

## STAT5120, Regression Model Building, pt. 2, Allen Baumgarten (nominal Marlins fan)

1. Perform PCA on the Iris data. <http://www.instantr.com/2012/12/18/performing-a-principal-component-analysis-in-r/>

To view the dataset, simply type *iris* at the R prompt. We will not attempt to build a regression model for this dataset because the response (Species) is categorical, and so linear regression won't work. Let's just explore the nature of the relationships between the predictor variables. Run PCA (not PCR) on the variables Sepal.Length, Sepal.Width, Petal.Length, and Petal.Width.

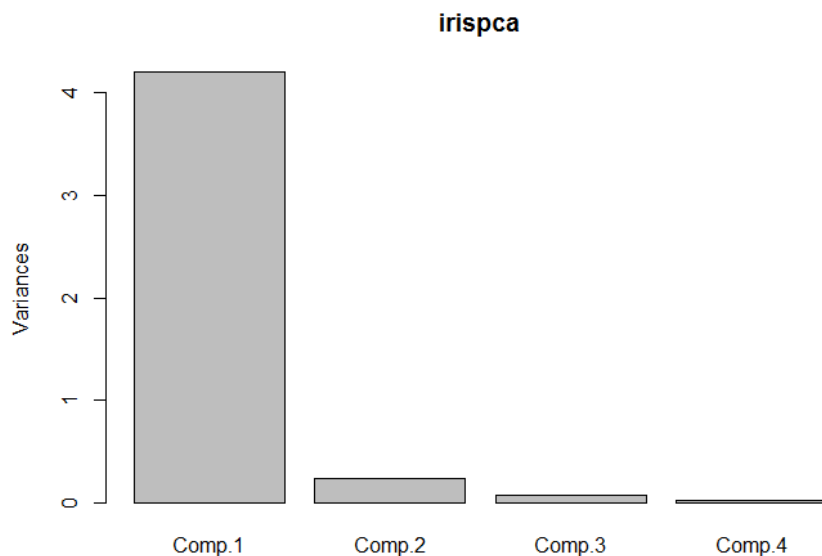
(a) List the eigenvalues in order from highest to lowest, along with the percentage of variation captured by each principle component.

Importance of components:

	Comp.1	Comp.2	Comp.3	Comp.4
Standard deviation	2.0494032	0.49097143	0.27872586	0.153870700
Proportion of Variance	0.9246187	0.05306648	0.01710261	0.005212184
Cumulative Proportion	0.9246187	0.97768521	0.99478782	1.000000000

(b) What is the total variation captured by the first component? **92.4%** What is the total variation captured by the first two components? **97.8%** The first three? **99.5%** All four? **100%**

(c) Make a scree plot. How many principle components do you think are enough to adequately describe the variation in the data? **I would propose that the first principle component is adequate to describe the variation in the data with 92.4% of the variation captured. One could, of course, add in the second principle component to take that percentage up.**



(d) What do the loadings for the components indicate? Be specific. **The loadings are “weights that are used to multiply the original coordinates of the variables to get the new ones (called scores) on the principle components,”<sup>1</sup> and these in particular indicate that there is a strong correlation between the Petal Length with the weight assigned to it in the first principal component.**

<sup>1</sup> Jones, Matthew O., “Chapter 11: Model Building II, Shrinkage Methods,” 2006-Present, 163.

Loadings:

	Comp.1	Comp.2	Comp.3	Comp.4
Sepal.Length	0.361	-0.657	-0.582	0.315
Sepal.Width	-0.730	0.598	-0.320	
Petal.Length	0.857	0.173	-0.480	
Petal.Width	0.358	0.546	0.754	

(e) What do the scores for the observations tell you? The scores are shown below and indicate that component #1 indeed captures most of the variation:

	Comp.1	Comp.2	Comp.3	Comp.4
[1,]	-2.684125626	-0.319397247	-0.027914828	0.0022624371
[2,]	-2.714141687	0.177001225	-0.210464272	0.0990265503
[3,]	-2.888990569	0.144949426	0.017900256	0.0199683897

2. Another way to describe the lasso method is that it estimates the regression coefficients by choosing them to be the values of the  $b_j$ ,  $j \in \{0, 1, \dots, p-1\}$  by minimizing

$$\sum_{i=1}^n \left( y_i - b_0 - \sum_{j=1}^{p-1} b_j x_{ij} \right)^2 \quad \text{subject to} \quad \sum_{k=1}^{p-1} |\beta_k| \leq s$$

for some number  $s$ . For parts (a) through (f), indicate which of the following occurs and justify your answer.

- i. remain constant.
- ii. monotonically increase.
- iii. monotonically decrease.
- iv. initially increase, then decrease.
- v. initially decrease, then increase.

- (a) As  $s$  increases from 0, the training SSE will **monotonically increase**
- (b) As  $s$  increases from 0, the training  $R^2$  will **initially increase, then decrease increase**
- (c) As  $s$  increases from 0, the test or validation SSE will **monotonically increase**
- (d) As  $s$  increases from 0, the test or validation  $R^2$  will **initially increase, then decrease**
- (e) As  $s$  increases from 0, the squared bias will **initially decrease, then increase**
- (f) As  $s$  increases from 0, the variance will **remain constant**

3. Consider estimating regression coefficients by choosing the  $b_j$ ,  $j \in \{0, 1, \dots, p-1\}$  that minimizes

$$\sum_{i=1}^n \left( y_i - b_0 - \sum_{j=1}^{p-1} b_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p-1} b_j^2$$

for fixed  $\lambda$ . For parts (a) through (f), indicate which of the following occurs and justify your answer.

- i. remain constant.
- ii. monotonically increase.
- iii. monotonically decrease.
- iv. initially increase, then decrease.
- v. initially decrease, then increase.

- (a) As  $\lambda$  increases from 0, the training SSE will **remain constant**
- (b) As  $\lambda$  increases from 0, the training  $R^2$  will **monotonically increase**
- (c) As  $\lambda$  increases from 0, the test or validation SSE will **monotonically decrease**
- (d) As  $\lambda$  increases from 0, the test or validation  $R^2$  will **initially increase, then decrease**
- (e) As  $\lambda$  increases from 0, the squared bias will **initially decrease, then increase**
- (f) As  $\lambda$  increases from 0, the variance will **remain constant**

4. Load and read the documentation for the *College* data set from the ISLR package. We want to build a model to predict the number of applications received using the other variables.

(a) Split the data set into a training set and a validation/test set, approximately 70%, 30%, respectively. [Split data into training and test groups \(see code below\)](#).

(b) Fit a linear least-squares regression model on the training set. Compute the test MSE and test  $R^2$ .

Residuals:

	Min	1Q	Median	3Q	Max
	-5235.2	-343.5	5.7	284.5	7185.2

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-613.21658	462.63041	-1.325	0.18558
PrivateYes	-323.84919	169.29370	-1.913	0.05630 .
Accept	1.70689	0.04854	35.164	< 2e-16 ***
Enroll	-1.35509	0.22586	-6.000	3.68e-09 ***
Top10perc	45.42084	6.57841	6.905	1.46e-11 ***
Top25perc	-15.83576	5.27942	-3.000	0.00283 **

F.Undergrad	0.09912	0.03885	2.551	0.01101 *
P.Undergrad	0.01581	0.05051	0.313	0.75440
Outstate	-0.09220	0.02185	-4.220	2.88e-05 ***
Room.Board	0.11873	0.05396	2.200	0.02821 *
Books	-0.03743	0.25967	-0.144	0.88545
Personal	0.05974	0.07197	0.830	0.40686
PhD	-5.59724	5.12251	-1.093	0.27504
Terminal	-5.29911	5.53622	-0.957	0.33892
S.F.Ratio	21.40193	15.11700	1.416	0.15744
perc.alumni	1.97445	4.65425	0.424	0.67158
Expend	0.10761	0.01487	7.238	1.63e-12 ***
Grad.Rate	8.15148	3.29431	2.474	0.01366 *

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 992.5 on 526 degrees of freedom  
Multiple R-squared: 0.9257, Adjusted R-squared: 0.9232  
F-statistic: 385.2 on 17 and 526 DF, p-value: < 2.2e-16

(c) Fit a ridge regression model on the training set. Use cross-validation to choose the tuning parameter  $\lambda$ . Give the test MSE and test  $R^2$ .

	Length	Class	Mode
coef	357	-none-	numeric
scales	17	-none-	numeric
Inter	1	-none-	numeric
lambda	21	-none-	numeric
ym	1	-none-	numeric
xm	17	-none-	numeric
GCV	21	-none-	numeric
kHKB	1	-none-	numeric
kLW	1	-none-	numeric

(d) Fit a lasso regression model on the training set. Use cross-validation to choose the tuning parameter  $\lambda$ . Give the test MSE and test  $R^2$ . [Attempted a lasso regression model but unable to get this to work...](#)

(e) Fit a principle components regression model on the training set and use cross-validation to choose the number of principle components. Give the test MSE and test  $R^2$ , and the number of principle components. [Attempted a PC regression model but unable to get this to work...](#)

(f) Fit a partial least squares regression model on the training set and use cross-validation to choose the number of new model features. Give the test MSE and test  $R^2$ , and the number of new features used in the model.

(g) Compare the five models. Which ones seem better? Is there much difference between the test  $R^2$  and test MSE values? How well do these models predict the number of college applications?

5. Prove the form of the ridge regression coefficients:

$$\hat{\beta} = (X^T X + \lambda I^*)^{-1} X^T Y.$$

Proving this mathematically is a little over my head at this point, regrettably. I did find the proof itself mapped out as follows and can make some sense of it. The following, however, is NOT my work but is from a lecture given at Stanford (author acknowledged and footnoted below).<sup>2</sup>

## Proving that $\hat{\beta}_\lambda^{\text{ridge}}$ is biased

- Let  $\mathbf{R} = \mathbf{Z}^\top \mathbf{Z}$
- Then:

$$\begin{aligned}\hat{\beta}_\lambda^{\text{ridge}} &= (\mathbf{Z}^\top \mathbf{Z} + \lambda \mathbf{I}_p)^{-1} \mathbf{Z}^\top \mathbf{y} \\ &= (\mathbf{R} + \lambda \mathbf{I}_p)^{-1} \mathbf{R} (\mathbf{R}^{-1} \mathbf{Z}^\top \mathbf{y}) \\ &= [\mathbf{R}(\mathbf{I}_p + \lambda \mathbf{R}^{-1})]^{-1} \mathbf{R} [(\mathbf{Z}^\top \mathbf{Z})^{-1} \mathbf{Z}^\top \mathbf{y}] \\ &= (\mathbf{I}_p + \lambda \mathbf{R}^{-1})^{-1} \mathbf{R}^{-1} \mathbf{R} \hat{\beta}^{\text{ls}} \\ &= (\mathbf{I}_p + \lambda \mathbf{R}^{-1}) \hat{\beta}^{\text{ls}}\end{aligned}$$

- So:

$$\begin{aligned}\mathbb{E}(\hat{\beta}_\lambda^{\text{ridge}}) &= \mathbb{E}\{(\mathbf{I}_p + \lambda \mathbf{R}^{-1}) \hat{\beta}^{\text{ls}}\} \\ &= (\mathbf{I}_p + \lambda \mathbf{R}^{-1}) \beta \\ &\stackrel{(\text{if } \lambda \neq 0)}{\neq} \beta.\end{aligned}$$

<sup>2</sup> "Regularization: Ridge Regression and the LASSO" Lecture: Statistics 305, Autumn Quarter 2006/2007. Accessed on 4/8/18 at <http://statweb.stanford.edu/~tibs/sta305files/Rudyregularization.pdf>

## APPENDIX: R SCRIPTS

### Question 1:

```
> head(iris)
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
1         5.1         3.5          1.4          0.2    setosa
2         4.9         3.0          1.4          0.2    setosa
3         4.7         3.2          1.3          0.2    setosa
4         4.6         3.1          1.5          0.2    setosa
5         5.0         3.6          1.4          0.2    setosa
6         5.4         3.9          1.7          0.4    setosa

> irispca<-princomp(iris[-5])
> summary(irispca)
Importance of components:

              Comp.1   Comp.2   Comp.3   Comp.4
Standard deviation  2.0494032 0.49097143 0.27872586 0.153870700
Proportion of Variance 0.9246187 0.05306648 0.01710261 0.005212184
Cumulative Proportion 0.9246187 0.97768521 0.99478782 1.000000000

> irispca$loadings

Loadings:
              Comp.1 Comp.2 Comp.3 Comp.4
Sepal.Length  0.361  -0.657 -0.582  0.315
Sepal.Width   -0.730   0.598 -0.320
Petal.Length  0.857   0.173 -0.480
Petal.Width   0.358   0.546  0.754

              Comp.1 Comp.2 Comp.3 Comp.4
SS loadings    1.00  1.00  1.00  1.00
Proportion Var  0.25  0.25  0.25  0.25
Cumulative Var  0.25  0.50  0.75  1.00

> irispca$scores
              Comp.1   Comp.2   Comp.3   Comp.4
[1,] -2.684125626 -0.319397247 -0.027914828 0.0022624371
[2,] -2.714141687  0.177001225 -0.210464272 0.0990265503
[3,] -2.888990569  0.144949426  0.017900256 0.0199683897

> screeplot(irispca)
```

### Question 4:

```
> library(ISLR)
Warning message:
package 'ISLR' was built under R version 3.4.4
> head(College)
      Private Apps Accept Enroll Top10perc Top25perc F.Undergrad
Abilene Christian University  Yes 1660 1232 721    23    52    2885
Adelphi University           Yes 2186 1924 512    16    29    2683
Adrian College               Yes 1428 1097 336    22    50    1036
Agnes Scott College          Yes 417  349 137    60    89    510
Alaska Pacific University    Yes 193  146  55    16    44    249
```

Albertson College	Yes	587	479	158	38	62	678
	P.Undergrad	Outstate	Room.Board	Books	Personal	PhD	Terminal
Abilene Christian University		537	7440	3300	450	2200	70 78
Adelphi University		1227	12280	6450	750	1500	29 30
Adrian College		99	11250	3750	400	1165	53 66
Agnes Scott College		63	12960	5450	450	875	92 97
Alaska Pacific University		869	7560	4120	800	1500	76 72
Albertson College		41	13500	3335	500	675	67 73
	S.F.Ratio	perc.alumni	Expend	Grad.Rate			
Abilene Christian University		18.1	12	7041	60		
Adelphi University		12.2	16	10527	56		
Adrian College		12.9	30	8735	54		
Agnes Scott College		7.7	37	19016	59		
Alaska Pacific University		11.9	2	10922	15		
Albertson College		9.4	11	9727	55		

```

> college_training <- College[1:544,]
> college_test <- College[545:777,]
> regmod_collegetrain <- lm(college_training$Apps ~.,college_training)
> summary(regmod_collegetrain)

```

Call:  
lm(formula = college\_training\$Apps ~ ., data = college\_training)

Residuals:

Min	1Q	Median	3Q	Max
-5235.2	-343.5	5.7	284.5	7185.2

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-613.21658	462.63041	-1.325	0.18558
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Outstate	-0.09220	0.02185	-4.220	2.88e-05 ***
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Books	-0.03743	0.25967	-0.144	0.88545
Personal	0.05974	0.07197	0.830	0.40686
PhD	-5.59724	5.12251	-1.093	0.27504
Terminal	-5.29911	5.53622	-0.957	0.33892
S.F.Ratio	21.40193	15.11700	1.416	0.15744
perc.alumni	1.97445	4.65425	0.424	0.67158
Expend	0.10761	0.01487	7.238	1.63e-12 ***
Grad.Rate	8.15148	3.29431	2.474	0.01366 *

---  
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Residual standard error: 992.5 on 526 degrees of freedom  
 Multiple R-squared: 0.9257, Adjusted R-squared: 0.9232  
 F-statistic: 385.2 on 17 and 526 DF, p-value: < 2.2e-16

```
> library(MASS)
> regmod_ridge <- lm.ridge(college_training$Apps ~.,college_training, lambda = seq(0, 5e-8, len=21))
> summary(regmod_ridge)
```

	Length	Class	Mode
coef	357	-none-	numeric
scales	17	-none-	numeric
Inter	1	-none-	numeric
lambda	21	-none-	numeric
ym	1	-none-	numeric
xm	17	-none-	numeric
GCV	21	-none-	numeric
kHKB	1	-none-	numeric
kLW	1	-none-	numeric

```
> lasso_regmod <- lars(college_training$Apps, college_training$Enroll)
Error in rep(1, n) : invalid 'times' argument
> head(college_training)
```

	Private Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad
Abilene Christian University	Yes	1660	1232	721	23	52 2885
Adelphi University	Yes	2186	1924	512	16	29 2683
Adrian College	Yes	1428	1097	336	22	50 1036
Agnes Scott College	Yes	417	349	137	60	89 510
Alaska Pacific University	Yes	193	146	55	16	44 249
Albertson College	Yes	587	479	158	38	62 678

	P.Undergrad	Outstate	Room.Board	Books	Personal	PhD	Terminal
Abilene Christian University	537	7440	3300	450	2200	70	78
Adelphi University	1227	12280	6450	750	1500	29	30
Adrian College	99	11250	3750	400	1165	53	66
Agnes Scott College	63	12960	5450	450	875	92	97
Alaska Pacific University	869	7560	4120	800	1500	76	72
Albertson College	41	13500	3335	500	675	67	73

	S.F.Ratio	perc.alumni	Expend	Grad.Rate
Abilene Christian University	18.1	12	7041	60
Adelphi University	12.2	16	10527	56
Adrian College	12.9	30	8735	54
Agnes Scott College	7.7	37	19016	59
Alaska Pacific University	11.9	2	10922	15
Albertson College	9.4	11	9727	55

```
> lasso_regmod <- lars(college_training[,-2], college_training$Enroll)
Error in one %*% x : requires numeric/complex matrix/vector arguments
> regmod_plsr <- plsr(college_training$Apps ~., data=college_training, ncomp=50, validation="CV")
Error in plsr(college_training$Apps ~., data = college_training, ncomp = 50, :
could not find function "plsr"
```