoded to appropriate values for the computerized modelling process. There are four basic types of potential risk factors in the IMSystem:

1). Binary variable

Binary variables include sex and the risk factors associated with the 16 possible ICD-9-CM diagnoses. Binary variables are coded to a value of '1' or '0'.

2). Ordinal variable

Ordinal variables are coded as either continuous or design (dummy) variables based on their actual effect on the outcome. The scatter plot or contingency table between the outcome and the ordinal variable can help to determine which coding is appropriate. The missing values for ordinal variables can be recoded into a separate category. In the IMSystem, the ASA-PS score is coded as an ordinal design variable and parity is coded as a continuous variable.

3). Continuous variable

Continuous variables, such as patient age, are handled based on the actual effect on the outcome. Initially, the relationship between age and the indicator rate is examined via scatter plot and bivariate regression analysis. The data are aggregated by age or age group to produce the scatter plot.

The scatter plot clearly shows the relationship between two variables. If a linear relationship exists, age is operationalized in the model as a continuous variable. Generally, truncation is necessary to improve model performance. In the event of a nonlinear relationship, age may need an algebraic transformation or be recoded as a design variable based on it's actual effect on the indicator rate.

4). Categorical variable

Categorical variables such as race and primary payment source are recoded as design (dummy) variables for inclusion in the risk adjustment models. The categories should represent distinct socio-economic types. Their effects on the indicator rate can be evaluated by analysis of a contingency table or examination of the univariate logistic model. In some cases, the categorical risk factor may need to be redefined several times during analysis until the categorical risk factor fits the logistic regression model well. The missing values are coded into a missing category in order to be included in predicting the outcome.

Risk Factor Screening

There is considerable redundancy of information since several diagnostic findings report a common underlying physiologic process. Therefore, the process of model development includes further screening to identify risk factors that are able to predict the event of interest with statistical significance. All binary risk factors associated with ICD-9-CM codes are screened by reviewing the results of either the likelihood Chi-square test or the univariate logistic model. The more conservative p-value is used to assess the significance of the risk factor. For example, if the estimated regression coefficient is significant at the 0.25 level or less, the risk factor is selected for inclusion in the multiple regression model.

Following screening, all risk factors are checked for collinearity. Two simple methods are used. One method is to use the 'VIF' option in PROC REG. A second method is to examine results of the pairwise correlation matrix. Neither method is very sensitive for detecting collinearity but can be used for reference. Collinearity among risk factors is also checked further during the modelling process.

Model Building

The model building process is accomplished using the following steps:

First, a full risk adjustment model is developed with all screened risk factors. The coefficient and odds ratio for each risk factor is reviewed carefully to compare it's crude effect in the univariate logistic regression model to it's effect in the full risk adjustment model. If the coefficient for the risk factor changes dramatically, in particular, if it changes direction, then collinearity exists and it is necessary to investigate the problematic risk factors in detail.

In the second step, statistically nonsignificant risk factors for the indicator outcome are dropped by the stepwise selection method.
Stepwise selection with the 'SLS=0.1' option will retain only those risk factors whose regression coefficient estimates are significant at level 0.1 in the model. The less significant risk factors ($p > 0.1$) are dropped from the model.

The option 'include' in the PROC LOGISTIC is used to insure that important biological factors or categorical variables are retained in the model while the stepwise selection is processing.

Stepwise selection deals directly with redundancy and identifies the risk factors that strongly and independently affect the probability of the outcome. If collinearity between risk factors still exists in the model, interpretation of the effects of such factors on the outcome is complex. In such cases, it is determined whether to avoid simultaneous inclusion in the model or whether it is necessary to add interaction terms to the model.

In the third step, the model resulting from the stepwise selection is reviewed for both clinical and statistical validity. Very large estimated coefficients or standard errors, as well as unreasonable estimates should be investigated further. After all statistically significant risk factors are reviewed and identified, the final model is run for assessing model fit.

Model Fit Assessment

Several methods are used for assessing model fit. If the majority of goodness-of-fit tools yield the same results, it is reasonable to conclude that the model has good fit. Three basic assessment methods are used to evaluate the performance of IMSystem risk adjustment models.

The first method to assess model fit is the Likelihood ratio chi-square test (-2 LOG L), which can be directly obtained from the output of the PROC LOGISTIC procedure. It is used to assess the overall model performance. A significant p-value provides evidence that at least one of the regression coefficients for the risk factor is nonzero. It is also used to assess whether one risk factor increases the predictive power of the model when comparing the reduced model to the full model.

The second method to assess model fit is the C-index which is used to determine the predictive power of a logistic regression model. The C-index is derived from calculating the proportion of concordant pairs and is equivalent to the area under a receiver operation characteristic curve (ROC curve). Both the C-index and ROC curve can be obtained from the output of the SAS PROC LOGISTIC.

C-index's weakness is that it is not sensitive for comparing differences between models or assessing the effect of adding an additional risk factor into the model. The 'RSQ' option computes generalized coefficients of determination which is similar to the R-Squared in the linear regression model. However, the 'RSQ' and 'OUTROC' options of the PROC LOGISTIC are only available in SAS release 6.10 and later releases (see output 1).

A third measure for determining a model's predictive ability is to examine the correlation between the observed indicator rates and their predicted rates based on grouped data. The data are ranked by the predicted probabilities first, and then aggregated into a number of groups based on an equal number of observations in each group. Next, the bivariate regression model and its scatter plot are used to compare the actual indicator rates to their predicted rates for the grouped data.
A scatter plot is generated using the 'plot' option in PROC REG. The logistic model is said to be highly predictive if the trend of the scatter plot is linear, the regression model coefficient is close to 1, and the R-squared is 0.7 or above. Otherwise, the model lacks fit and needs refinement or further reevaluation of the risk factors. The results generated using this method may depend on the number of observation in each group.

Model Application

Once the final risk adjustment model is determined, the model can be applied to calculate a predicted probability of an indicator event for each episode of care in the denominator population. The predicted probability for each EOC is generated using the 'output' option in PROC LOGISTIC. The

dependent variable requires manipulation in order to exclude the observations with missing variables from the model development but to include them in the model prediction efficiently.

Predicted Rate and its Confidences

After outcomes are adjusted by the model, each EOC has both an actual outcome and a predicted probability of an outcome. The patient level data is aggregated to the hospital level, yielding two indicator rates, one is it's actual or observed indicator rate, the other is it's predicted indicator rate accounting for patient risk factors identified in the model. The IMSystem characterizes the performance of a hospital by comparing the difference between the observed and the predicted indicator rates. The IMSystem uses the 95% confidence intervals for the mean of the predicted indicator rates to determine if the difference is statistically significant. The computation of the standard deviation is based solely on the binomial or sampling variance.

The 95% confidence intervals are only calculated when the numerator has at least 5 cases or the denominator has at least 30 cases in order to provide reasonable confidence intervals. The minimum requirement for the number of numerator and denominator is based solely on a concern for small hospitals and not for statistical soundness.

Based on the predicted rate and its 95% confidence intervals, a comparison chart is constructed to allow a hospital to visually evaluate it's performance. The difference between the predicted rate and actual indicator rate for a specific hospital generally reflects how far the hospital's performance is from what should be expected based on the patient mix of participating IMSystem hospitals. The comparison chart is intended to give a hospital a straight-forward presentation of the observed rate compared to it's predicted rate and to help determine if opportunities for improvement exist (see output 3).

Risk Adjusted Rate

The standardized rate or risk adjusted rate for making comparisons across hospitals is derived from the following formula:

$$Rate_{Adjusted} = (Rate_{Observed} / Rate_{Predicted}) * Rate_{IMSystem}$$

The IMSystem rate is the indicator rate for all reporting hospitals and represents the average rate for the entire database, not the average of the means of the individual hospitals. The risk adjusted rate can be thought of as a 'standardized' or 'normalized' indicator rate, so it can be used for comparisons among the reporting hospitals. The IMSystem also provides the percentile of the risk adjusted indicator rate to show the hospital's performance relative to all reporting hospitals (see output 2).

Conclusions

Risk adjustment techniques used in the IMSystem have demonstrated that they are appropriate in assessing health care quality. The majority of the risk adjustment models have good predictive ability with a relatively high C-Index. The SAS system has the tools to handle the data modelling process efficiently. However, both expert clinical and statistical input at each stage of the analysis is required because model building is a highly interactive and iterative process.

References

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Output 1:

The LOGISTIC Procedure

Data Set: WORK.TMP
Response Variable: INDM
Response Levels: 2
Number of Observations: 127280
Link Function: Logit

Response Profile

Ordered Value	INDM	Count
1	1	26878
2	0	100402

WARNING: 4959 observation(s) were deleted due to missing values for the response or explanatory variables.

Model Fitting Information and Testing Global Null Hypothesis BETA=0

Criterion	Intercept Only	Intercept and Covariates	Chi-Square for Covariates
AIC	131229.12	90445.935	
SC	131238.87	90680.035	
-2 LOG L	131227.12	90397.935	40829.180 with 23 DF (p=0.0001)
Score			44416.432 with 23 DF (p=0.0001)

RSquare = 0.2744 Max-rescaled RSquare = 0.4265

Analysis of Maximum Likelihood Estimates

Variable	DF	Parameter Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square	Standardized Estimate	Odds Ratio
INTERCPT	1	-3.8448	0.0495	6038.6778	0.0001		
AGET	1	0.0471	0.00155	922.9042	0.0001	0.156874	1.048
PAY1	1	-0.0789	0.0230	11.7650	0.0006	-0.017471	0.924
PAY2	1	0.1629	0.0220	54.8668	0.0001	0.040726	1.177
PAY3	1	-0.2614	0.0389	45.0982	0.0001	-0.034954	0.770
RF05	1	0.5906	0.0399	219.0335	0.0001	0.060675	1.805
RF20	1	1.2303	0.0248	2460.2447	0.0001	0.193347	3.422
RF21	1	2.9490	0.0281	10988.5438	0.0001	0.419288	19.086
RF22	1	0.3959	0.0532	55.4384	0.0001	0.030202	1.486
RF23	1	0.3229	0.0349	85.8452	0.0001	0.040150	1.381
RF24	1	1.9627	0.1169	281.7625	0.0001	0.063513	7.119
RF25	1	0.6812	0.0342	396.8998	0.0001	0.089930	1.976
RF26	1	0.3812	0.0418	82.9771	0.0001	0.039432	1.464
RF27	1	0.7821	0.1042	56.3683	0.0001	0.029923	2.186
RF28	1	1.4615	0.0482	920.7550	0.0001	0.116796	4.312
RF29	1	0.9041	0.0484	348.3712	0.0001	0.073125	2.470
RF31	1	1.1639	0.0405	826.5822	0.0001	0.110898	3.203
RF34	1	2.4944	0.1763	200.2829	0.0001	0.053095	12.114
RF35	1	1.3550	0.0613	488.8820	0.0001	0.081252	3.877
RF36	1	1.5819	0.0775	416.2163	0.0001	0.074080	4.864
RF37	1	1.6423	0.0760	466.8023	0.0001	0.076289	5.167
RF38	1	4.7430	0.0733	4181.3045	0.0001	0.498599	114.781
RF39	1	1.5702	0.0241	4244.0993	0.0001	0.254001	4.807
RF40	1	0.6218	0.0502	153.6603	0.0001	0.049843	1.862

Association of Predicted Probabilities and Observed Responses

Concordant = 84.4%	Somers' D = 0.694
Discordant = 15.0%	Gamma = 0.698
Tied = 0.6%	Tau-a = 0.231
(2698604956 pairs)	c = 0.847

Output 2:

IMSystem Indicator 6
Observed, Predicted and Risk Adjusted Rate

HCO_ID 00000000

Indicator 6		QUARTR				
		95Q3	95Q4	96Q1	96Q2	total
Numerator	Your Hosp	138	106	100	118	462
Denominator	Your Hosp	758	637	646	667	2708
observed rate	Your Hosp	0.182	0.166	0.155	0.177	0.171
Risk Adjusted	Your Hosp	0.178	0.166	0.163	0.167	0.170
percentile	Your Hosp	29	13	15	34	15
Overall Indicator rate	All Hosp	0.209	0.216	0.214	0.200	0.210

Output 3: