PCA: Houses

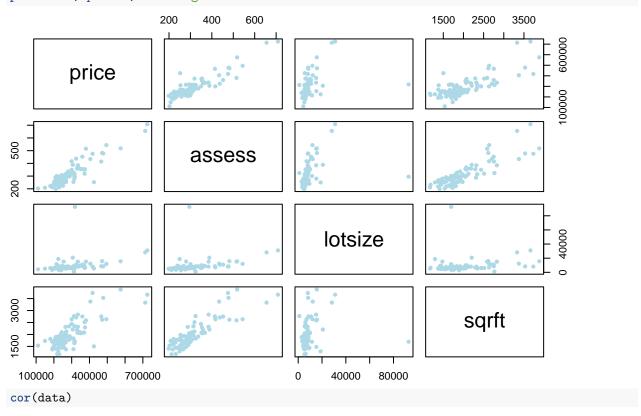
Gustavo Cepparo and Milica Cudina

First, we read in our house data.

```
data=read.csv("housepriceall.csv",header=TRUE)
attach(data)
```

Let me do a bit of exploratory data analysis.

```
plot(data, pch=20, col="lightblue")
```



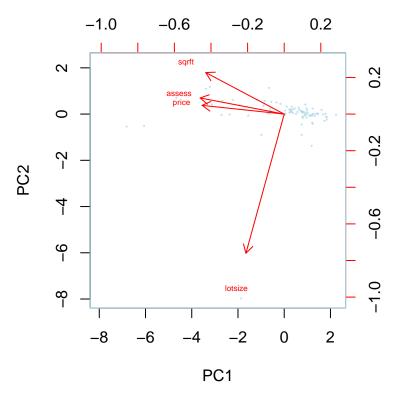
```
## price assess lotsize sqrft
## price 1.0000000 0.9052794 0.3471245 0.7879065
## assess 0.9052794 1.0000000 0.3281463 0.8656345
## lotsize 0.3471245 0.3281463 1.0000000 0.1838422
## sqrft 0.7879065 0.8656345 0.1838422 1.0000000
```

Obviously, the scale of the price is different from the scale of the square footage. Also, the assessed price and the price are artificially on a different scale. Let's look at the means and variances.

```
apply(data, 2, mean)
```

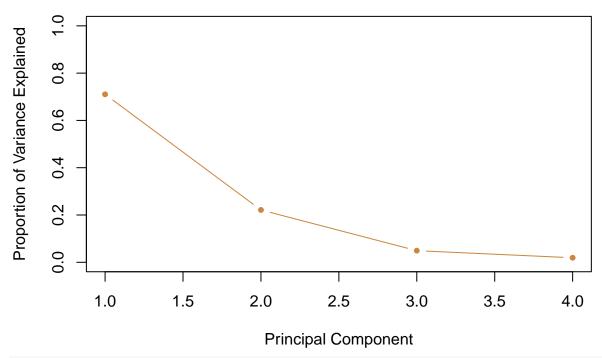
```
## price assess lotsize sqrft
## 293546.0341 315.7364 9019.8636 2013.6932
```

```
apply(data, 2, sd)
                                   lotsize
                                                   sqrft
          price
                       assess
## 102713.44517
                     95.31444 10174.15041
                                               577.19158
Let's take a look at what the principal component analysis is telling us.
pr.out<-prcomp(data, scale=TRUE)</pre>
Here are the outputs of prcomp.
pr.out$center
         price
                     assess
                                lotsize
                                               sqrft
## 293546.0341
                  315.7364
                              9019.8636
                                          2013.6932
pr.out$scale
          price
                       assess
                                   lotsize
                                                   sqrft
## 102713.44517
                     95.31444 10174.15041
                                              577.19158
pr.out$rotation
##
                  PC1
                               PC2
                                          PC3
                                                       PC4
## price
           -0.5608750 0.05950919 -0.6507820 0.50829197
## assess -0.5742342 0.11020662 -0.1214913 -0.80209066
## lotsize -0.2615396 -0.95073388 0.1633602 0.03186797
           -0.5359770 0.28358110 0.7314616 0.31188825
## sqrft
dim(pr.out$x)
## [1] 88 4
Of course, it's much better to look at the biplot.
biplot(pr.out, scale=0, cex=0.5, xlabs=rep("*", length(price)),
       col=c("lightblue", "red"))
```



How many principal components are "sufficient"?

```
#transforming standard deviations to variances
pr.var=pr.out$sdev^2
#pr.var
#proportion of variance explained
pve=pr.var/sum(pr.var)
#pve
#plots
plot(pve,xlab="Principal Component", ylab="Proportion of Variance Explained", col="peru", pch=20, ylim=c(0,1),type='b')
```



plot(cumsum(pve),xlab="Principal Component", ylab="Cumulative Proportion of Variance Explained", col="p
ylim=c(0,1),type='b')

