Question 8.2

Using crime data from http://www.statsci.org/data/general/uscrime.txt (http://www.statsci.org/data/general/uscrime.txt) (file uscrime.txt, description at http://www.statsci.org/data/general/uscrime.html (http://www.statsci.org/data/general/uscrime.html)), use regression (a useful R function is lm or glm) to predict the observed crime rate in a city with the following data:

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

Show your model (factors used and their coefficients), the software output, and the quality of fit.

What each variables mean

```
Variable         Description
```

M percentage of males aged 14–24 in total state population So indicator variable for a southern state Ed mean years of schooling of the population aged 25 years or over Po1 per capita expenditure on police protection in 1960 Po2 per capita expenditure on police protection in 1959 LF labour force participation rate of civilian urban males in the age-group 14-24 M.F number of males per 100 females Pop state population in 1960 in hundred thousands NW percentage of nonwhites in the population U1 unemployment rate of urban males 14–24 U2 unemployment rate of urban males 35–39 Wealth wealth: median value of transferable assets or family income Ineq income inequality: percentage of families earning below half the median income Prob probability of imprisonment: ratio of number of commitments to number of offenses Time average time in months served by offenders in state prisons before their first release Crime crime rate: number of offenses per 100,000 population in 1960

Notes/Analysis:

Only one of Po1 and Po2, and only one of U1 and U2, remain in the final regression, because of high collinearity. Data gives association not causal relationships. For example, does crime really increase with police expenditure? Crime is negatively associated with probability of imprisonment. Crime is slightly better modelled on a log scale.

Approach followed

1) Identify the Predictors that are most crucial to the linear model How?

```
 * Identify the denstity of the data observation points
 * Create Correlation plot to identify the correlation between the predictors and
"Crime" output(last field in input)
 * Confirm with the correction measurement
```

2) The above steps identify the predictors that are impacts the output 3) Using the information, create a new dataset with the predictors that matters and Output and create a Linear model 4) Study the co-efficients for each predictors, p -value adn R sqaured value 5) using this model co-efficients, establish a prediction for the new data point and predict the Crime#

In [19]:
```
##########LIBRARY##########
library("ggplot2")
#install.packages("devtools")
#install.packages("corrplot")
library("devtools")
library("corrplot") # to use Correlation plot
library(tidyr) # to get "gather" function
library(plyr) #to use arrange function
```

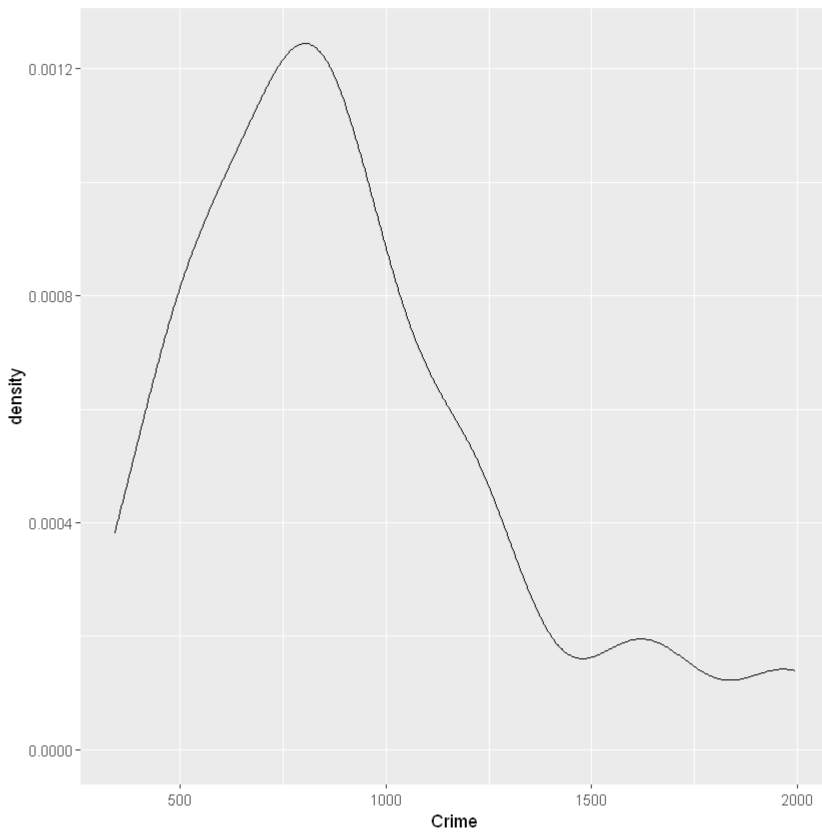
In [7]:
```
##########INGEST FILE##########

#crime<- read.table("C:\\Preethi\\R\\USCrimes.txt",header=TRUE,stringsAsFactor
s = FALSE,sep="\t")
#head(data,10)
#colClasses = c("numeric", "numeric", "numeric")
#colClasses
crime = read.table("C:\\Preethi\\R\\USCrimes.txt",header=TRUE,stringsAsFactors
= FALSE,sep="\t") %>% as_tibble()
head(crime,2)
```

A tibble: 2 × 16

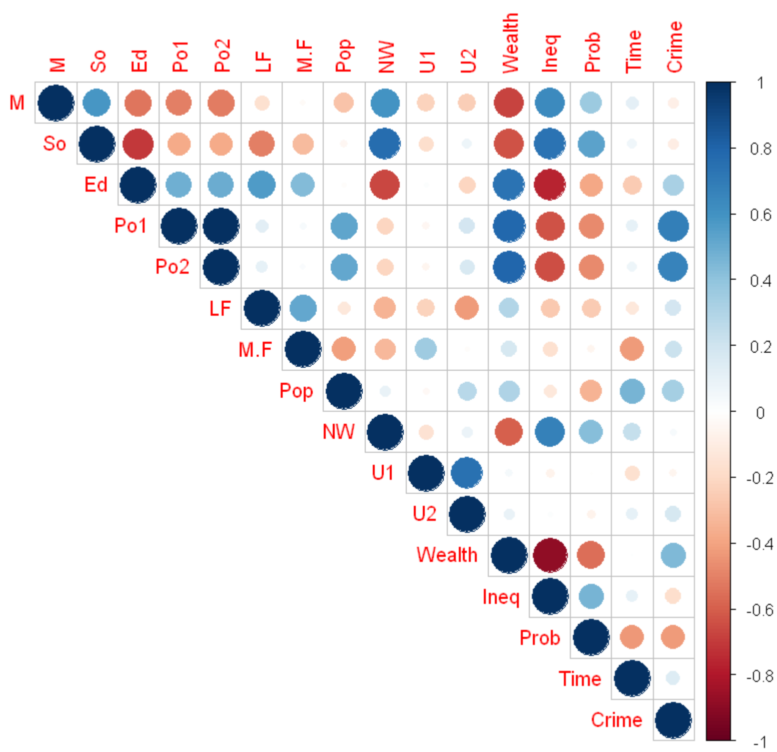
M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq
<dbl>	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>	<dbl>
15.1	1	9.1	5.8	5.6	0.510	95.0	33	30.1	0.108	4.1	3940	26.1
14.3	0	11.3	10.3	9.5	0.583	101.2	13	10.2	0.096	3.6	5570	19.4

study relationship of predictors with Crime output

In [12]:
```
# show density of data spread
ggplot(data = crime, aes(x = Crime)) +geom_density()
#negative skew
```



In [9]:
```
# to show correlation f predictors
corrplot(cor(crime),type = 'upper')
#1. observation Po1 and Po2;U1  only one of U1 and U2 are highly corelated
#Only one of P01 or P02 and U1 and U2 will be used for Regression (PO:per Capi
ta expenditure;U:Unemployement rate)
#2.Crime is negatively associated with probability of imprisonment(prob)-in re
d.
#3.Wealth and Inequ has high negative corelation.
```

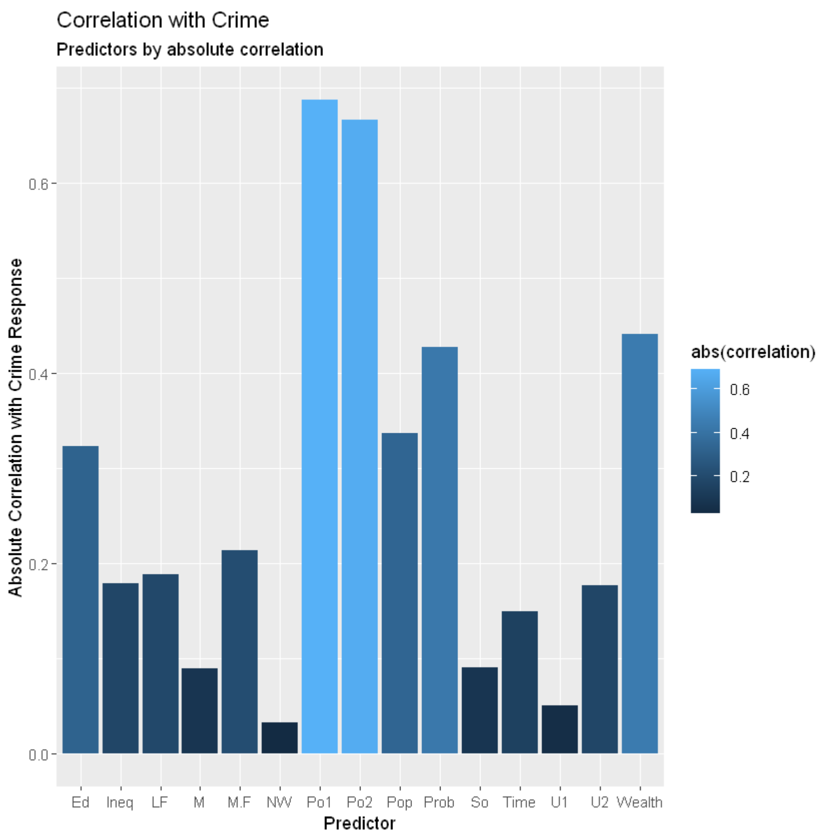


In [40]:
```
cor(crime$Crime, crime[,1:15]) %>%
        as_tibble() %>%
        gather(predictor, correlation) %>% #transform crosstab to rows
        arrange(desc(correlation)) #sort by desc
#highest Correlation to "y=Crime" is most likely predictor(red circle in correlation plot)
```

A tibble: 15 × 2

predictor	correlation
<chr>	<dbl>
Po1	0.68760446
Po2	0.66671414
Wealth	0.44131995
Pop	0.33747406
Ed	0.32283487
M.F	0.21391426
LF	0.18886635
U2	0.17732065
Time	0.14986606
NW	0.03259884
U1	-0.05047792
M	-0.08947240
So	-0.09063696
Ineq	-0.17902373
Prob	-0.42742219

In [30]:
```
# study relationship of predictors with Crime output
cor(crime$Crime, crime[,1:15]) %>%
        as_tibble() %>%
        gather(predictor, correlation) %>%
        arrange(desc(correlation)) %>%
        ggplot(data = ., aes(x = predictor, y = abs(correlation), fill = abs(c
orrelation))) +
        geom_col() +
        labs(title = 'Correlation with Crime',
             subtitle = 'Predictors by absolute correlation') +
        xlab('Predictor') +
        ylab('Absolute Correlation with Crime Response')
```



In [41]:
```
#create data frame based on predictors that matters
crime_df = crime %>%
        dplyr::select(Crime, Po1,Wealth,Prob,Ed,Pop,Ineq,M.F)
```

Predictors that matters

Result(y): Crime crime rate: number of offenses per 100,000 population in 1960

PREDICTORS that impacts results

Po1 per capita expenditure on police protection in 1960 Wealth wealth: median value of transferable assets or family income Prob probability of imprisonment: ratio of number of commitments to number of offenses Ed mean years of schooling of the population aged 25 years or over Pop state population in 1960 in hundred thousands Ineq income inequality: percentage of families earning below half the median income M.F number of males per 100 females

In [42]:

```
# develop predictor data and response labels
crime_x = data.frame(crime_df) %>% dplyr::select(., -Crime) #exclude "Y-outpu
t"
crime_y = data.frame(crime_df) %>% dplyr::select(., Crime) #include only Y-out
put"
```

In [43]:

```
#Just curios on Box Cox transformation
transform_df = caret::preProcess(crime_x,  method = c('center', 'scale', 'nzv'
, 'BoxCox'))
transform_df
```

```
Created from 47 samples and 7 variables

Pre-processing:
  - Box-Cox transformation (7)
  - centered (7)
  - ignored (0)
  - scaled (7)

Lambda estimates for Box-Cox transformation:
-0.4, 1.8, 0.4, 2, 0.1, -0.3, -2
```

Linear model

In [76]:

```
lm.crime_matters <- lm(Crime~., data=crime_df) #Out Crime related(~) to inpu
t);use only the impactful predictors
```

In [77]:
```
summary(lm.crime_matters)
```

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

Residuals:
    Min      1Q  Median      3Q     Max 
-487.51 -128.62   13.12  137.85  436.04 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -4.506e+03  1.370e+03  -3.290  0.00213 ** 
Po1          1.185e+02  2.031e+01   5.834 8.81e-07 ***
Wealth       8.053e-02  9.945e-02   0.810  0.42298    
Prob        -3.884e+03  1.757e+03  -2.211  0.03300 *  
Ed           1.019e+02  5.278e+01   1.930  0.06086 .  
Pop         -1.196e+00  1.247e+00  -0.959  0.34335    
Ineq         8.811e+01  2.006e+01   4.392 8.33e-05 ***
M.F          1.447e+01  1.437e+01   1.007  0.32020    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 218.9 on 39 degrees of freedom
Multiple R-squared:  0.7285,	Adjusted R-squared:  0.6798 
F-statistic: 14.95 on 7 and 39 DF,  p-value: 2.697e-09
```

Co-efficients of the Predictors

Accurary of the model is obtained from the Adjusted R square of the mode p values of the co-efficients are low proving that co-efficients matters to the model

In [63]:
```
#Display Coefficiensts of predictors as table
coef(lm.crime_matters) %>% as.data.frame()
```

A data.frame: 8 × 1

	.
	<dbl>
(Intercept)	-4.506418e+03
Po1	1.184710e+02
Wealth	8.053154e-02
Prob	-3.883680e+03
Ed	1.018860e+02
Pop	-1.195830e+00
Ineq	8.810809e+01
M.F	1.447042e+01

Predict new observations' Crime fit

In [64]:
```
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 [71]:
```
# crime prediction for new point of observation based on model
crime_pred = predict(lm.crime_matters, new_observe) %>%
        as_tibble()
crime_pred
```

A tibble: 1 × 1

value
<dbl>
988.2651

Predicted Crime for the new data point : 988.26

Notes

https://www.learnbymarketing.com/tutorials/linear-regression-in-r/ (https://www.learnbymarketing.com/tutorials/linear-regression-in-r/)

In [ ]: