

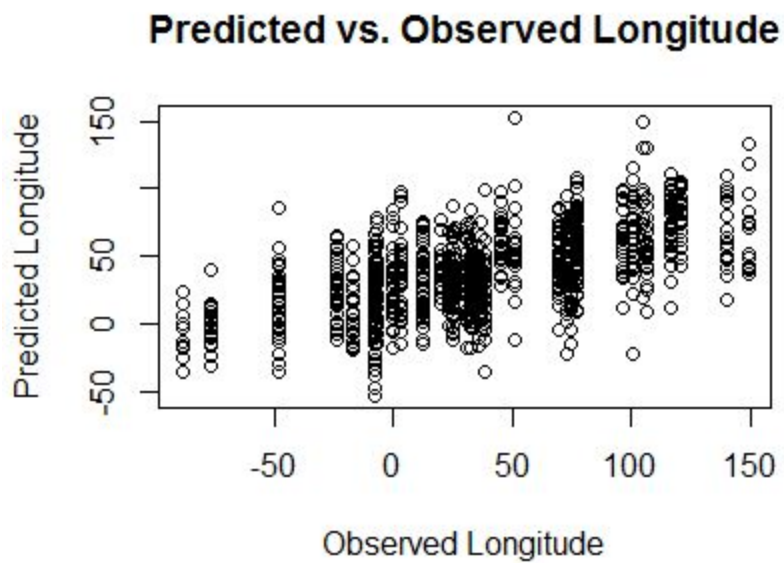
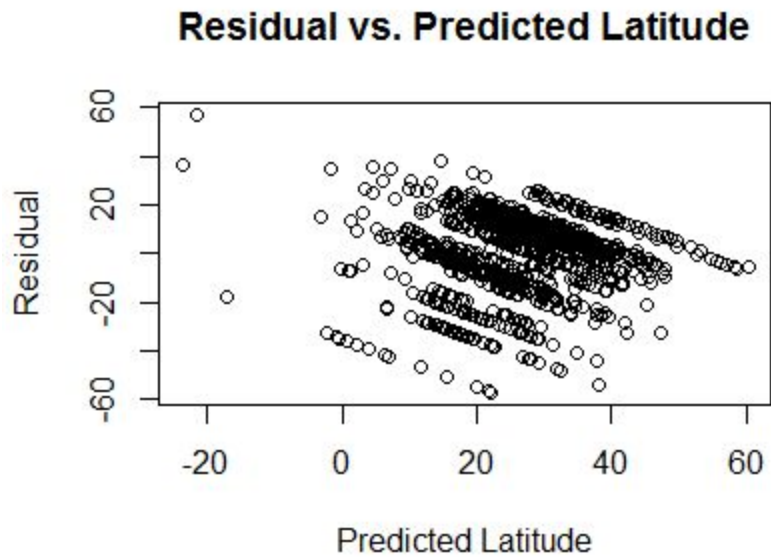
Assignment 6 Report

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Q1.

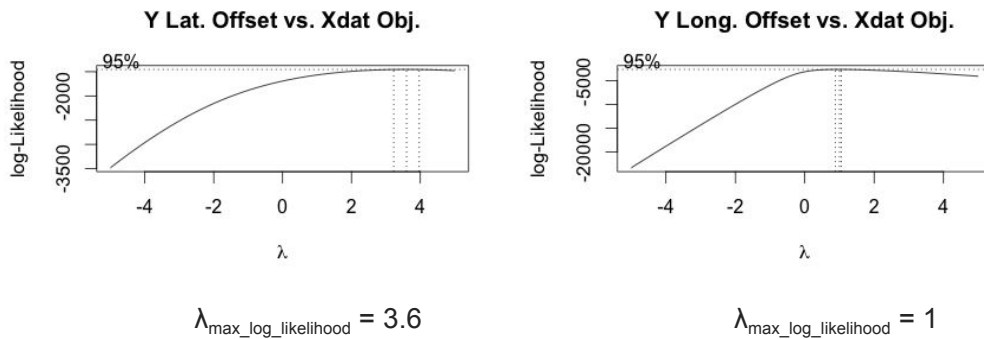
- 1) Build a straightforward linear regression of latitude (resp. longitude) against features. What is the R-squared? Plot a graph evaluating each regression. (see regression.R)

R-squared: 0.3645767



- 2) Does a Box-Cox transformation improve the regressions? **Notice that the dependent variable has some negative values, which Box-Cox doesn't like. You can deal with this by remembering that these are angles, so you get to choose the origin.** Why do you say so? For the rest of the exercise, use the transformation if it does improve things, otherwise, use the raw data. (see regression.R)

Offset of 90 was chosen to generate the below graphs:

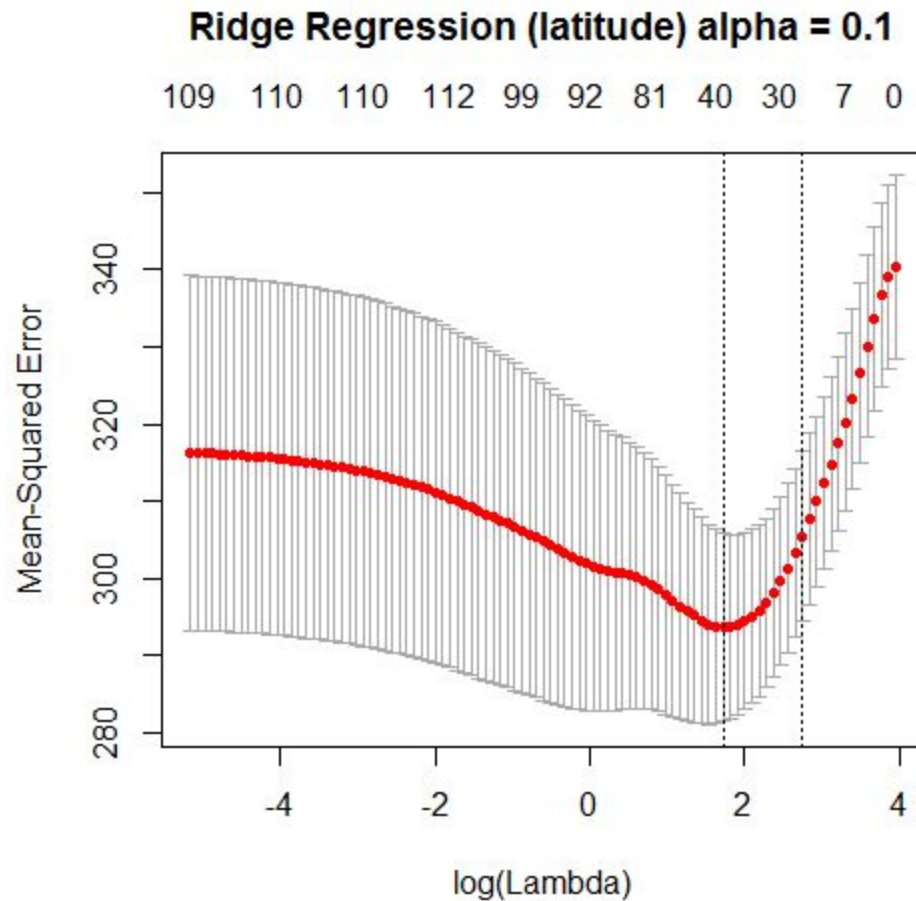


Box-Cox transformation does not improve the regressions. Box-Cox produced values $R^2_{lat} = 0.248$ and $R^2_{long} = 0.365$, which are not higher than the values produced by the previously performed linear regression.

- 3) Use glmnet to produce... (see q1.R) Note: a 70/30 split was used
- Unregularized regression
- Longitude mean square error: 279.5661
- Latitude mean square error: 1978.276
- a) A regression regularized by L2 (equivalently, a **ridge** regression). You should estimate the regularization coefficient that produces the minimum error. Is the regularized regression better than the unregularized regression?

Latitude

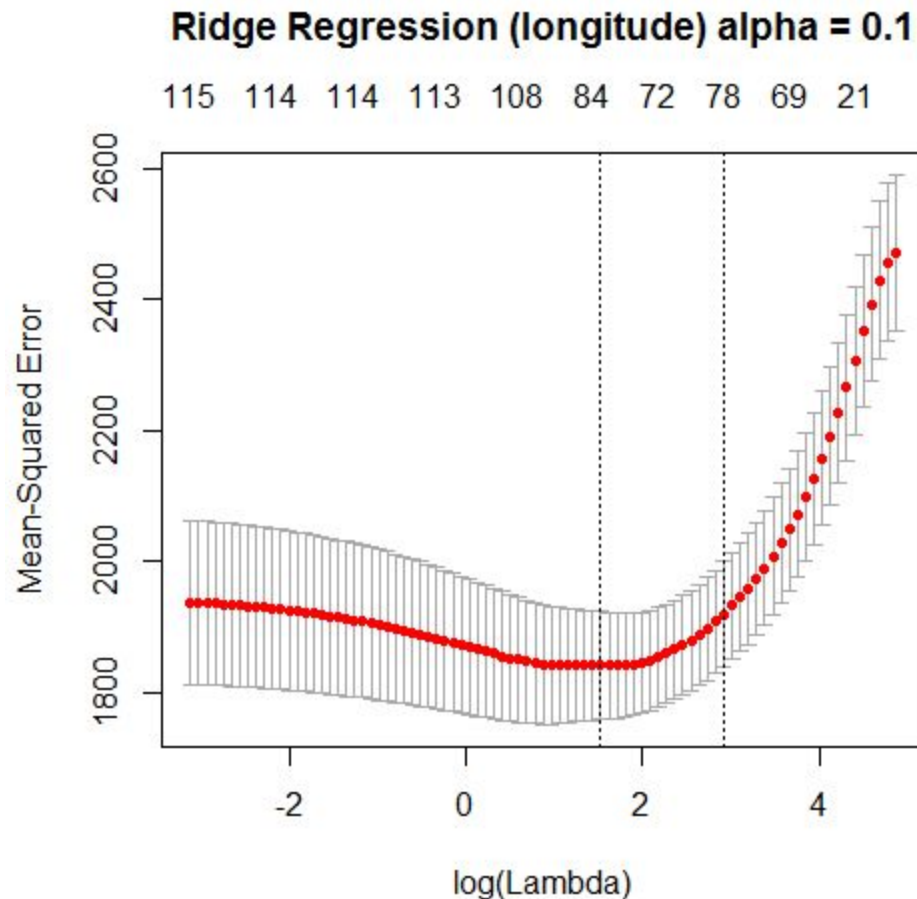
Alpha	Best Regularization Coefficient	Mean Square Error
0	14.911032	265.9078
0.1	5.613908	259.9988
0.2	4.072410	262.7145



There is a small level of variability of error. The number of nonzero components of beta ranges from 20 to 40 for regularization constants that produce data within the variability of error. As $\log(\lambda)$ increases, the number of nonzero components fall, ensuring that explanatory variables with small coefficients are dropped. Eventually, there are no nonzero constants as $\log(\lambda)$ approaches 4.

Longitude

Alpha	Best Regularization Coefficient	Mean Square Error
0	13.361476	1994.300
0.1	4.583613	1983.270
0.2	4.004997	1994.585



There is a moderate level of variability of error. The number of nonzero components of beta ranges from 72 to 84 for regularization constants that produce data within the variability of error. As $\log(\lambda)$ increases, the number of nonzero components fall, ensuring that explanatory variables with small coefficients are dropped, with the exception of extremely small $\log(\lambda)$ that range from -4 to -1, and when $\log(\lambda)$ is near the value producing the smallest MSE, resulting in a small local peak of the number of nonzero components.

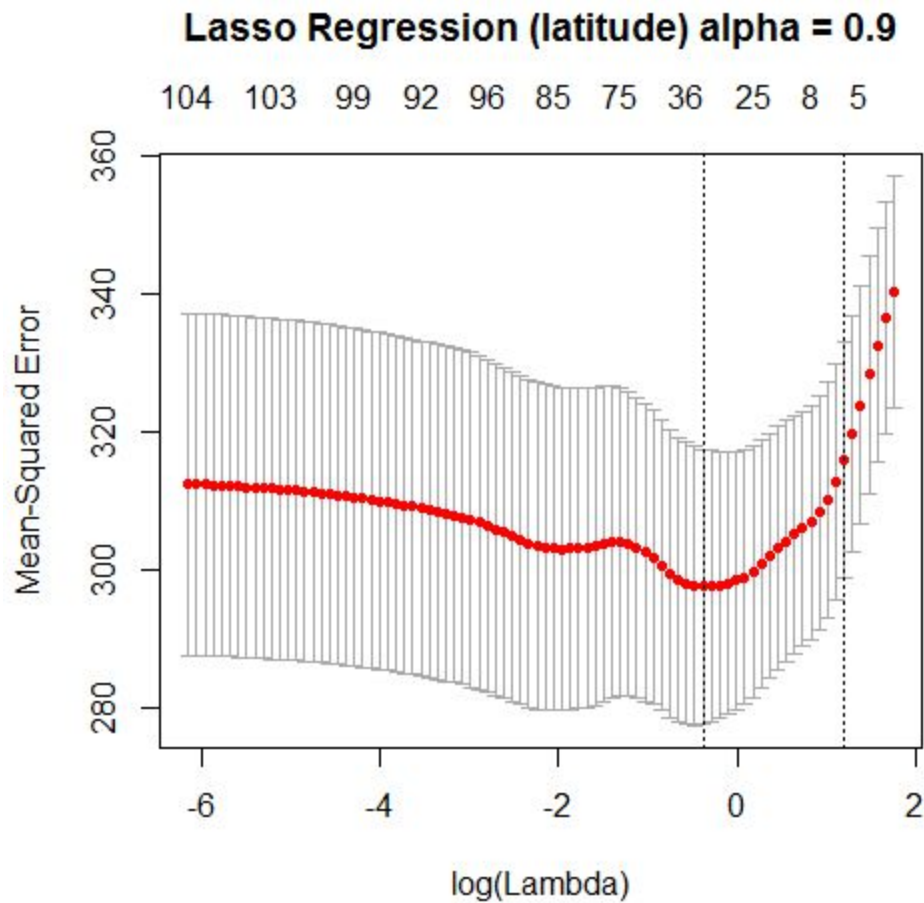
A ridge regression with $\alpha = 0$ is comparable with the unregularized regression.

- b) A regression regularized by L1 (equivalently, a **lasso** regression). You should estimate the regularization coefficient that produces the minimum error. How many variables are used by this regression? Is the regularized regression better than the unregularized regression?

Latitude

Alpha	Best Regularization Coefficient	Mean Square Error
0.8	0.7701571	255.1694

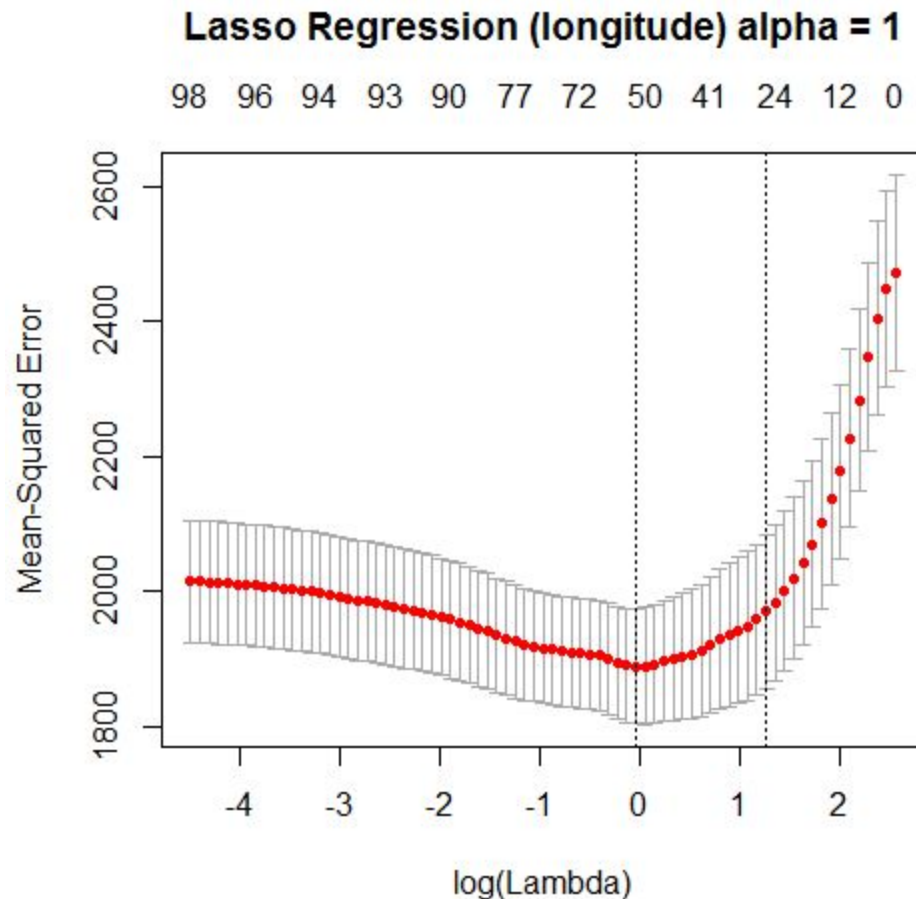
0.9	0.6845841	255.0576
1	0.6761972	255.9621



There is a large level of variability of error. The number of nonzero components of beta ranges from 6 to 35 for regularization constants that produce data within the variability of error. As $\log(\lambda)$ increases, the number of nonzero components fall, ensuring that explanatory variables with small coefficients are dropped.

Longitude

Alpha	Best Regularization Coefficient	Mean Square Error
0.8	1.2060084	1992.582
0.9	1.1765268	1995.617
1	0.9648067	1991.925



There is a moderate level of variability of error. The number of nonzero components of beta ranges from 25 to 51 for regularization constants that produce data within the variability of error. As $\log(\lambda)$ increases, the number of nonzero components fall, ensuring that explanatory variables with small coefficients are dropped.

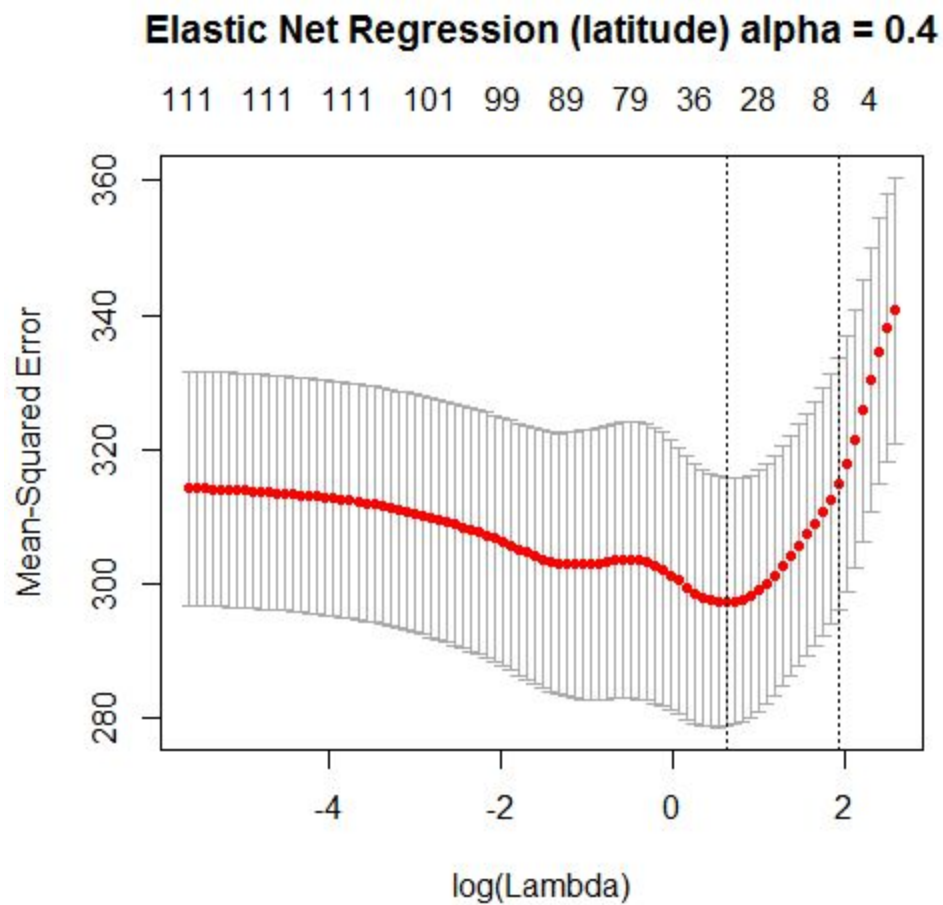
A lasso regression with $\alpha = 1$ is worse than the unregularized regression.

- c) A regression regularized by elastic net (equivalently, a regression regularized by a convex combination of L1 and L2). Try three values of alpha, the weight setting how big L1 and L2 are. You should estimate the regularization coefficient that produces the minimum error. How many variables are used by this regression? Is the regularized regression better than the unregularized regression?

Latitude

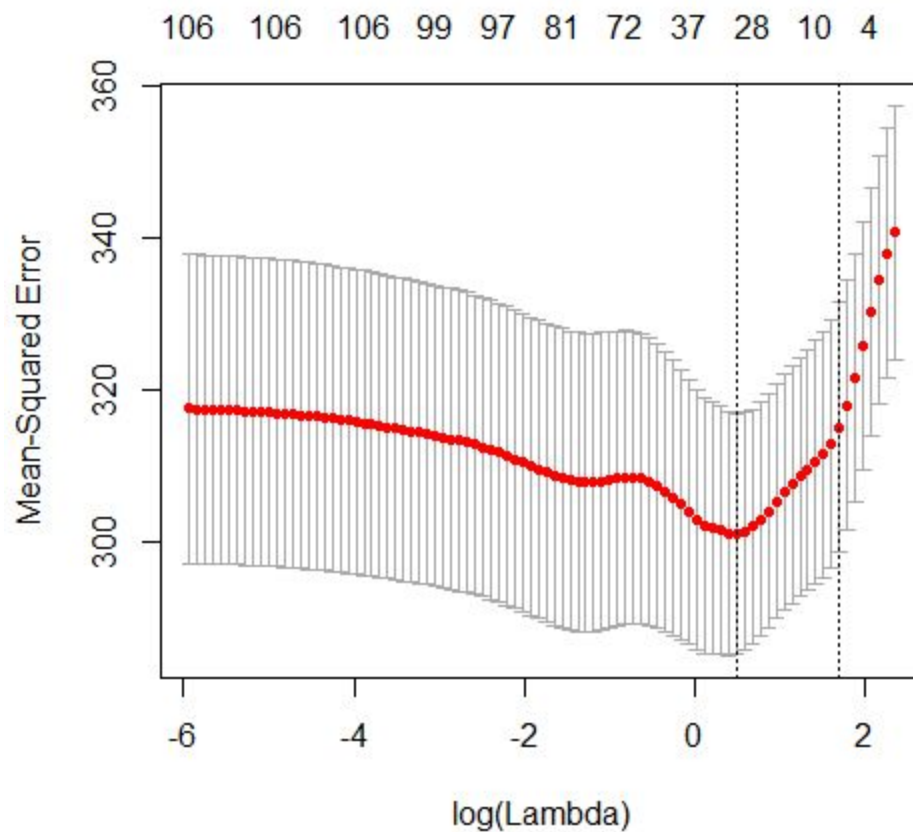
Alpha	Best Regularization Coefficient	Mean Square Error
0.4	1.855314	258.6537
0.5	1.628964	259.7221

0.6	1.026876	255.5064
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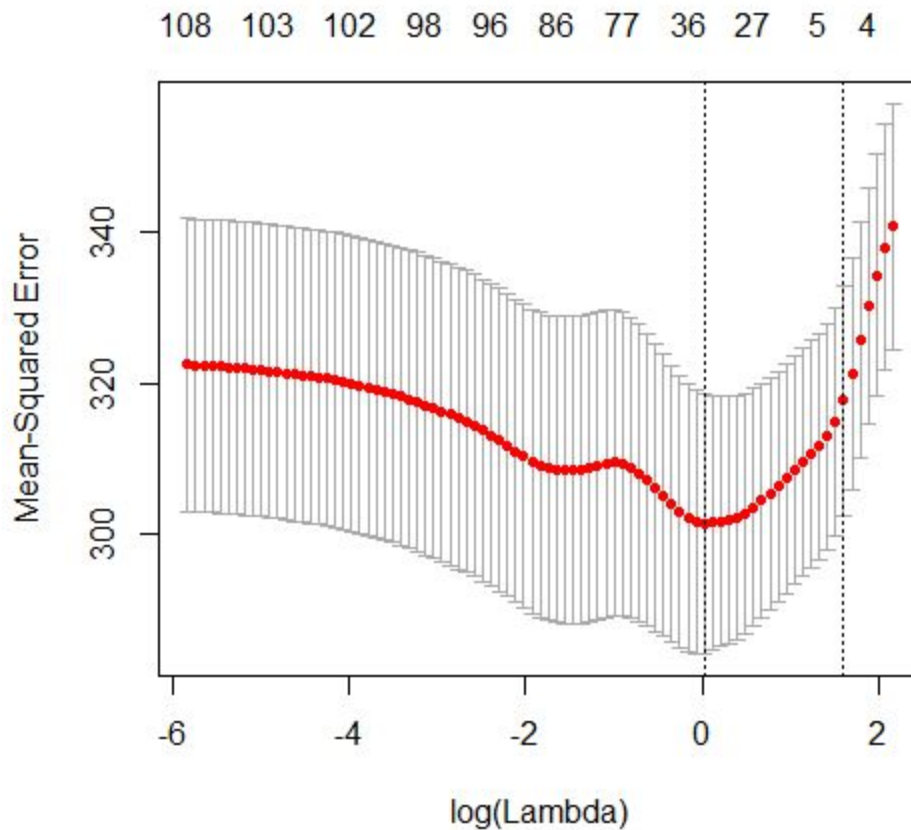
There is a moderate level of variability of error. The number of nonzero components of beta ranges from 7 to 35 for regularization constants that produce data within the variability of error. As $\log(\lambda)$ increases, the number of nonzero components fall, ensuring that explanatory variables with small coefficients are dropped, with the exception of extremely $\log(\lambda)$ that range from -6 to -4.

Elastic Net Regression (latitude) $\alpha = 0.5$



There is a moderate level of variability of error. The number of nonzero components of β ranges from 8 to 30 for regularization constants that produce data within the variability of error. As $\log(\lambda)$ increases, the number of nonzero components fall, ensuring that explanatory variables with small coefficients are dropped.

Elastic Net Regression (latitude) alpha = 0.6

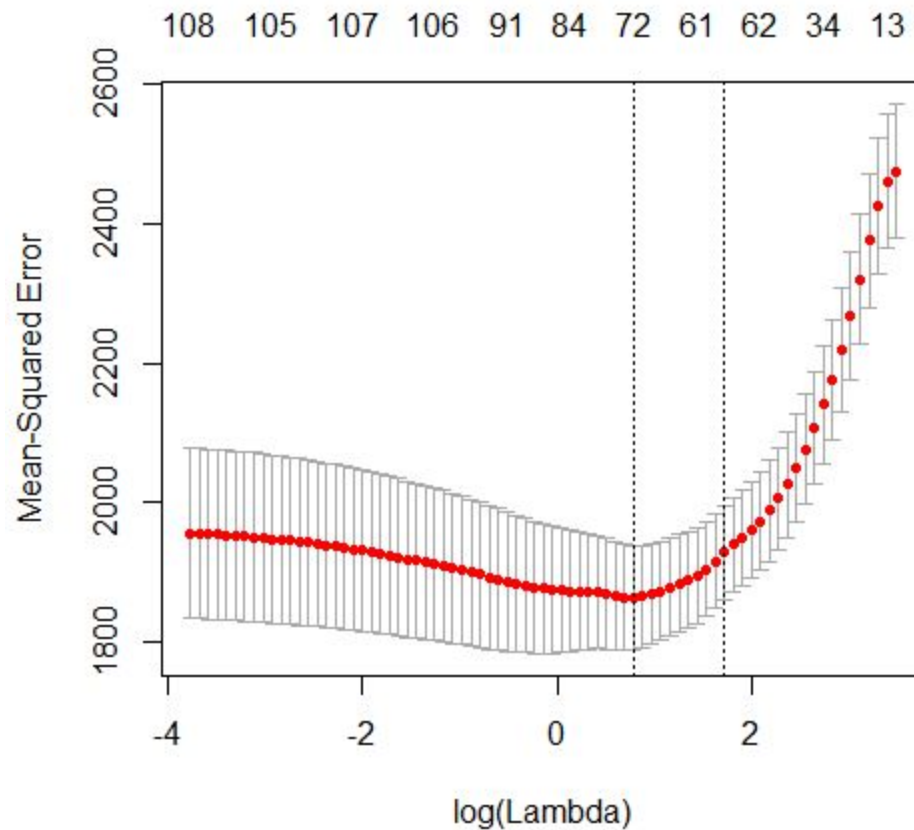


There is a large level of variability of error. The number of nonzero components of beta ranges from 4.5 to 35 for regularization constants that produce data within the variability of error. As $\log(\lambda)$ increases, the number of nonzero components fall, ensuring that explanatory variables with small coefficients are dropped, with the exception of $\log(\lambda)$ that lie just to the right of the variability of error, where it remains relatively constant, and for $\log(\lambda)$ that range from -6 to -2.

Longitude

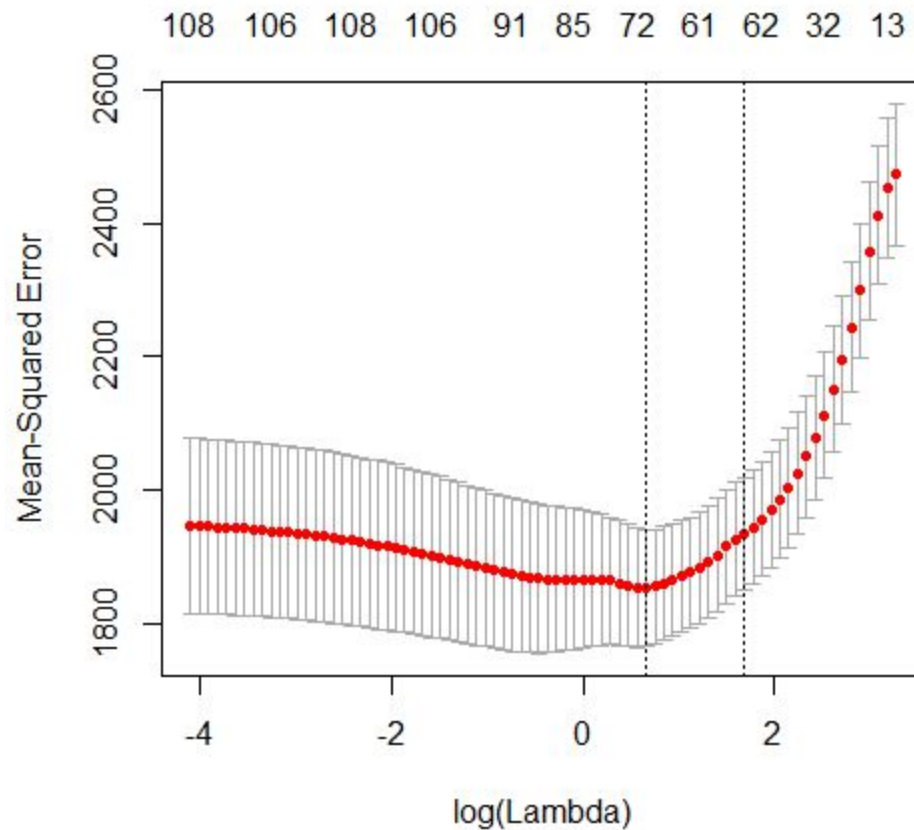
Alpha	Best Regularization Coefficient	Mean Square Error
0.4	1.4369538	2074.148
0.5	0.7219591	2061.794
0.6	0.9579692	2070.515

Elastic Net Regression (longitude) alpha = 0.4



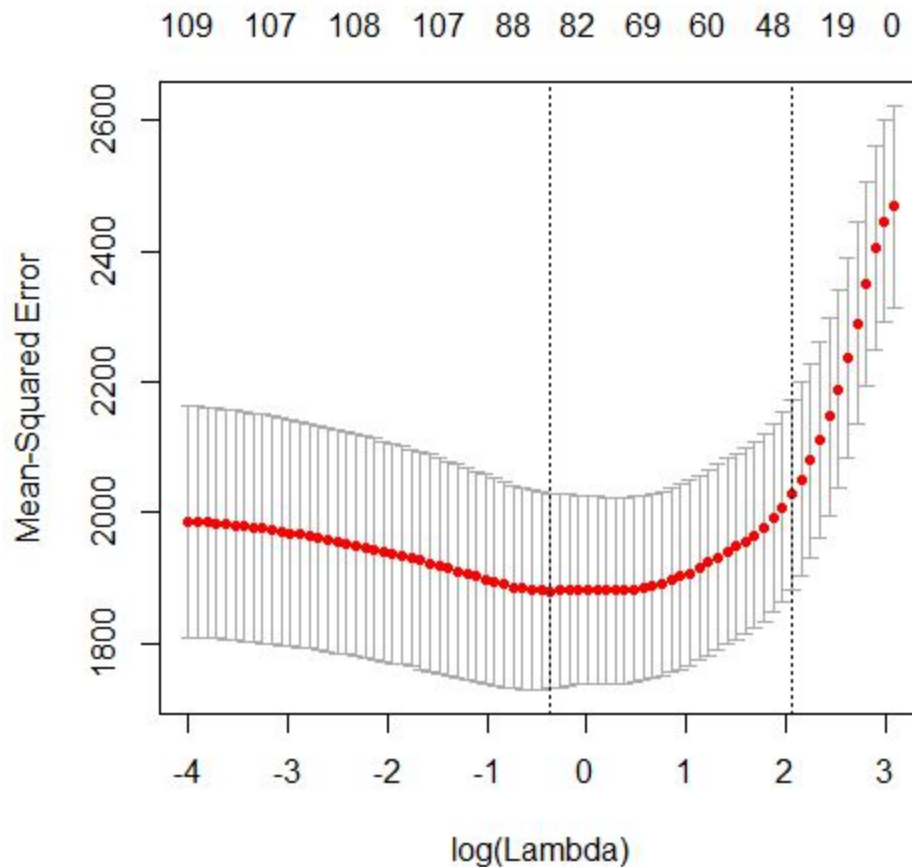
There is a moderate level of variability of error. The number of nonzero components of beta ranges from 61 to 72 for regularization constants that produce data within the variability of error. As $\log(\lambda)$ increases, the number of nonzero components fall, ensuring that explanatory variables with small coefficients are dropped, with the exception of $\log(\lambda)$ that lie just to the right of the variability of error, where it remains relatively constant.

Elastic Net Regression (longitude) alpha = 0.5



There is a moderate level of variability of error. The number of nonzero components of beta ranges from 61 to 72 for regularization constants that produce data within the variability of error. As $\log(\lambda)$ increases, the number of nonzero components fall, ensuring that explanatory variables with small coefficients are dropped, with the exception of $\log(\lambda)$ that lie just to the right of the variability of error, where it remains relatively constant.

Elastic Net Regression (longitude) alpha = 0.6



There is a large variability of error. The number of nonzero components of beta ranges from 46 to 85 for regularization constants that produce data within the variability of error. As $\log(\lambda)$ increases, the number of nonzero components fall, ensuring that explanatory variables with small coefficients are dropped.

A regression regularized by elastic net with $\alpha = 0.6$ is worse than the unregularized regression.

Q2.

The unregularized regression ended up yielding the best accuracy result. This is likely due to the fact that outlier points were not removed, potentially interfering with the ability of the regularization to better model the data.

Lasso regression outperformed ridge regression with this dataset. The elastic net regression did not vary too greatly with different values of alpha. The small differences peaked at an alpha value of 0.7

Without removing outlier points, unregularized regression is the best strategy for this problem.

Accuracy for each regularization scheme (80-20 train-test split) in classification

Unregularized:

Train: 81.0%

Test: 81.1%

Lasso:

Regularization Constant: 0.000668381

Train: 78.95%

Test: 79.22%

Ridge:

Regularization Constant: 0.01473867

Train: 78.7%

Test: 78.95%

Elastic Net:

alpha = 0.1:

Regularization Coef: 0.0034849438

Train: 78.888%

Test: 79.2%

alpha = 0.2:

Regularization Coef: 0.0027745080

Train: 78.892%

Test: 79.2%

alpha = 0.3:

Regularization Coef: 0.0020300128

Train: 78.921%

Test: 79.2%

alpha = 0.4:

Regularization Coef: 0.0018338682

Train: 78.904

Test: 79.2%

alpha = 0.5:

Regularization Coef: 0.0009213781

Train: 78.971%

Test: 79.233%

alpha = 0.6:

Regularization Coef: 0.0011139683

Train: 78.933%

Test: 79.2%

alpha = 0.7:

Regularization Coef: 0.0005463888

Train: 78.996%

Test: 79.233%

alpha = 0.8:

Regularization Coef: 0.0010063340

Train: 78.925%

Test: 79.2%

alpha = 0.9:

Regularization Coef: 0.0008150525

Train: 78.938%

Test: 79.183%