Team Sigma: Galvin Li, Dominic Matriccino, & Kevin Nguyen

Background: Our regression problem is to determine if we can predict the passenger fare using a variety of covariates. Our classification problem is to determine if we can predict whether a passenger survived the Titanic's sinking using a variety of covariates. The variables for port of embarkation and passenger class were converted into factors with three levels each, and the variables for sex and survival were converted into factors with two levels each. The data frame of 891 observations was split 70-30 into a training set (623 observations) and a testing set (268 observations), and there were no missing values.

Regression Problem: Four methods were chosen to approach the regression problem: a naive method, OLS, ridge, and lasso regression. For the naive method, the sample mean of the fares for the training set's passengers - 30.93614 pounds - was used as the prediction for the fares of the test set's passengers. For ridge regression and lasso regression, the tuning parameter was chosen via 10-fold cross validation. We found that the optimal lambda for ridge regression was 1.929175, and the optimal lambda for lasso was 0.06617977 (Appendix F). Interestingly, at the optimal lambda for lasso, no variable selection was performed as there were still nine covariates in the model. Appendices D and E present the outputs of OLS, ridge, and lasso regression. From it, we can see that both ridge and lasso regression's coefficients were shrunk towards zero, but ridge regression's shrinkage was generally more severe. The MSPEs for all four methods are shown in Appendix B. Overall, when the models were applied to testing data, the naive sample mean method (MSPE = 3580.933) was determined to have the worst performance while OLS (MSPE = 2249.013) had the best performance. It's likely that OLS performed better than both shrinkage methods because the increase in bias was greater than the decrease in variance. Lasso (MSPE = 2251.337) performed better than ridge regression (MSPE = 2277.664), and this might be because lasso's less severe coefficient shrinkage allowed it to be less biased and more closely resemble OLS's model than ridge regression. The signs of the coefficients of all three regression models inform us that survival and traveling with more family members were associated with more expensive fares while embarking from Southampton and Queenstown, being older, being male, and having a lower class ticket were associated with a less expensive fare.

Classification Problem: For our classification question we decided that it would be best to use logistic regression given that we have a mix of categorical and quantitative input variables. Also, logistic regression is superior to methods such as linear discriminant analysis because it does not require the usual linear regression assumptions such as normality and homoscedasticity. After fitting the model, however, we still needed to check that multicollinearity is not going to affect our model, which is one of the few assumptions of logistic regression. To check this we simply checked the variance inflation factors for all of our input variables and all the VIF coefficients were below 2, which means we can be pretty certain that multicollinearity is not present (Appendix G). After fitting our model and checking the VIF coefficients, we tested our model on test data. Using our 267 test observations we received an accuracy rate of roughly 74.25%. This was lower than all three of the other methods that we looked at such as naive bayes, LDA and QDA (Appendix C). The FPR is 14.89% and the FNR is 31.61%. It is no surprise that our FNR is higher than FPR given the unbalance in our data. Overall, logistic regression underwhelmed us in its prediction ability as it had the lowest accuracy.

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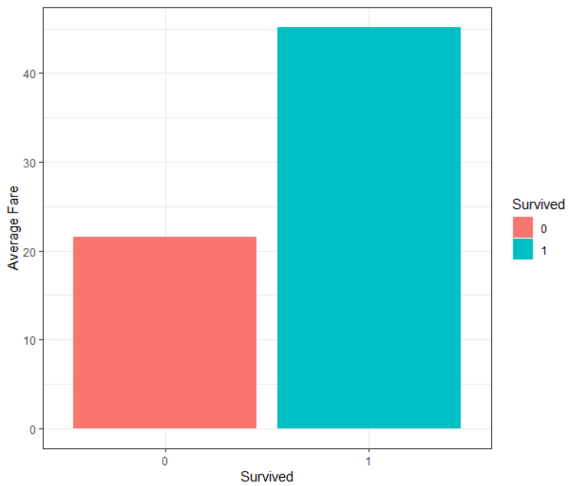
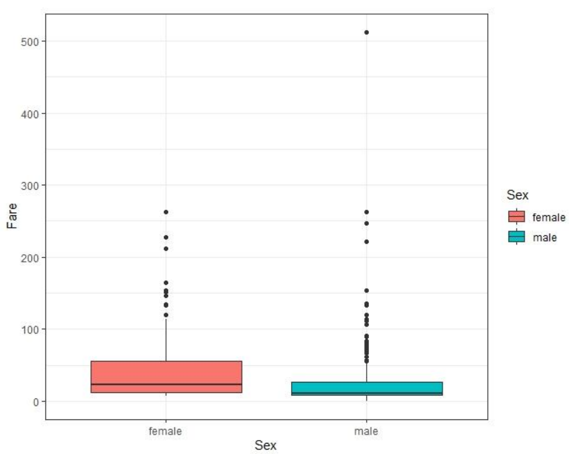
Appendix A: Exploratory Data Analysis	
Figure	**Description**
	This figure illustrates the average fare for survivors vs. non-survivors. Survivors paid, on average, more than double the fare of non-survivors. There appears to be a positive association between survival and fare.
	This figure illustrates the fare for females vs. males. Females had a higher median fare. Furthermore, the fare is much more spread out among females compared to males. In general, it appears females paid a higher fare than males. However, the figure indicates the distribution of the fare is positively skewed for both sexes.

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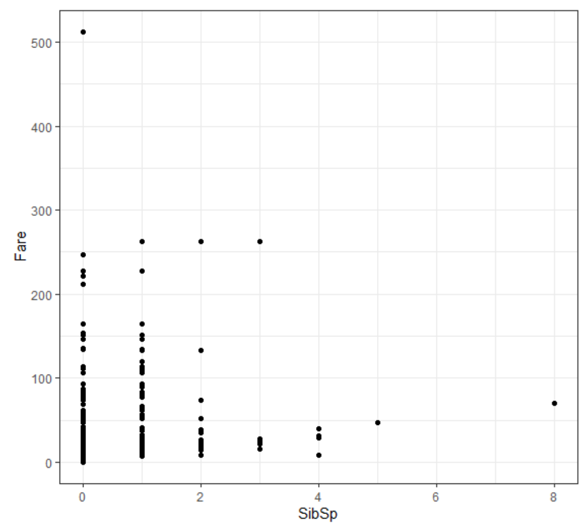
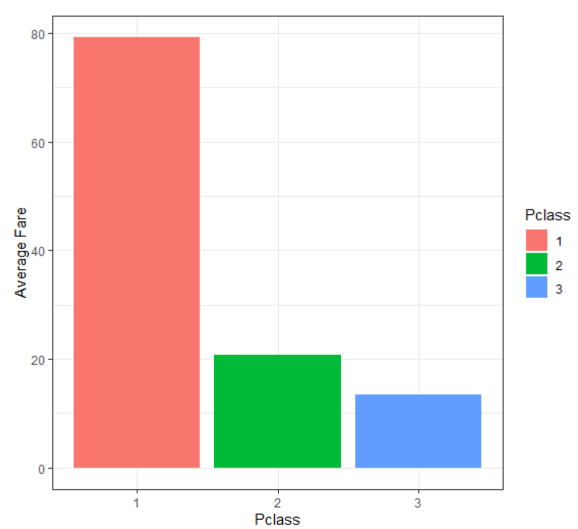
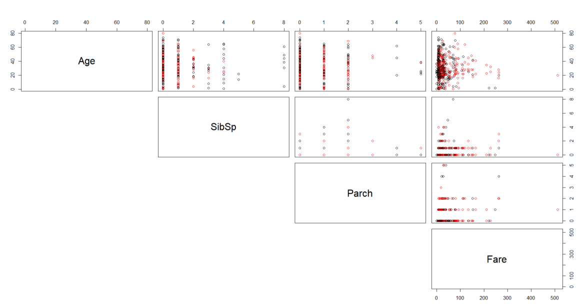


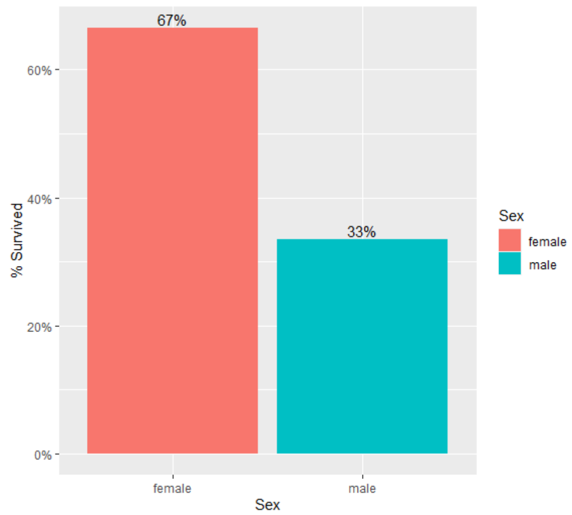
This figure illustrates the fare vs. the number of siblings/spouses a passenger had on board with them on the Titanic. There appears to be no clear linear trend between the variables. But, the figure illustrates positively skewed data for the variable SibSp.



This figure illustrates the average fare vs. the passenger ticket class. First-class passengers had a substantially higher fare than second- and third-class passengers. Second-class passengers had only a moderately higher fare than third-class passengers. This result was to be expected as first-class tickets always cost more



This figure illustrates the relationships between the quantitative variables with each dot colored depending on if the passenger survived. The red dots represent the passengers that did survive and the black dots represent the passengers who did not survive.



This figure illustrates out of all the passengers who survived, 67% were female and 33% were male. There appears to be a possible correlation between sex and survival.

Appendix B: Comparison of Regression Methods MSPE

Naive	**OLS**	**Ridge**	**Lasso**
3580.933	2249.013	2277.664	2251.337

Appendix C: Comparison of Classification Methods Accuracy

Naive Bayes	**Logistic Regression**	**LDA**	**QDA**
0.7873134	0.7425373	0.7835821	0.7947761

Appendix D: Output of OLS Regression

```
> coef(ols)
10 x 1 sparse Matrix of class "dgCMatrix"
                      s0
(Intercept)  84.17065181
Survived1     2.42799654
Pclass2     -55.67538242
Pclass3     -63.82541180
Sexmale      -4.85521247
Age          -0.09276794
SibSp         5.91449883
Parch         9.78408209
EmbarkedQ    -8.71219024
EmbarkedS   -10.56070301
```

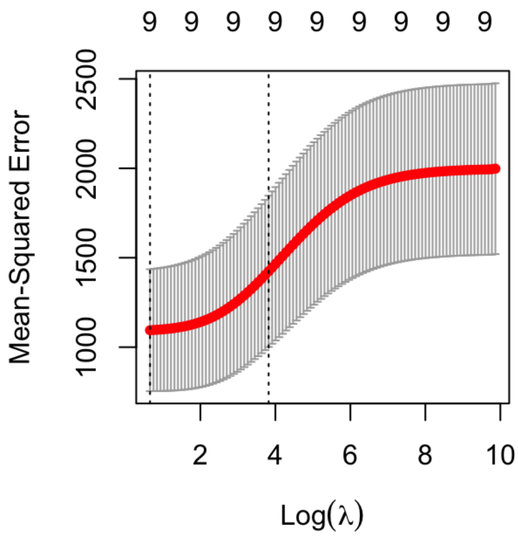
Appendix E: Output of Ridge and Lasso Regression

```
> coef(ridge)
10 x 1 sparse Matrix of class "dgCMatrix"
                      s0
(Intercept)  79.74395258
Survived1     3.73376898
Pclass2     -49.59379815
Pclass3     -57.83536302
Sexmale      -4.70008288
Age          -0.08825074
SibSp         5.66840616
Parch         9.33682209
EmbarkedQ   -10.36478845
EmbarkedS   -11.16773614
```

```
> coef(lasso)
10 x 1 sparse Matrix of class "dgCMatrix"
                      s0
(Intercept)  83.63459779
Survived1     2.41821872
Pclass2     -55.34919744
Pclass3     -63.60080242
Sexmale      -4.77519873
Age          -0.08785925
SibSp         5.86926270
Parch         9.73838705
EmbarkedQ    -8.36146707
EmbarkedS   -10.34147756
```

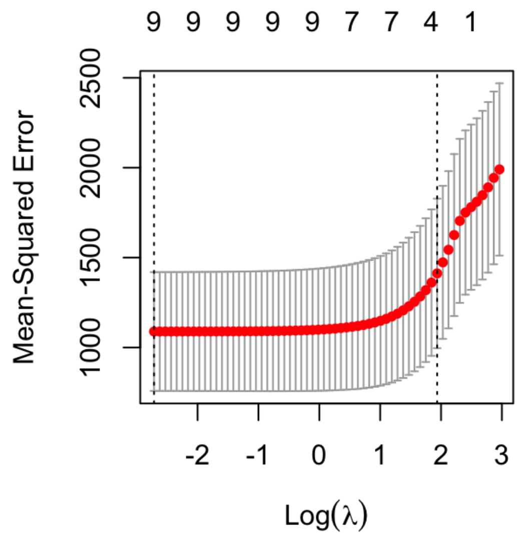
Appendix F: Cross-Validation for Ridge and Lasso Regression

Ridge




```
> lambda.ridge
[1] 1.929175
```

Lasso




```
> lambda.lasso
[1] 0.06617977
```

Appendix G: VIF Coefficients

```
             GVIF Df GVIF^(1/(2*Df))
Sex      1.254601  1        1.120090
Pclass   1.837180  2        1.164228
SibSp    1.259110  1        1.122101
Embarked 1.232959  2        1.053749
Parch    1.341439  1        1.158205
Fare     1.691259  1        1.300484
Age      1.030148  1        1.014962
```

Appendix H: Logistic Regression Output

```
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  2.763758   0.475662   5.810 6.23e-09 ***
Sexmale     -2.762089   0.242728 -11.379  < 2e-16 ***
Pclass2     -0.453617   0.339489  -1.336  0.18149
Pclass3     -1.492784   0.325893  -4.581 4.64e-06 ***
SibSp       -0.207360   0.111829  -1.854  0.06370 .
EmbarkedQ   -0.628973   0.451793  -1.392  0.16387
EmbarkedS   -0.817231   0.276475  -2.956  0.00312 **
Parch       -0.096304   0.139925  -0.688  0.49129
Fare         0.002637   0.003260   0.809  0.41863
Age          0.004619   0.007453   0.620  0.53541
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 837.59  on 622  degrees of freedom
Residual deviance: 571.49  on 613  degrees of freedom
AIC: 591.49
```