Case Study 2, Pt. 2

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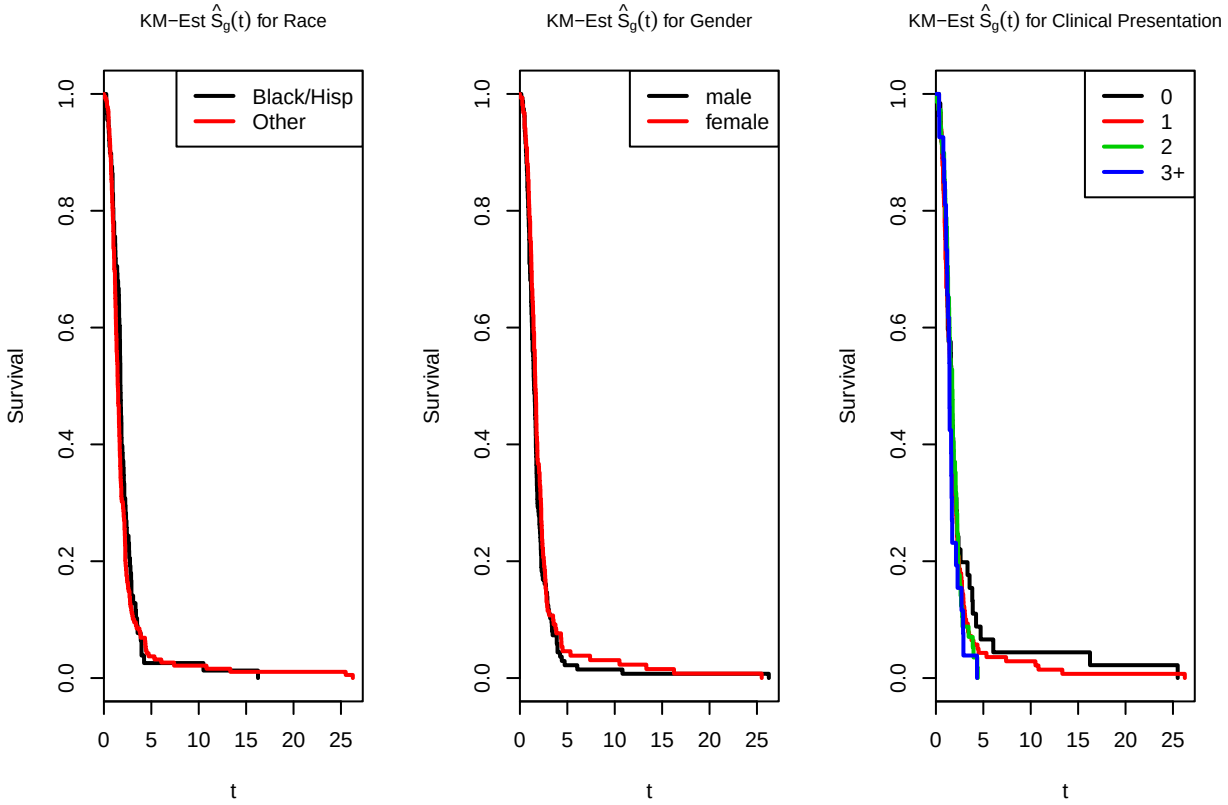
Introduction

The data are from a study of time to critical neurological assessment for patients with stroke-like symptoms who are admitted to the emergency room. We are interested in the factors predictive of the time to assessment following admission to the ED for n=335 patients with mild to moderate motor impairment. The goal of the analysis is to perform inferences on the impact of clinical presentation, gender, and race on time to neurological assessment, where clinical presentation is measured as the number of the four major stroke symptoms: headache, loss of motor skills or weakness, trouble talking or understanding, and vision problems.

Kaplan-Meier Analysis for Race, Gender, and Clinical Presentation

The first graph we created below is the overall survival curve. This curve shows how long the entire population in our dataset no matter the race, gender, or clinical condition will wait for evaluation. The graph also includes an upper and lower 95% confidence interval. Using this graph we know how the population is expected to wait. We can compare this estimated survival curve to the separate estimated survival curve for the different gender, race, and clincial condition groupings.



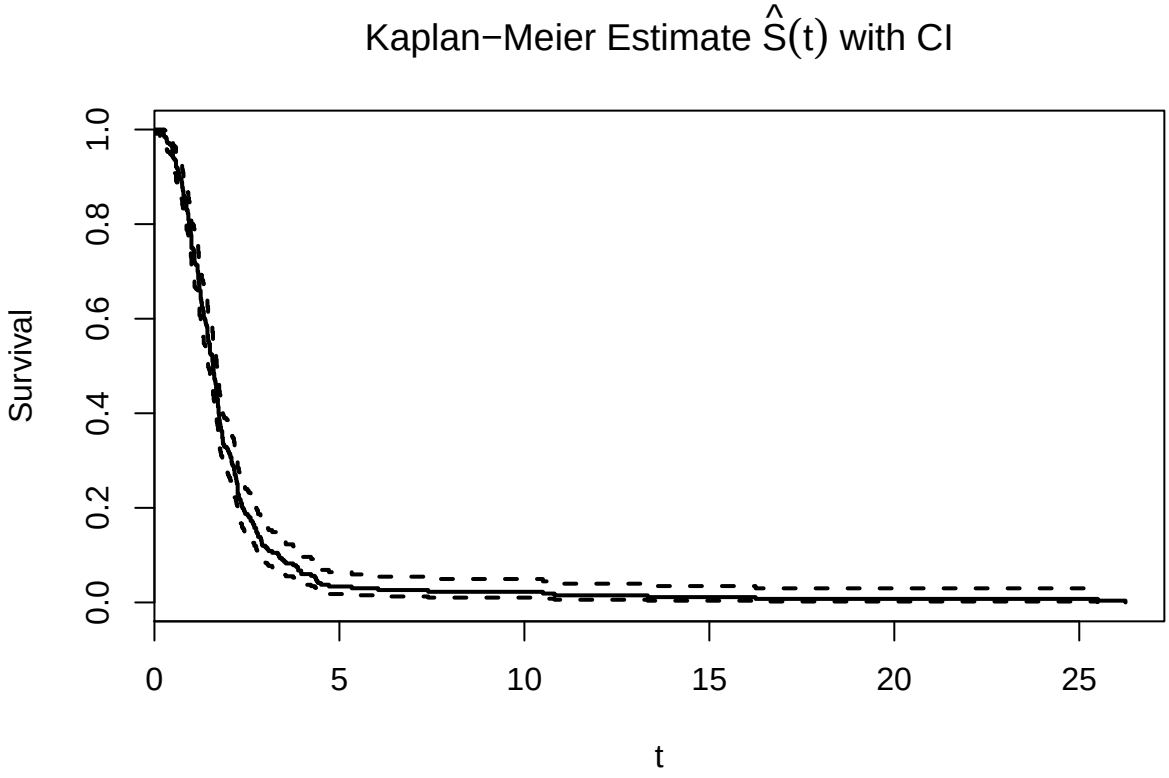


Figure 1: hello

From our Kaplan-Meier estimates for three different variables (race, gender, and the number of major stroke symptoms a patient shows), we observe that the survival curves are generally similar between 0-5 minute time range. However, thereappears a difference between the estimated survival curves for different number of symptoms a patient shows; specifically, people showing more symptoms tend to wait a shorter amount of time for their treatment. Overall, the survival curves are proportional, which is a key assumption to fit a Cox Proportional Hazard model.

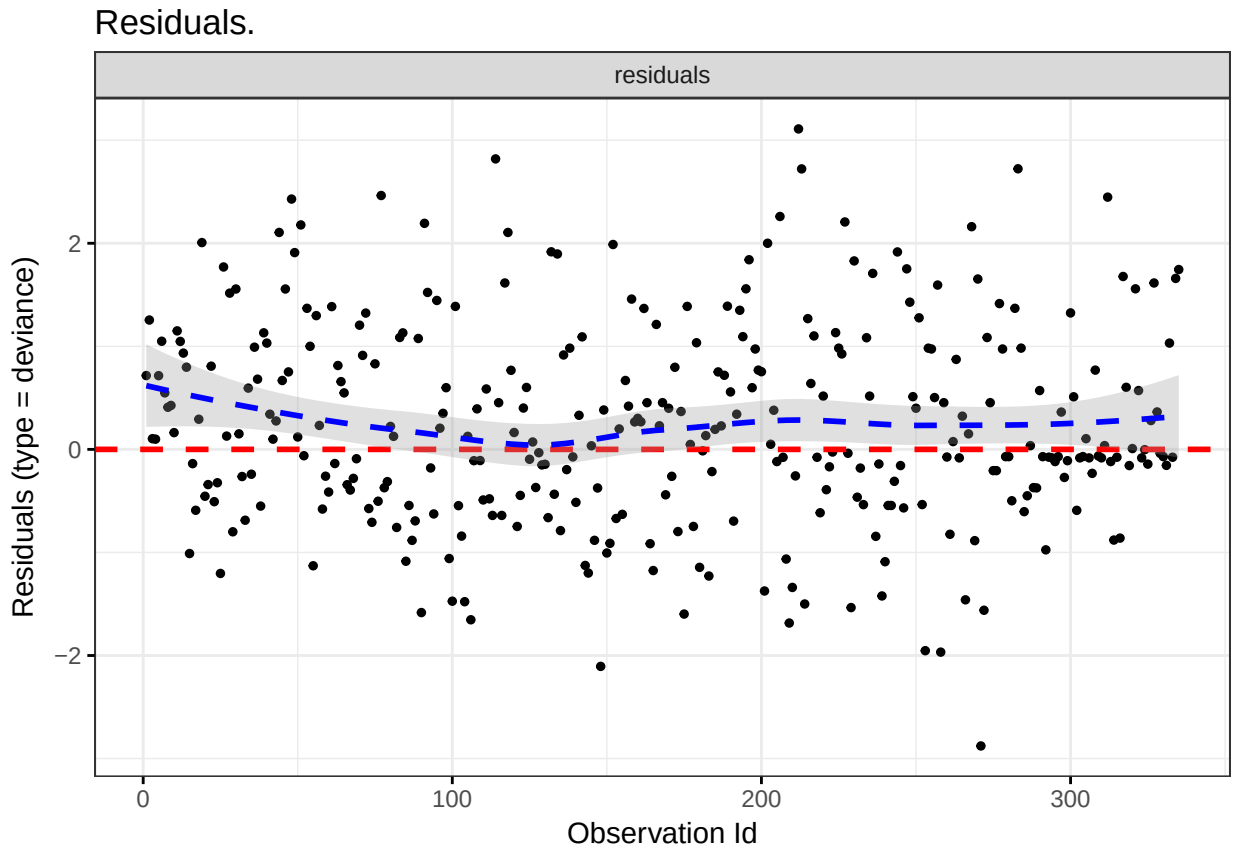
Cox Proportional Hazard

Below are models using Cox Proportional Hazard Model. This type of regression looks into the effects of variables upon the event in the data set which in this case is a CT scan. This model does assume the effects of the predictor variables upon survival are constant over time and are additive in one scale. We began by creating the models. They are Cox PH models for waiting time until event (CT scan) based on gender (female vs male), race (Black or Hispanic vs. non-Black or non-Hispanic), and number of symptoms (0,1,2, or 3+). Before analyzing any of these model we checked to see if the models are appropriate for the data by looking at the assumptions. Discussion is below.

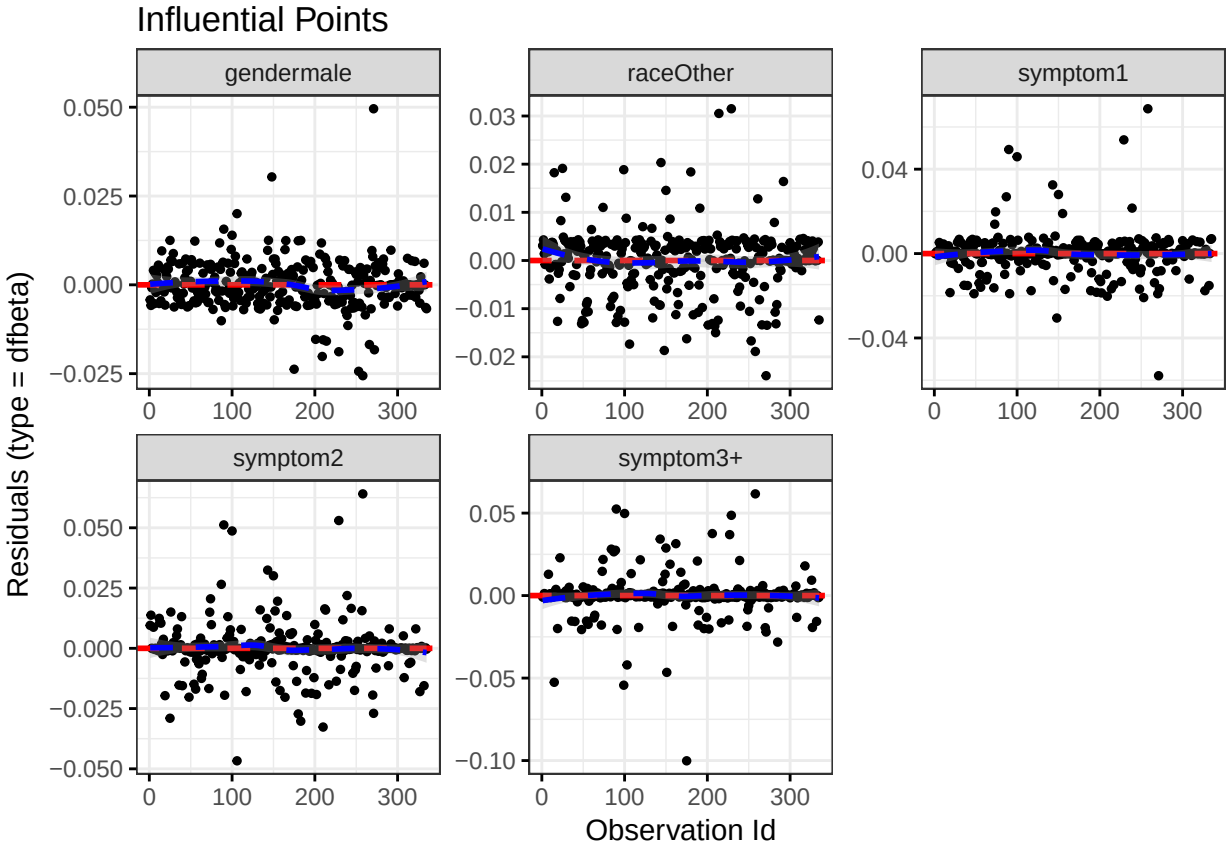
Diagnostics

Looking at the diagnostics for the model, we will first investigate the residuals and then look into the influential points. If the model assumptions hold we will then look into the proportional hazard assumption before continuing on into a results analysis section.

Looking at the residuals we see no pattern in the graph and a generally even spread number of points above and below 0.



Next, we investigate the influential points. For gender, although there are a few close to or above +/-.025 all of the points are below .05 so we do not consider any of the points influential. For race/ethnicity, looking into the influential points here, there are points as high as .04; however, again since there are no points are above/below .05 so we do not consider any of the points influential. Finally, for clinical presentation (0,1,2 or 3+ symptoms), looking into the influential points, there are different results. This time there are points as high as and higher than .05. Noticing this we acknowledge there are some points that will affect the fit of the model.



Finally, we checked the assumption of proportional hazard using the cox.zph() function. We check to see if the test is statistically significance (p-value under .05). Because none of the p-values for the covariates are singificant we can assume the hazards are proportional.

	rho	chisq	p
gendermale	0.0428024	0.4949243	0.4817389
raceOther	-0.1043511	2.9934221	0.0836033
symptom1	0.0160123	0.0690484	0.7927274
symptom2	0.0931383	2.3895166	0.1221514
symptom3+	0.0642341	1.1439961	0.2848095
GLOBAL	NA	7.5916755	0.1802215

Since all of the assumptions of the Cox Proportional Hazard model are met. We continue with looking into the results of the model.

Results

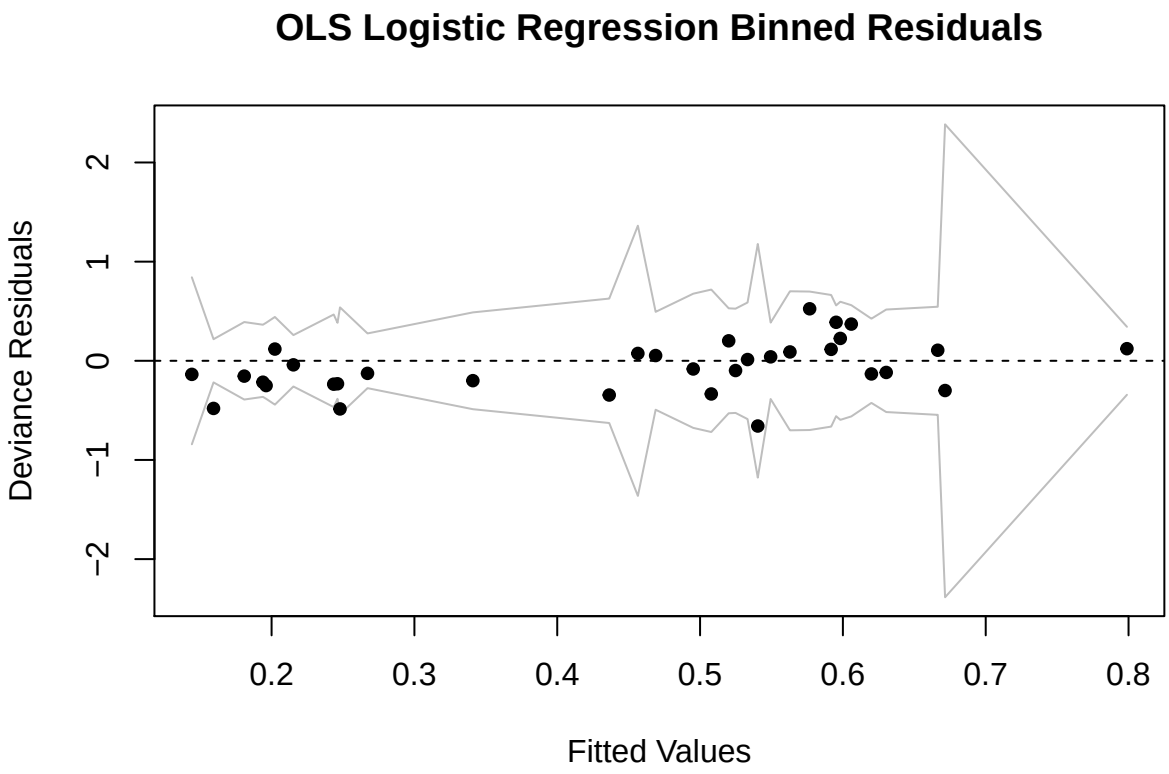
Looking at the summary of the model, we see if the patient is a male all else held constant we are 95% confident that the wait time until event will be between 0.6790 and 1.092 longer than female. If a patient is non black or non hispanic al else held constant we are 95% confident their wait time will be between 0.9052 and 1.527 more than black and hispanic patients. If a patient has 1 symptom, and all other factors are held constant, we are 95% confident they will wait between 0.8587 and 1.644 longer than a patient with 0 symptoms. If a patient had 2 symptoms all else held constant we are 95% confident they wait will wait between 0.8134 and 1.745 longer than a patient with 0 symptoms. Finally, we are 95% confident a patient with 3+ symptoms will wait between 1.505 and 0.132 longer than a patient with no symptoms.

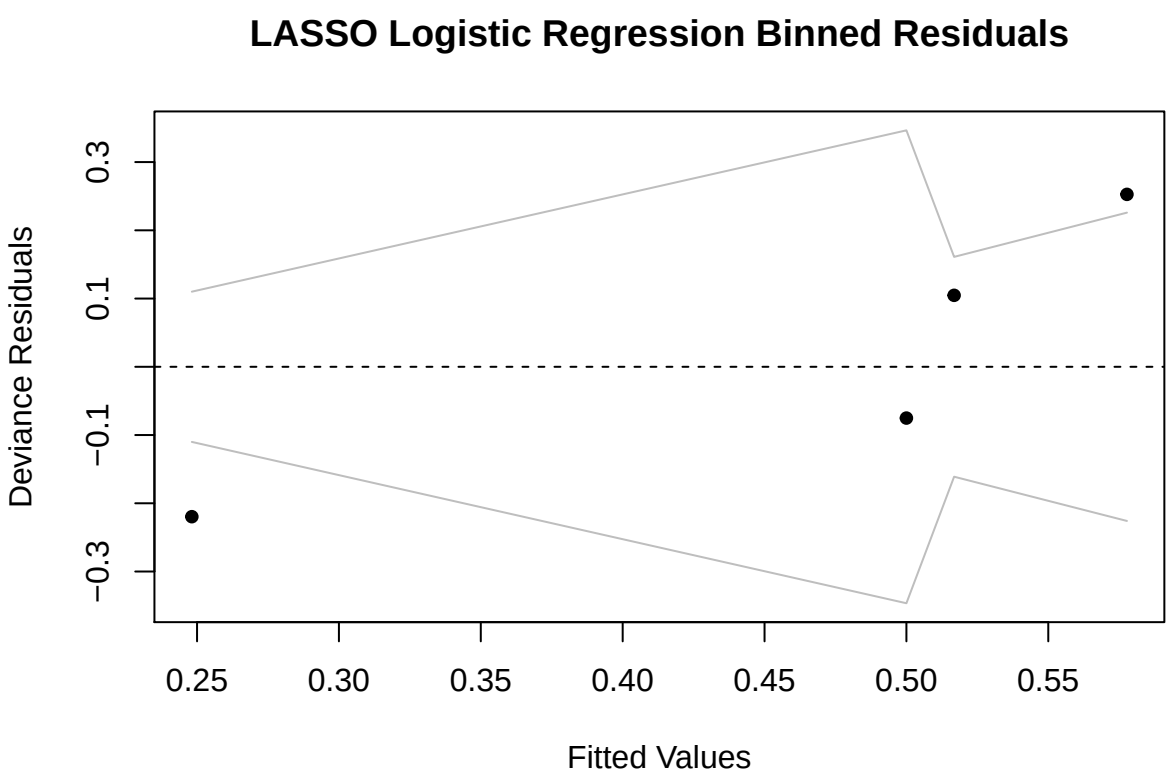
We note 3 things: first the 95% confidence interval contains 0 so this model suggests there is no gender, race, or clinical presentation bias. We also note that none of the variables are significant predictors in the model which supports the idea the wait response time is not influenced by gender, race, or clinical presentation. Finally, we do know the R-squared value is .016 so only 1.6% of the variance of the data is explained in the model. The summary statistics are reported below:

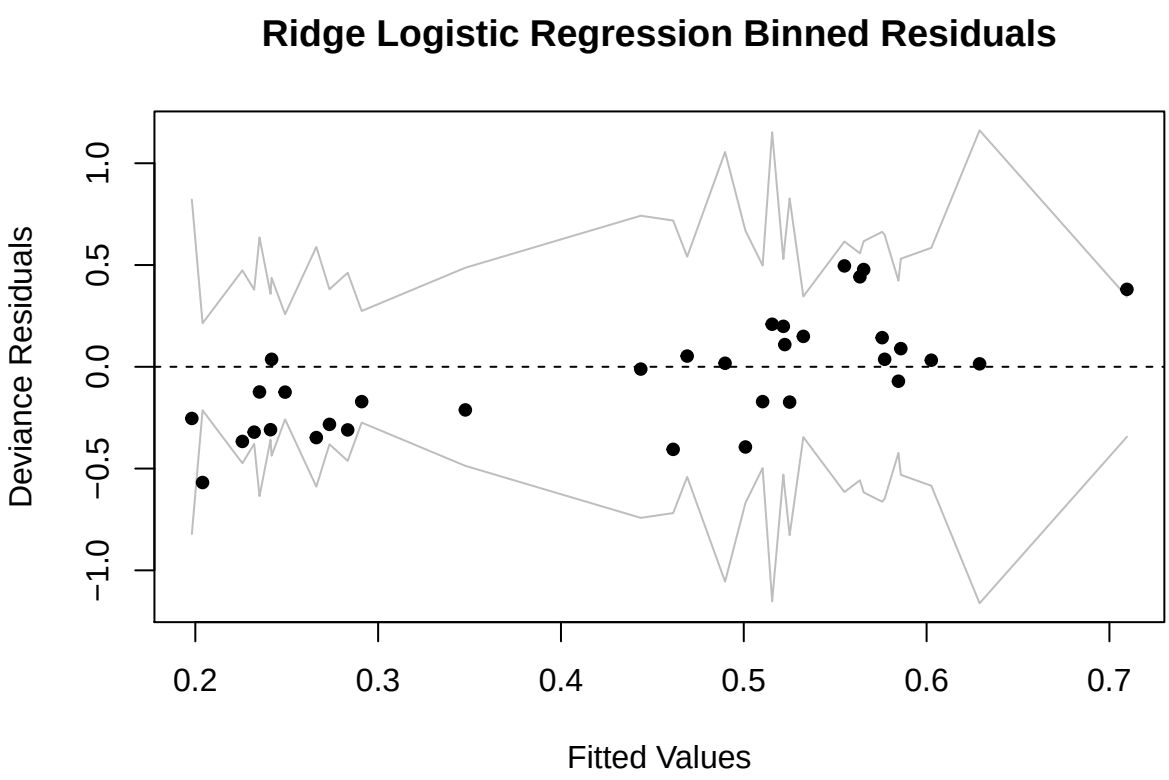
```
## Call:
## coxph(formula = Surv(nctdel, fail) ~ gender + race + symptom,
##     data = dat)
##
##   n= 335, number of events= 277
##
##               coef exp(coef) se(coef)      z Pr(>|z|)
## gendermale -0.1496    0.8610   0.1212 -1.235    0.217
## raceOther   0.1620    1.1758   0.1335  1.214    0.225
## symptom1    0.1724    1.1881   0.1657  1.040    0.298
## symptom2    0.1750    1.1913   0.1947  0.899    0.369
## symptom3+   0.3674    1.4439   0.2441  1.505    0.132
##
##            exp(coef) exp(-coef) lower .95 upper .95
## gendermale     0.861     1.1614    0.6790     1.092
## raceOther      1.176     0.8505    0.9052     1.527
## symptom1       1.188     0.8417    0.8587     1.644
## symptom2       1.191     0.8394    0.8134     1.745
## symptom3+      1.444     0.6925    0.8949     2.330
##
## Concordance= 0.538  (se = 0.021 )
## Rsquare= 0.016   (max possible= 1 )
## Likelihood ratio test= 5.45  on 5 df,   p=0.3635
## Wald test            = 5.43  on 5 df,   p=0.3659
## Score (logrank) test = 5.45  on 5 df,   p=0.3635
```

Logistic Regression

To perform logistic regression on the data, we categorized the time-to-event variable into groups of 1 minute, with all events occuring after 5 minutes grouped together, since the sample size was so low after that time (only 9 observations). Our predictors consisted of these time categories, as well as the aforementioned categories of race, gender, and clinical presentation. The binned residual plots, deviance test results, and coefficients are all reported below. We attempted three approaches to logistic regresion: Ordinary Least Squares (OLS), LASSO, and Ridge. The `glmnet` package does not provide standard errors for its coefficients, so we cannot report confidence intervals for their estimates.


OLS Logistic Regression Binned Residuals
Deviance Residuals
2
1
0
−1
−2
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Fitted Values


LASSO Logistic Regression Binned Residuals
Deviance Residuals
0.3
0.1
−0.1
−0.3
0.25
0.30
0.35
0.40
0.45
0.50
0.55
Fitted Values



	p-value
OLS	0.0001892
LASSO Penalty	0.0000864
Ridge Penalty	0.0001004

	Lower	Upper
symptom0	-1.2347601	0.1283479
symptom1	-0.8127602	0.4191924
symptom2	-0.9683374	0.3673047
raceother	-0.2452423	0.4813876
male	-0.6261211	0.0438997
X1	-1.6083259	-0.2652622
X2	-0.1101020	1.2463909
X3	0.1159377	1.6605533
X4	-0.6473568	1.2666928
X5	-1.0553386	1.3368735
X6	-926.4904815	958.4814375

	Estimate
(Intercept)	0.0000
symptom0	0.0000
symptom1	0.0000

	Estimate
symptom2	0.0000
raceother	0.0000
male	0.0000
X1	-1.0942
X2	0.0517
X3	0.2040
X4	0.0000
X5	0.0000
X6	1.0824

	Estimate
(Intercept)	0.0000
symptom0	-0.1794
symptom1	-0.0396
symptom2	-0.0943
raceother	-0.0503
male	-0.1487
X1	-0.5957
X2	0.2244
X3	0.3408
X4	0.0587
X5	-0.0137
X6	1.0283

All three of our logistic regression approaches—OLS, LASSO, and Ridge—did not find much difference between these groups. In the OLS model, the only coefficients that do not contain zero in their 95% confidence interval are X1 and X3. In the LASSO and Ridge models, The majority of coefficients are close to zero or exactly zero, and all of the models fit the data poorly according to the deviance test. The residual plots also suggest a poor fit for all the models other than the OLS model. Therefore, we cannot confidently claim that any of these factors are predictive of the time to assessment.

Contributions

Nathaniel built the logistic regression model and the supporting visualizations and summary statistics. Sarah built and analyzed the Cox Proportional Hazard model.

References

http://influentialpoints.com/Training/coxs_proportional_hazards_modression_model-principles-properties-assumptions.htm#modmch

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