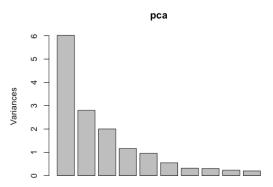
clear environment, load dataset

```
rm(list = ls())
set.seed(1)
dat <- read.table("uscrime.txt", stringsAsFactors = FALSE, header = TRUE)</pre>
```

using PCA (prcomp function) and scaling data; first goal is identifying the first "few" principal components to make our regression model and then compare that with the model of the total original variables

```
pca = prcomp(x=dat[,1:15], scale=TRUE)
plot(pca)
```

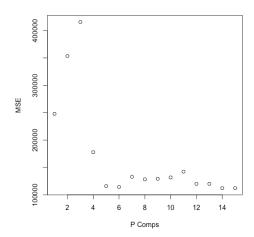


as perhaps expected, the most variance comes in the first principal variable; the variance seems to drastically reduce by the sixth or seventh variable; so we can target that area

another method may be brought in to determine the number of Principal Components that will be best to use; one idea is to use cross validation (20-fold as the option I went with) to see how "few" Principal Components to use

```
cv_res <- NULL
for (n_pca_comp in 1:ncol(pca$x)){
    pca_df <- as.data.frame(cbind(pca$x[,1:n_pca_comp], Crime=dat[,16]))
    cv <- cv.lm(pca_df, form.lm=Crime~., m=20, printit=FALSE)
    mean_squared_error <- attr(cv, 'ms')
    cv_res <- rbind(cv_res,data.frame(n_pca_comp, mean_squared_error))
}

plot(x=cv_res$n_pca_comp, y=cv_res$mean_squared_error, xlab="P Comps", ylab = "MSE")</pre>
```



This suggests that 6 principal components would b be best (14 and 15 also share a low mean squared error but in that case there wouldn't be any principal components, and besides we'll test against this (15) – the 6 PCs fits with what I found in last homework based on p-values

I'll also create a pca data frame for later use (pca_df) and run a linear regression model on it pcomps = 6

```
pca_df <- as.data.frame(cbind(pca$x[,1:pcomps], Crime=dat[,16]))
regression <- Im(Crime~., data=pca_df)
summary(regression)
```

Residuals:

Min 1Q Median 3Q Max -377.15 -172.23 25.81 132.10 480.38

Coefficients:

Estimate Std. Error t value Pr(>|t|)(Intercept) 905.09 $35.35 \ 25.604 < 2e-16 ***$ PC1 65.22 14.56 4.478 6.14e-05 *** PC2-70.08 21.35 -3.283 0.00214 ** PC325.19 25.23 0.998 0.32409 PC4 69.45 33.14 2.095 0.04252 * PC5 -229.04 36.50 -6.275 1.94e-07 *** PC6 -60.21 48.04 -1.253 0.21734

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

Residual standard error: 242.3 on 40 degrees of freedom Multiple R-squared: 0.6586, Adjusted R-squared: 0.6074

F-statistic: 12.86 on 6 and 40 DF, p-value: 4.869e-08

let's compare the regression model just created with the actual crime numbers

```
actual <- dat$Crime
predicted <- regression$fitted.values
rss <- sum((predicted - actual)^2)
tss <- sum((actual-mean(actual))^2)
rsq <- 1 - rss/tss
rsq
[1] 0.6586023
```

a new r-squared value of .65 from our principal component regression model to the actual crime; this is a a lower R-squared than my adjusted R-squared from last homework, so PCA did not appear to help reduce this measure

estimate in 8.2 was new crime for the "state" would be 1304, now looking for what this model will give me; had to look at equations on placing in new data; ended up doing manually

```
new_crime <- sum(
  coeff_convert[1,1] %*% new_state$M,
  coeff_convert[2,1] %*% new_state$So,
    .......coeff_convert[15,1] %*% new_state$Time,
    intercept2
)
new_crime
    [1] 1112.678</pre>
```

a near estimate but still off from last estimate by 15%; with a lower R-squared, I would trust the answer given in Homework 8.2 over this PCA method; but if we were given years and years of crime data (and perhaps other variables as well) being able to identify and deploy Principle Components would be very effective; this dataset simply isn't that large