

Krist Kikina  
STA 9890  
Prof. Kamiar Rahnama Rad

## US Census Demographic Data

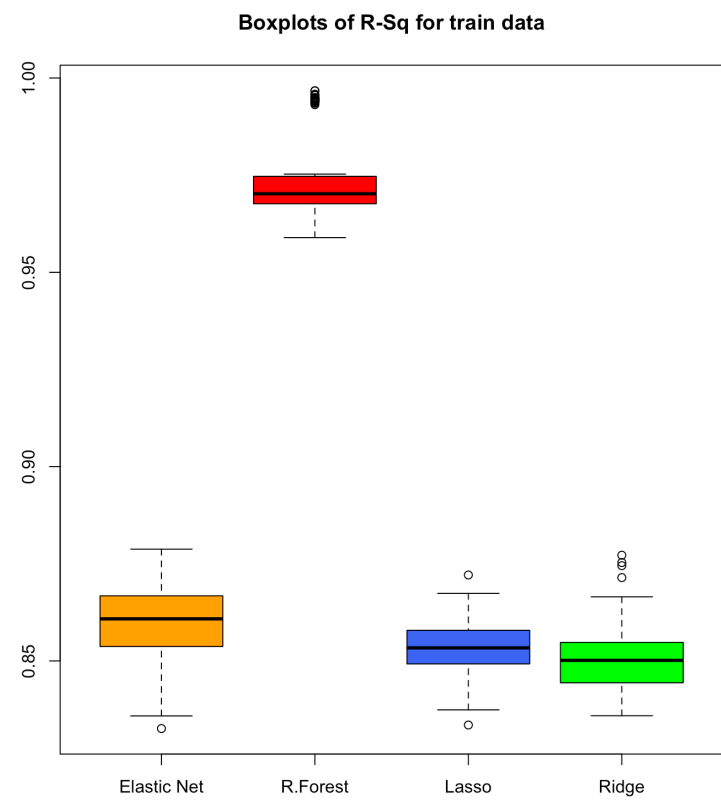
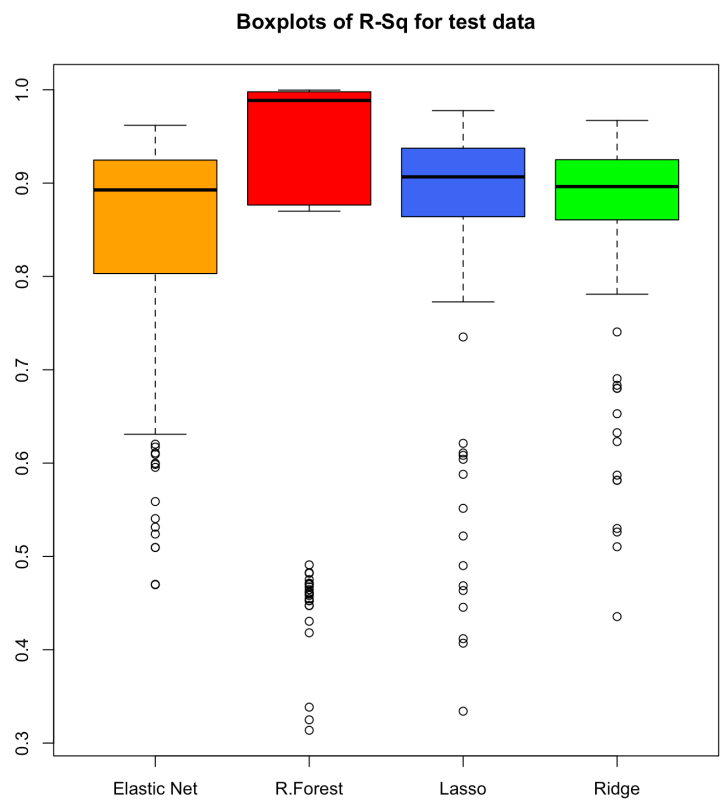
Demographic and Economic Data for Tracts and Counties

Observations: 3,220

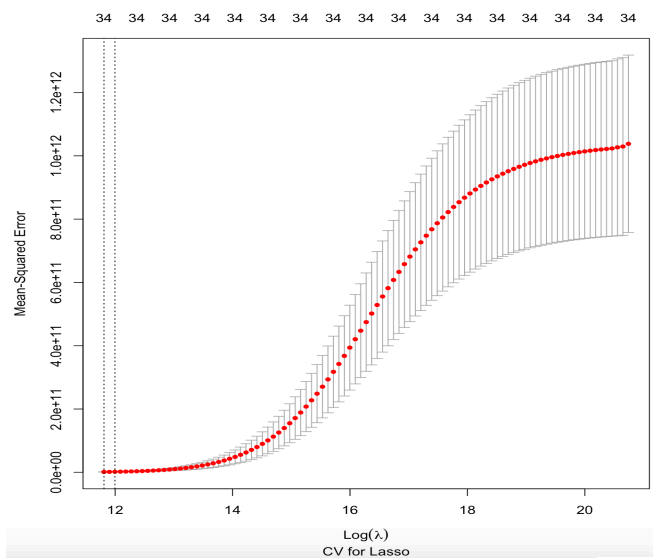
Variables: 37

\$ CountyId	<dbl> 1001, 1003, 1005, 1007, 1009, 1011, 1013, 1015, 1017, 1019, 1021, 1023, 1025,...
\$ State	<chr> "Alabama", "Alabama", "Alabama", "Alabama", "Alabama", "Alabama", "Alabama", "Alabama", ...
\$ County	<chr> "Autauga County", "Baldwin County", "Barbour County", "Bibb County", "Blount ...
\$ TotalPop	<dbl> 55036, 203360, 26201, 22580, 57667, 10478, 20126, 115527, 33895, 25855, 43805...
\$ Men	<dbl> 26899, 99527, 13976, 12251, 28490, 5616, 9416, 55593, 16320, 12862, 21554, 62...
\$ Women	<dbl> 28137, 103833, 12225, 10329, 29177, 4862, 10710, 59934, 17575, 12993, 22251, ...
\$ Hispanic	<dbl> 2.7, 4.4, 4.2, 2.4, 9.0, 0.3, 0.3, 3.6, 2.2, 1.6, 7.7, 0.5, 0.2, 3.1, 2.4, 6.0...
\$ White	<dbl> 75.4, 83.1, 45.7, 74.6, 87.4, 21.6, 52.2, 72.7, 56.2, 91.8, 80.4, 56.3, 53.0,...
\$ Black	<dbl> 18.9, 9.5, 47.8, 22.0, 1.5, 75.6, 44.7, 20.4, 39.3, 5.0, 9.5, 42.1, 45.7, 14.0...
\$ Native	<dbl> 0.3, 0.8, 0.2, 0.4, 0.3, 1.0, 0.1, 0.2, 0.3, 0.5, 0.4, 0.0, 0.1, 0.9, 0.3, 1.0...
\$ Asian	<dbl> 0.9, 0.7, 0.6, 0.0, 0.1, 0.7, 1.1, 1.0, 1.0, 0.1, 0.4, 0.1, 0.5, 0.0, 0.5, 1.0...
\$ Pacific	<dbl> 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.1, 0.0, 0.0, 0.0...
\$ VotingAgeCitizen	<dbl> 41016, 155376, 20269, 17662, 42513, 8212, 15459, 88383, 26259, 20620, 31776, ...
\$ Income	<dbl> 55317, 52562, 33368, 43404, 47412, 29655, 36326, 43686, 37342, 40041, 43501, ...
\$ IncomeErr	<dbl> 2838, 1348, 2551, 3431, 2630, 5376, 2701, 1491, 2011, 2316, 2877, 2797, 2336,...
\$ IncomePerCap	<dbl> 27824, 29364, 17561, 20911, 22021, 20856, 19004, 23638, 22002, 23010, 23368, ...
\$ IncomePerCapErr	<dbl> 2024, 735, 798, 1889, 850, 2355, 943, 793, 1205, 1354, 1925, 1307, 1203, 1553...
\$ Poverty	<dbl> 13.7, 11.8, 27.2, 15.2, 15.6, 28.5, 24.4, 18.6, 18.8, 16.1, 19.4, 22.3, 25.3,...
\$ ChildPoverty	<dbl> 20.1, 16.1, 44.9, 26.6, 25.4, 50.4, 34.8, 26.6, 29.1, 20.0, 27.8, 32.8, 30.7,...
\$ Professional	<dbl> 35.3, 35.7, 25.0, 24.4, 28.5, 19.7, 26.9, 29.0, 24.3, 28.8, 25.3, 23.6, 21.6,...
\$ Service	<dbl> 18.0, 18.2, 16.8, 17.6, 12.9, 17.1, 17.3, 17.5, 13.5, 14.8, 14.5, 15.4, 14.3,...
\$ Office	<dbl> 23.2, 25.6, 22.6, 19.7, 23.3, 18.6, 18.5, 23.7, 23.0, 18.1, 23.7, 22.0, 24.8,...
\$ Construction	<dbl> 8.1, 9.7, 11.5, 15.9, 15.8, 14.0, 11.6, 10.4, 11.6, 11.9, 15.5, 17.1, 13.7, 1.0...
\$ Production	<dbl> 15.4, 10.8, 24.1, 22.4, 19.5, 30.6, 25.7, 19.4, 27.6, 26.5, 21.0, 21.9, 25.6,...
\$ Drive	<dbl> 86.0, 84.7, 83.4, 86.4, 86.8, 73.1, 83.6, 85.0, 87.1, 85.0, 83.2, 81.8, 83.7,...
\$ Carpool	<dbl> 9.6, 7.6, 11.1, 9.5, 10.2, 15.7, 12.6, 9.2, 9.7, 12.1, 12.6, 13.7, 11.9, 6.0,...
\$ Transit	<dbl> 0.1, 0.1, 0.3, 0.7, 0.1, 0.3, 0.0, 0.2, 0.2, 0.4, 0.1, 0.0, 0.2, 0.0, 0.0, 0.0...
\$ Walk	<dbl> 0.6, 0.8, 2.2, 0.3, 0.4, 6.2, 0.9, 1.3, 0.6, 0.3, 0.6, 1.7, 0.7, 2.8, 0.9, 1.0...
\$ OtherTransp	<dbl> 1.3, 1.1, 1.7, 1.7, 0.4, 1.7, 0.9, 1.1, 0.5, 0.3, 1.8, 1.2, 2.7, 0.6, 0.1, 1.0...
\$ WorkAtHome	<dbl> 2.5, 5.6, 1.3, 1.5, 2.1, 3.0, 2.0, 3.2, 2.0, 2.0, 1.7, 1.6, 0.9, 3.0, 2.7, 2.0...
\$ MeanCommute	<dbl> 25.8, 27.0, 23.4, 30.0, 35.0, 29.8, 23.2, 24.8, 23.6, 26.5, 32.5, 32.7, 23.9,...
\$ Employed	<dbl> 24112, 89527, 8878, 8171, 21380, 4290, 7727, 47392, 14527, 9879, 17675, 4301,...
\$ PrivateWork	<dbl> 74.1, 80.7, 74.1, 76.0, 83.9, 81.4, 79.1, 74.9, 84.5, 74.8, 81.1, 79.9, 83.1,...
\$ PublicWork	<dbl> 20.2, 12.9, 19.1, 17.4, 11.9, 13.6, 15.3, 19.9, 11.8, 17.1, 14.0, 14.8, 11.8,...
\$ SelfEmployed	<dbl> 5.6, 6.3, 6.5, 6.3, 4.0, 5.0, 5.3, 5.1, 3.7, 8.1, 4.5, 4.9, 5.1, 7.7, 8.2, 5.0...
\$ FamilyWork	<dbl> 0.1, 0.1, 0.3, 0.3, 0.1, 0.0, 0.3, 0.1, 0.0, 0.0, 0.4, 0.4, 0.0, 0.0, 0.0, 0.0...
\$ Unemployment	<dbl> 5.2, 5.5, 12.4, 8.2, 4.9, 12.1, 7.6, 10.1, 6.4, 5.3, 6.7, 9.8, 15.2, 6.4, 7.8...

Side by Side Boxplots of  $R^2_{\text{train}}$  and  $R^2_{\text{test}}$

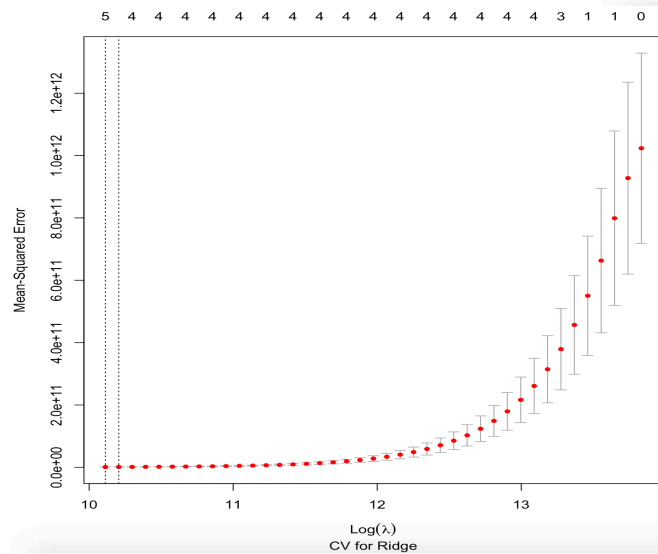
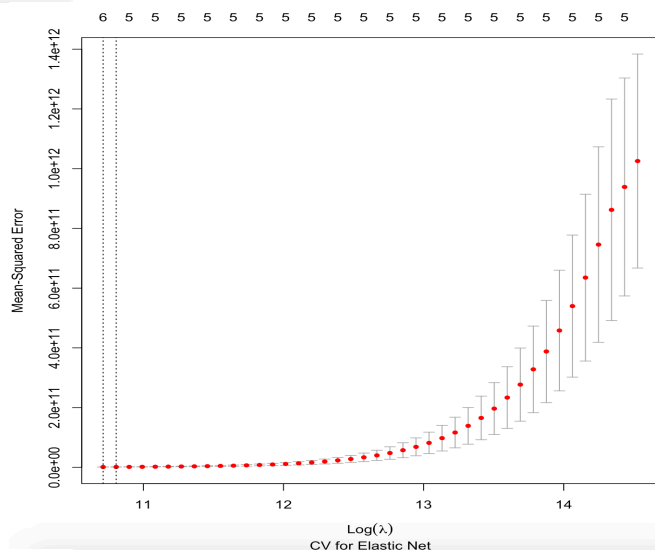


10-fold CV curves for lasso, elastic-net  $\alpha = 0.5$ , ridge.



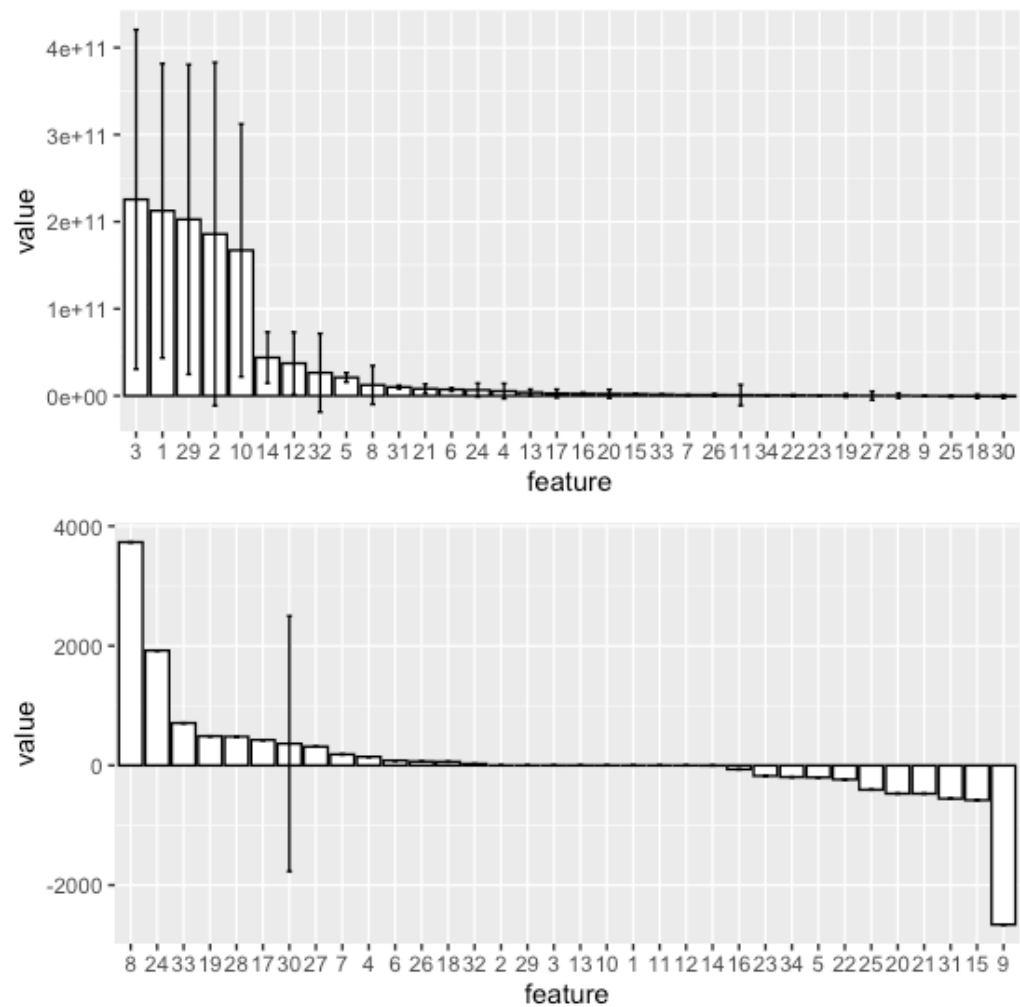
Lasso

Elastic-Net



Ridge

Bar-plots (with bootstrapped error bars) of the estimated coefficients, and the importance of the parameters. If you have something interesting to say about coefficients that are (or are not important) say it.



➔ order of features that have a strong impact and response.

Summary:

Picking winning model using cross-validation (comparing elastic net, ridge, and lasso)

```
> cv.fit
```

```
Call: cv.glmnet(x = X, y = y, nfolds = 10, alpha = a)
```

Measure: Mean-Squared Error

	Lambda	Measure	SE	Nonzero
min	44927	1.127e+09	295970910	6
1se	49307	1.320e+09	360236475	6

```
> cv.fit.la
```

```
Call: cv.glmnet(x = X, y = y, nfolds = 10, alpha = b)
```

Measure: Mean-Squared Error

	Lambda	Measure	SE	Nonzero
min	134664	1.215e+09	549702326	34
1se	162203	1.693e+09	779582657	34

```
> cv.fit.ri
```

```
Call: cv.glmnet(x = X, y = y, nfolds = 10, alpha = c)
```

Measure: Mean-Squared Error

	Lambda	Measure	SE	Nonzero
min	24653	1.018e+09	152895123	5
1se	27057	1.142e+09	193981597	4

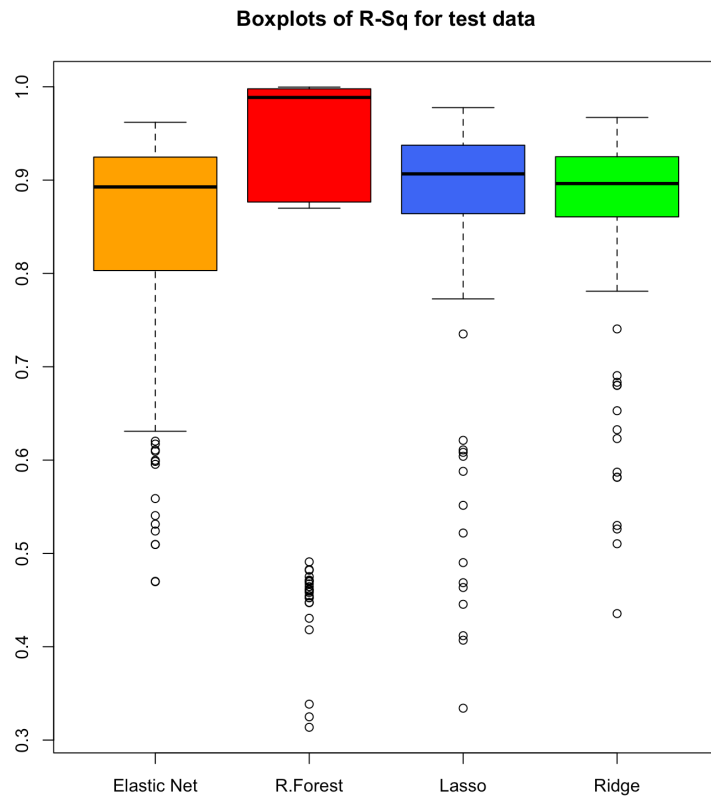
```
> cv.fit.la = cv.glmnet(X, y, alpha = b, r
```

From the summaries on the left, Ridge Regression results in the lowest lambda for the usual rule and the lowest standard error.

Elastic-Net: compromise between Lasso and Ridge. It penalizes a mix of both absolute and squared size.

Lasso: penalizes the absolute size of coefficients. It offers automatic feature selection, because it can remove some features.

Ridge: Penalizes squared size of coefficients. Ridge offers feature shrinkage. Leads to smaller coefficients.



From the boxplots, we have random forest as the best model.

The other three tend to perform similarly to each other.

Time needed to train each model was the longest for the random forest.