

## Problem 1: James 2.4, Exercise 8

### Part a

```
> college <- read.csv(file="datasets/College.csv")
> head(college)
```

		X	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books
1	Abilene Christian University	Yes	1660	1232	721	23	52	2885	537	7440	3300	450	
2	Adelphi University	Yes	2186	1924	512	16	29	2683	1227	12280	6450	750	
3	Adrian College	Yes	1428	1097	336	22	50	1036	99	11250	3750	400	
4	Agnes Scott College	Yes	417	349	137	60	89	510	63	12960	5450	450	
5	Alaska Pacific University	Yes	193	146	55	16	44	249	869	7560	4120	800	
6	Albertson College	Yes	587	479	158	38	62	678	41	13500	3335	500	

	Personal	PhD	Terminal	S.F.Ratio	perc.alumni	Expend	Grad.Rate
1	2200	70	78	18.1	12	7041	60
2	1500	29	30	12.2	16	10527	56
3	1165	53	66	12.9	30	8735	54
4	875	92	97	7.7	37	19016	59
5	1500	76	72	11.9	2	10922	15
6	675	67	73	9.4	11	9727	55

### Part b

	row.names	Private	Apps	Accept	Enroll	Top10perc	Top25perc
1	Abilene Christian University	Yes	1660	1232	721	23	52
2	Adelphi University	Yes	2186	1924	512	16	29
3	Adrian College	Yes	1428	1097	336	22	50
4	Agnes Scott College	Yes	417	349	137	60	89
5	Alaska Pacific University	Yes	193	146	55	16	44
6	Albertson College	Yes	587	479	158	38	62
7	Albertus Magnus College	Yes	353	340	103	17	45
8	Albion College	Yes	1899	1720	489	37	68
9	Albright College	Yes	1038	839	227	30	63
10	Alderson-Broadbudd College	Yes	582	498	172	21	44

## Part c

## Part i

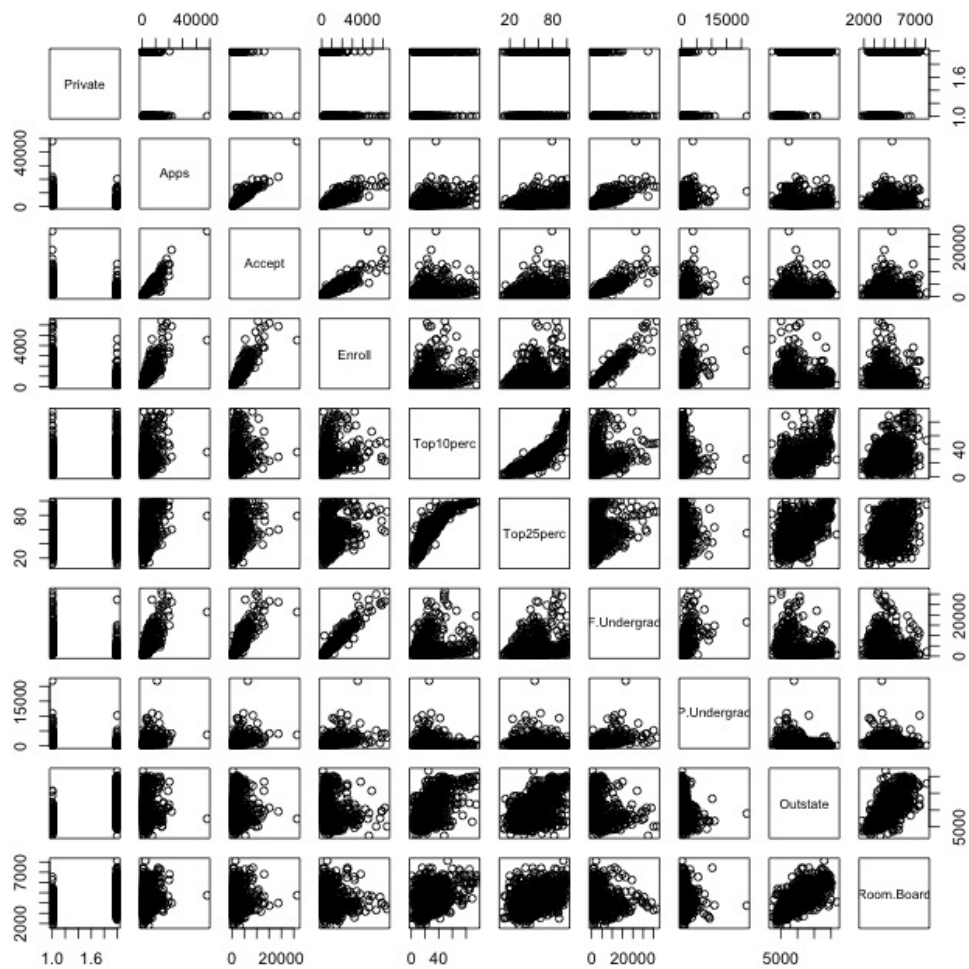
```
> summary(college)
```

Private	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate
No :212	Min. : 81	Min. : 72	Min. : 35	Min. : 1.00	Min. : 9.0	Min. : 139	Min. : 1.0	Min. : 2340
Yes:565	1st Qu.: 776	1st Qu.: 684	1st Qu.: 242	1st Qu.:15.00	1st Qu.: 41.0	1st Qu.: 992	1st Qu.: 95.0	1st Qu.: 7320
	Median : 1558	Median : 1110	Median : 434	Median :23.00	Median : 54.0	Median : 1707	Median : 353.0	Median : 9990
	Mean : 3002	Mean : 2019	Mean : 780	Mean :27.56	Mean : 55.8	Mean : 3700	Mean : 855.3	Mean :10441
	3rd Qu.: 3624	3rd Qu.: 2424	3rd Qu.: 902	3rd Qu.:35.00	3rd Qu.: 69.0	3rd Qu.: 4005	3rd Qu.: 967.0	3rd Qu.:12925
	Max. :48094	Max. :26330	Max. :6392	Max. :96.00	Max. :100.0	Max. :31643	Max. :21836.0	Max. :21700

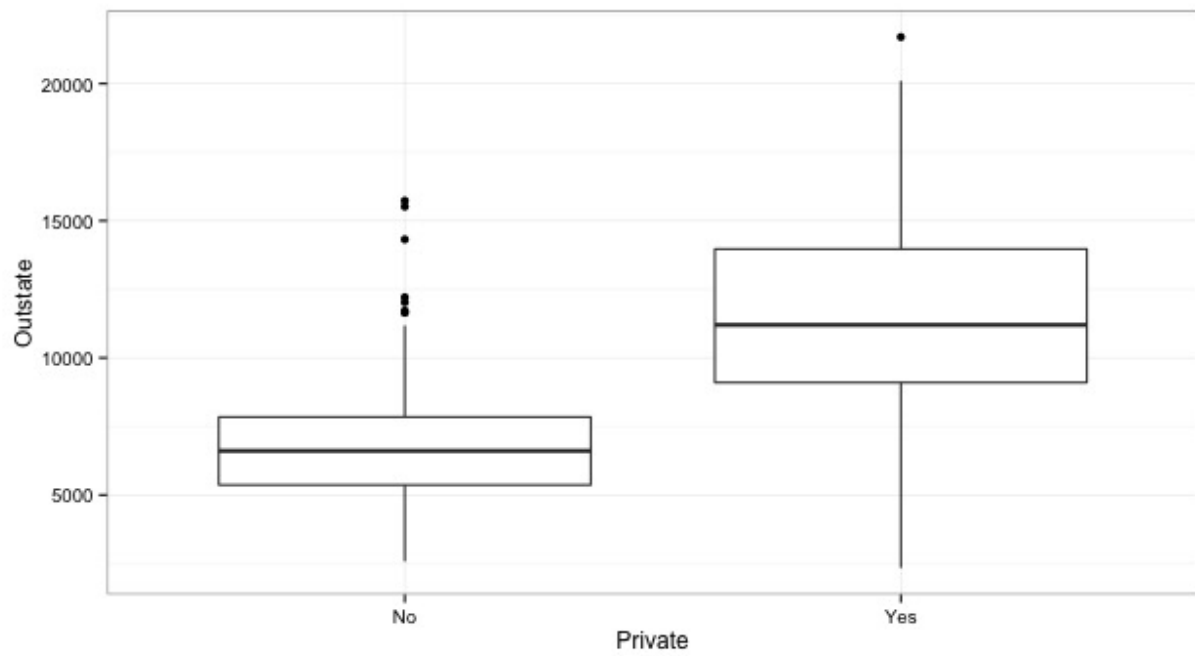
  

Room.Board	Books	Personal	PhD	Terminal	S.F.Ratio	perc.alumni	Expend	Grad.Rate
Min. :1780	Min. : 96.0	Min. : 250	Min. : 8.00	Min. : 24.0	Min. : 2.50	Min. : 0.00	Min. : 3186	Min. : 10.00
1st Qu.:3597	1st Qu.: 470.0	1st Qu.: 850	1st Qu.: 62.00	1st Qu.: 71.0	1st Qu.:11.50	1st Qu.:13.00	1st Qu.: 6751	1st Qu.: 53.00
Median :4200	Median : 500.0	Median :1200	Median : 75.00	Median : 82.0	Median :13.60	Median :21.00	Median : 8377	Median : 65.00
Mean :4358	Mean : 549.4	Mean :1341	Mean : 72.66	Mean : 79.7	Mean :14.09	Mean :22.74	Mean : 9660	Mean : 65.46
3rd Qu.:5050	3rd Qu.: 600.0	3rd Qu.:1700	3rd Qu.: 85.00	3rd Qu.: 92.0	3rd Qu.:16.50	3rd Qu.:31.00	3rd Qu.:10830	3rd Qu.: 78.00
Max. :8124	Max. :2340.0	Max. :6800	Max. :103.00	Max. :100.0	Max. :39.80	Max. :64.00	Max. :56233	Max. :118.00

## Part ii

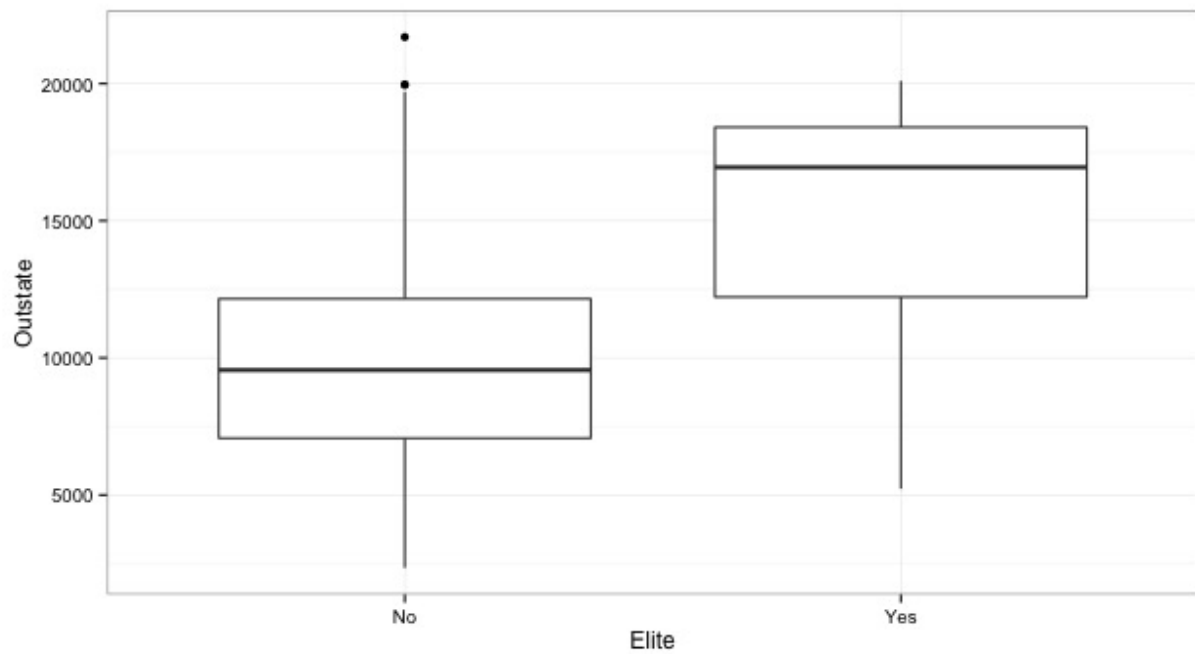


### Part iii

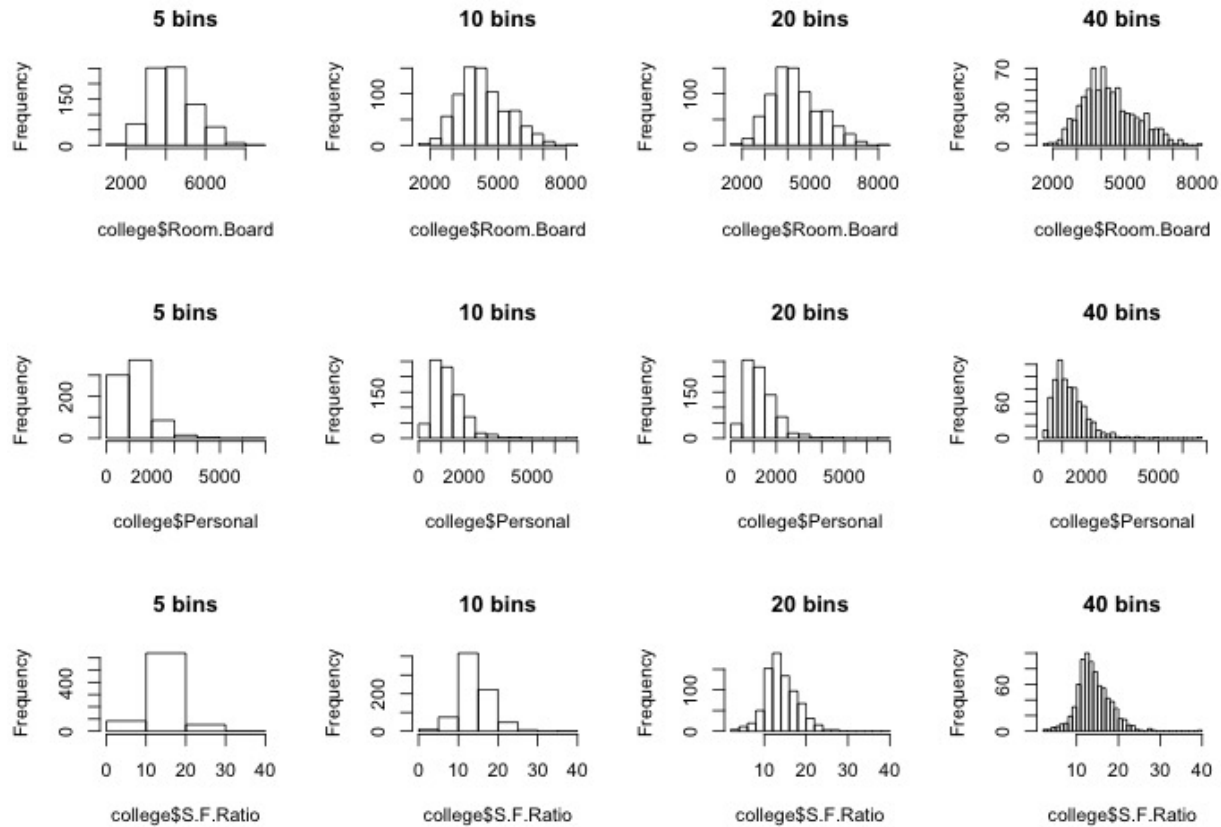


### Part iv

There are 78 colleges categorized as "Elite".

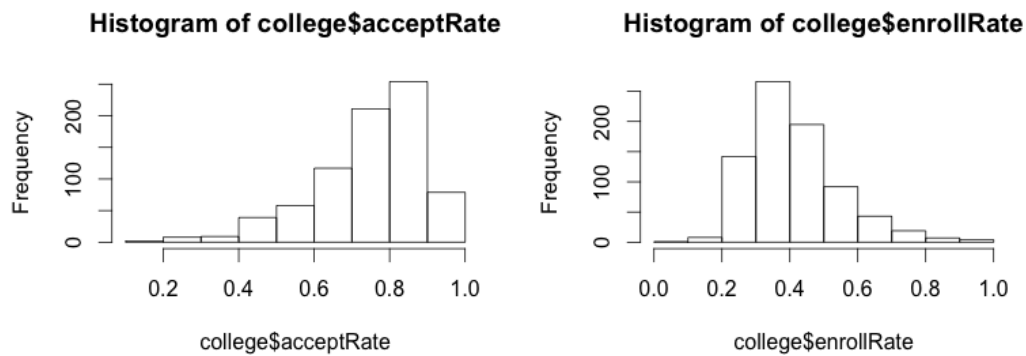


## Part v



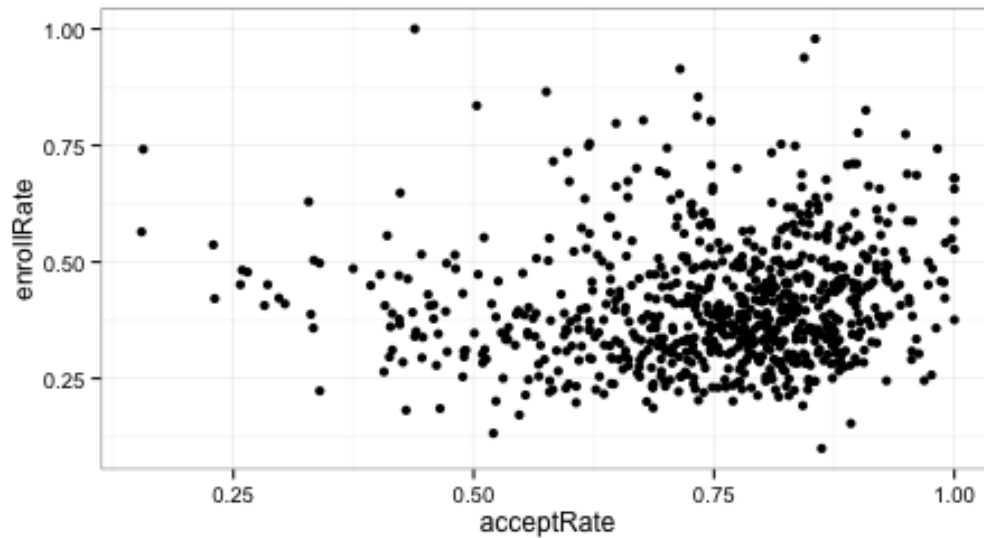
## Part vi

I chose to explore acceptance and enrollment rates, with acceptance rate defined as the number of students accepted per application received (`college$Accept/college$Apps`), and enrollment rate defined as the number of students enrolled per applicant accepted (`college$Enroll/college$Accept`).



Somewhat surprisingly, there's little correlation between acceptance and enrollment rate.

```
> cor(college$acceptRate, college$enrollRate)
[1] 0.0824304
```



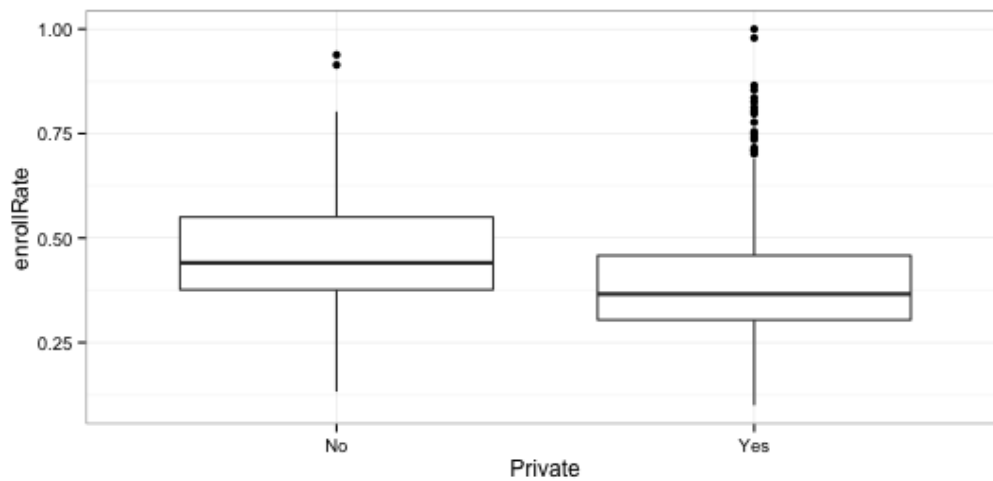
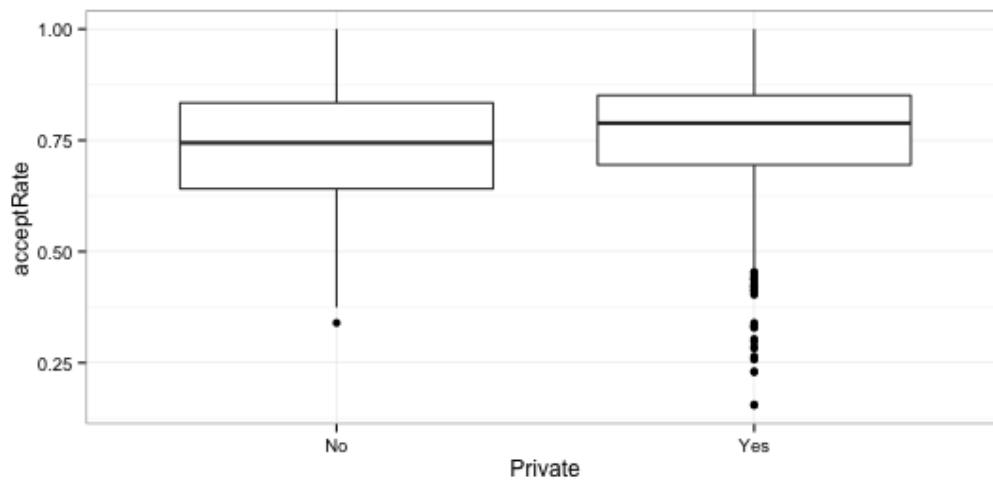
I also looked at summary statistics by public vs private schools.

```
> college %>%
+   group_by(Private) %>%
+   summarize(min.acceptRate=min(acceptRate),
+             median.acceptRate=median(acceptRate),
+             mean.acceptRate=mean(acceptRate),
+             max.acceptRate=max(acceptRate),
+             min.enrollRate=min(enrollRate),
+             median.enrollRate=median(enrollRate),
+             mean.enrollRate=mean(enrollRate),
+             max.enrollRate=max(enrollRate)) %>%
+   as.data.frame()
```

	Private	min.acceptRate	median.acceptRate	mean.acceptRate	max.acceptRate	min.enrollRate
1	No	0.3397060	0.7443387	0.7265305	1	0.13242009
2	Yes	0.1544863	0.7885653	0.7545812	1	0.09975397

	median.enrollRate	mean.enrollRate	max.enrollRate
1	0.4405908	0.4620216	0.9382716
2	0.3660934	0.3932510	1.0000000



## Problem 2: [James](#) 2.4, Exercise 9

### Part a

Quantitative predictors: mpg, cylinders, displacement, horsepower, weight, acceleration, year

Qualitative predictors: origin, name

### Part b

	statistic	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	name
1	min	9.0	3	68	46	1613	8.0	70	NA	NA
2	max	46.6	8	455	230	5140	24.8	82	NA	NA

### Part c

	statistic	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin
1	mean	23.445918	5.471939	194.412	104.46939	2977.5842	15.541327	75.979592	NA
2	sd	7.805007	1.705783	104.644	38.49116	849.4026	2.758864	3.683737	NA

### Part d

	statistic	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin
1	min	11.000000	3.000000	68.00000	46.00000	1649.0000	8.500000	70.000000	NA
2	max	46.600000	8.000000	455.00000	230.00000	4997.0000	24.800000	82.000000	NA
3	mean	24.404430	5.373418	187.24051	100.72152	2935.9715	15.726899	77.145570	NA
4	sd	7.867283	1.654179	99.67837	35.70885	811.3002	2.693721	3.106217	NA

### Part e

MPG generally increased between 1970 and 1982.

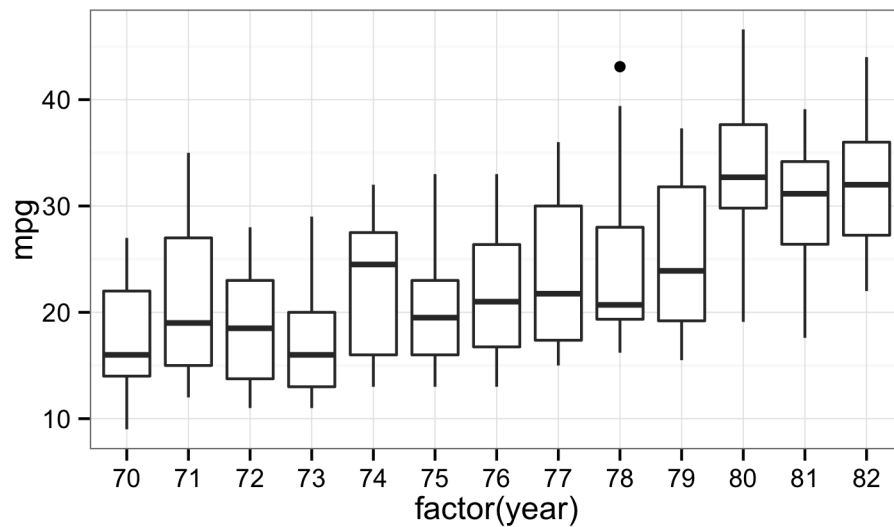


Figure 1: MPG vs year

As the number of cylinders increases, MPG generally decreases.

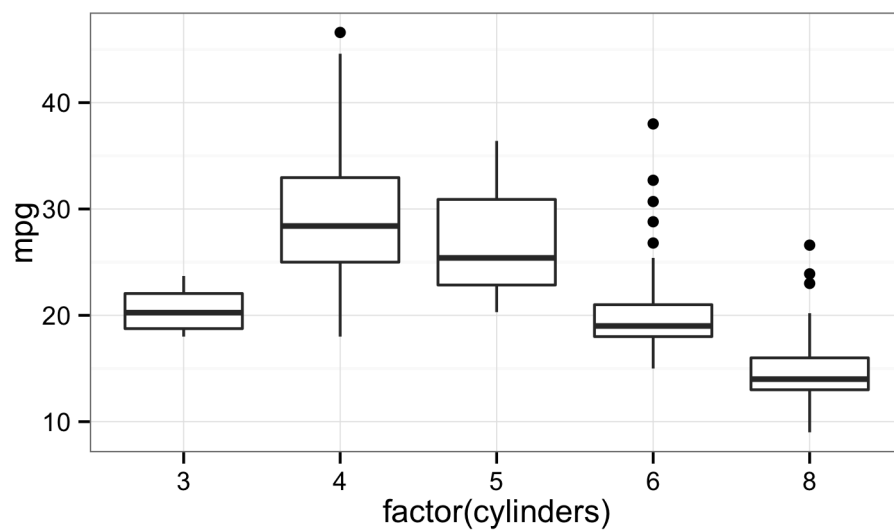
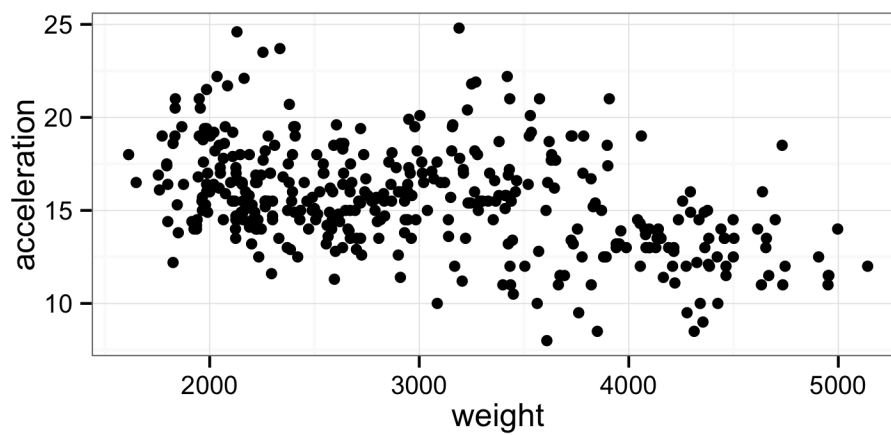


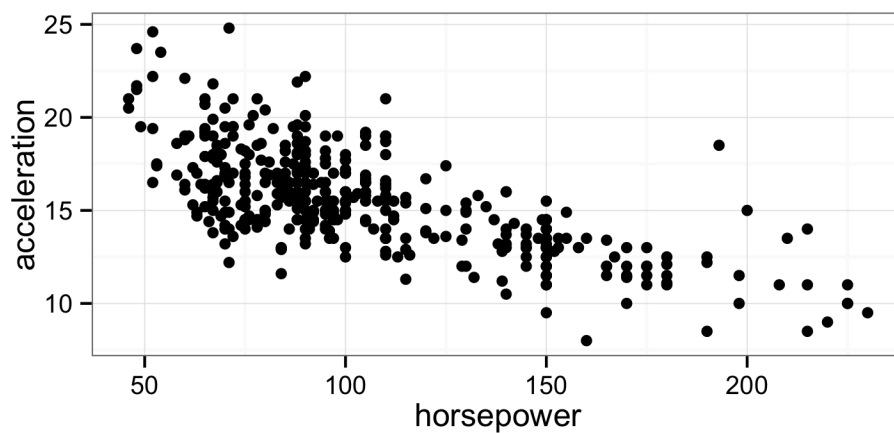
Figure 2: MPG vs number of cylinders

There isn't a particularly strong relationship between weight and acceleration (at least not one that is easily seen graphically).

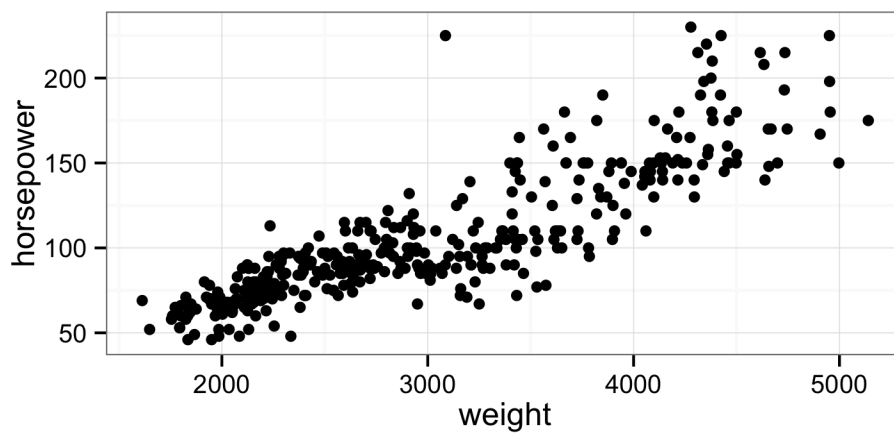


But there is a strong negative relationship between horsepower and acceleration.

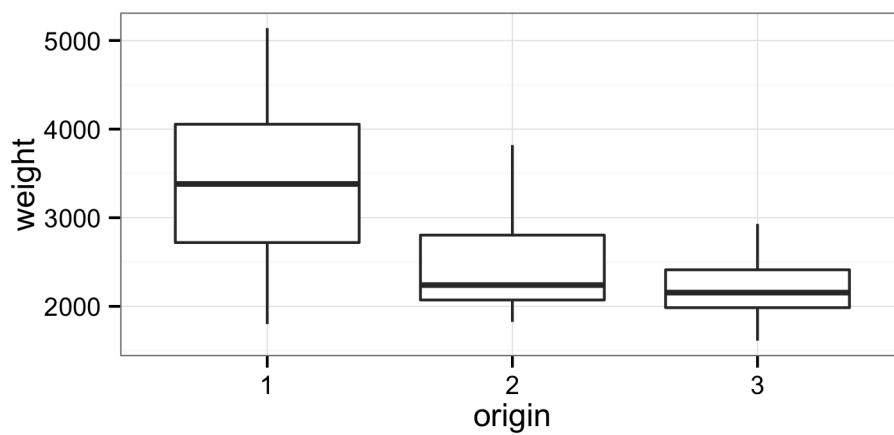




And unsurprisingly, as the weight of a car increases, so does its horsepower.



Japanese cars (3) are usually lighter than American (1) and European (2) cars.



Japanese cars also have higher MPG.

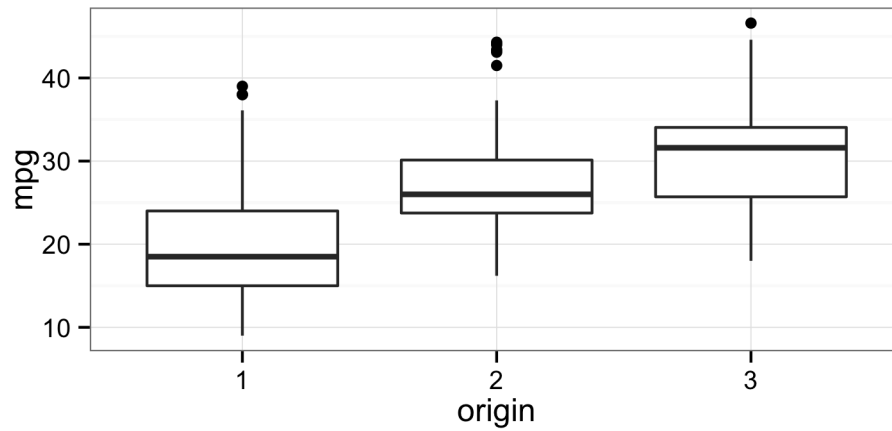


Figure 3: MPG by origin

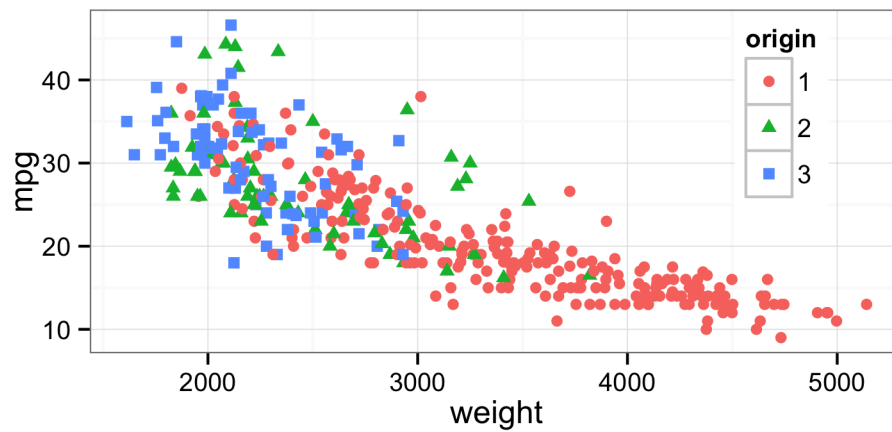


Figure 4: MPG vs weight, by origin

## Part f

As shown in **Part e**, the year (Figure 1), number of cylinders (Figure 2), origin (Figure 3), and weight (Figure 4) of a car are all useful in predicting MPG. Displacement is also a useful predictor, but acceleration is not (see Figures 5 and 6 below).

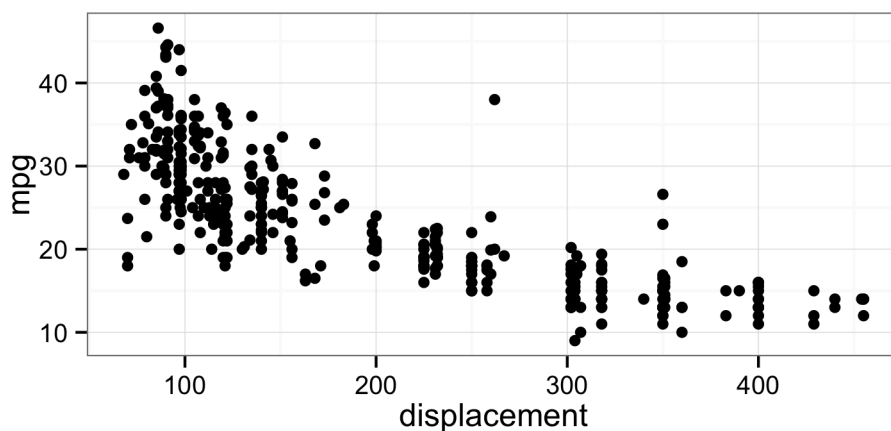


Figure 5: MPG vs displacemet

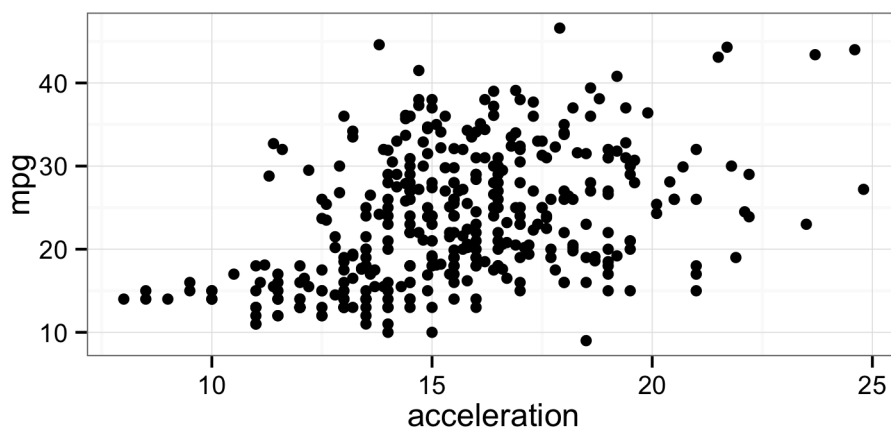


Figure 6: MPG vs acceleration

### Problem 3: [James 2.4](#), Exercise 10

#### Part a

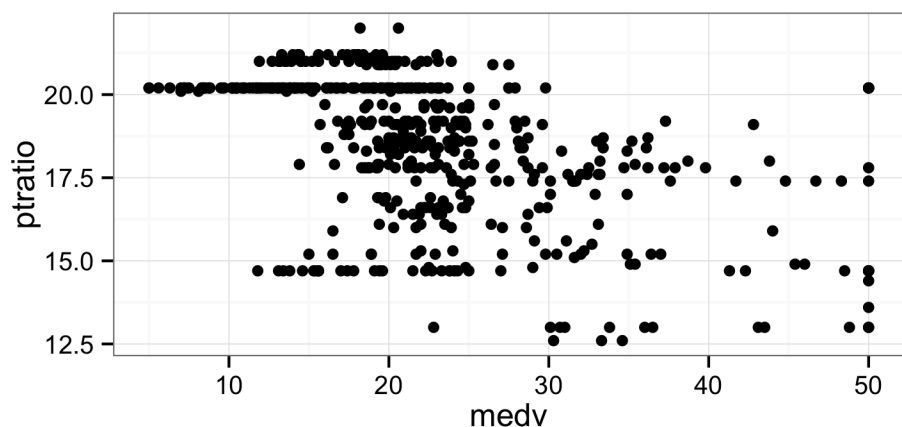
In the `Boston` dataset there are 506 rows and 14 columns. Each row represents a town in Boston. The column definitions, as written in the help file, are:

- `crim`: per capita crime rate by town.
- `zn`: proportion of residential land zoned for lots over 25,000 sq.ft.
- `indus`: proportion of non-retail business acres per town.
- `chas`: Charles River dummy variable (= 1 if tract bounds river; 0 otherwise).
- `nox`: nitrogen oxides concentration (parts per 10 million).
- `rm`: average number of rooms per dwelling.

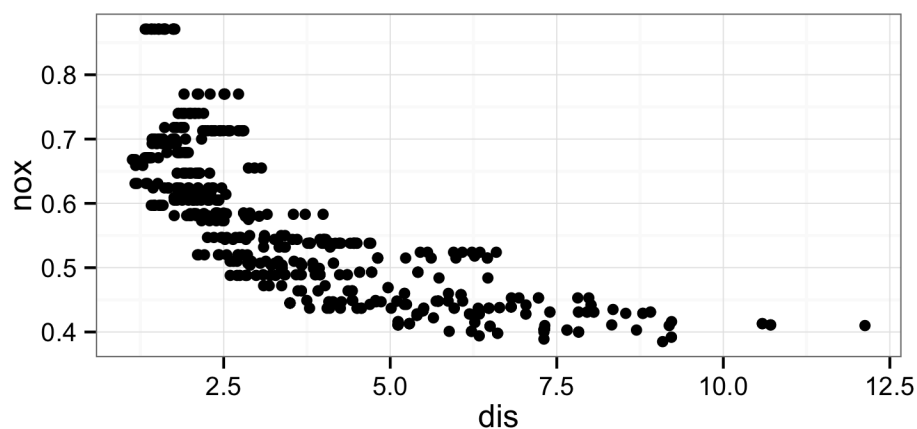
**age**: proportion of owner-occupied units built prior to 1940.  
**dis**: weighted mean of distances to five Boston employment centres.  
**rad**: index of accessibility to radial highways.  
**tax**: full-value property-tax rate per \$10,000.  
**ptratio**: pupil-teacher ratio by town.  
**black**:  $1000(Bk - 0.63)^2$  where Bk is the proportion of blacks by town.  
**lstat**: lower status of the population (percent).  
**medv**: median value of owner-occupied homes in \$1000s.

## Part b

Pupil-teacher ratio decreases slightly as home value increases.



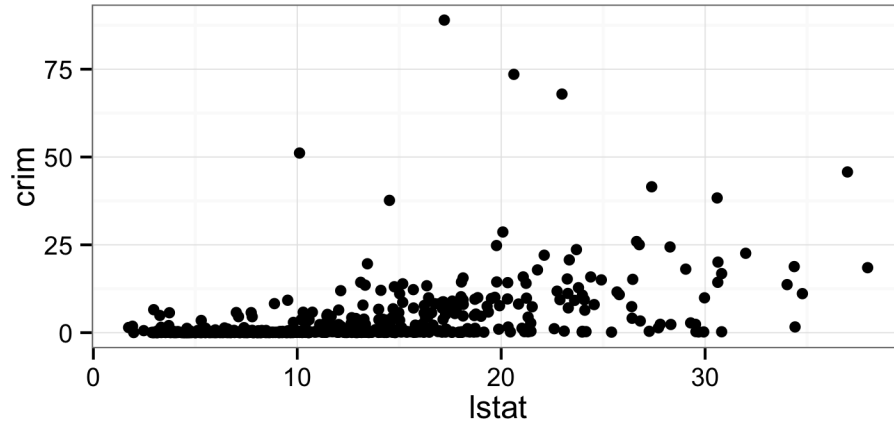
As distance from employment centers increases, nitrogen oxides concentration decreases.



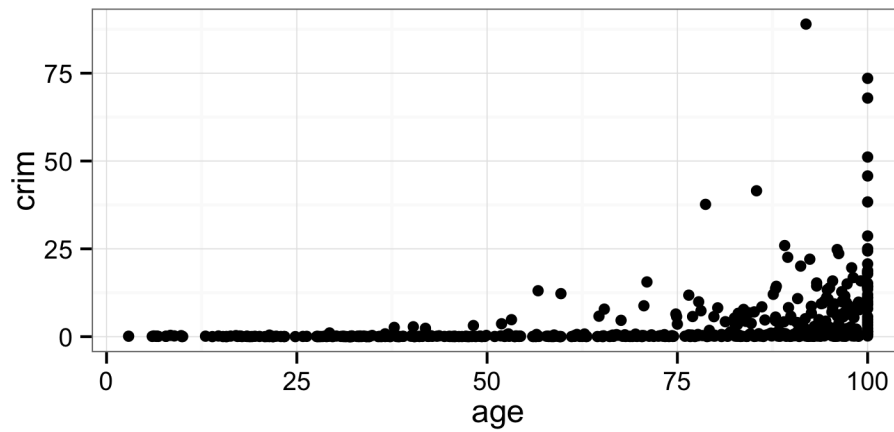
For plots incorporating crime rate (**crim**), see **Part c**.

### Part c

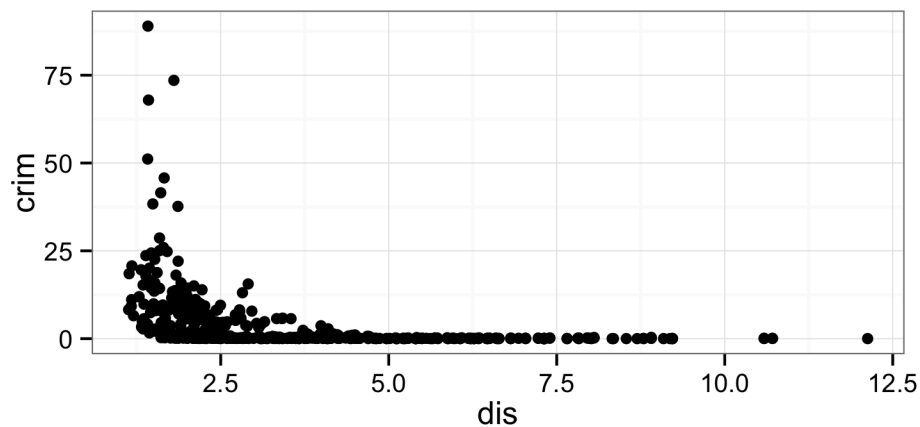
Crime rates are associated with many of the predictors. As "lower status of the population (percent)" increases, crime rates do too.



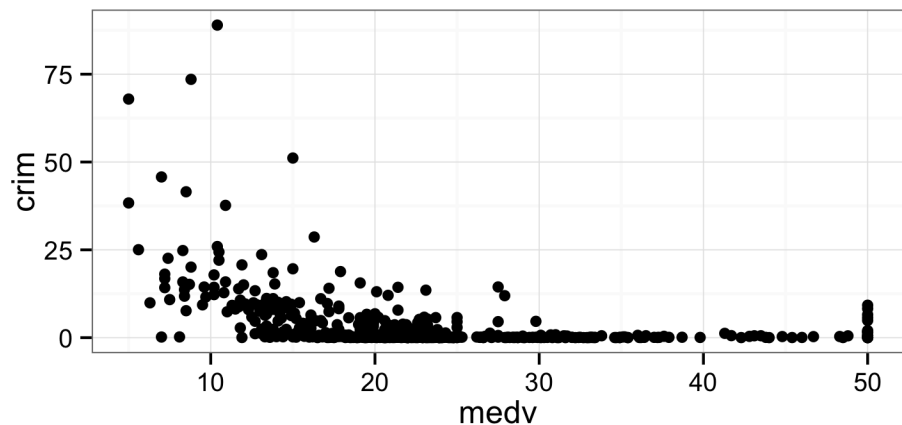
Similarly, towns with a higher proportion of buildings built before 1940 have higher crime rates as well.



Towns further from employment centers have lower crime rates.



And crime rates decrease as the median home value increases.



### Part d

Yes, some suburbs of Boston appear to have particularly high crime rates. The suburbs in rows 381, 399, 401, 405, 406, 411, 414, 415, 418, 419, and 428 each have a per capita crime rate of more than 25. Crime rate ranges from 0.00632 to 88.97620.

There also appear to be some towns with incredibly high tax rates. There are 137 towns with full-value property-tax rate per \$10,000 of more than 600. Tax rate ranges from 187 to 711. A subset of the 137 towns are listed below:

```
[1] 357 358 359 360 361 362 363 364 365 366 367 368 369 370 371 372 373
...
[121] 477 478 479 480 481 482 483 484 485 486 487 488 489 490 491 492 493
```

It doesn't look like any towns have particularly high pupil-teacher ratios. Pupil-teacher ratio ranges from 12.6 to 22.0. 20.2 students/teacher appears to be a very popular ratio.

Range of each predictor:

	stat	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
1	min	0.00632	0	0.46	0	0.385	3.561	2.9	1.1296	1	187	12.6	0.32	1.73	5
2	max	88.97620	100	27.74	1	0.871	8.780	100.0	12.1265	24	711	22.0	396.90	37.97	50

## Part e

35 town in the dataset bound the Charles river

## Part f

Among towns in the dataset, the median pupil-teacher ratio is 19.05.

## Part g

The towns in row numbers 399 and 406 have the lowest median values of owner-occupied homes at \$5,000.

For those towns:

	rowNum	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
1	399	38.3518	0	18.1	0	0.693	5.453	100	1.4896	24	666	20.2	396.90	30.59	5
2	406	67.9208	0	18.1	0	0.693	5.683	100	1.4254	24	666	20.2	384.97	22.98	5

Crime rates here are on the upper end of the range, and the towns have an average number of rooms per dwelling. Neither town borders the Charles river, and 100% of owner-occupied buildings in both towns were built before 1940.

## Part h

There are 64 towns that average more than 7 rooms per dwelling, and 13 towns that average more than 8 rooms per dwelling.

Towns with more than 8 rooms per dwelling:

	rowNum	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
1	98	0.12083	0	2.89	0	0.4450	8.069	76.0	3.4952	2	276	18.0	396.90	4.21	38.7
2	164	1.51902	0	19.58	1	0.6050	8.375	93.9	2.1620	5	403	14.7	388.45	3.32	50.0
3	205	0.02009	95	2.68	0	0.4161	8.034	31.9	5.1180	4	224	14.7	390.55	2.88	50.0
4	225	0.31533	0	6.20	0	0.5040	8.266	78.3	2.8944	8	307	17.4	385.05	4.14	44.8
5	226	0.52693	0	6.20	0	0.5040	8.725	83.0	2.8944	8	307	17.4	382.00	4.63	50.0
6	227	0.38214	0	6.20	0	0.5040	8.040	86.5	3.2157	8	307	17.4	387.38	3.13	37.6
7	233	0.57529	0	6.20	0	0.5070	8.337	73.3	3.8384	8	307	17.4	385.91	2.47	41.7
8	234	0.33147	0	6.20	0	0.5070	8.247	70.4	3.6519	8	307	17.4	378.95	3.95	48.3
9	254	0.36894	22	5.86	0	0.4310	8.259	8.4	8.9067	7	330	19.1	396.90	3.54	42.8
10	258	0.61154	20	3.97	0	0.6470	8.704	86.9	1.8010	5	264	13.0	389.70	5.12	50.0
11	263	0.52014	20	3.97	0	0.6470	8.398	91.5	2.2885	5	264	13.0	386.86	5.91	48.8
12	268	0.57834	20	3.97	0	0.5750	8.297	67.0	2.4216	5	264	13.0	384.54	7.44	50.0
13	365	3.47428	0	18.10	1	0.7180	8.780	82.9	1.9047	24	666	20.2	354.55	5.29	21.9

These towns all have very low crime rates and have lower values for `lstat`. They generally have `medv` values towards the higher end of the range.

## Problem 4: Yale Faces B

### Part a

The *CroppedYale/yaleB01/yaleB01p00A - 005E + 10.pgm* image is of class `pixmapGrey` (part of the `pixmap` package). The original image is made up of 32,256 pixels (192 x 168).

### Part b

A pixel value in a `pixmapGrey`-classed pgm image ranges from 0 to 1. A value of 0 corresponds to a black pixel, and a value of 1 corresponds to a white pixel.

In `faces_matrix`, which combines images 1 and 2, the pixel values range from 0.007843137 to 1.000000000.