

Management of CABG Patient Mortality  
Using SAS Logistic Regression by Cohorts:  
Age, Sex and Cleveland Clinic defined risk factors  
*Five years of data and analysis compressed onto a 3 X 5 pocket guide*

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Abstract

In this environment of dwindling healthcare reimbursement dollars and heightened focus on quality, it is important to optimize outcomes as well as other quality indicators, particularly in your most profitable product line(s). Coronary Artery Bypass Graft (CABG), which is an open-heart procedure, is just that at Christian Hospital NE, part of the BJC Healthcare System in St. Louis. We needed a quick and easy way to assist our cardiovascular surgeons in assessing a patient's mortality risk for this procedure at presentation. In order to do this, we did several things: 1) utilized work done previously by the Cleveland Clinic on mortality and morbidity risk factors, 2) collected five years worth of data on our CABG patient population, 3) conducted statistical analysis that included logistic regression by cohorts (using techniques learned at the 2002 SESUG annual conference), as well as other statistical methodology, and 4) Voila! produced a 3 X 5 inch pocket guide useable at the patient's bedside for quick reference. This pocket guide quantified the predicted mortality risk by age and sex of the patient, as well as the risk factors found to be most important to our mid-western patient population. These factors were: creatinine clearance (how well the patient's kidneys were functioning), hematocrit (the level of red blood cells) and the predicted probability pre-operative score based on the other 10 indicators utilized in the Cleveland Clinic model.

Initially, we based our research and analysis on both the Society of Thoracic Surgeons (STS) a national professional organization located in New York (*Edwards, et al.*), and the previously published work of the Cleveland Clinic (*Higgins, et al.*). The STS model incorporated pre-operative, intra-operative and post-operative variables. Due to the time and cost of data collection, we focused on the pre-operative variables, particularly those that were also included in the Cleveland Clinic research. The Cleveland article summarized analysis of 29 pre-operative risk factors, and stated that 9 were

found to be useful preoperative predictive estimates of mortality: emergency procedure (6), preoperative serum creatinine levels  $\geq 168\mu\text{mol/L}$  (4), left ventricular dysfunction (3), preoperative hematocrit of  $\leq .34$  (2), increasing age (2), chronic pulmonary disease (2), prior vascular surgery (2), re-operation (3), and mitral valve insufficiency (3). Cleveland Clinic developed a scoring system from 1 to 6 to weight each factor based on their potential association to mortality using a  $\chi^2$  or Fisher's Exact Test. Odds ratios (ORs) were calculated to measure the degree of association, and the Hosmer – Lemeshow  $\chi^2$  statistic was used to determine goodness of fit of the model. Each risk factor listed above is followed by its Cleveland Clinic score assignment in parenthesis. The point values were based on the univariate OR, the degree of significance in the logistic model and clinical considerations.

Cleveland Clinic used receiver operating characteristic curves to measure and compare the accuracy of the logistic and clinical models without having to choose a specific cutoff point. The curve for both the logistic and clinical models was .74. Different weights were evaluated for each factor to optimize performance of the clinical model. Theoretically, the maximum severity score is 31 points. The highest observed score for the Cleveland data was 18 points, (our highest score to date is 22). Note that this CABG survival challenge is scored like golf – low man wins!

We then set up a data collection instrument built in a Microsoft Access database, as that was the application accessible to the staff in the Cardiovascular Care Unit, where the data was being input. We identified an experienced critical care nurse (CCRN) to abstract the medical records daily. For analysis, the Access dataset was exported to SAS, of course.

Data collection tool:

As suspected, as a patient’s score increased, the mortality rate also increased, even when we focused on the patients who underwent a CABG only, eliminating the impact that multiple procedures such as mitral or aortic valve repair, might have on the results. We did include the low percentage of patients that had a CABG following an unsuccessful PTCA (about 3% of those having this procedure) and those who had undergone a catheterization prior to the CABG.

We did some initial analysis using the variables common to the STS and the Cleveland model to determine which was a good fit for our patient population using the Hosmer – Lemeshow Goodness of Fit test. The desirable outcome of this test is non-significance, indicating that the model prediction does not significantly differ from the observed. We also calculated parameter estimates and odds ratios (OR) from the bi-variate and multivariate logistic models.

We found that the Cleveland Clinic model was a better fit for our patient population, and thus focused on the pre-operative variables found in that model. There was good agreement between

the predicted and observed mortality rates when grouped by their Cleveland Clinic severity score. Due to the low occurrence of the death on patients with scores 0 – 2, the scores were grouped together. As a result of the low frequency of patients with a score  $\geq 10$ , those patients were grouped together.

Fairly early on, we ran the Hosmer and Lemeshow Goodness of Fit Model to determine the Cleveland Clinic model accuracy of prediction for our CABG data. At this point in time, we had grouped the Total Scores into the seven (7) groups defined below. Note: even though we did not have any patients with a score greater than 14 at this time, we had developed a category for scores 15 and over.

Also note that we wanted to predict the mortality rate where discharge disposition of expired equals 1. Therefore, we have to use the “descending” option, abbreviated DES in our logistic regression model.

SAS Code:

```

title "Hosmer and Lemeshow
Goodness of Fit Model";
title2 "Cleveland Clinic score
total (ntotal=1=1-2 2=3-4 3=5-6
4=7-8 5=9-10 6=11-14 7=15+)";
PROC LOGISTIC DES DATA =
justcabg;
MODEL expired = ntotal /
LACKFIT;
run;

```

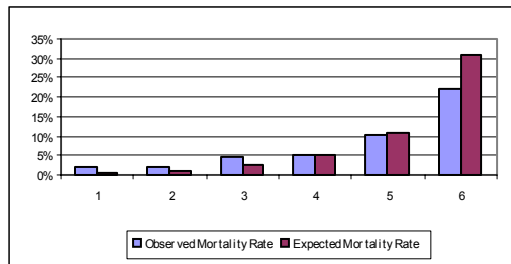
SAS Output:

Partition for the Hosmer and Lemeshow Test

Group	Ttl	Obs.	Expected	Obs.	Expected
1	276	2	1.73	274	274.27
2	501	2	6.32	499	494.68
3	319	14	8.05	305	310.95
4	244	12	12.18	232	231.82
5	179	18	17.23	161	161.77
6	159	35	37.50	124	121.50

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
7.7971	4	0.0993



During last year's SESUG meeting, I

SAS Output:

Classification Table

Prob Level	Correct		Incorrect		Percentages				
	Event	Non-event	Event	Non-event	Correct	Sensitivity	Specificity	False POS	False NEG
.061	53	1310	286	30	81.2	63.9	82.1	84.4	2.2

We also graphically displayed the probability of expiring (y axis) and the Cleveland Clinic total score (x axis).

SAS Code:

```

* STEP ONE clear out the work data
library and then create a SAS data set

```

participated in a weekend workshop presented by Andrew H. Karp, "Building and Applying Predictive Models Using the SAS System". There, I learned that the number of data groups impacts the results of this measure.

As a result, we used another method to access the "fit" of our logistic regression model and displayed the results in a classification table (option CTABLE). This gave us the percent correctly classified by the model, or the efficiency. This procedure also calculates **Sensitivity** (the number of cases predicted to have the event of interest divided by the total number which actually had the event, illustrating the ability of the model to correctly capture or predict the event among those in the sample for which the event actually occurred) and **Specificity** (the number of cases predicted to NOT have the event of interest divided by the total number which did NOT actually have the event, i.e., the ability of the model to rule out the event among those in which it did not occur).

SAS Code for logistic regression with "ctable" option, generated with the proportion of expired patients as the "pprob" or prior probability of the event outcome:

```

proc logistic DES data =
justcabg ;
MODEL expired=newtotal/
ctable pprob = .049;
title 'Predicting Discharge
Status Based on total Cleveland
Clinic Severity Score';
title2 'Using the CTABLE and
PPROB Options';
run;

```

```

containing values of the independent
variable at 1 point increments*;
proc datasets library = work
nolist kill;
run;
quit;
data a;

```

```

do newtotal=1 to 25 by 1;
/*must be the same name as the
independent var */
output;
end;
run;

**STEP TWO run above to generate
cc_SCORES**;
```

```

data cc_scores(Keep= newtotal
expired);
set justcabg;
run;

***STEP THREE create data set (PE)
used to generate the response curve**;
```

```

proc logistic data = cc_SCORES
DESCENDING NOPRINT
outest=parameter_estimates
;
model expired = newtotal;
run;

****data element entitled
newtotal is the parameter
estimate ****;
```

```

* STEP FOUR: Use PROC SCORE to apply
the parameter estimates created in STEP
THREE;
* to the data set containing the values
of newtotal from 1 to 25 PROC SCORE
creates a * dataset, called SCORED,
with the LOGITS obtained apply the PE to
the newtotal which is * the Cleveland
Clinic score;
```

```

PROC SCORE data=a out=SCORED
score=parameter_estimates
type=parms;
var newtotal;
run;

**This data set contains logit estimates,
NOT the Posterior Probability, which is
computed in a';

**STEP FIVE: the logits generated by
PROC SCORE are converted to probabilities
in the
* Data step below. **;
```

```

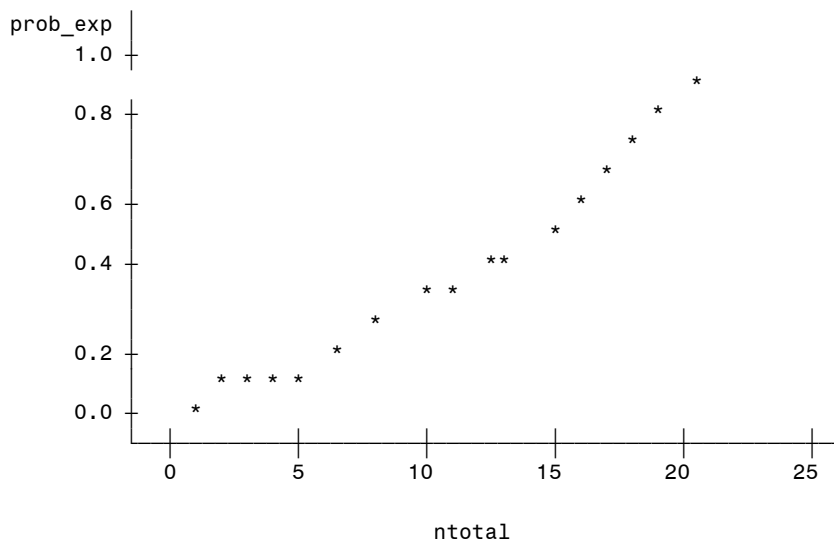
data c ;
set scored;
prob_exp=1/(1+exp(-expired));
label prob_exp =
"Predicted Prob *of Being*
Discharged Expired";
run;
proc print data = c;
run;

*****STEP SIX *****;
```

```

proc plot data = c;
Plot prob_exp * newtotal = '*' ;
/* plotted symbol */
title 'Plot of Probabilities of
CABG Pts being Discharge Expired
by CC Score (newtotal)';
run;
quit;
```

Plot of Probabilities of CABG Pts being Discharge Expired by CC Score (ntotal)  
Using Cleveland Clinic Scoring Methodology  
Plot of prob\_exp\*ntotal. Symbol used is '\*'.



This graph demonstrates a key aspect of logistic regression modeling: the change in probability of outcome is not the same across all values of the independent variable, the clinical score. Probability starts to escalate at 10 points and continues to increase at an increasing rate.

It was at this point we asked ourselves “how we could proactively apply this information to assist our Cardiologists and Cardio-thoracic surgeons?” As you know in healthcare, the provider has little control over its customer base – you service those patients who walk in your back door or are directed to your front door by your medical staff, i.e., “you get who you get.” As a result, we wanted to identify those risk factors that the physicians had some control over when a patient presented. There are really only two: serum creatinine, which indicates renal dysfunction, and hematocrit, which is an indicator of anemia. If a candidate for CABG has poor renal function, we can treat them medically to improve renal function (defined as serum creatinine < 168  $\mu$  mol/L). We actually found that the Cockcroft –Gault calculated creatinine clearance measure was a more accurate predictor of renal function of our patients, and defined poor output as CRCL  $\leq$  50. Likewise if a patient’s hematocrit is low, we can give that patient blood or blood products until his values improve (defined as a hematocrit > .34) and then take him to surgery.

What we found was startling. Globally (for both sexes), if a patient’s CRCL was  $\leq$  50, he or she was over four times (OR = 4.3) as likely to expire as those with a CRCL > 51. Since our overall mortality rate is 2.7%, this increases mortality to over 11%! If a patient’s hematocrit < .34, he or she were 1.7 times as likely to expire as those with a hematocrit > .34. In addition, and if you are older than 75 years of age, you are three times as likely to expire (ORs = 3.1). We stratified the data by gender to display on a 3” X 5” card so the physician could predict probability of expiration prior to surgery, and calculate the benefit of medically treating the patient’s renal dysfunction and low red blood cell count prior to the procedure.

Sample SAS code:

```
Proc logistic DES data = justcabg;
Model exp = ageGE75 critLT34 crclLE50;
Run;
```

### Model Information: Response Profile:

Dataset	Justcabg	Ordered Value	Respond	Total Freq.
Response Variable	Expired	1	1	45
Number of Response Levels	2	2	0	1596
Number of obs	1678			
Model	Binary logit			
Optimization technique	Fischer’s Scoring			

### Model fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	663.008	566.843
SC	668.434	588.547
-2 Log L	661.008	558.843

### Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	Degrees of Freedom	Pr > ChiSq
Likelihood Ratio	102.1655	3	<.0001
Score	143.0100	3	<.0001
Wald	95.7692	3	<.0001

Since the *Intercept and Covariates* AIC value is lower than *Intercept Only* we can state that this model is better than no model at all. The *p-values* indicate it is statistically significant.

### Analysis of Maximum Likelihood Estimates

Parameter	DF	Est.	Stand. Error	Chi-Square	Pr > ChiSq
Intercept	1	-4.057	0.207	383.556	<.0001
AGE75_2	1	1.133	0.2519	20.247	<.0001
CRITLT34_2	1	0.537	0.2386	5.067	0.0244
crclle50	1	1.460	0.2597	31.635	<.0001

*Depending on your threshold, the hematocrit < .34 may or may not be considered statistically significant, whereas both age  $\geq$  75 and CRCL  $\leq$  50 are SS.*

Effect	Odds Ratio Estimates		
	Point Est.	95% Wald Confidence Limits	
AGEge75	3.107	1.896	5.090
CRITlt34	1.711	1.072	2.731
crc1LE50	4.308	2.590	7.166

From here it was a relatively simple step to develop a summary of the predicted mortality risk by gender and by age group for the two risk factors that could be controlled medically by the cardiologist or the cardio-vascular surgeon. This was put on a 3 X 5 card that was laminated to hold up to daily wear and tear. The goal is to validate and/or update the expected mortality every six months as new data is entered into the system and analyzed.

Analysis of the other variables is updated monthly and shared with the *CABG Operations Improvement Team* as well as the cardiologists, cardiovascular surgeons and anesthesiologists. Other indicators that are being tracked include cross-clamp time, blood product usage, ventilation hours, length of stay for pre-op, post-op and CVU, mortality rate stratified by the Cleveland Clinic score groupings, deep wound infection rates, case volumes and average cost per case. These indicators are control charted each month.

### A sample 3 X 5 pocket guide :

#### Front:

**Overall Mortality Rate 2.7% - Male Mortality Rate 1.94%**

Gender	Age Range	Lab Values	Relative Risk Factor	Calculated Expected Mortality
Male	65-74		1.2	2.3%
	65-74	CRCL < 50	7.6	14.7%
	65-74	Crit < .34	1.1	2.1%
Male	75 +		2.7	5.2%
	75 +	CRCL < 50	4.9	9.5%
	75+	Crit < .34	1.25	2.4%

#### Bibliography

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- Higgins, TL, et al, Stratification of Morbidity and Mortality Outcome by Preoperative Risk Factors in Coronary Artery Bypass Patients – A Clinical Severity Score, JAMA, May 6, 1992, Vol. 267 No. 17.
- Karp, AH, Building and Applying Predictive Models Using the SAS System, Sierra

Gender	Age Range	Lab Values	Relative Risk Factor	Calculated Expected Mortality
Female	65-74		0.68	2.9%
	65-74	CRCL < 50	4.6	19.3%
	65-74	Crit < .34	3.6	15.1%
Female	75 +		3.4	14.3%
	75 +	CRCL < 50	3.2	13.4%
	75+	Crit < .34	3.6	15.1%

#### Back:

**Overall Mortality Rate 2.7% - Female**

**Mortality Rate 4.19%**

Gender	Age Range	Lab Values	Relative Risk Factor	Calculated Expected Mortality
Female	65-74		0.68	2.9%
	65-74	CRCL < 50	4.6	19.3%
	65-74	Crit < .34	3.6	15.1%
Female	75 +		3.4	14.3%
	75 +	CRCL < 50	3.2	13.4%
	75+	Crit < .34	3.6	15.1%

Information Services, Inc., 2002.

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