

SM2_Portfolio_1

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Principal Component analysis

Task 1

First let's look at the structure of the data:

```
USA <- USArrests[, -3]
summary(USA)
```

```
##      Murder      Assault      Rape
##  Min.   : 0.800   Min.   : 45.0   Min.   : 7.30
##  1st Qu.: 4.075   1st Qu.:109.0   1st Qu.:15.07
##  Median : 7.250   Median :159.0   Median :20.10
##  Mean   : 7.788   Mean   :170.8   Mean   :21.23
##  3rd Qu.:11.250   3rd Qu.:249.0   3rd Qu.:26.18
##  Max.   :17.400   Max.   :337.0   Max.   :46.00
```

We have four columns and would like to perform PCA on the data minus the UrbanPop feature. First we will carry out PCA using the covariance matrix, S, manually:

```
S.USA <- cov(USA)
ev.USA <- eigen(S.USA)
ev.USA
```

```
## eigen() decomposition
## $values
## [1] 6996.480738  48.658639   6.725962
##
## $vectors
##      [,1]      [,2]      [,3]
## [1,] -0.04180743  0.02555358  0.99879886
## [2,] -0.99630506 -0.07612980 -0.03975532
## [3,] -0.07502247  0.99677042 -0.02864195
```

Notice that the eigenvectors in the matrix are already sorted by the size of their eigenvalues and so have decreasing sample variance. Thus the matrix of our principal components is exactly the matrix of eigenvalues above.

Now we will carry out PCA using the correlation matrix, R, and the help of the *prcomp* command.

```
pc_USArrests <- prcomp(~Murder + Assault + Rape, USArrests, scale. = TRUE, retx=TRUE); pc_USArrests # W

## Standard deviations (1, ..., p=3):
## [1] 1.5357670 0.6767949 0.4282154
##
## Rotation (n x k) = (3 x 3):
```

##	PC1	PC2	PC3
## Murder	-0.5826006	0.5339532	-0.6127565
## Assault	-0.6079818	0.2140236	0.7645600
## Rape	-0.5393836	-0.8179779	-0.1999436

pc_USArrests\$x

##	PC1	PC2	PC3
## Alabama	-1.198027832	0.83381177	-0.162178476
## Alaska	-2.308747325	-1.52396221	0.038335742
## Arizona	-1.503330652	-0.49830384	0.878223112
## Arkansas	-0.175989446	0.32473260	0.071111741
## California	-2.045235843	-1.27257704	0.381539326
## Colorado	-1.263413283	-1.42640632	-0.083693139
## Connecticut	1.627064626	0.17860374	0.290256038
## Delaware	0.074812801	0.41561083	0.998446677
## Florida	-2.830731325	0.42331809	0.208151641
## Georgia	-1.842343065	0.88277323	-1.080609032
## Hawaii	1.302403647	-0.53528688	-0.772523404
## Idaho	1.469223571	-0.15225639	0.414302742
## Illinois	-1.079579292	0.27941102	0.291234322
## Indiana	0.513394603	-0.20015992	-0.442228830
## Iowa	2.156636865	-0.11239443	-0.054668600
## Kansas	0.832079409	-0.08014103	-0.191017094
## Kentucky	0.478831591	0.50650575	-0.730308649
## Louisiana	-1.644731071	1.04957018	-0.373768062
## Maine	2.174592271	0.25034567	0.281818786
## Maryland	-1.790861674	0.18886129	0.551385569
## Massachusetts	0.895952687	-0.04050899	0.382293578
## Michigan	-1.989964308	-0.46614937	-0.129836314
## Minnesota	1.765715718	-0.32440018	-0.055072348
## Mississippi	-1.517623726	1.60645578	-0.271636024
## Missouri	-0.616205380	-0.44134841	-0.252834582
## Montana	0.967991307	0.04418005	-0.211907462
## Nebraska	1.240695366	-0.19093752	-0.039096727
## Nevada	-2.609154480	-1.41350501	-0.404109160
## New Hampshire	2.266374551	0.03511068	0.006998662
## New Jersey	0.277745503	0.13462220	-0.001387439
## New Mexico	-1.942431655	-0.21292600	0.307911561
## New York	-1.330622591	0.19467099	0.193797219
## North Carolina	-1.614416593	1.51406566	0.901426577
## North Dakota	2.654501432	0.03705123	0.126761976
## Ohio	0.425915739	-0.20485611	-0.400616435
## Oklahoma	0.374013508	-0.08879455	0.012150589
## Oregon	0.007484513	-1.08883723	0.126183190
## Pennsylvania	1.036129757	0.20425023	-0.249615405
## Rhode Island	1.308026751	0.59975203	0.923110514
## South Carolina	-1.747107574	0.97782271	0.035740543
## South Dakota	1.637375231	0.02980135	-0.036558286
## Tennessee	-1.176095386	0.21275256	-0.724219698
## Texas	-1.123432710	0.30710594	-0.504726135
## Utah	0.887958106	-0.83848257	0.144173194
## Vermont	2.220758807	-0.12420650	-0.125927856
## Virginia	0.043078167	0.09584025	-0.224223254
## Washington	0.408525962	-0.96439783	0.190536108

```
## West Virginia    1.621260055  0.55554584 -0.275017445
## Wisconsin       2.153811966 -0.02739623 -0.127792014
## Wyoming          0.527690701  0.34566289  0.169682461
```

The **sdev** component tells us the standard deviations of the principal components which corresponds to the squareroot of the eigenvalues of the covariance matrix, $(\sqrt{\lambda_1}, \sqrt{\lambda_2}, \sqrt{\lambda_3})^T = \text{diag}(\Lambda)$. The **rotation** component contains the matrix of the principal components, ie. the eigenvectors of the correlation matrix, R , $\mathbf{A} = [v_1 \ v_2 \ v_3]$ where \mathbf{A} is the matrix of principal components (the eigenvectors of R) and v_i is the i -th eigenvector. Finally \mathbf{x} contains the data transformed by the principal component matrix (ie. our now uncorrelated data), in the notes: $\mathbf{Y} = \mathbf{XA}$.

The correlation matrix can be interpreted as the sample covariance matrix of the scaled data. So whether we should use the covariance matrix or correlation matrix depends on the variances of the predictor variables. Recalling the variances:

```
diag(S.USA)
```

```
##      Murder      Assault      Rape
## 18.97047 6945.16571  87.72916
```

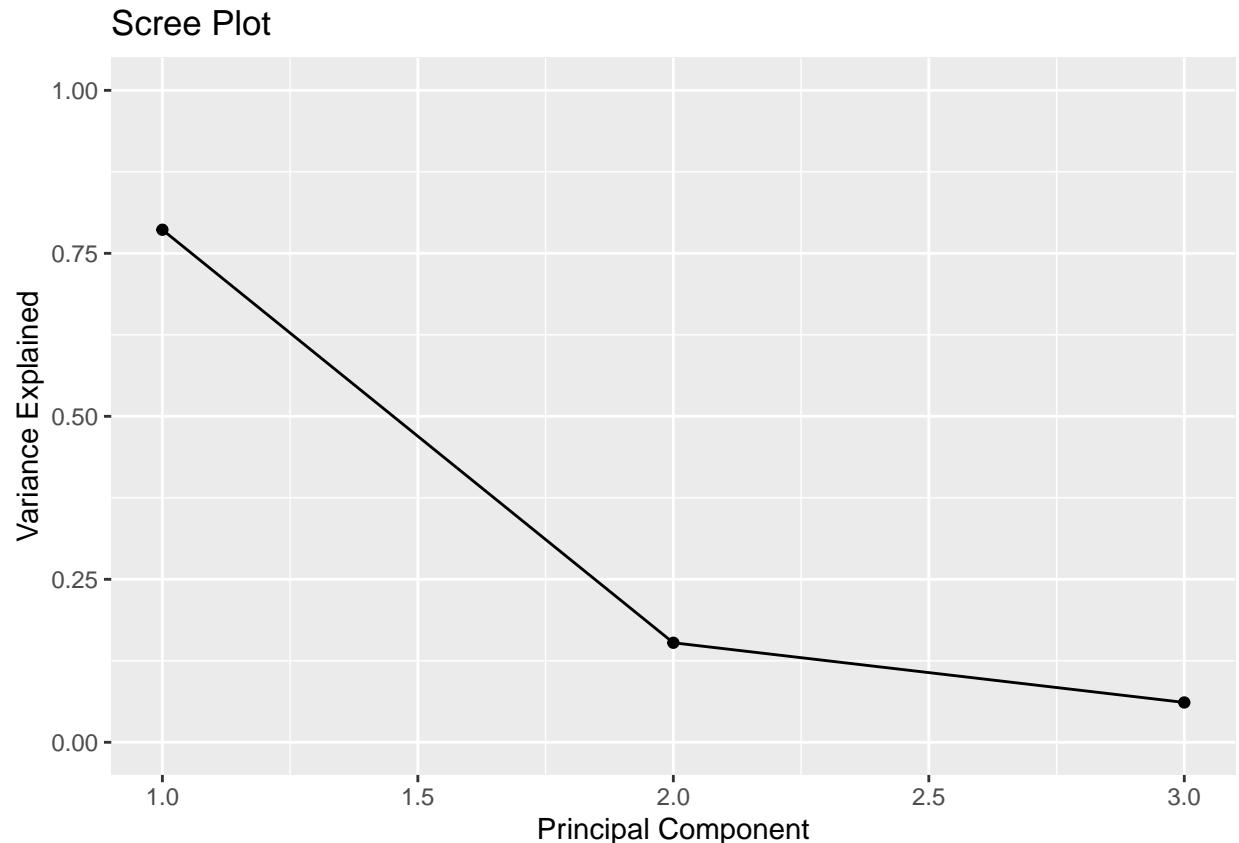
We see that the variances of the predictor variables greatly differ by orders of magnitude, therefore it is sensible to work with the scaled data, ie. the correlation matrix R .

Now we will plot a **scree plot** which is a plot of the variance explained by each principal component, ie. the percentage of the variance accounted for by the principal component.

```
var_prcnt = pc_USArrests$sdev^2 / sum(pc_USArrests$sdev^2)

qplot(c(1:3), var_prcnt) +
  geom_line() +
  xlab("Principal Component") +
  ylab("Variance Explained") +
  ggtitle("Scree Plot") +
  ylim(0, 1)
```

```
## Warning: `qplot()` was deprecated in ggplot2 3.4.0.
```



From the scree plot we can see the first principal component accounts for a very large percentage of the variance with the 3rd principal component accounting for less than 12% of the variance.

We will now compute the Kaiser's criterion:

```
max(which(pc_USArrests$sdev > sum(pc_USArrests$sdev)/length(pc_USArrests$sdev)))
```

```
## [1] 1
```

and now the number of PC's to keep according to Horn's parallel analysis:

```
M <- 1000
n <- nrow(USA)
p <- ncol(USA)
lambdas <- matrix(NA, M, p)
for(i in 1:M){
  M <- matrix( rnorm(p*n,mean=0,sd=1), n, p) # generate matrix with N(0,1) entries
  R <- cor(M) # find correlation matrix
  S <- diag(pc_USArrests$sdev) %*% R %*% diag(pc_USArrests$sdev) # scale
  lambdas[i,] <- eigen(S)$values # find the eigenvalues
}
mean_lambda <- colMeans(lambdas) # find the mean of the eigenvalues
```

```
# find the largest index of eigenvalues larger than the mean eigenvalue of our M standard normal matrices
max(which(pc_USArrests$sdev > mean_lambda))
```

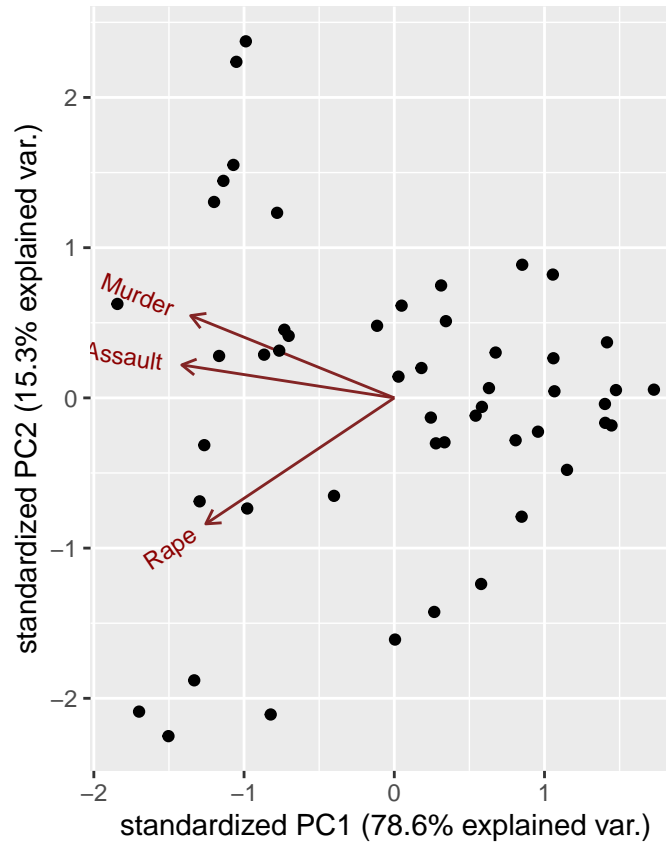
```
## [1] 3
```

Kaiser's criterion tells us to only keep the first principal component, ie. let $q = 1$, whereas Horn's parallel analysis suggests not throwing away any of the principal components, ie. $q = 3$. Horn's parallel analysis takes

into account the sampling error that arises from the fact that we don't have infinite observations (only n) unlike Kaiser's criterion, therefore we will select $q = 3$. Looking at the scree plot we can back up this decision as throwing away the second two principal components would amount to losing close to 25% of the variance.

Now we will produce a biplot:

```
ggbiplot(pc_USArrests)
```



The black dots are the datapoints transformed by our PC's, here we plot the first component versus the second. The red arrows tell us which predictor variables contribute to which principal components. Here we see that higher values in murder and assault contribute to a larger value of PC2 for example. From the plot we see that all the features have negative values for the first component which means the first component is an average of all three features and suggests that all three features are correlated with each other. For the second component we see that larger values in murder and assault lead to a higher value and rape to a lower value, ie. it contrasts rape against the other features.

Task 2

We will be working with the iris dataset:

```
summary(iris)
```

##	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width
##	Min. :4.300	Min. :2.000	Min. :1.000	Min. :0.100
##	1st Qu.:5.100	1st Qu.:2.800	1st Qu.:1.600	1st Qu.:0.300
##	Median :5.800	Median :3.000	Median :4.350	Median :1.300
##	Mean :5.843	Mean :3.057	Mean :3.758	Mean :1.199
##	3rd Qu.:6.400	3rd Qu.:3.300	3rd Qu.:5.100	3rd Qu.:1.800
##	Max. :7.900	Max. :4.400	Max. :6.900	Max. :2.500

```
##          Species
##  setosa      :50
##  versicolor:50
##  virginica  :50
##
##
##
```

Ideally we would like to use the covariance matrix as this will preserve variance, however, if the predictor variables are scaled differently this could lead to one predictor variable accounting for a large percentage of the variance. In this case we would prefer to standardize the data and use the correlation matrix. Let us assess the variances of the predictor variables:

```
diag(cov(iris[, -5]))
```

```
## Sepal.Length Sepal.Width Petal.Length Petal.Width
##      0.6856935      0.1899794      3.1162779      0.5810063
```

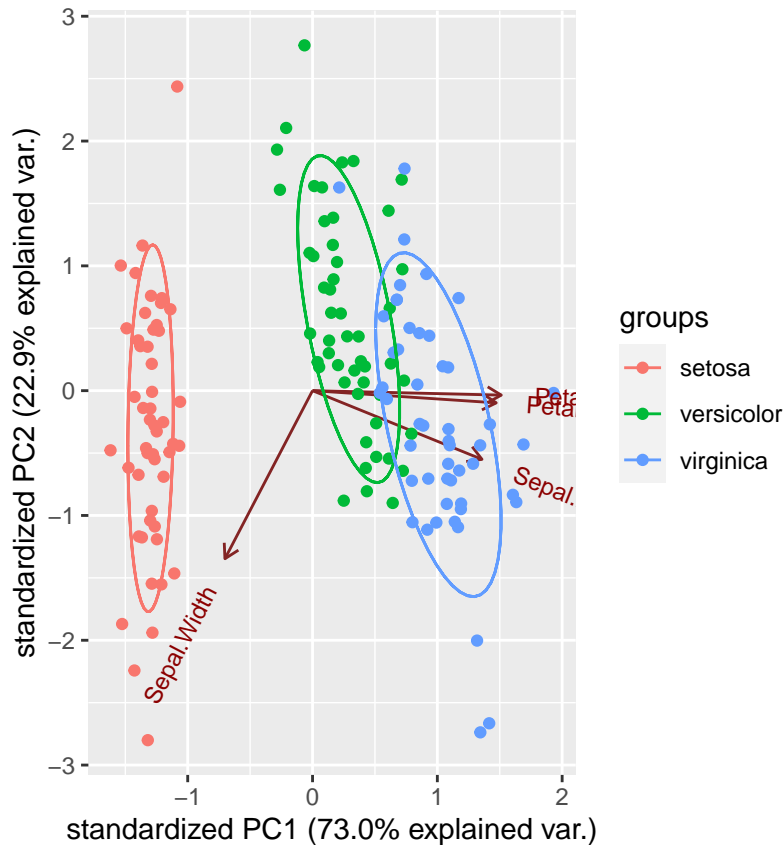
We see that the variances do differ and even though they all use the same measurement on the same scale the variances are very different, for example Petal.length has a variance of 13 times Sepal.Width so we will use the correlation matrix:

```
pc_iris <- prcomp(~Sepal.Length + Sepal.Width + Petal.Length + Petal.Width , iris, scale.= TRUE, retx=
```

```
## Standard deviations (1, .., p=4):
## [1] 1.7083611 0.9560494 0.3830886 0.1439265
##
## Rotation (n x k) = (4 x 4):
##           PC1          PC2          PC3          PC4
## Sepal.Length  0.5210659 -0.37741762  0.7195664  0.2612863
## Sepal.Width  -0.2693474 -0.92329566 -0.2443818 -0.1235096
## Petal.Length  0.5804131 -0.02449161 -0.1421264 -0.8014492
## Petal.Width   0.5648565 -0.06694199 -0.6342727  0.5235971
```

Let's now plot the two dimensional reduction of observations and color the data-points according to their species:

```
ggbiplot(pc_iris, ellipse=TRUE, groups = iris$Species)
```



From the plot we see that using our first two principal components has resulted in a two-dimensional reduction of the data-set where the points are clustered according to group, ie. all the points belonging to the setosa species appear together in the feature space and the same can be said for versicolor and virginica, although the between group scatterness between these two is much lower (ie. they appear much closer together in feature space).

Task 3

For this task we will be working with the communities and crime dataset, let's start by loading in and summarising the dataset:

```
library(mogavs)
data(crimeData)
summary(crimeData)
```

##	x.V6	x.V7	x.V8	x.V9
##	Min. :0.00000	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.:0.01000	1st Qu.:0.3500	1st Qu.:0.0200	1st Qu.:0.6300
##	Median :0.02000	Median :0.4400	Median :0.0600	Median :0.8500
##	Mean :0.05759	Mean :0.4634	Mean :0.1796	Mean :0.7537
##	3rd Qu.:0.05000	3rd Qu.:0.5400	3rd Qu.:0.2300	3rd Qu.:0.9400
##	Max. :1.00000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	x.V10	x.V11	x.V12	x.V13
##	Min. :0.0000	Min. :0.000	Min. :0.0000	Min. :0.0000
##	1st Qu.:0.0400	1st Qu.:0.010	1st Qu.:0.3400	1st Qu.:0.4100
##	Median :0.0700	Median :0.040	Median :0.4000	Median :0.4800
##	Mean :0.1537	Mean :0.144	Mean :0.4242	Mean :0.4939
##	3rd Qu.:0.1700	3rd Qu.:0.160	3rd Qu.:0.4700	3rd Qu.:0.5400

##	Max.	:1.0000	Max.	:1.000	Max.	:1.0000	Max.	:1.0000
##	x.V14		x.V15		x.V16		x.V17	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.00000	Min.	:0.0000
##	1st Qu.:	:0.2500	1st Qu.:	:0.3000	1st Qu.:	:0.00000	1st Qu.:	:0.0000
##	Median	:0.2900	Median	:0.4200	Median	:0.03000	Median	:1.0000
##	Mean	:0.3363	Mean	:0.4232	Mean	:0.06407	Mean	:0.6963
##	3rd Qu.:	:0.3600	3rd Qu.:	:0.5300	3rd Qu.:	:0.07000	3rd Qu.:	:1.0000
##	Max.	:1.0000	Max.	:1.0000	Max.	:1.00000	Max.	:1.0000
##	x.V18		x.V19		x.V20		x.V21	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.:	:0.2000	1st Qu.:	:0.4400	1st Qu.:	:0.1600	1st Qu.:	:0.3700
##	Median	:0.3200	Median	:0.5600	Median	:0.2300	Median	:0.4800
##	Mean	:0.3611	Mean	:0.5582	Mean	:0.2916	Mean	:0.4957
##	3rd Qu.:	:0.4900	3rd Qu.:	:0.6900	3rd Qu.:	:0.3700	3rd Qu.:	:0.6200
##	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000
##	x.V22		x.V23		x.V24		x.V25	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.:	:0.3500	1st Qu.:	:0.1425	1st Qu.:	:0.3600	1st Qu.:	:0.2300
##	Median	:0.4750	Median	:0.2600	Median	:0.4700	Median	:0.3300
##	Mean	:0.4711	Mean	:0.3178	Mean	:0.4792	Mean	:0.3757
##	3rd Qu.:	:0.5800	3rd Qu.:	:0.4400	3rd Qu.:	:0.5800	3rd Qu.:	:0.4800
##	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000
##	x.V26		x.V27		x.V28		x.V29	
##	Min.	:0.0000	Min.	:0.000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.:	:0.2200	1st Qu.:	:0.240	1st Qu.:	:0.1725	1st Qu.:	:0.1100
##	Median	:0.3000	Median	:0.320	Median	:0.2500	Median	:0.1700
##	Mean	:0.3503	Mean	:0.368	Mean	:0.2911	Mean	:0.2035
##	3rd Qu.:	:0.4300	3rd Qu.:	:0.440	3rd Qu.:	:0.3800	3rd Qu.:	:0.2500
##	Max.	:1.0000	Max.	:1.000	Max.	:1.0000	Max.	:1.0000
##	x.V30		x.V31		x.V32		x.V33	
##	Min.	:0.0000	Min.	: 0.0000	Min.	:0.0000	Min.	:0.00000
##	1st Qu.:	:0.1900	1st Qu.:	: 0.1700	1st Qu.:	:0.2600	1st Qu.:	:0.01000
##	Median	:0.2800	Median	: 0.2500	Median	:0.3450	Median	:0.02000
##	Mean	:0.3224	Mean	: 0.3804	Mean	:0.3863	Mean	:0.05551
##	3rd Qu.:	:0.4000	3rd Qu.:	: 0.3600	3rd Qu.:	:0.4800	3rd Qu.:	:0.05000
##	Max.	:1.0000	Max.	:191.0542	Max.	:1.0000	Max.	:1.00000
##	x.V34		x.V35		x.V36		x.V37	
##	Min.	:0.000	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.:	:0.110	1st Qu.:	:0.1600	1st Qu.:	:0.2300	1st Qu.:	:0.2100
##	Median	:0.250	Median	:0.2700	Median	:0.3600	Median	:0.3100
##	Mean	:0.303	Mean	:0.3158	Mean	:0.3833	Mean	:0.3617
##	3rd Qu.:	:0.450	3rd Qu.:	:0.4200	3rd Qu.:	:0.5100	3rd Qu.:	:0.4600
##	Max.	:1.000	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000
##	x.V38		x.V39		x.V40		x.V41	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.:	:0.2200	1st Qu.:	:0.3800	1st Qu.:	:0.2500	1st Qu.:	:0.3200
##	Median	:0.3200	Median	:0.5100	Median	:0.3700	Median	:0.4100
##	Mean	:0.3635	Mean	:0.5011	Mean	:0.3964	Mean	:0.4406
##	3rd Qu.:	:0.4800	3rd Qu.:	:0.6275	3rd Qu.:	:0.5200	3rd Qu.:	:0.5300
##	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000
##	x.V42		x.V43		x.V44		x.V45	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.:	:0.2400	1st Qu.:	:0.3100	1st Qu.:	:0.3300	1st Qu.:	:0.3100
##	Median	:0.3700	Median	:0.4000	Median	:0.4700	Median	:0.4000

##	Mean	:0.3912	Mean	:0.4413	Mean	:0.4612	Mean	:0.4345
##	3rd Qu.	:0.5100	3rd Qu.	:0.5400	3rd Qu.	:0.5900	3rd Qu.	:0.5000
##	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000
##	x.V46		x.V47		x.V48		x.V49	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.	:0.3600	1st Qu.	:0.3600	1st Qu.	:0.4000	1st Qu.	:0.4900
##	Median	:0.5000	Median	:0.5000	Median	:0.4700	Median	:0.6300
##	Mean	:0.4876	Mean	:0.4943	Mean	:0.4877	Mean	:0.6109
##	3rd Qu.	:0.6200	3rd Qu.	:0.6300	3rd Qu.	:0.5600	3rd Qu.	:0.7600
##	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000
##	x.V50		x.V51		x.V52		x.V53	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.	:0.4900	1st Qu.	:0.530	1st Qu.	:0.4800	1st Qu.	:0.3900
##	Median	:0.6400	Median	:0.700	Median	:0.6100	Median	:0.5100
##	Mean	:0.6207	Mean	:0.664	Mean	:0.5829	Mean	:0.5014
##	3rd Qu.	:0.7800	3rd Qu.	:0.840	3rd Qu.	:0.7200	3rd Qu.	:0.6200
##	Max.	:1.0000	Max.	:1.000	Max.	:1.0000	Max.	:1.0000
##	x.V54		x.V55		x.V56		x.V57	
##	Min.	:0.0000	Min.	:0.00000	Min.	:0.00	Min.	:0.00000
##	1st Qu.	:0.4200	1st Qu.	:0.00000	1st Qu.	:0.09	1st Qu.	:0.00000
##	Median	:0.5400	Median	:0.01000	Median	:0.17	Median	:0.01000
##	Mean	:0.5267	Mean	:0.03629	Mean	:0.25	Mean	:0.03006
##	3rd Qu.	:0.6500	3rd Qu.	:0.02000	3rd Qu.	:0.32	3rd Qu.	:0.02000
##	Max.	:1.0000	Max.	:1.00000	Max.	:1.00	Max.	:1.00000
##	x.V58		x.V59		x.V60		x.V61	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.	:0.1600	1st Qu.	:0.2000	1st Qu.	:0.2500	1st Qu.	:0.2800
##	Median	:0.2900	Median	:0.3400	Median	:0.3900	Median	:0.4300
##	Mean	:0.3202	Mean	:0.3606	Mean	:0.3991	Mean	:0.4279
##	3rd Qu.	:0.4300	3rd Qu.	:0.4800	3rd Qu.	:0.5300	3rd Qu.	:0.5600
##	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000
##	x.V62		x.V63		x.V64		x.V65	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.	:0.0300	1st Qu.	:0.0300	1st Qu.	:0.0300	1st Qu.	:0.0300
##	Median	:0.0900	Median	:0.0800	Median	:0.0900	Median	:0.0900
##	Mean	:0.1814	Mean	:0.1821	Mean	:0.1848	Mean	:0.1829
##	3rd Qu.	:0.2300	3rd Qu.	:0.2300	3rd Qu.	:0.2300	3rd Qu.	:0.2300
##	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000
##	x.V66		x.V67		x.V68		x.V69	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.	:0.7300	1st Qu.	:0.0300	1st Qu.	:0.1500	1st Qu.	:0.1400
##	Median	:0.8700	Median	:0.0600	Median	:0.2000	Median	:0.1900
##	Mean	:0.7859	Mean	:0.1506	Mean	:0.2676	Mean	:0.2519
##	3rd Qu.	:0.9400	3rd Qu.	:0.1600	3rd Qu.	:0.3100	3rd Qu.	:0.2900
##	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000
##	x.V70		x.V71		x.V72		x.V73	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000
##	1st Qu.	:0.3400	1st Qu.	:0.3900	1st Qu.	:0.2700	1st Qu.	:0.4400
##	Median	:0.4400	Median	:0.4800	Median	:0.3600	Median	:0.5600
##	Mean	:0.4621	Mean	:0.4944	Mean	:0.4041	Mean	:0.5626
##	3rd Qu.	:0.5500	3rd Qu.	:0.5800	3rd Qu.	:0.4900	3rd Qu.	:0.7000
##	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000	Max.	:1.0000
##	x.V74		x.V75		x.V76		x.V77	
##	Min.	:0.0000	Min.	:0.0000	Min.	:0.0000	Min.	:0.00000

##	1st Qu.:0.0600	1st Qu.:0.4000	1st Qu.:0.0000	1st Qu.:0.01000
##	Median :0.1100	Median :0.5100	Median :0.5000	Median :0.03000
##	Mean :0.1863	Mean :0.4952	Mean :0.3147	Mean :0.07682
##	3rd Qu.:0.2200	3rd Qu.:0.6000	3rd Qu.:0.5000	3rd Qu.:0.07000
##	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.00000
##	x.V78	x.V79	x.V80	x.V81
##	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.:0.6300	1st Qu.:0.4300	1st Qu.:0.0600	1st Qu.:0.2900
##	Median :0.7700	Median :0.5400	Median :0.1300	Median :0.4200
##	Mean :0.7195	Mean :0.5487	Mean :0.2045	Mean :0.4333
##	3rd Qu.:0.8600	3rd Qu.:0.6700	3rd Qu.:0.2700	3rd Qu.:0.5600
##	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	x.V82	x.V83	x.V84	x.V85
##	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.:0.3500	1st Qu.:0.0600	1st Qu.:0.1000	1st Qu.:0.0900
##	Median :0.5200	Median :0.1850	Median :0.1900	Median :0.1800
##	Mean :0.4942	Mean :0.2645	Mean :0.2431	Mean :0.2647
##	3rd Qu.:0.6700	3rd Qu.:0.4200	3rd Qu.:0.3300	3rd Qu.:0.4000
##	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	x.V86	x.V87	x.V88	x.V89
##	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.:0.0900	1st Qu.:0.0900	1st Qu.:0.1700	1st Qu.:0.2000
##	Median :0.1700	Median :0.1800	Median :0.3100	Median :0.3300
##	Mean :0.2635	Mean :0.2689	Mean :0.3464	Mean :0.3725
##	3rd Qu.:0.3900	3rd Qu.:0.3800	3rd Qu.:0.4900	3rd Qu.:0.5200
##	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	x.V90	x.V91	x.V92	x.V93
##	Min. :0.000	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.:0.220	1st Qu.:0.2100	1st Qu.:0.3700	1st Qu.:0.3200
##	Median :0.370	Median :0.3400	Median :0.4800	Median :0.4500
##	Mean :0.423	Mean :0.3841	Mean :0.4901	Mean :0.4498
##	3rd Qu.:0.590	3rd Qu.:0.5300	3rd Qu.:0.5900	3rd Qu.:0.5800
##	Max. :1.000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	x.V94	x.V95	x.V96	x.V97
##	Min. :0.0000	Min. :0.00000	Min. :0.00000	Min. :0.0000
##	1st Qu.:0.2500	1st Qu.:0.00000	1st Qu.:0.00000	1st Qu.:0.0600
##	Median :0.3700	Median :0.00000	Median :0.00000	Median :0.1300
##	Mean :0.4038	Mean :0.02944	Mean :0.02278	Mean :0.2156
##	3rd Qu.:0.5100	3rd Qu.:0.01000	3rd Qu.:0.00000	3rd Qu.:0.2800
##	Max. :1.0000	Max. :1.00000	Max. :1.00000	Max. :1.0000
##	x.V98	x.V99	x.V100	x.V101
##	Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.0000
##	1st Qu.:0.4700	1st Qu.:0.4200	1st Qu.:0.5200	1st Qu.:0.5600
##	Median :0.6300	Median :0.5400	Median :0.6700	Median :0.7000
##	Mean :0.6089	Mean :0.5351	Mean :0.6264	Mean :0.6515
##	3rd Qu.:0.7775	3rd Qu.:0.6600	3rd Qu.:0.7700	3rd Qu.:0.7900
##	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	x.V102	x.V103	x.V104	x.V105
##	Min. : -0.53937	Min. : -0.5378	Min. :0.0000	Min. : -0.6192
##	1st Qu.: -0.02460	1st Qu.: 0.1400	1st Qu.:0.8852	1st Qu.: 0.1600
##	Median : 0.03000	Median : 0.2963	Median :0.9600	Median : 0.3200
##	Mean : 0.03604	Mean : 0.3776	Mean :0.9551	Mean : 0.3664
##	3rd Qu.: 0.10392	3rd Qu.: 0.6238	3rd Qu.:1.0181	3rd Qu.: 0.5688
##	Max. : 1.00000	Max. : 1.4801	Max. :1.5258	Max. : 1.3772

```

##      x.V106      x.V107      x.V108      x.V109
## Min.   :-0.63745 Min.   :-0.8905 Min.   :-0.858872 Min.   :-0.5377
## 1st Qu.: -0.05187 1st Qu.: 0.0800 1st Qu.: 0.005023 1st Qu.: 0.1400
## Median : 0.03000 Median : 0.2022 Median : 0.183860 Median : 0.2964
## Mean   : 0.02585 Mean   : 0.2395 Mean   : 0.173225 Mean   : 0.3775
## 3rd Qu.: 0.10100 3rd Qu.: 0.4048 3rd Qu.: 0.328242 3rd Qu.: 0.6238
## Max.   : 1.09156 Max.   : 2.2631 Max.   : 3.074837 Max.   : 1.4799
##      x.V110      x.V111      x.V112      x.V113
## Min.   :-0.7876 Min.   :-0.2461 Min.   :-0.73744 Min.   :-0.43847
## 1st Qu.: 0.5704 1st Qu.: 0.6571 1st Qu.: -0.04077 1st Qu.: -0.03827
## Median : 0.7444 Median : 0.8415 Median : 0.07946 Median : 0.04984
## Mean   : 0.7225 Mean   : 0.8149 Mean   : 0.10467 Mean   : 0.08496
## 3rd Qu.: 0.8935 3rd Qu.: 0.9831 3rd Qu.: 0.22227 3rd Qu.: 0.16339
## Max.   : 1.5377 Max.   : 1.6100 Max.   : 1.18392 Max.   : 1.16911
##      x.V114      x.V115      x.V116      x.V117
## Min.   :-0.99924 Min.   :-0.70307 Min.   :-0.488758 Min.   :-1.4252
## 1st Qu.: -0.13445 1st Qu.: -0.02781 1st Qu.: -0.069858 1st Qu.: 0.2955
## Median : 0.01267 Median : 0.10000 Median : 0.014724 Median : 0.4752
## Mean   : 0.04463 Mean   : 0.12893 Mean   : 0.003826 Mean   : 0.4718
## 3rd Qu.: 0.21179 3rd Qu.: 0.25901 3rd Qu.: 0.072606 3rd Qu.: 0.6400
## Max.   : 1.71153 Max.   : 1.13316 Max.   : 1.000000 Max.   : 6.5607
##      x.V118      x.V119      x.V120      x.V121
## Min.   :-2.04213 Min.   :0.00000 Min.   :0.0000 Min.   :0.0000
## 1st Qu.: 0.01546 1st Qu.:0.02000 1st Qu.:0.1000 1st Qu.:0.0200
## Median : 0.20044 Median :0.04000 Median :0.1700 Median :0.0700
## Mean   : 0.20550 Mean   :0.06523 Mean   :0.2329 Mean   :0.1617
## 3rd Qu.: 0.42598 3rd Qu.:0.07000 3rd Qu.:0.2800 3rd Qu.:0.1900
## Max.   : 1.53559 Max.   :1.00000 Max.   :1.0000 Max.   :1.0000
##      x.V122      x.V123      x.V124      x.V125
## Min.   :-0.708426 Min.   :-0.44286 Min.   :-0.9850 Min.   :-1.9221
## 1st Qu.: 0.005435 1st Qu.: -0.01398 1st Qu.: 0.4115 1st Qu.: 0.0000
## Median : 0.093085 Median : 0.04000 Median : 0.6622 Median : 0.3896
## Mean   : 0.110848 Mean   : 0.04666 Mean   : 0.6364 Mean   : 0.3753
## 3rd Qu.: 0.224945 3rd Qu.: 0.11472 3rd Qu.: 0.8490 3rd Qu.: 0.7615
## Max.   : 1.000000 Max.   : 1.00000 Max.   : 1.9686 Max.   : 2.4168
##      x.V126      x.V127      y
## Min.   :0.00000 Min.   :-0.6075 Min.   :0.000
## 1st Qu.:0.00000 1st Qu.: 0.1200 1st Qu.:0.070
## Median :0.00000 Median : 0.2800 Median :0.150
## Mean   :0.09405 Mean   : 0.3560 Mean   :0.238
## 3rd Qu.:0.00000 3rd Qu.: 0.5883 3rd Qu.:0.330
## Max.   :1.00000 Max.   : 1.7307 Max.   :1.000

```

We see that this dataset contains a large number of variables, each of these variables tell us something different about a community such as its state, population, percentage of people under the poverty level and whether or not a gang unit is deployed in that community among a total of 127 variables (not including the target variable). Among these the first 5 variables are non predictive and so won't be used in constructing a model, leaving 122 predictor variables (note that the dataframe from the *mogavs* package does not include the first 5 attributes). The target variable is *y* which is the total number of violent crimes per 100k population.

We would like to fit a regression model of the form $Z_i \sim f(\alpha + \beta^T x_i^0)$ using PCR to estimate the model parameters. The first thing to do is decide whether PCA should be applied to the covariance matrix or the correlation matrix. One thing to note is that in the original dataset all values were standardized between 0 and 1 and the dataset in *mogavs* is the same bar the fact that they impute missing values so we may find some values outside of this range. Knowing this it would make sense to use the covariance matrix for PCA as

it will preserve variance and as all the attributes are already scaled.

Let's now carry out our PCA and print out a summary of our results:

```
pc_crimeData <- prcomp(~ . -y , crimeData, scale. = TRUE, retx=TRUE); summary(pc_crimeData)
```

```
## Importance of components:
##          PC1      PC2      PC3      PC4      PC5      PC6      PC7
## Standard deviation  5.1263 4.2852 3.14023 2.8484 2.52280 2.44983 2.1274
## Proportion of Variance 0.2154 0.1505 0.08083 0.0665 0.05217 0.04919 0.0371
## Cumulative Proportion 0.2154 0.3659 0.44674 0.5132 0.56542 0.61461 0.6517
##          PC8      PC9      PC10     PC11     PC12     PC13     PC14
## Standard deviation  1.92926 1.79021 1.56346 1.46739 1.39980 1.30804 1.28740
## Proportion of Variance 0.03051 0.02627 0.02004 0.01765 0.01606 0.01402 0.01359
## Cumulative Proportion 0.68222 0.70849 0.72852 0.74617 0.76223 0.77626 0.78984
##          PC15     PC16     PC17     PC18     PC19     PC20     PC21
## Standard deviation  1.26287 1.19862 1.14023 1.12564 1.05175 0.99584 0.97054
## Proportion of Variance 0.01307 0.01178 0.01066 0.01039 0.00907 0.00813 0.00772
## Cumulative Proportion 0.80291 0.81469 0.82535 0.83573 0.84480 0.85293 0.86065
##          PC22     PC23     PC24     PC25     PC26     PC27     PC28
## Standard deviation  0.96633 0.92222 0.89262 0.85634 0.84920 0.82465 0.77804
## Proportion of Variance 0.00765 0.00697 0.00653 0.00601 0.00591 0.00557 0.00496
## Cumulative Proportion 0.86830 0.87527 0.88181 0.88782 0.89373 0.89930 0.90426
##          PC29     PC30     PC31     PC32     PC33     PC34     PC35
## Standard deviation  0.76580 0.73427 0.72819 0.70541 0.6899 0.68415 0.67038
## Proportion of Variance 0.00481 0.00442 0.00435 0.00408 0.0039 0.00384 0.00368
## Cumulative Proportion 0.90907 0.91349 0.91784 0.92191 0.9258 0.92965 0.93334
##          PC36     PC37     PC38     PC39     PC40     PC41     PC42
## Standard deviation  0.66397 0.62569 0.60702 0.58972 0.57603 0.56650 0.55393
## Proportion of Variance 0.00361 0.00321 0.00302 0.00285 0.00272 0.00263 0.00252
## Cumulative Proportion 0.93695 0.94016 0.94318 0.94603 0.94875 0.95138 0.95389
##          PC43     PC44     PC45     PC46     PC47     PC48     PC49
## Standard deviation  0.54304 0.52869 0.5180 0.49787 0.49653 0.4687 0.45403
## Proportion of Variance 0.00242 0.00229 0.0022 0.00203 0.00202 0.0018 0.00169
## Cumulative Proportion 0.95631 0.95860 0.9608 0.96283 0.96486 0.9667 0.96835
##          PC50     PC51     PC52     PC53     PC54     PC55     PC56
## Standard deviation  0.45164 0.44451 0.43885 0.42861 0.4130 0.41005 0.3987
## Proportion of Variance 0.00167 0.00162 0.00158 0.00151 0.0014 0.00138 0.0013
## Cumulative Proportion 0.97002 0.97164 0.97322 0.97472 0.9761 0.97750 0.9788
##          PC57     PC58     PC59     PC60     PC61     PC62     PC63
## Standard deviation  0.38490 0.37296 0.37131 0.36040 0.3487 0.32963 0.32066
## Proportion of Variance 0.00121 0.00114 0.00113 0.00106 0.0010 0.00089 0.00084
## Cumulative Proportion 0.98001 0.98115 0.98228 0.98335 0.9843 0.98524 0.98608
##          PC64     PC65     PC66     PC67     PC68     PC69     PC70
## Standard deviation  0.31633 0.30719 0.29810 0.2913 0.28788 0.27641 0.26830
## Proportion of Variance 0.00082 0.00077 0.00073 0.0007 0.00068 0.00063 0.00059
## Cumulative Proportion 0.98690 0.98767 0.98840 0.9891 0.98978 0.99040 0.99099
##          PC71     PC72     PC73     PC74     PC75     PC76     PC77
## Standard deviation  0.25982 0.25450 0.25103 0.23801 0.23588 0.22980 0.22319
## Proportion of Variance 0.00055 0.00053 0.00052 0.00046 0.00046 0.00043 0.00041
## Cumulative Proportion 0.99155 0.99208 0.99259 0.99306 0.99351 0.99395 0.99435
##          PC78     PC79     PC80     PC81     PC82     PC83     PC84
## Standard deviation  0.21832 0.21411 0.21056 0.20020 0.19450 0.18859 0.18256
## Proportion of Variance 0.00039 0.00038 0.00036 0.00033 0.00031 0.00029 0.00027
## Cumulative Proportion 0.99475 0.99512 0.99548 0.99581 0.99612 0.99641 0.99669
```

```
##          PC85    PC86    PC87    PC88    PC89    PC90    PC91
## Standard deviation 0.17283 0.16885 0.16837 0.16166 0.1563 0.1556 0.14596
## Proportion of Variance 0.00024 0.00023 0.00023 0.00021 0.0002 0.0002 0.00017
## Cumulative Proportion 0.99693 0.99717 0.99740 0.99761 0.9978 0.9980 0.99819
##          PC92    PC93    PC94    PC95    PC96    PC97    PC98
## Standard deviation 0.14342 0.13589 0.13405 0.13088 0.12553 0.11681 0.11606
## Proportion of Variance 0.00017 0.00015 0.00015 0.00014 0.00013 0.00011 0.00011
## Cumulative Proportion 0.99835 0.99851 0.99865 0.99879 0.99892 0.99903 0.99915
##          PC99    PC100    PC101    PC102    PC103    PC104    PC105
## Standard deviation 0.11383 0.10552 0.10317 0.09484 0.09310 0.08754 0.08136
## Proportion of Variance 0.00011 0.00009 0.00009 0.00007 0.00007 0.00006 0.00005
## Cumulative Proportion 0.99925 0.99934 0.99943 0.99950 0.99957 0.99964 0.99969
##          PC106    PC107    PC108    PC109    PC110    PC111    PC112
## Standard deviation 0.07377 0.07086 0.06453 0.06077 0.05462 0.05390 0.04860
## Proportion of Variance 0.00004 0.00004 0.00003 0.00003 0.00002 0.00002 0.00002
## Cumulative Proportion 0.99974 0.99978 0.99981 0.99984 0.99987 0.99989 0.99991
##          PC113    PC114    PC115    PC116    PC117    PC118    PC119
## Standard deviation 0.04829 0.04163 0.03993 0.03839 0.03532 0.02948 0.02670
## Proportion of Variance 0.00002 0.00001 0.00001 0.00001 0.00001 0.00001 0.00001
## Cumulative Proportion 0.99993 0.99994 0.99996 0.99997 0.99998 0.99999 0.99999
##          PC120    PC121    PC122
## Standard deviation 0.02461 0.02171 0.0009488
## Proportion of Variance 0.00000 0.00000 0.0000000
## Cumulative Proportion 1.00000 1.00000 1.0000000
```

Let's first fit a linear model (carry out PCR) using all the principal components and print out a summary:

```
Regr_data <- data.frame(y = crimeData$y, pc_crimeData$x) # Create data frame from target variable and o
lmodel.all <- lm(y ~ ., data = Regr_data)
summary(lmodel.all)
```

```
##
## Call:
## lm(formula = y ~ ., data = Regr_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.53580 -0.07223 -0.01285  0.05017  0.74159
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.380e-01  2.960e-03  80.405  < 2e-16 ***
## PC1         -2.824e-02  5.775e-04 -48.899  < 2e-16 ***
## PC2          1.689e-02  6.909e-04  24.453  < 2e-16 ***
## PC3         -1.483e-02  9.428e-04 -15.728  < 2e-16 ***
## PC4          1.046e-02  1.039e-03  10.066  < 2e-16 ***
## PC5          1.147e-02  1.173e-03  9.773   < 2e-16 ***
## PC6          6.699e-03  1.208e-03  5.543  3.39e-08 ***
## PC7          8.480e-03  1.392e-03  6.093  1.34e-09 ***
## PC8          2.970e-02  1.535e-03  19.355  < 2e-16 ***
## PC9          2.270e-03  1.654e-03  1.373  0.170058
## PC10         -7.410e-03  1.894e-03  -3.913  9.43e-05 ***
## PC11         -5.313e-03  2.018e-03  -2.634  0.008519 **
## PC12          7.854e-03  2.115e-03  3.713  0.000210 ***
## PC13          4.048e-03  2.263e-03  1.789  0.073829 .
```

## PC14	5.263e-03	2.300e-03	2.289	0.022200	*
## PC15	6.344e-03	2.344e-03	2.706	0.006865	**
## PC16	6.188e-03	2.470e-03	2.505	0.012321	*
## PC17	-7.919e-03	2.596e-03	-3.050	0.002322	**
## PC18	4.489e-03	2.630e-03	1.707	0.088016	.
## PC19	5.542e-03	2.815e-03	1.969	0.049102	*
## PC20	8.705e-03	2.973e-03	2.928	0.003450	**
## PC21	1.290e-02	3.050e-03	4.227	2.48e-05	***
## PC22	-2.973e-03	3.064e-03	-0.970	0.332027	
## PC23	2.298e-03	3.210e-03	0.716	0.474090	
## PC24	-5.209e-03	3.317e-03	-1.570	0.116471	
## PC25	-4.470e-03	3.457e-03	-1.293	0.196176	
## PC26	9.165e-03	3.486e-03	2.629	0.008635	**
## PC27	-1.379e-02	3.590e-03	-3.842	0.000126	***
## PC28	-1.758e-02	3.805e-03	-4.621	4.08e-06	***
## PC29	-4.117e-03	3.866e-03	-1.065	0.286982	
## PC30	6.348e-04	4.032e-03	0.157	0.874918	
## PC31	-1.347e-02	4.066e-03	-3.314	0.000939	***
## PC32	-4.061e-03	4.197e-03	-0.968	0.333316	
## PC33	-1.522e-02	4.291e-03	-3.546	0.000400	***
## PC34	3.100e-03	4.327e-03	0.716	0.473816	
## PC35	-1.231e-02	4.416e-03	-2.787	0.005377	**
## PC36	1.203e-02	4.459e-03	2.699	0.007016	**
## PC37	-4.692e-03	4.732e-03	-0.992	0.321556	
## PC38	9.079e-03	4.877e-03	1.862	0.062808	.
## PC39	-1.714e-02	5.020e-03	-3.414	0.000655	***
## PC40	5.089e-03	5.139e-03	0.990	0.322231	
## PC41	1.344e-02	5.226e-03	2.572	0.010180	*
## PC42	1.112e-02	5.344e-03	2.081	0.037585	*
## PC43	-1.348e-02	5.452e-03	-2.472	0.013534	*
## PC44	2.579e-02	5.600e-03	4.605	4.40e-06	***
## PC45	2.223e-03	5.715e-03	0.389	0.697364	
## PC46	-1.482e-02	5.946e-03	-2.493	0.012767	*
## PC47	-1.077e-02	5.962e-03	-1.806	0.071123	.
## PC48	7.530e-03	6.316e-03	1.192	0.233337	
## PC49	-1.258e-02	6.520e-03	-1.930	0.053758	.
## PC50	-5.006e-03	6.555e-03	-0.764	0.445139	
## PC51	7.567e-03	6.660e-03	1.136	0.256063	
## PC52	-1.773e-03	6.746e-03	-0.263	0.792723	
## PC53	9.487e-03	6.907e-03	1.374	0.169753	
## PC54	1.004e-02	7.169e-03	1.400	0.161694	
## PC55	-4.562e-03	7.220e-03	-0.632	0.527561	
## PC56	-1.955e-02	7.426e-03	-2.632	0.008551	**
## PC57	6.022e-03	7.692e-03	0.783	0.433741	
## PC58	3.771e-03	7.938e-03	0.475	0.634808	
## PC59	1.252e-02	7.973e-03	1.571	0.116417	
## PC60	-1.736e-02	8.214e-03	-2.113	0.034750	*
## PC61	-1.016e-02	8.491e-03	-1.196	0.231810	
## PC62	2.453e-02	8.981e-03	2.731	0.006367	**
## PC63	-3.102e-02	9.232e-03	-3.360	0.000794	***
## PC64	2.753e-02	9.359e-03	2.941	0.003308	**
## PC65	1.188e-02	9.637e-03	1.233	0.217691	
## PC66	2.647e-02	9.931e-03	2.665	0.007756	**
## PC67	8.890e-05	1.016e-02	0.009	0.993022	

## PC68	1.083e-02	1.028e-02	1.053	0.292650	
## PC69	-2.372e-02	1.071e-02	-2.215	0.026877	*
## PC70	-2.273e-03	1.103e-02	-0.206	0.836848	
## PC71	-1.116e-02	1.139e-02	-0.979	0.327532	
## PC72	-1.188e-02	1.163e-02	-1.021	0.307182	
## PC73	-7.115e-05	1.179e-02	-0.006	0.995187	
## PC74	3.207e-02	1.244e-02	2.579	0.009996	**
## PC75	-1.077e-02	1.255e-02	-0.858	0.390975	
## PC76	2.725e-02	1.288e-02	2.116	0.034515	*
## PC77	-1.002e-02	1.326e-02	-0.755	0.450263	
## PC78	3.872e-02	1.356e-02	2.855	0.004350	**
## PC79	4.661e-03	1.383e-02	0.337	0.736077	
## PC80	1.701e-02	1.406e-02	1.210	0.226598	
## PC81	-4.873e-03	1.479e-02	-0.330	0.741771	
## PC82	3.826e-02	1.522e-02	2.514	0.012034	*
## PC83	2.435e-02	1.570e-02	1.551	0.121102	
## PC84	-2.334e-02	1.622e-02	-1.439	0.150313	
## PC85	2.667e-03	1.713e-02	0.156	0.876301	
## PC86	3.643e-02	1.753e-02	2.078	0.037851	*
## PC87	3.902e-02	1.758e-02	2.219	0.026601	*
## PC88	1.098e-02	1.831e-02	0.600	0.548873	
## PC89	9.069e-02	1.894e-02	4.788	1.82e-06	***
## PC90	9.816e-03	1.902e-02	0.516	0.605940	
## PC91	-3.004e-03	2.028e-02	-0.148	0.882274	
## PC92	2.258e-02	2.064e-02	1.094	0.274180	
## PC93	1.265e-02	2.179e-02	0.581	0.561580	
## PC94	-3.359e-02	2.209e-02	-1.521	0.128442	
## PC95	-5.407e-02	2.262e-02	-2.390	0.016934	*
## PC96	1.111e-02	2.358e-02	0.471	0.637640	
## PC97	-2.393e-02	2.534e-02	-0.944	0.345234	
## PC98	8.628e-03	2.551e-02	0.338	0.735218	
## PC99	-1.765e-02	2.601e-02	-0.679	0.497512	
## PC100	2.800e-02	2.806e-02	0.998	0.318424	
## PC101	4.068e-02	2.869e-02	1.418	0.156473	
## PC102	-2.381e-02	3.122e-02	-0.763	0.445652	
## PC103	-7.881e-03	3.180e-02	-0.248	0.804281	
## PC104	-1.229e-01	3.382e-02	-3.635	0.000285	***
## PC105	-2.535e-02	3.639e-02	-0.697	0.486131	
## PC106	-4.821e-03	4.013e-02	-0.120	0.904394	
## PC107	7.911e-03	4.178e-02	0.189	0.849838	
## PC108	4.691e-03	4.588e-02	0.102	0.918574	
## PC109	8.734e-02	4.871e-02	1.793	0.073135	.
## PC110	7.491e-02	5.420e-02	1.382	0.167131	
## PC111	5.931e-02	5.493e-02	1.080	0.280417	
## PC112	-1.108e-01	6.092e-02	-1.819	0.069127	.
## PC113	-9.026e-02	6.131e-02	-1.472	0.141163	
## PC114	-2.550e-02	7.112e-02	-0.359	0.719951	
## PC115	-1.710e-01	7.414e-02	-2.307	0.021184	*
## PC116	2.912e-02	7.712e-02	0.378	0.705779	
## PC117	2.628e-02	8.382e-02	0.313	0.753953	
## PC118	-7.354e-02	1.004e-01	-0.732	0.464013	
## PC119	1.062e-01	1.109e-01	0.958	0.338237	
## PC120	-1.459e-01	1.203e-01	-1.213	0.225353	
## PC121	2.200e-01	1.364e-01	1.613	0.106926	

```
## PC122      -1.510e+00  3.120e+00  -0.484 0.628602
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1322 on 1871 degrees of freedom
## Multiple R-squared:  0.6979, Adjusted R-squared:  0.6782
## F-statistic: 35.43 on 122 and 1871 DF,  p-value: < 2.2e-16
```

We can then obtain our values for α, β from our a, γ :

```
gamma <- as.matrix(lmodel.all$coefficients[2:123])
A <- as.matrix(pc_crimeData$rotation)
beta <- A %*% gamma
beta
```

```
##           [,1]
## x.V6      1.158459e-03
## x.V7     -1.361135e-02
## x.V8      4.538361e-02
## x.V9     -7.049684e-03
## x.V10    -2.308081e-03
## x.V11     1.909909e-02
## x.V12     2.332894e-02
## x.V13    -5.082177e-02
## x.V14    -2.634251e-02
## x.V15     4.441465e-02
## x.V16    -1.391306e-02
## x.V17     2.451993e-02
## x.V18    -2.539889e-02
## x.V19    -5.788102e-03
## x.V20     1.330137e-02
## x.V21    -3.069719e-02
## x.V22     1.141787e-03
## x.V23    -2.309006e-03
## x.V24    -9.657565e-03
## x.V25     6.832491e-02
## x.V26     1.132749e-02
## x.V27    -7.277088e-02
## x.V28    -6.069770e-03
## x.V29    -8.368736e-03
## x.V30     4.862996e-03
## x.V31    -6.854617e-03
## x.V32     8.908148e-03
## x.V33     1.194985e-02
## x.V34    -2.305494e-02
## x.V35    -2.510318e-02
## x.V36     1.133176e-02
## x.V37     2.425019e-03
## x.V38     8.277392e-03
## x.V39     4.280229e-02
## x.V40    -1.248538e-02
## x.V41    -5.203969e-03
## x.V42     1.900786e-02
## x.V43     2.879510e-02
## x.V44     1.181022e-01
```



```
## x.V45    5.023253e-02
## x.V46    8.924443e-02
## x.V47   -2.055924e-01
## x.V48   -2.387217e-02
## x.V49   -1.805277e-02
## x.V50   -6.916394e-02
## x.V51    3.868461e-03
## x.V52   -2.083202e-03
## x.V53    1.515117e-02
## x.V54   -3.667834e-02
## x.V55   -6.307376e-03
## x.V56    2.246601e-02
## x.V57   -1.644652e-02
## x.V58    2.109581e-02
## x.V59   -2.244550e-02
## x.V60   -8.421989e-03
## x.V61    1.283928e-02
## x.V62   -1.988285e-02
## x.V63    1.180013e-02
## x.V64    5.019217e-02
## x.V65   -4.273388e-02
## x.V66   -1.601103e-02
## x.V67   -4.444079e-02
## x.V68   -2.758476e-03
## x.V69   -1.709937e-02
## x.V70    1.293402e-01
## x.V71   -1.540354e-02
## x.V72   -5.931697e-02
## x.V73   -1.339625e-01
## x.V74    4.501633e-02
## x.V75    3.197326e-02
## x.V76    1.249994e-02
## x.V77    1.919219e-02
## x.V78   -1.087915e-02
## x.V79    1.003147e-01
## x.V80    1.261731e-02
## x.V81   -1.354420e-02
## x.V82   -4.995937e-03
## x.V83   -4.340051e-03
## x.V84    1.609763e-04
## x.V85   -7.506953e-02
## x.V86    3.010632e-02
## x.V87    3.264191e-02
## x.V88   -5.903674e-02
## x.V89    2.062651e-02
## x.V90   -5.571917e-03
## x.V91    4.690232e-02
## x.V92    2.657209e-03
## x.V93   -9.194261e-03
## x.V94   -1.535766e-02
## x.V95    1.135041e-02
## x.V96    1.643288e-02
## x.V97    2.548713e-02
## x.V98    8.313771e-03
```

```
## x.V99 -9.888430e-03
## x.V100 -8.435677e-04
## x.V101 5.405756e-04
## x.V102 -1.379793e-01
## x.V103 -1.053692e+00
## x.V104 -8.016928e-02
## x.V105 -3.247578e-03
## x.V106 -6.656172e-03
## x.V107 -6.407702e-03
## x.V108 1.279992e-02
## x.V109 1.081014e+00
## x.V110 -1.020243e-02
## x.V111 -2.399313e-03
## x.V112 -8.275559e-03
## x.V113 -1.245445e-02
## x.V114 -2.289675e-03
## x.V115 1.026542e-02
## x.V116 9.385233e-04
## x.V117 -2.249574e-03
## x.V118 -4.328249e-03
## x.V119 5.114529e-04
## x.V120 -2.539817e-03
## x.V121 -1.471767e-02
## x.V122 1.344588e-02
## x.V123 6.582734e-02
## x.V124 -9.821415e-03
## x.V125 6.403888e-05
## x.V126 7.002727e-03
## x.V127 -2.750836e-02
```

```
a <- lmodel.all$coefficients[1]
alpha <- a - t(beta) %*% colMeans(crimeData[, -ncol(crimeData)])
alpha
```

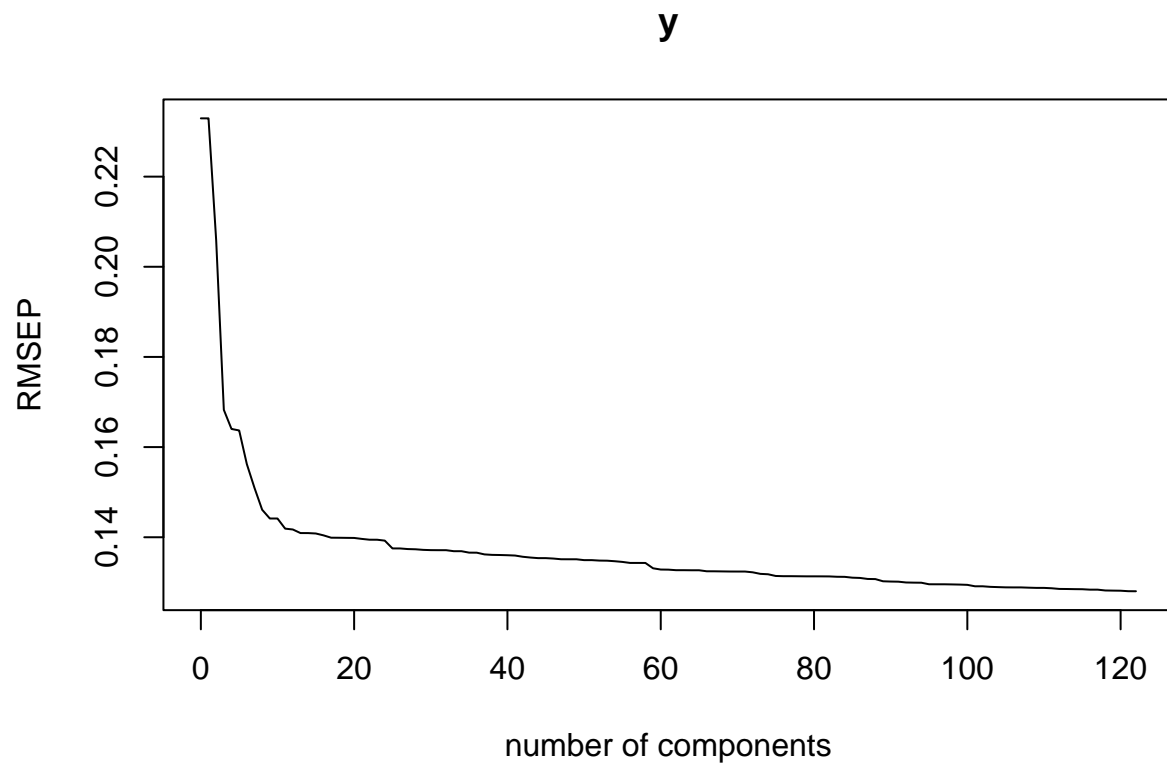
```
##           [,1]
## [1,] 0.3812796
```

Now we would like to see how the performance of our PCR differs as we change the number of principal components. To analyse this we will fit multiple PCR's and measure their performance in terms of the Root Mean Squared Error of Prediction (RMSEP) for different numbers of components:

```
library(pls)
```

```
##
## Attaching package: 'pls'
## The following object is masked from 'package:stats':
##
##      loadings
```

```
model <- pcr(y~ ., ncol(crimeData)-1, data=crimeData)
validationplot(model)
```



We see a very quick initial decrease in RMSEP when we increase the number of components, followed by a more gradual decrease. This indicates that somewhere around 10 components the performance increase we get from including more principal components has diminished very significantly. So ideally we should set $q=10$ as this is a good trade off between performance and keeping dimensionality low.