

Lab 3: Reducing Crime (Draft)

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Introduction

Crime poses substantial economic and intangible cost to society. Based on Bureau of Justice Statistics and FBI data, U.S. crime rates reached a broad peak between the 1970s through early 1990s and has declined significantly after that. The current crime rates are about the same as those in the 1960s. This is partly the result of a series of policies targeted at reducing crime rate. A good understanding of factors associated with crime is important for effective policymaking and resource allocation.

In this study, we will research the crime data for a selection of counties in North Carolina in 1987 to understand the determinants of crime and generate policy suggestions to the local government.

Data Description

The data set includes 25 variables that describe the various statistics of each county. All variables are numeric except for the probability of conviction variable, which is expressed as characters and will be converted to numbers. There are 97 observations but 6 are NA values. The variables have been grouped by the following major categories:

Table 1: Data Description

No.	Category	Fields
1	Crime Rate	crm rte
2	Crime Punishment	prbarr, prbconv, prbpris, avgsen
3	Population	density, pctmin80, pctymle
4	Economic	taxpc
5	Geographic	county, west, central, urban
6	Income	wcon, wtuc, wtrd, wfir, wser, wmfg, wfed, wsta, wloc
7	Crime Type	mix
8	Law Enforcement	polpc
9	Time Period	year

Data Cleaning

In the 97 observations, 6 consists of missing values in all fields. These rows have been removed. The “proconv” variable should be numeric but is expressed as characters. That has been converted to numbers.

```
library(car)
```

```
## Loading required package: carData
```

```
dfCrime <- read.csv('crime_v2.csv', stringsAsFactors = FALSE)
```

```
dfCrime <- na.omit(dfCrime)
```

```
dfCrime$prbconv <- as.numeric(dfCrime$prbconv)
```

```
summary(dfCrime)
```

```
##      county      year      crm rte      prbarr
```

```

## Min. : 1.0 Min. :87 Min. :0.005533 Min. :0.09277
## 1st Qu.: 52.0 1st Qu.:87 1st Qu.:0.020927 1st Qu.:0.20568
## Median :105.0 Median :87 Median :0.029986 Median :0.27095
## Mean :101.6 Mean :87 Mean :0.033400 Mean :0.29492
## 3rd Qu.:152.0 3rd Qu.:87 3rd Qu.:0.039642 3rd Qu.:0.34438
## Max. :197.0 Max. :87 Max. :0.098966 Max. :1.09091
## prbconv prbpris avgsen polpc
## Min. :0.06838 Min. :0.1500 Min. : 5.380 Min. :0.0007459
## 1st Qu.:0.34541 1st Qu.:0.3648 1st Qu.: 7.340 1st Qu.:0.0012308
## Median :0.45283 Median :0.4234 Median : 9.100 Median :0.0014853
## Mean :0.55128 Mean :0.4108 Mean : 9.647 Mean :0.0017022
## 3rd Qu.:0.58886 3rd Qu.:0.4568 3rd Qu.:11.420 3rd Qu.:0.0018768
## Max. :2.12121 Max. :0.6000 Max. :20.700 Max. :0.0090543
## density taxpc west central
## Min. :0.00002 Min. : 25.69 Min. :0.0000 Min. :0.0000
## 1st Qu.:0.54741 1st Qu.: 30.66 1st Qu.:0.0000 1st Qu.:0.0000
## Median :0.96226 Median : 34.87 Median :0.0000 Median :0.0000
## Mean :1.42884 Mean : 38.06 Mean :0.2527 Mean :0.3736
## 3rd Qu.:1.56824 3rd Qu.: 40.95 3rd Qu.:0.5000 3rd Qu.:1.0000
## Max. :8.82765 Max. :119.76 Max. :1.0000 Max. :1.0000
## urban pctmin80 wcon wtuc
## Min. :0.00000 Min. : 1.284 Min. :193.6 Min. :187.6
## 1st Qu.:0.00000 1st Qu.: 9.845 1st Qu.:250.8 1st Qu.:374.6
## Median :0.00000 Median :24.312 Median :281.4 Median :406.5
## Mean :0.08791 Mean :25.495 Mean :285.4 Mean :411.7
## 3rd Qu.:0.00000 3rd Qu.:38.142 3rd Qu.:314.8 3rd Qu.:443.4
## Max. :1.00000 Max. :64.348 Max. :436.8 Max. :613.2
## wtrd wfir wser wmfgr
## Min. :154.2 Min. :170.9 Min. : 133.0 Min. :157.4
## 1st Qu.:190.9 1st Qu.:286.5 1st Qu.: 229.7 1st Qu.:288.9
## Median :203.0 Median :317.3 Median : 253.2 Median :320.2
## Mean :211.6 Mean :322.1 Mean : 275.6 Mean :335.6
## 3rd Qu.:225.1 3rd Qu.:345.4 3rd Qu.: 280.5 3rd Qu.:359.6
## Max. :354.7 Max. :509.5 Max. :2177.1 Max. :646.9
## wfed wsta wloc mix
## Min. :326.1 Min. :258.3 Min. :239.2 Min. :0.01961
## 1st Qu.:400.2 1st Qu.:329.3 1st Qu.:297.3 1st Qu.:0.08073
## Median :449.8 Median :357.7 Median :308.1 Median :0.10186
## Mean :442.9 Mean :357.5 Mean :312.7 Mean :0.12884
## 3rd Qu.:478.0 3rd Qu.:382.6 3rd Qu.:329.2 3rd Qu.:0.15175
## Max. :598.0 Max. :499.6 Max. :388.1 Max. :0.46512
## pctymle
## Min. :0.06216
## 1st Qu.:0.07443
## Median :0.07771
## Mean :0.08396
## 3rd Qu.:0.08350
## Max. :0.24871

```

Analysis of Key Relationships

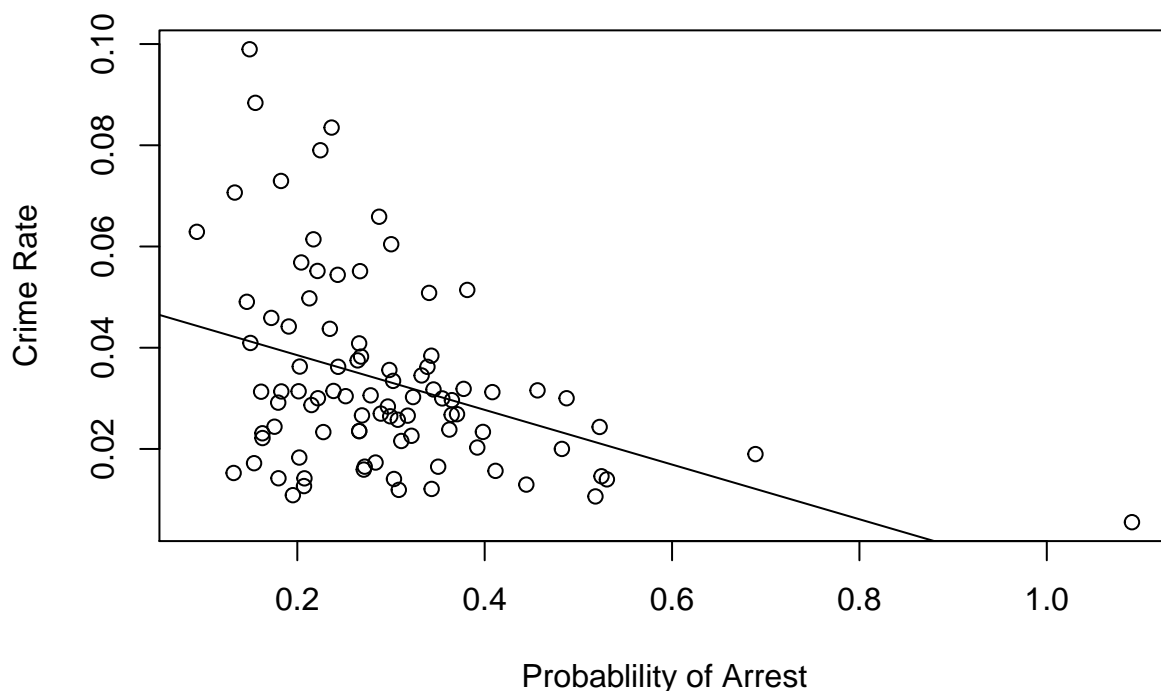
Punishment and Crime

In this section, we will investigate the effect of punishment on crime rate. Specifically, punishment is broken into two major categories:

- 1) Certainty of punishment, proxied by various ratio such as arrest:offense, conviction:arrest, and sentenced:conviction. We created a new variable that combines (by multiplying) the 3 certainty of punishment ratios to obtain the ratio for sentenced:offense to get a better sense of the extent in which criminals expect to be in prisoned after committing a crime. We expect the probability of arrest and the probability of being sentenced to be strong deterrents for crime.
- 2) Severity of punishment, measured by the average sentence in days.

```
dfCrime$prbPrisonToCrime = dfCrime$prbarr * dfCrime$prbconv * dfCrime$prbpris
plot(dfCrime$prbarr, dfCrime$crmrate, xlab = "Probability of Arrest",
     ylab = "Crime Rate", main = "Probability of Arrest vs Crime Rate")
abline(lm(crmrate ~ prbarr, data=dfCrime))
```

Probability of Arrest vs Crime Rate



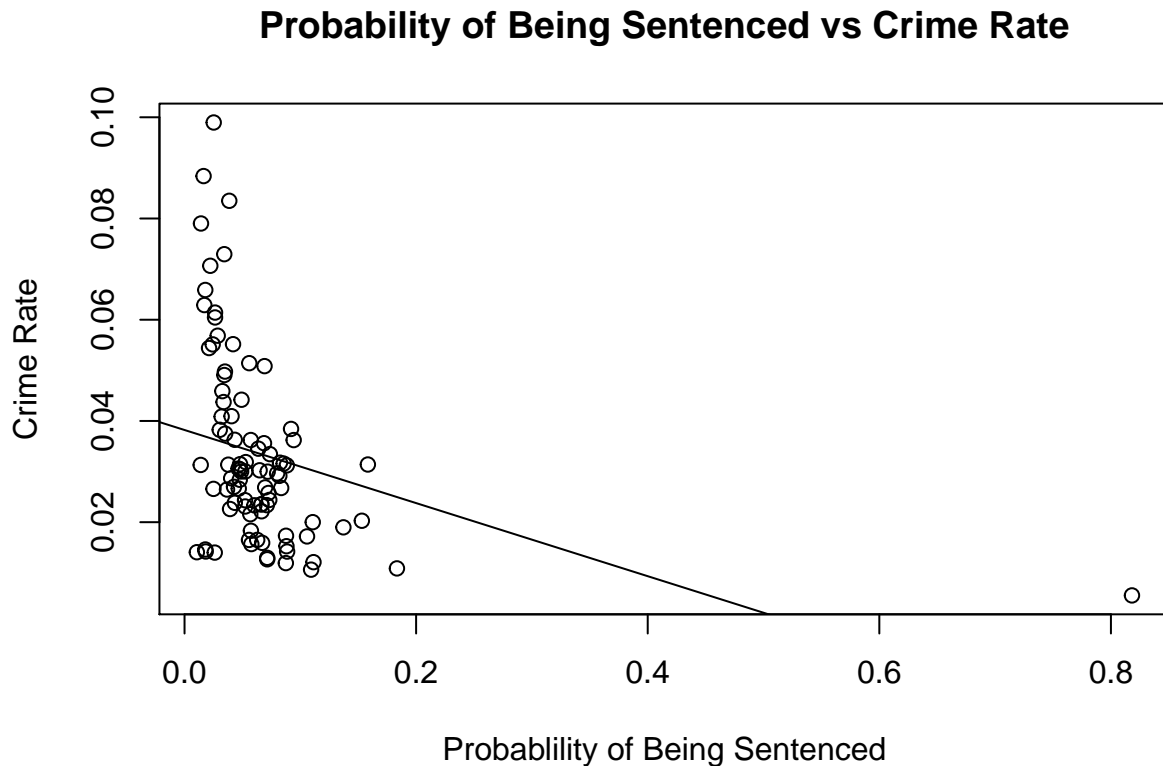
```
lm(crmrate ~ prbarr, data=dfCrime)

##
## Call:
## lm(formula = crmrate ~ prbarr, data = dfCrime)
##
## Coefficients:
## (Intercept)      prbarr
##    0.04933    -0.05403

summary(lm(crmrate ~ prbarr, data=dfCrime))$r.square
```

```
## [1] 0.1547083
```

```
plot(dfCrime$prbPrisonToCrime, dfCrime$crmrte, xlab = "Probablility of Being Sentenced",  
      ylab = "Crime Rate", main = "Probability of Being Sentenced vs Crime Rate")  
abline(lm(crmrte ~ prbPrisonToCrime, data=dfCrime))
```



```
lm(crmrte ~ prbPrisonToCrime, data=dfCrime)
```

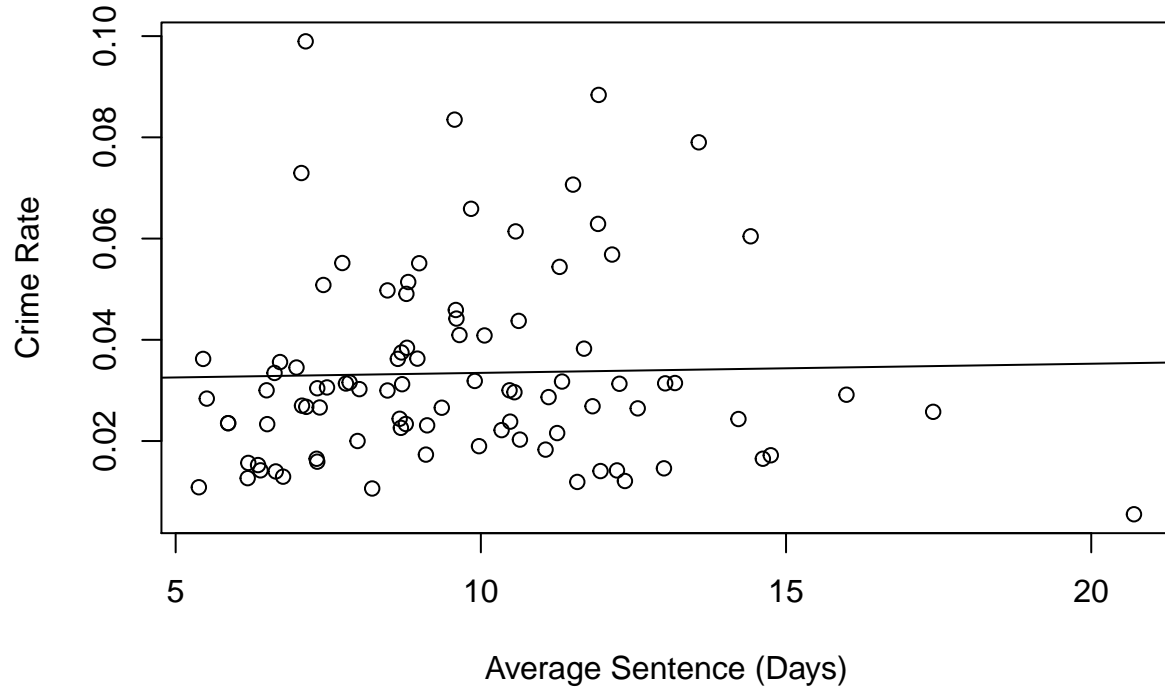
```
##  
## Call:  
## lm(formula = crmrte ~ prbPrisonToCrime, data = dfCrime)  
##  
## Coefficients:  
##      (Intercept)  prbPrisonToCrime  
##           0.03822           -0.07221
```

```
summary(lm(crmrte ~ prbPrisonToCrime, data=dfCrime))$r.square
```

```
## [1] 0.1093573
```

```
plot(dfCrime$avgssen, dfCrime$crmrte, xlab = "Average Sentence (Days)",  
      ylab = "Crime Rate", main = "Average Sentence vs Crime Rate")  
abline(lm(crmrte ~ avgssen, data=dfCrime))
```

Average Sentence vs Crime Rate



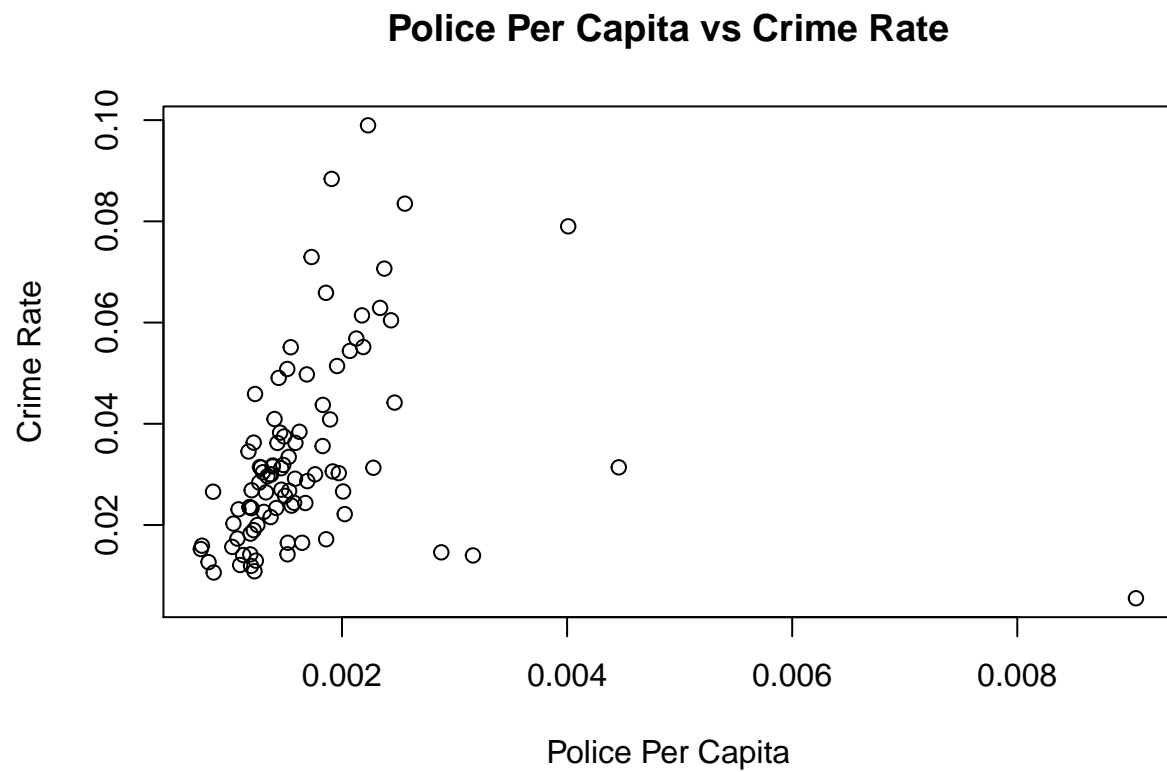
```
lm(crmrte ~ avgssen, data=dfCrime)
```

```
##
## Call:
## lm(formula = crmrte ~ avgssen, data = dfCrime)
##
## Coefficients:
## (Intercept)      avgssen
##  0.0316530    0.0001811
```

```
summary(lm(crmrte ~ avgssen, data=dfCrime))$r.square
```

```
## [1] 0.0007513802
```

```
plot(dfCrime$polpc, dfCrime$crmrte, xlab = "Police Per Capita", ylab = "Crime Rate", main = "Police Per
```



Population and Crime

In this section, we will investigate the effect of population and demographics on crime rate.

```
plot(dfCrime$density, dfCrime$crmrte, xlab = "Population Density (People Per Square Mile)", ylab = "Crime Rate")  
abline(lm(crmrte ~ density, data=dfCrime))
```

Population Density vs Crime Rate



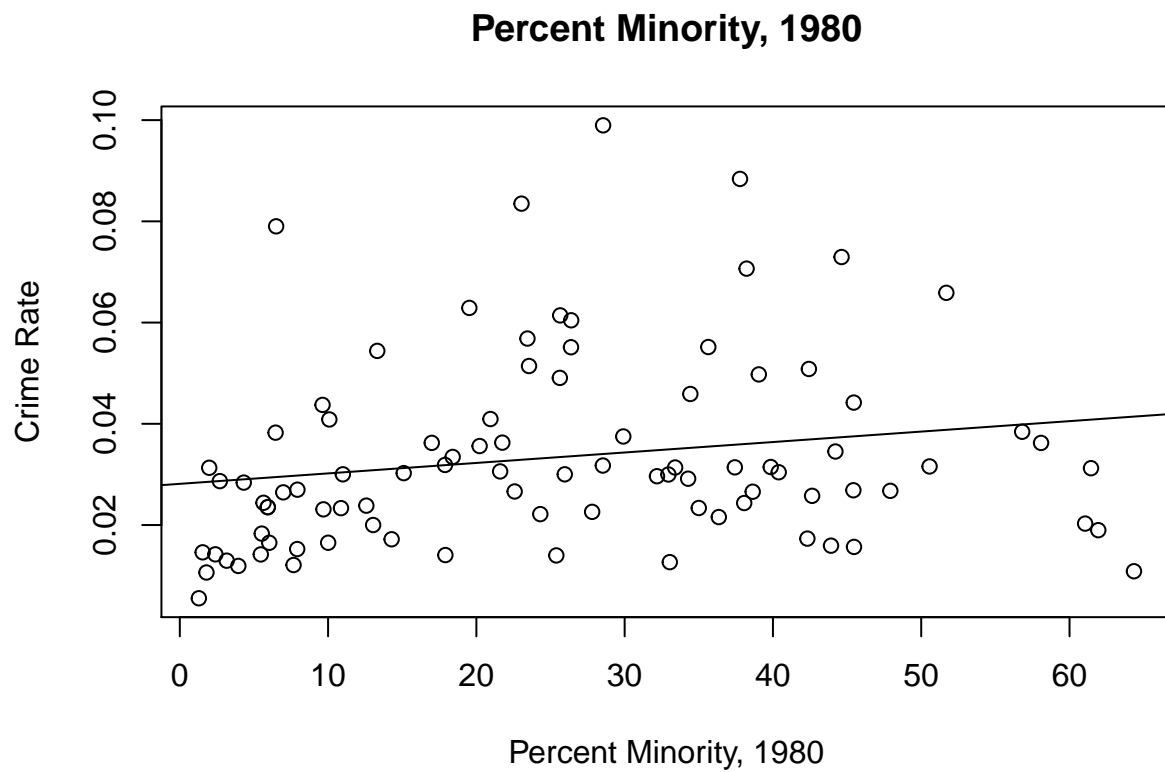
```
lm(crmrte ~ density, data=dfCrime)
```

```
##  
## Call:  
## lm(formula = crmrte ~ density, data = dfCrime)  
##  
## Coefficients:  
## (Intercept)      density  
##    0.020463    0.009054
```

```
summary(lm(crmrte ~ density, data=dfCrime))$r.square
```

```
## [1] 0.5313873
```

```
plot(dfCrime$pctmin80, dfCrime$crmrte, xlab = "Percent Minority, 1980", ylab = "Crime Rate", main = "Pe  
abline(lm(crmrte ~ pctmin80, data=dfCrime))
```



```
lm(crmrte ~ pctmin80, data=dfCrime)
```

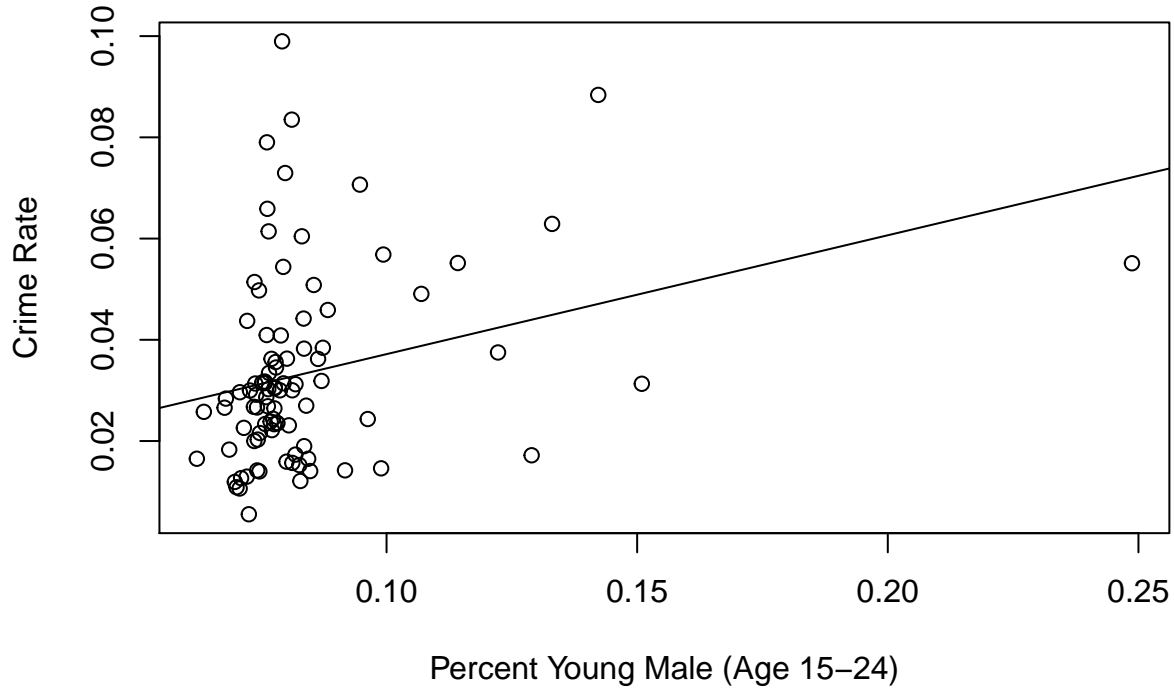
```
##
## Call:
## lm(formula = crmrte ~ pctmin80, data = dfCrime)
##
## Coefficients:
## (Intercept)      pctmin80
##  0.0281357      0.0002065
```

```
summary(lm(crmrte ~ pctmin80, data=dfCrime))$r.square
```

```
## [1] 0.03489294
```

```
plot(dfCrime$pctymle, dfCrime$crmrte, xlab = "Percent Young Male (Age 15-24)", ylab = "Crime Rate", main = "Percent Young Male, 1980")
abline(lm(crmrte ~ pctymle, data=dfCrime))
```


Percent Young Male vs Crime Rate



```
lm(crmrte ~ pctymle, data=dfCrime)
```

```
##
## Call:
## lm(formula = crmrte ~ pctymle, data = dfCrime)
##
## Coefficients:
## (Intercept)      pctymle
##      0.01368      0.23487
```

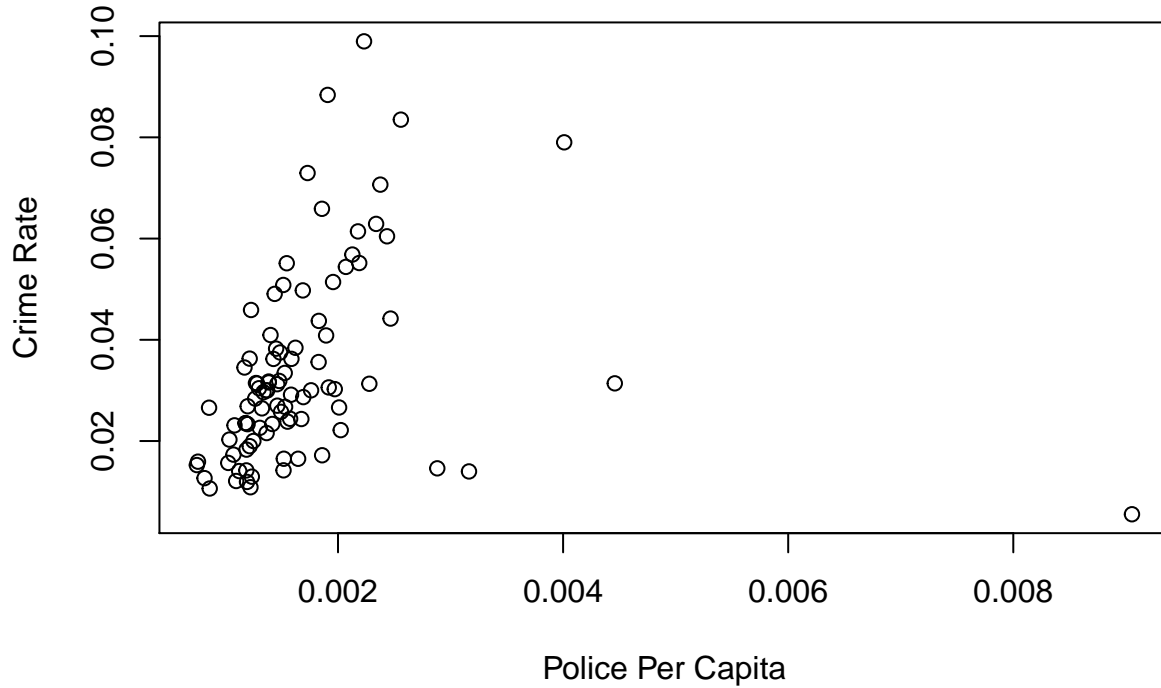
```
summary(lm(crmrte ~ pctymle, data=dfCrime))$r.square
```

```
## [1] 0.08482568
```

I thought police coverage per capita would be a determinant of crime, but given the positive correlation, it could be the other way around - crime rate driving police coverage.

```
plot(dfCrime$polpc, dfCrime$crmrte, xlab = "Police Per Capita", ylab = "Crime Rate", main = "Police Per
```

Police Per Capita vs Crime Rate



Here is an interesting row of data with probability of arrest > 1 . this county also has the lowest crime rate, longest average sentence, and most police per capita.

```
dfCrime[51,]
```

```
##   county year   crmrte prbarr prbconv prbpris avgsen   polpc
## 51    115   87 0.005532 1.09091    1.5    0.5   20.7 0.00905433
##      density taxpc west central urban pctmin80   wcon   wtuc
## 51 0.3858093 28.1931    1      0      0 1.28365 204.2206 503.2351
##      wtrd   wfir   wser  wmfgr wfed   wsta   wloc mix   pctymle
## 51 217.4908 342.4658 245.2061 448.42 442.2 340.39 386.12 0.1 0.07253495
##      prbPrisonToCrime
## 51          0.8181825
```

Additional variables that we would wish to collect?

- Need average income (take average of the given income variables?)
- Need a sense of poverty rate
- Type of crime?