Question 8.1

Using the same crime data set uscrime.txt as in Question 8.2, apply Principal Component Analysis and then create a regression model using the first few principal components. Specify your new model in terms of the original variables (not the principal components), and compare its quality to that of your solution to Question 8.2. You can use the R function prcomp for PCA. (Note that to first scale the data, you can include scale. = TRUE to scale as part of the PCA function. Don’t forget that, to make a prediction for the new city, you’ll need to unscale the coefficients (i.e., do the scaling calculation in reverse)!)

Approach Followed

1) After data is ingested, I followed series of steps to see the co-correlation of the predictors among themself and its impact on the Crime responses using Corelation plots, Corelation matrix and the Correlation tables. In my opinion Corelation tables were the best approach to quickly see the correlated fields. 2) This step is followed by creating eigen values and eigen vectors for X(Tranpose)*X; X being the matrix of the Crime data set.I used Caret transformation to get predictors, box cox tranformation and find princial componentswhich suggested that "PCA needed 9 components to capture 95 percent of the variance" 3) Based on this recommendationm I set my "n" values for PCA as 9.Using prcomp, I created PCA and obtained first "9" components using which I created linear regression model(using lm). The model gave the adjusted R squared :0.69;R squared :0.61

4) Now, per the requirement, we have to express themodel in terms of originalvairbales and NOT principal components. To achieve this I obtain my components PC1 through PC(and then used pca rotation adn transform function to get the original Coefficients.One item to notice is since the co-efficients are scaled earlier, I need to unscale it to get the exact co-efficients of the model. 5) To scale, it subtracts the mean and divides by the standard deviation, for each variable.I used this logic to unscale the co-efficients 6) Compare the PCA model accuracy vs. the original model' accuracy.The Original model R2 squared is 0.80 and Adju R2 .70 which is more than the PCA model accuracy. Then i ran a loop from 1 through all PCA components to see any of its accuracy beat the original model.. But none. As noted in the lectures,overfitting could have occured with less data points with original linear regression model 7)Finally the prediction for the new City using predict function. I used both the model to predict the outcome of Crime. Predicted value of new data using PCR is 1112 vs. 155 crime data value using original regression with all the predictors

#PCA generated crime ratio 7 times more than the linear regression model with all predictors for the new data value

In [203]:
```
# Clear environment
rm(list = ls())
# Setting the random number generator seed so that our results are reproducible
set.seed(1)
```

In [204]:
```
##########LIBRARY##########
library("ggplot2")
#install.packages("devtools")
#install.packages("corrplot")
library("devtools")
#library("corrplot") # to use Correlation plot
library(tidyr) # to use "as tibble,
library(plyr) #to use arrange function
library(car) #Scatterplotmatrix
library(GGally) #for ggpairs graph
library(pls)# to get pca fit
```

INGESTION OF DATA AND STUDY THE RELATIONSHIPS

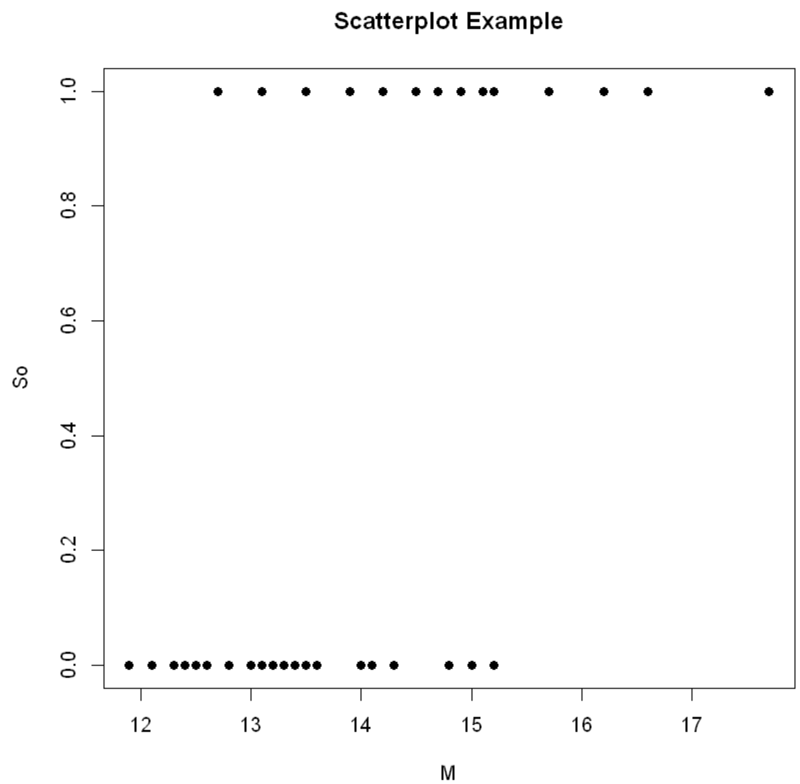
In [205]:
```
##########INGEST FILE##########

#crime<- read.table("C:\\Preethi\\R\\USCrimes.txt",header=TRUE,stringsAsFactors = FALSE,sep="\t")
data = read.table("C:\\Preethi\\R\\USCrimes.txt",header=TRUE,stringsAsFactors = FALSE,sep="\t") %>% as.data.frame
head(data,2)
```

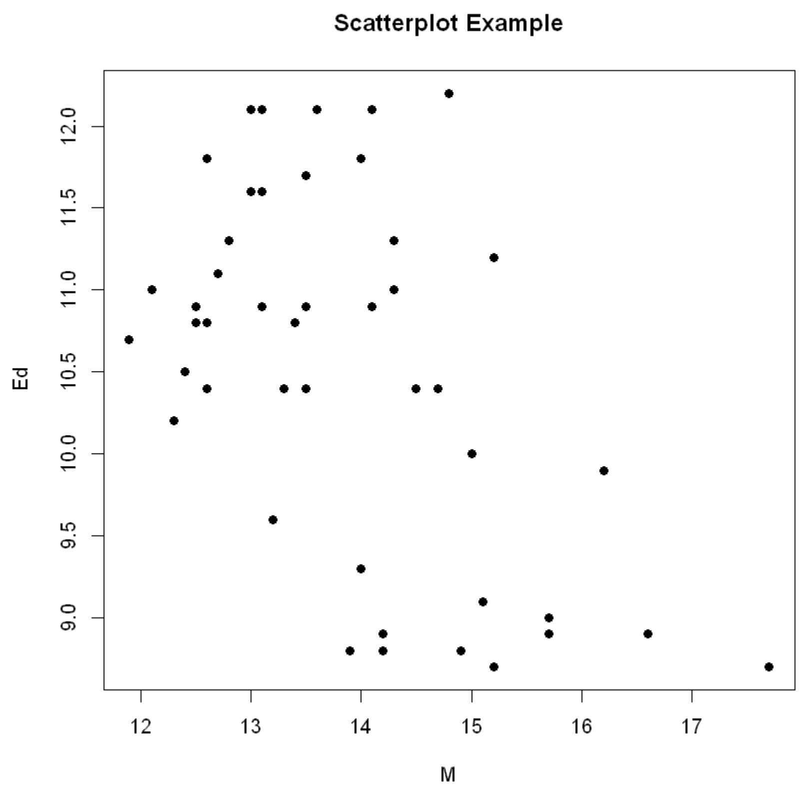
A data.frame: 2 × 16

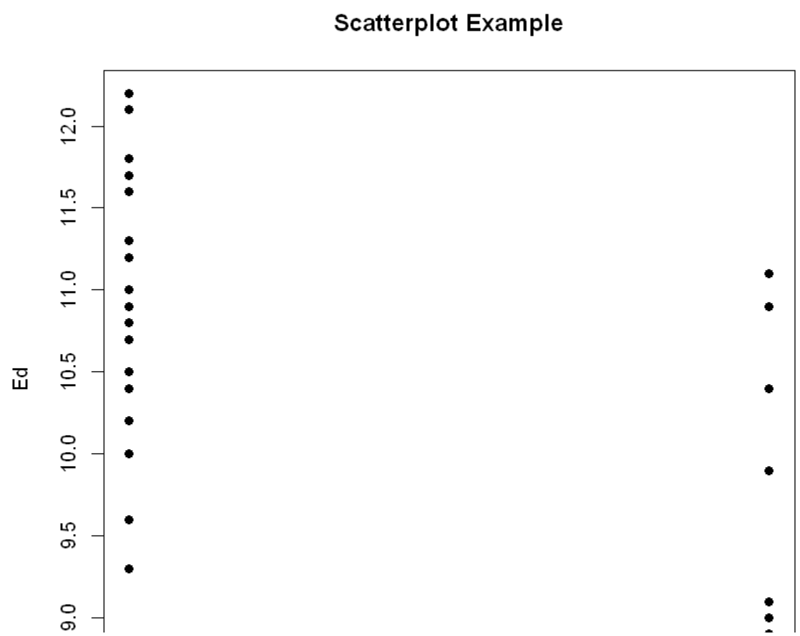
	M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob	Time	Crime
	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>
1	15.1	1	9.1	5.8	5.6	0.510	95.0	33	30.1	0.108	4.1	3940	26.1	0.084602	26.2011	791
2	14.3	0	11.3	10.3	9.5	0.583	101.2	13	10.2	0.096	3.6	5570	19.4	0.029599	25.2999	1635

In [225]:

```
##EXPLORING DATA######
#2-D graphs for each predictors to understand relationship and correlation of predictors
#Just reduced to 2 charts to avoid overfill of assignment with scatterplot
for (i in 1:3){
  for (j in 1:3){
    if (i<j){
      plot(data[,i],data[,j], main="Scatterplot Example",xlab=colnames(data)[i],ylab=colnames(data)[j], pch=19)
    }
  }
}
```

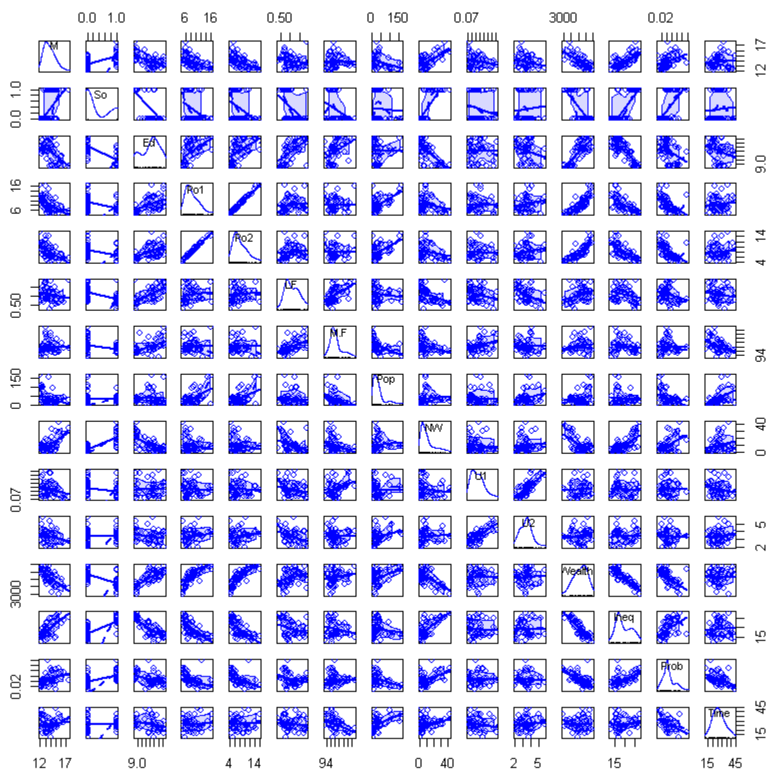



Scatterplot Example
Ed
12.0
11.5
11.0
10.5
10.0
9.5
9.0
12
13
14
15
16
17
M

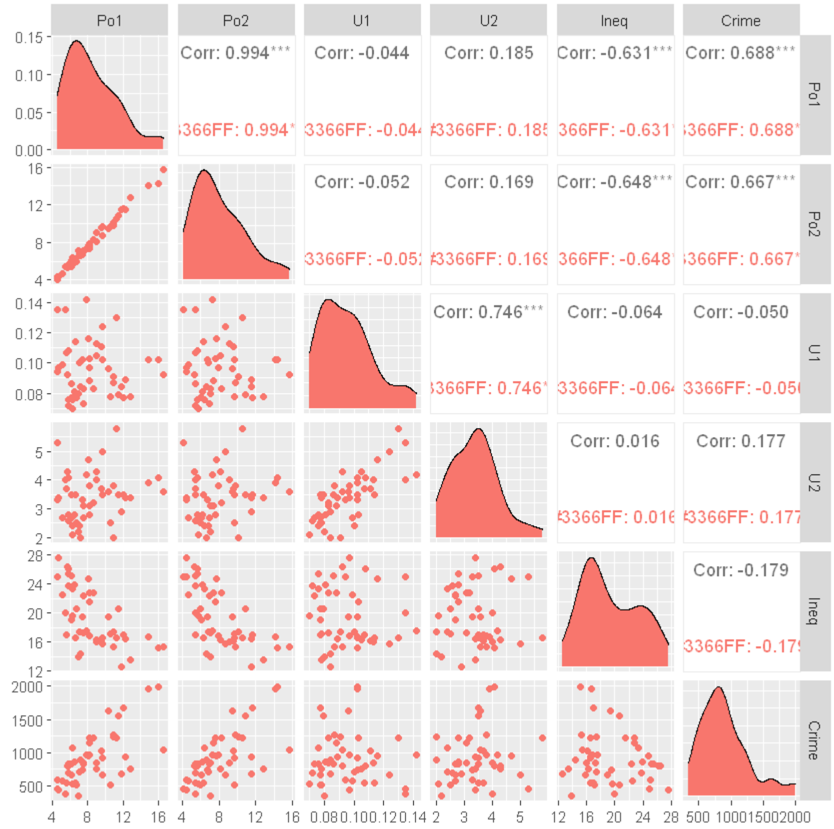

Scatterplot Example
Ed
12.0
11.5
11.0
10.5
10.0
9.5
9.0

In [144]:
```
#library(car)
#All predictors scatterplot
scatterplotMatrix(~ M+So+Ed+Po1+Po2+LF+M.F+Pop+NW+U1+U2+Wealth+Ineq+Prob+Time, data = data)
#too tough to read
```

```
Warning message in smoother(x[subs], y[subs], col = smoother.args$col[i], log.x = FALSE, :
"could not fit smooth"
```



In [141]:
```
#USING SUBSET OF PREDICTORS
ggpairs(data, columns = c("Po1", "Po2", "U1", "U2", "Ineq", "Crime"),
                    mapping=ggplot2::aes(color= "#3366FF"))
```



In [142]:
```
#STUDY THE CORRELATION OF THE PREDICTORS (CLOSER TO 1, MORE CORRELATED THE PREDICTORS ARE..)
corr <- cor(data)
round(corr, 2)
#Observation co-relation between predictors
# high POSITIVE Correlation
##Po1-Po2;U1-U2;Po1/Po2-Wealth;So-NW;So-Ineq;Ed-Wealth
# high NEGATIVE Correlation
## So-Ed;Ed-Ineq;P
```

A matrix: 16 × 16 of type dbl

	M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob	Time	Crime
M	1.00	0.58	-0.53	-0.51	-0.51	-0.16	-0.03	-0.28	0.59	-0.22	-0.24	-0.67	0.64	0.36	0.11	-0.09
So	0.58	1.00	-0.70	-0.37	-0.38	-0.51	-0.31	-0.05	0.77	-0.17	0.07	-0.64	0.74	0.53	0.07	-0.09
Ed	-0.53	-0.70	1.00	0.48	0.50	0.56	0.44	-0.02	-0.66	0.02	-0.22	0.74	-0.77	-0.39	-0.25	0.32
Po1	-0.51	-0.37	0.48	1.00	0.99	0.12	0.03	0.53	-0.21	-0.04	0.19	0.79	-0.63	-0.47	0.10	0.69
Po2	-0.51	-0.38	0.50	0.99	1.00	0.11	0.02	0.51	-0.22	-0.05	0.17	0.79	-0.65	-0.47	0.08	0.67
LF	-0.16	-0.51	0.56	0.12	0.11	1.00	0.51	-0.12	-0.34	-0.23	-0.42	0.29	-0.27	-0.25	-0.12	0.19
M.F	-0.03	-0.31	0.44	0.03	0.02	0.51	1.00	-0.41	-0.33	0.35	-0.02	0.18	-0.17	-0.05	-0.43	0.21
Pop	-0.28	-0.05	-0.02	0.53	0.51	-0.12	-0.41	1.00	0.10	-0.04	0.27	0.31	-0.13	-0.35	0.46	0.34
NW	0.59	0.77	-0.66	-0.21	-0.22	-0.34	-0.33	0.10	1.00	-0.16	0.08	-0.59	0.68	0.43	0.23	0.03
U1	-0.22	-0.17	0.02	-0.04	-0.05	-0.23	0.35	-0.04	-0.16	1.00	0.75	0.04	-0.06	-0.01	-0.17	-0.05
U2	-0.24	0.07	-0.22	0.19	0.17	-0.42	-0.02	0.27	0.08	0.75	1.00	0.09	0.02	-0.06	0.10	0.18
Wealth	-0.67	-0.64	0.74	0.79	0.79	0.29	0.18	0.31	-0.59	0.04	0.09	1.00	-0.88	-0.56	0.00	0.44
Ineq	0.64	0.74	-0.77	-0.63	-0.65	-0.27	-0.17	-0.13	0.68	-0.06	0.02	-0.88	1.00	0.47	0.10	-0.18
Prob	0.36	0.53	-0.39	-0.47	-0.47	-0.25	-0.05	-0.35	0.43	-0.01	-0.06	-0.56	0.47	1.00	-0.44	-0.43
Time	0.11	0.07	-0.25	0.10	0.08	-0.12	-0.43	0.46	0.23	-0.17	0.10	0.00	0.10	-0.44	1.00	0.15
Crime	-0.09	-0.09	0.32	0.69	0.67	0.19	0.21	0.34	0.03	-0.05	0.18	0.44	-0.18	-0.43	0.15	1.00

CHECKING THEORY : EIGEN VALUES AND VECTORS

In [23]:
```
#Eigen values & vectors
X <- as.matrix(data)
X_Trans_X <- t(X)%*%X
ev <- eigen(X_Trans_X)
#Eigenvalues
ev$values
#Eigenvectors
#ev$vectors
```

1380740012.90473 · 5384801.42652306 · 59330.4704502898 · 20626.7567816144 · 2187.41595483789 · 1677.27232653165 · 151.07239653922 · 88.021838531293 · 41.095517797618 · 24.8002928942946 · 9.65667653420426 · 2.80155722968799 · 1.96793750526589 · 0.0256320722571422 · 0.00769541551602604 · 0.00252687018876677

In [136]:
```
#Find Determinant of X(Transpose)*X -lamba(identity matrix) for 1st Eigen value and vector and test the theory
#diag(ncol(data))
identity_mat <-diag(ncol(data))
det(X_Trans_X-ev$values[2]*identity_mat)
```

4.25568663425159e+94

In [206]:
```
#Caret to transform predictors, box cox tranformation and find princial components
pca_data <-caret::preProcess(
                        data %>% dplyr::select(-Crime),
                        method=c('center','scale','nzv','pca'))
pca_data # suggestion is to use PCA for 9 components out of 15 components
#linear combination of predictors for each principal component
pca_data$rotation
```

```
Created from 47 samples and 15 variables

Pre-processing:
  - centered (15)
  - ignored (0)
  - principal component signal extraction (15)
  - scaled (15)

PCA needed 9 components to capture 95 percent of the variance
```

A matrix: 15 × 9 of type dbl

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
M	-0.30371194	0.06280357	0.1724199946	-0.02035537	-0.35832737	-0.449132706	-0.15707378	-0.55367691	0.154747
So	-0.33088129	-0.15837219	0.0155433104	0.29247181	-0.12061130	-0.100500743	0.19649727	0.22734157	-0.65599
Ed	0.33962148	0.21461152	0.0677396249	0.07974375	-0.02442839	-0.008571367	-0.23943629	-0.14644678	-0.44326
Po1	0.30863412	-0.26981761	0.0506458161	0.33325059	-0.23527680	-0.095776709	0.08011735	0.04613156	0.194254
Po2	0.31099285	-0.26396300	0.0530651173	0.35192809	-0.20473383	-0.119524780	0.09518288	0.03168720	0.195120
LF	0.17617757	0.31943042	0.2715301768	-0.14326529	-0.39407588	0.504234275	-0.15931612	0.25513777	0.143934
M.F	0.11638221	0.39434428	-0.2031621598	0.01048029	-0.57877443	-0.074501901	0.15548197	-0.05507254	-0.24378
Pop	0.11307836	-0.46723456	0.0770210971	-0.03210513	-0.08317034	0.547098563	0.09046187	-0.59078221	-0.20244
NW	-0.29358647	-0.22801119	0.0788156621	0.23925971	-0.36079387	0.051219538	-0.31154195	0.20432828	0.189841
U1	0.04050137	0.00807439	-0.6590290980	-0.18279096	-0.13136873	0.017385981	-0.17354115	-0.20206312	0.020693
U2	0.01812228	-0.27971336	-0.5785006293	-0.06889312	-0.13499487	0.048155286	-0.07526787	0.24369650	0.055760
Wealth	0.37970331	-0.07718862	0.0100647664	0.11781752	0.01167683	-0.154683104	-0.14859424	0.08630649	-0.23196

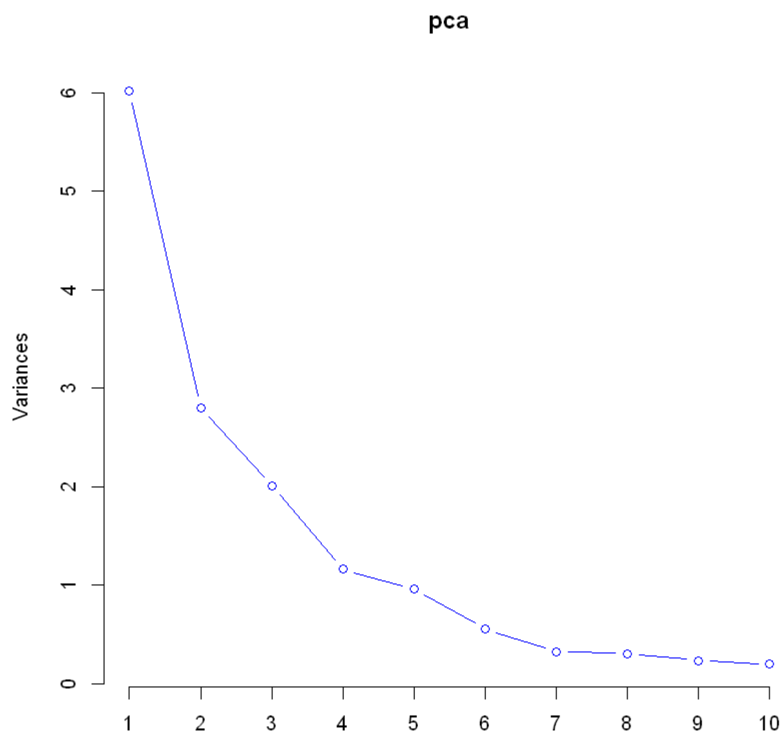
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Ineq	-0.36579778	-0.02752240	-0.0002944563	-0.08066612	-0.21672823	0.272027031	0.37483032	0.07184018	-0.02494
Prob	-0.25888661	0.15831708	-0.1176726436	0.49303389	0.16562829	0.283535996	-0.56159383	-0.08598908	-0.05306
Time	-0.02062867	-0.38014836	0.2235664632	-0.54059002	-0.14764767	-0.148203050	-0.44199877	0.19507812	-0.23551

PCA COMPUTATION USING PRCOMP

In [207]:
```
pca <- prcomp(data[,1:15], scale. = TRUE)
summary(pca)
```

```
Importance of components:
                          PC1    PC2    PC3     PC4     PC5     PC6     PC7
Standard deviation     2.4534 1.6739 1.4160 1.07806 0.97893 0.74377 0.56729
Proportion of Variance 0.4013 0.1868 0.1337 0.07748 0.06389 0.03688 0.02145
Cumulative Proportion  0.4013 0.5880 0.7217 0.79920 0.86308 0.89996 0.92142
                           PC8     PC9    PC10    PC11    PC12    PC13   PC14
Standard deviation     0.55444 0.48493 0.44708 0.41915 0.35804 0.26333 0.2418
Proportion of Variance 0.02049 0.01568 0.01333 0.01171 0.00855 0.00462 0.0039
Cumulative Proportion  0.94191 0.95759 0.97091 0.98263 0.99117 0.99579 0.9997
                          PC15
Standard deviation     0.06793
Proportion of Variance 0.00031
Cumulative Proportion  1.00000
```

In [150]:
```
plot(pca, type="lines",col="blue")
```



In [208]:

```
#get first 9 Principal componet
PCs <- pca$x[,1:9]
head(PCs,5)
```

A matrix: 5 × 9 of type dbl

PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
-4.199284	-1.0938312	-1.11907395	0.67178115	0.05528338	0.3073383	-0.56640816	-0.007801727	0.22350995
1.172663	0.6770136	-0.05244634	-0.08350709	-1.17319982	-0.5832373	0.19561119	0.154566472	0.43677720
-4.173725	0.2767750	-0.37107658	0.37793995	0.54134525	0.7187223	0.10330693	0.351138883	0.06299232
3.834962	-2.5769060	0.22793998	0.38262331	-1.64474650	0.7294884	0.26699499	-1.547460841	-0.37954181
1.839300	1.3309856	1.27882805	0.71814305	0.04159032	-0.3940902	0.07050766	-0.543237437	0.22463245

Build linear regression model with the first 9 principal components

In [209]:
```
PCcrime <- cbind(PCs, data$Crime) #Create new data matrix with first 5 PCs and crime rate
#PCcrime
model <- lm(V10~., data = as.data.frame(PCcrime)) #Create regression model based on 5 principal components
#model
summary(model) #PCA: Adjusted R squared :0.69;R squared :0.61
```

```
Call:
lm(formula = V10 ~ ., data = as.data.frame(PCcrime))

Residuals:
   Min     1Q Median     3Q    Max 
-455.9 -132.5   21.5  139.9  393.0 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   905.09      34.91  25.928  < 2e-16 ***
PC1            65.22      14.38   4.535 5.88e-05 ***
PC2           -70.08      21.08  -3.325  0.00201 ** 
PC3            25.19      24.92   1.011  0.31857    
PC4            69.45      32.73   2.122  0.04061 *  
PC5          -229.04      36.04  -6.355 2.08e-07 ***
PC6           -60.21      47.44  -1.269  0.21228    
PC7           117.26      62.20   1.885  0.06728 .  
PC8            28.72      63.64   0.451  0.65446    
PC9           -37.18      72.76  -0.511  0.61244    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 239.3 on 37 degrees of freedom
Multiple R-squared:  0.692,	Adjusted R-squared:  0.6171 
F-statistic: 9.239 on 9 and 37 DF,  p-value: 3.588e-07
```

Specify the new model in terms of the original variables (not the principal components), UNSCALE data in revrse

In [212]:
```
# Get coefficients in terms of original data from PCA coefficients
model$coefficient
beta0 <- model$coefficients[1] #intercept
betas <- model$coefficients[2:10] #PC
print(paste("Intercept Co-efficient: ",beta0))
betas
```

(Intercept): 905.085106382979 **PC1:** 65.215930138666 **PC2:** -70.0831185497858 **PC3:** 25.1940780425772 **PC4:** 69.446030796839 **PC5:** -229.042822001686 **PC6:** -60.2132861756709 **PC7:** 117.255897957602 **PC8:** 28.7165560702805 **PC9:** -37.1756419454256

```
[1] "Intercept Co-efficient:  905.085106382979"
```

PC1: 65.215930138666 **PC2:** -70.0831185497858 **PC3:** 25.1940780425772 **PC4:** 69.446030796839 **PC5:** -229.042822001686 **PC6:** -60.2132861756709 **PC7:** 117.255897957602 **PC8:** 28.7165560702805 **PC9:** -37.1756419454256

In [213]:
```
# Transform the PC coefficients into coefficients for the original variables

#pca$rotation[,1:4]
alphas <- pca$rotation[,1:9] %*% betas
t(alphas) #tranform PC co-efficients into original variable co-efficients
```

A matrix: 1 × 15 of type dbl

M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq
47.76773	97.85583	4.661941	126.6093	123.4647	29.18835	138.325	27.10574	57.26768	-25.10066	25.54553	38.92574	52.665

In [214]:
```
# Above is SCALED  coefficients
#To convert into original
# When scaling, this function subtracts the mean and divides by the standard deviation, for each variable.
# So, alpha * (x - mean)/sd = originalAlpha * x.
# That means:
# (1) originalAlpha = alpha/sd
# (2) we have to modify the constant term a0 by alpha*mean/sd

originalAlpha <- alphas/sapply(data[,1:15],sd)
originalBeta0 <- beta0 - sum(alphas*sapply(data[,1:15],mean)/sapply(data[,1:15],sd))
originalBeta0
```

(Intercept): -5742.13576339317

In [216]:
```
# Here are the coefficients for unscaled data:
t(originalAlpha)
```

A matrix: 1 × 15 of type dbl

M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	In
38.00853	204.3025	4.167285	42.60219	44.15555	722.2726	46.94177	0.7119751	5.569224	-1392.255	30.24768	0.04034134	13

In [217]:
```
#ORIGINAL MODEL Now let's compare with the regression model from the previous homework

model2 <- lm( Crime ~ ., data = data)
summary(model2) #R2 .80 and Adju R2 .70 (vs.#PCA: Adjusted R squared :0.69;R squared :0.61)
```

```
Call:
lm(formula = Crime ~ ., data = data)

Residuals:
    Min      1Q  Median      3Q     Max 
-395.74  -98.09   -6.69  112.99  512.67 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -5.984e+03  1.628e+03  -3.675 0.000893 ***
M            8.783e+01  4.171e+01   2.106 0.043443 *  
So          -3.803e+00  1.488e+02  -0.026 0.979765    
Ed           1.883e+02  6.209e+01   3.033 0.004861 ** 
Po1          1.928e+02  1.061e+02   1.817 0.078892 .  
Po2         -1.094e+02  1.175e+02  -0.931 0.358830    
LF          -6.638e+02  1.470e+03  -0.452 0.654654    
M.F          1.741e+01  2.035e+01   0.855 0.398995    
Pop         -7.330e-01  1.290e+00  -0.568 0.573845    
NW           4.204e+00  6.481e+00   0.649 0.521279    
U1          -5.827e+03  4.210e+03  -1.384 0.176238    
U2           1.678e+02  8.234e+01   2.038 0.050161 .  
Wealth       9.617e-02  1.037e-01   0.928 0.360754    
Ineq         7.067e+01  2.272e+01   3.111 0.003983 ** 
Prob        -4.855e+03  2.272e+03  -2.137 0.040627 *  
Time        -3.479e+00  7.165e+00  -0.486 0.630708    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 209.1 on 31 degrees of freedom
Multiple R-squared:  0.8031,	Adjusted R-squared:  0.7078 
F-statistic: 8.429 on 15 and 31 DF,  p-value: 3.539e-07
```

Compare quality of PCA Model vs. Original Model based on straightforward regression model

In [ ]:
```
# These results suggest that we are better off using a more straightforward regression model
# instead of PCA before using regression.
# If we had used all 15 principal components, we would have obtained
# an R-squared value of 0.803, which is the same R-squared value when using all
# 15 regular predictors in a basic linear regression model.
```

In [166]:
```
 # all possibilities: for i=1..15, run a regression using the first i principal components
r2 <- numeric(15) # create a vector to store the R-squared values
for (i in 1:15) {
  pclist <- pca$x[,1:i]  # use the first i prinicipal components
  pcc <- cbind(data[,16],pclist)  # create data set
  model <- lm(V1~.,data = as.data.frame(pcc)) # fit model
  r2[i] <- 1 - sum(model$residuals^2)/sum((data$Crime - mean(data$Crime))^2) # calculate R-squared
}
r2
```

0.171135123438665 · 0.263133909632497 · 0.271641569122873 · 0.309112068654877 · 0.645194053656692 · 0.658602327815706 · 0.688181873005123 · 0.689876527649446 · 0.692049141529042 · 0.696287251226172 · 0.697386539400947 · 0.769265609989774 · 0.77236636338524 · 0.791144655274498 · 0.803086758316909

In [167]:
```
# All PCA first "n" components generate model R-square less than original model R square value of 0.80.
#As noted earlier, with smaller subset of data, we are running into overfitting yielding high R square for origir
```

Predict new observations' Crime fit

crime prediction for new point of observation based on Original vs PCA model

In [218]:
```
#datapoint from previous homework
new_observe = data.frame(
        M = 14.0,
        So = 0,
        Ed = 10.0,
        Po1 = 12.0,
        Po2 = 15.5,
        LF = 0.640,
        M.F = 94.0 ,
        Pop = 150,
        NW = 1.1,
        U1 = 0.120,
        U2 = 3.6 ,
        Wealth = 3200,
        Ineq = 20.1 ,
        Prob = 0.04 ,
        Time = 39.0
)
```

In [219]:
```
#ORIGINAL Prediction
#model2 <- lm( Crime ~ ., data = data)
crime_pred_orig = predict(model2, new_observe) %>%
        as_tibble()
crime_pred_orig
```

A tibble: 1
× 1

value
<dbl>
155.4349

In [221]:
```
#PCA FITTED PREDICTION
library(pls)# to get pcr fit
# Run principal component regression function with only the first 4 principal components

numcomp <- 9
pcr.fit <- pcr(Crime ~ ., data = data, scale = TRUE, ncomp = numcomp)
summary(pcr.fit)
head(pcr.fit$scores,5)
```

```
Data:   X dimension: 47 15
        Y dimension: 47 1
Fit method: svdpc
Number of components considered: 9
TRAINING: % variance explained
       1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
X        40.13    58.81    72.17    79.92    86.31    90.00    92.14    94.19
Crime    17.11    26.31    27.16    30.91    64.52    65.86    68.82    68.99
       9 comps
X        95.76
Crime    69.20
```

A matrix: 5 × 9 of type dbl

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Comp 7	Comp 8	Comp 9
1	-4.199284	-1.0938312	-1.11907395	0.67178115	0.05528338	0.3073383	-0.56640816	-0.007801727	0.22350995
2	1.172663	0.6770136	-0.05244634	-0.08350709	-1.17319982	-0.5832373	0.19561119	0.154566472	0.43677720
3	-4.173725	0.2767750	-0.37107658	0.37793995	0.54134525	0.7187223	0.10330693	0.351138883	0.06299232
4	3.834962	-2.5769060	0.22793998	0.38262331	-1.64474650	0.7294884	0.26699499	-1.547460841	-0.37954181
5	1.839300	1.3309856	1.27882805	0.71814305	0.04159032	-0.3940902	0.07050766	-0.543237437	0.22463245

In [222]:
```
#use model to make predictions on a test set
test <- pcr(Crime ~ ., data = data, scale=TRUE, validation="CV") #Cross validation
summary(test)
#Root Mean Square error(RMSE)
#If we use interceptonly , the square error is  390.9
#If we use first components  , the square error is dropped to 364
#If we add in second  components  , the square error is dropped to 354
```

```
Data:   X dimension: 47 15
        Y dimension: 47 1
Fit method: svdpc
Number of components considered: 15

VALIDATION: RMSEP
Cross-validated using 10 random segments.
       (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
CV           390.9    364.8    354.1    364.0    366.9    262.5    262.8
adjCV        390.9    364.0    352.6    362.2    367.0    260.3    260.4
       7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
CV       259.6    266.7    270.6     276.6     298.8     264.5     276.4
adjCV    253.7    263.7    267.7     273.2     298.6     260.1     271.9
       14 comps  15 comps
CV        271.2     266.2
adjCV     265.7     261.0

TRAINING: % variance explained
       1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
X        40.13    58.81    72.17    79.92    86.31    90.00    92.14    94.19
Crime    17.11    26.31    27.16    30.91    64.52    65.86    68.82    68.99
       9 comps  10 comps  11 comps  12 comps  13 comps  14 comps  15 comps
X        95.76     97.09     98.26     99.12     99.58     99.97    100.00
Crime    69.20     69.63     69.74     76.93     77.24     79.11     80.31
```

In [223]:
```
pcr_pred <- predict(test, new_observe, ncomp=4)
pcr_pred
# predicted value of new data using PCR is  1112 vs. 155 crime data value using original regression with all the
#PCA generated crime ratio 7 times more than the linear regression model with all predictors for the new data val
```

1112.67763659883

In [ ]:
```
##########THE END of PCA REGRESSION ASSIGNMENT##############
```