

# Crime and Communities

**Group Member 1 Name:** Khang V. Tran **Group Member 1 SID:** 25181590

**Group Member 2 Name:** Christian Philip Hoeck **Group Member 2 SID:** \_\_\_\_\_

The crime and communities dataset contains crime data from communities in the United States. The data combines socio-economic data from the 1990 US Census, law enforcement data from the 1990 US LEMAS survey, and crime data from the 1995 FBI UCR. More details can be found at <https://archive.ics.uci.edu/ml/datasets/Communities+and+Crime+Unnormalized>.

The dataset contains 125 columns total;  $p = 124$  predictive and 1 target (ViolentCrimesPerPop). There are  $n = 1994$  observations. These can be arranged into an  $n \times p = 1994 \times 127$  feature matrix  $\mathbf{X}$ , and an  $n \times 1 = 1994 \times 1$  response vector  $\mathbf{y}$  (containing the observations of ViolentCrimesPerPop).

Once downloaded (from bCourses), the data can be loaded as follows.

```
library(readr)
CC <- read_csv("../data_files/crime_and_communities_data.csv")
print(dim(CC))
```

```
## [1] 1994 125
```

```
y <- CC$ViolentCrimesPerPop
X <- subset(CC, select = -c(ViolentCrimesPerPop))
```

## Dataset exploration

In this section, you should provide a thorough exploration of the features of the dataset. Things to keep in mind in this section include:

- Which variables are categorical versus numerical?
- What are the general summary statistics of the data? How can these be visualized?
- Is the data normalized? Should it be normalized?
- Are there missing values in the data? How should these missing values be handled?
- Can the data be well-represented in fewer dimensions?

**YOUR CODE GOES HERE**

## Examine Categorical vs. Quantitative data

Let's look at the structure of the data

```
str(X)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':   1994 obs. of  124 variables:
## $ population      : num  11980 23123 29344 16656 140494 ...
## $ householdsize   : num   3.1 2.82 2.43 2.4 2.45 2.6 2.45 2.46 2.62 2.54 ...
## $ racepctblack     : num   1.37 0.8 0.74 1.7 2.51 ...
## $ racePctWhite     : num  91.8 95.6 94.3 97.3 95.7 ...
## $ racePctAsian     : num   6.5 3.44 3.43 0.5 0.9 1.47 0.4 1.25 0.92 0.77 ...
## $ racePctHispanic : num   1.88 0.85 2.35 0.7 0.95 ...
## $ agePct12t21      : num  12.5 11 11.4 12.6 18.1 ...
## $ agePct12t29      : num  21.4 21.3 25.9 25.2 32.9 ...
## $ agePct16t24      : num  10.9 10.5 11 12.2 20 ...
## $ agePct65up       : num  11.3 17.2 10.3 17.6 13.3 ...
## $ numbUrban        : num  11980 23123 29344 0 140494 ...
## $ pctUrban         : num  100 100 100 0 100 100 100 100 100 100 ...
## $ medIncome        : num  75122 47917 35669 20580 21577 ...
## $ pctWWage         : num  89.2 79 82 68.2 75.8 ...
## $ pctWFarmSelf     : num   1.55 1.11 1.15 0.24 1 0.39 0.67 2.93 0.86 1.54 ...
## $ pctWInvInc       : num  70.2 64.1 55.7 39 41.1 ...
## $ pctWSocSec       : num  23.6 35.5 22.2 39.5 29.3 ...
## $ pctWPubAsst      : num   1.03 2.75 2.94 11.71 7.12 ...
## $ pctWRetire       : num  18.4 22.9 14.6 18.3 14.1 ...
## $ medFamInc        : num  79584 55323 42112 26501 27705 ...
## $ perCapInc        : num  29711 20148 16946 10810 11878 ...
## $ whitePerCap      : num  30233 20191 17103 10909 12029 ...
## $ blackPerCap      : num  13600 18137 16644 9984 7382 ...
## $ indianPerCap     : num   5725 0 21606 4941 10264 ...
## $ AsianPerCap      : num  27101 20074 15528 3541 10753 ...
## $ OtherPerCap      : num   5115 5250 5954 2451 7192 ...
## $ HispPerCap       : num  22838 12222 8405 4391 8104 ...
## $ NumUnderPov      : num   227 885 1389 2831 23223 ...
## $ PctPopUnderPov   : num   1.96 3.98 4.75 17.23 17.78 ...
## $ PctLess9thGrade  : num   5.81 5.61 2.8 11.05 8.76 ...
## $ PctNotHSGrad     : num   9.9 13.72 9.09 33.68 23.03 ...
## $ PctBSorMore      : num  48.2 29.9 30.1 10.8 20.7 ...
## $ PctUnemployed    : num   2.7 2.43 4.01 9.86 5.72 4.85 8.19 4.18 8.39 7.19 ...
## $ PctEmploy        : num  64.5 62 69.8 54.7 59 ...
## $ PctEmplManu      : num  14.7 12.3 15.9 31.2 14.3 ...
## $ PctEmplProfServ  : num  28.8 29.3 21.5 27.4 26.8 ...
## $ PctOccupManu     : num   5.49 6.39 8.79 26.76 14.72 ...
## $ PctOccupMgmtProf : num  50.7 37.6 32.5 22.7 23.4 ...
## $ MalePctDivorce   : num   3.67 4.23 10.1 10.98 11.4 ...
## $ MalePctNevMarr   : num   26.4 28 25.8 28.1 33.3 ...
## $ FemalePctDiv     : num   5.22 6.45 14.76 14.47 14.46 ...
## $ TotalPctDiv      : num   4.47 5.42 12.55 12.91 13.04 ...
## $ PersPerFam       : num   3.22 3.11 2.95 2.98 2.89 3.14 2.95 3 3.11 2.99 ...
## $ PctFam2Par       : num  91.4 86.9 78.5 64 71.9 ...
## $ PctKids2Par      : num  90.2 85.3 78.8 62.4 69.8 ...
## $ PctYoungKids2Par : num  95.8 96.8 92.4 65.4 79.8 ...
## $ PctTeen2Par      : num  95.8 86.5 75.7 67.4 75.3 ...
## $ PctWorkMomYoungKids : num  44.6 51.1 66.1 59.6 63 ...
```

```

## $ PctWorkMom : num 58.9 62.4 74.2 70.3 70.5 ...
## $ NumKidsBornNeverMar : num 31 43 164 561 1511 ...
## $ PctKidsBornNeverMar : num 0.36 0.24 0.88 3.84 1.58 1.18 4.66 1.64 4.71 2.47 ...
## $ NumImmig : num 1277 1920 1468 339 2091 ...
## $ PctImmigRecent : num 8.69 5.21 16.42 13.86 21.33 ...
## $ PctImmigRec5 : num 13 8.65 23.98 13.86 30.56 ...
## $ PctImmigRec8 : num 21 13.3 32.1 15.3 38 ...
## $ PctImmigRec10 : num 30.9 22.5 35.6 15.3 45.5 ...
## $ PctRecentImmig : num 0.93 0.43 0.82 0.28 0.32 1.05 0.11 0.47 0.72 0.53 ...
## $ PctRecImmig5 : num 1.39 0.72 1.2 0.28 0.45 1.49 0.2 0.67 1.07 1.05 ...
## $ PctRecImmig8 : num 2.24 1.11 1.61 0.31 0.57 2.2 0.25 0.93 1.63 1.66 ...
## $ PctRecImmig10 : num 3.3 1.87 1.78 0.31 0.68 2.55 0.29 1.07 2.31 1.94 ...
## $ PctSpeakEnglOnly : num 85.7 87.8 93.1 95 96.9 ...
## $ PctNotSpeakEnglWell : num 1.37 1.81 1.14 0.56 0.6 0.6 0.28 0.43 2.51 0.81 ...
## $ PctLargHouseFam : num 4.81 4.25 2.97 3.93 3.08 5.08 3.85 2.59 6.7 3.66 ...
## $ PctLargHouseOccup : num 4.17 3.34 2.05 2.56 1.92 3.46 2.55 1.54 4.1 2.51 ...
## $ PersPerOccupHous : num 2.99 2.7 2.42 2.37 2.28 2.55 2.36 2.32 2.45 2.42 ...
## $ PersPerOwnOccHous : num 3 2.83 2.69 2.51 2.37 2.89 2.42 2.77 2.47 2.5 ...
## $ PersPerRentOccHous : num 2.84 1.96 2.06 2.2 2.16 2.09 2.27 1.91 2.44 2.31 ...
## $ PctPersOwnOccup : num 91.5 89 64.2 58.2 57.8 ...
## $ PctPersDenseHous : num 0.39 1.01 2.03 1.21 2.11 1.47 1.9 1.67 6.14 3.41 ...
## $ PctHousLess3BR : num 11.1 23.6 47.5 45.7 53.2 ...
## $ MedNumBR : num 3 3 3 3 2 3 2 2 2 2 ...
## $ HousVacant : num 64 240 544 669 5119 ...
## $ PctHousOccup : num 98.4 97.2 95.7 91.2 91.8 ...
## $ PctHousOwnOcc : num 91 84.9 57.8 54.9 55.5 ...
## $ PctVacantBoarded : num 3.12 0 0.92 2.54 2.09 1.41 6.39 0.45 5.64 2.77 ...
## $ PctVacMore6Mos : num 37.5 18.33 7.54 57.85 26.22 ...
## $ MedYrHousBuilt : num 1959 1958 1976 1939 1966 ...
## $ PctHousNoPhone : num 0 0.31 1.55 7 6.13 ...
## $ PctWOFullPlumb : num 0.28 0.14 0.12 0.87 0.31 0.28 0.49 0.19 0.33 0.3 ...
## $ OwnOccLowQuart : num 215900 136300 74700 36400 37700 ...
## $ OwnOccMedVal : num 262600 164200 90400 49600 53900 ...
## $ OwnOccHiQuart : num 326900 199900 112000 66500 73100 ...
## $ OwnOccQrange : num 111000 63600 37300 30100 35400 60400 26100 39200 38800 41400 ...
## $ RentLowQ : num 685 467 370 195 215 463 186 241 192 234 ...
## $ RentMedian : num 1001 560 428 250 280 ...
## $ RentHighQ : num 1001 672 520 309 349 ...
## $ RentQrange : num 316 205 150 114 134 361 139 146 177 142 ...
## $ MedRent : num 1001 627 484 333 340 ...
## $ MedRentPctHousInc : num 23.8 27.6 24.1 28.7 26.4 24.4 26.3 25.2 29.6 23.8 ...
## $ MedOwnCostPctInc : num 21.1 20.7 21.7 20.6 17.3 20.8 15.1 20.7 19.4 17.1 ...
## $ MedOwnCostPctIncNoMtg : num 14 12.5 11.6 14.5 11.7 12.5 12.2 12.8 13 12.9 ...
## $ NumInShelters : num 11 0 16 0 327 0 21 125 43 1 ...
## $ NumStreet : num 0 0 0 0 4 0 0 15 4 0 ...
## $ PctForeignBorn : num 10.66 8.3 5 2.04 1.49 ...
## $ PctBornSameState : num 53.7 77.2 44.8 88.7 64.3 ...
## $ PctSameHouse85 : num 65.3 71.3 36.6 56.7 42.3 ...
## $ PctSameCity85 : num 78.1 90.2 61.3 90.2 70.6 ...
## $ PctSameState85 : num 89.1 96.1 82.8 96.2 85.7 ...
## $ LemasSwornFT : num NA NA NA NA NA NA NA NA 198 NA ...
## [list output truncated]

```

The structure of the data is partially omitted due to the high number of features. Let's try getting the class of each feature

```
apply(X = X, MARGIN = 2, FUN = class)
```

##	population	householdsize	racepctblack
##	"numeric"	"numeric"	"numeric"
##	racePctWhite	racePctAsian	racePctHisp
##	"numeric"	"numeric"	"numeric"
##	agePct12t21	agePct12t29	agePct16t24
##	"numeric"	"numeric"	"numeric"
##	agePct65up	numbUrban	pctUrban
##	"numeric"	"numeric"	"numeric"
##	medIncome	pctWWage	pctWFarmSelf
##	"numeric"	"numeric"	"numeric"
##	pctWInvInc	pctWSocSec	pctWPubAsst
##	"numeric"	"numeric"	"numeric"
##	pctWRetire	medFamInc	perCapInc
##	"numeric"	"numeric"	"numeric"
##	whitePerCap	blackPerCap	indianPerCap
##	"numeric"	"numeric"	"numeric"
##	AsianPerCap	OtherPerCap	HispPerCap
##	"numeric"	"numeric"	"numeric"
##	NumUnderPov	PctPopUnderPov	PctLess9thGrade
##	"numeric"	"numeric"	"numeric"
##	PctNotHSGrad	PctBSorMore	PctUnemployed
##	"numeric"	"numeric"	"numeric"
##	PctEmploy	PctEmplManu	PctEmplProfServ
##	"numeric"	"numeric"	"numeric"
##	PctOccupManu	PctOccupMgmtProf	MalePctDivorce
##	"numeric"	"numeric"	"numeric"
##	MalePctNevMarr	FemalePctDiv	TotalPctDiv
##	"numeric"	"numeric"	"numeric"
##	PersPerFam	PctFam2Par	PctKids2Par
##	"numeric"	"numeric"	"numeric"
##	PctYoungKids2Par	PctTeen2Par	PctWorkMomYoungKids
##	"numeric"	"numeric"	"numeric"
##	PctWorkMom	NumKidsBornNeverMar	PctKidsBornNeverMar
##	"numeric"	"numeric"	"numeric"
##	NumImmig	PctImmigRecent	PctImmigRec5
##	"numeric"	"numeric"	"numeric"
##	PctImmigRec8	PctImmigRec10	PctRecentImmig
##	"numeric"	"numeric"	"numeric"
##	PctRecImmig5	PctRecImmig8	PctRecImmig10
##	"numeric"	"numeric"	"numeric"
##	PctSpeakEnglOnly	PctNotSpeakEnglWell	PctLargHouseFam
##	"numeric"	"numeric"	"numeric"
##	PctLargHouseOccup	PersPerOccupHous	PersPerOwnOccHous
##	"numeric"	"numeric"	"numeric"
##	PersPerRentOccHous	PctPersOwnOccup	PctPersDenseHous
##	"numeric"	"numeric"	"numeric"
##	PctHousLess3BR	MedNumBR	HousVacant
##	"numeric"	"numeric"	"numeric"
##	PctHousOccup	PctHousOwnOcc	PctVacantBoarded
##	"numeric"	"numeric"	"numeric"

##	PctVacMore6Mos	MedYrHousBuilt	PctHousNoPhone
##	"numeric"	"numeric"	"numeric"
##	PctW0FullPlumb	OwnOccLowQuart	OwnOccMedVal
##	"numeric"	"numeric"	"numeric"
##	OwnOccHiQuart	OwnOccQrange	RentLowQ
##	"numeric"	"numeric"	"numeric"
##	RentMedian	RentHighQ	RentQrange
##	"numeric"	"numeric"	"numeric"
##	MedRent	MedRentPctHousInc	MedOwnCostPctInc
##	"numeric"	"numeric"	"numeric"
##	MedOwnCostPctIncNoMtg	NumInShelters	NumStreet
##	"numeric"	"numeric"	"numeric"
##	PctForeignBorn	PctBornSameState	PctSameHouse85
##	"numeric"	"numeric"	"numeric"
##	PctSameCity85	PctSameState85	LemasSwornFT
##	"numeric"	"numeric"	"numeric"
##	LemasSwFTPerPop	LemasSwFTFieldOps	LemasSwFTFieldPerPop
##	"numeric"	"numeric"	"numeric"
##	LemasTotalReq	LemasTotReqPerPop	PolicReqPerOffic
##	"numeric"	"numeric"	"numeric"
##	PolicPerPop	RacialMatchCommPol	PctPolicWhite
##	"numeric"	"numeric"	"numeric"
##	PctPolicBlack	PctPolicHisp	PctPolicAsian
##	"numeric"	"numeric"	"numeric"
##	PctPolicMinor	OfficAssgnDrugUnits	NumKindsDrugsSeiz
##	"numeric"	"numeric"	"numeric"
##	PolicAveOTWorked	LandArea	PopDens
##	"numeric"	"numeric"	"numeric"
##	PctUsePubTrans	PolicCars	PolicOperBudg
##	"numeric"	"numeric"	"numeric"
##	LemasPctPolicOnPatr	LemasGangUnitDeploy	LemasPctOfficDrugUn
##	"numeric"	"numeric"	"numeric"
##	PolicBudgPerPop		
##	"numeric"		

Neither `str()` nor `apply(class)` shows any factor. Just to be certain, I examine the documentation from the source (UC Irvine): <https://archive.ics.uci.edu/ml/datasets/Communities+and+Crime+Unnormalized>

There exist in the original data the feature of states, county code, and community code, which are categorical. However, they are not included in the given data. On the other hand, all other quantitative features in the original data are. We can say that the data set is entirely quantitative.

## Summary Statistics

How many do I show?

`summary(X)`

```
##      population      householdsize      racepctblack      racePctWhite
## Min.   : 10005      Min.   :1.600      Min.   : 0.00      Min.   : 2.68
## 1st Qu.: 14359      1st Qu.:2.490      1st Qu.: 0.94      1st Qu.:75.88
## Median : 22681      Median :2.650      Median : 3.15      Median :89.61
## Mean   : 52251      Mean   :2.707      Mean   : 9.51      Mean   :83.49
## 3rd Qu.: 43154      3rd Qu.:2.850      3rd Qu.:11.96      3rd Qu.:95.99
## Max.   :7322564      Max.   :5.280      Max.   :96.67      Max.   :99.63
##
##      racePctAsian      racePctHisp      agePct12t21      agePct12t29
## Min.   : 0.0300      Min.   : 0.120      Min.   : 4.58      Min.   : 9.38
## 1st Qu.: 0.6125      1st Qu.: 0.920      1st Qu.:12.23      1st Qu.:24.38
## Median : 1.2400      Median : 2.340      Median :13.62      Median :26.77
## Mean   : 2.7508      Mean   : 8.482      Mean   :14.43      Mean   :27.62
## 3rd Qu.: 2.7375      3rd Qu.: 8.610      3rd Qu.:15.39      3rd Qu.:29.18
## Max.   :57.4600      Max.   :95.290      Max.   :54.40      Max.   :70.51
##
##      agePct16t24      agePct65up      numbUrban      pctUrban
## Min.   : 4.64      Min.   : 1.660      Min.   :      0      Min.   : 0.00
## 1st Qu.:11.34      1st Qu.: 8.922      1st Qu.:      0      1st Qu.: 0.00
## Median :12.54      Median :11.855      Median : 17348      Median :100.00
## Mean   :13.99      Mean   :12.005      Mean   : 46672      Mean   : 69.62
## 3rd Qu.:14.36      3rd Qu.:14.547      3rd Qu.: 41932      3rd Qu.:100.00
## Max.   :63.62      Max.   :52.770      Max.   :7322564      Max.   :100.00
##
##      medIncome      pctWWage      pctWFarmSelf      pctWInvInc
## Min.   : 11576      Min.   :31.68      Min.   :0.0000      Min.   : 7.91
## 1st Qu.: 23597      1st Qu.:73.22      1st Qu.:0.4700      1st Qu.:34.19
## Median : 30896      Median :78.38      Median :0.7000      Median :42.38
## Mean   : 33699      Mean   :78.08      Mean   :0.8933      Mean   :43.36
## 3rd Qu.: 41215      3rd Qu.:83.70      3rd Qu.:1.1100      3rd Qu.:52.07
## Max.   :123625      Max.   :96.62      Max.   :6.5300      Max.   :89.04
##
##      pctWSocSec      pctWPubAsst      pctWRetire      medFamInc
## Min.   : 4.81      Min.   : 0.500      Min.   : 3.46      Min.   :13785
## 1st Qu.:20.98      1st Qu.: 3.362      1st Qu.:12.99      1st Qu.:29307
## Median :26.79      Median : 5.720      Median :15.66      Median :36010
## Mean   :26.66      Mean   : 6.806      Mean   :16.06      Mean   :39553
## 3rd Qu.:31.84      3rd Qu.: 9.150      3rd Qu.:18.78      3rd Qu.:46683
## Max.   :76.39      Max.   :26.920      Max.   :45.51      Max.   :131315
##
##      perCapInc      whitePerCap      blackPerCap      indianPerCap
## Min.   : 5237      Min.   : 5472      Min.   :      0      Min.   :      0
## 1st Qu.:11548      1st Qu.:12596      1st Qu.: 6706      1st Qu.: 6336
## Median :13977      Median :15028      Median : 9664      Median : 9834
## Mean   :15522      Mean   :16535      Mean   :11472      Mean   :12257
## 3rd Qu.:17774      3rd Qu.:18610      3rd Qu.:14464      3rd Qu.:14690
## Max.   :63302      Max.   :68850      Max.   :212120      Max.   :480000
##
##      AsianPerCap      OtherPerCap      HispPerCap      NumUnderPov
```

##	Min. : 0	Min. : 0	Min. : 0	Min. : 78.0
##	1st Qu.: 8441	1st Qu.: 5500	1st Qu.: 7253	1st Qu.: 936.2
##	Median : 12331	Median : 8144	Median : 9676	Median : 2217.5
##	Mean : 14284	Mean : 9375	Mean : 10989	Mean : 7398.4
##	3rd Qu.: 17346	3rd Qu.: 11378	3rd Qu.: 13360	3rd Qu.: 5097.5
##	Max. : 106165	Max. : 137000	Max. : 54648	Max. : 1384994.0
##		NA's : 1		
##	PctPopUnderPov	PctLess9thGrade	PctNotHSGrad	PctBSorMore
##	Min. : 0.640	Min. : 0.200	Min. : 2.09	Min. : 1.63
##	1st Qu.: 4.692	1st Qu.: 4.770	1st Qu.: 14.20	1st Qu.: 14.09
##	Median : 9.650	Median : 7.920	Median : 21.66	Median : 19.62
##	Mean : 11.796	Mean : 9.444	Mean : 22.70	Mean : 22.99
##	3rd Qu.: 17.078	3rd Qu.: 12.245	3rd Qu.: 29.66	3rd Qu.: 28.93
##	Max. : 48.820	Max. : 49.890	Max. : 73.66	Max. : 73.63
##				
##	PctUnemployed	PctEmploy	PctEmplManu	PctEmplProfServ
##	Min. : 1.320	Min. : 24.82	Min. : 2.05	Min. : 8.69
##	1st Qu.: 4.090	1st Qu.: 56.35	1st Qu.: 11.94	1st Qu.: 20.11
##	Median : 5.485	Median : 62.27	Median : 16.66	Median : 23.41
##	Mean : 6.024	Mean : 61.78	Mean : 17.79	Mean : 24.58
##	3rd Qu.: 7.430	3rd Qu.: 67.50	3rd Qu.: 22.75	3rd Qu.: 27.63
##	Max. : 23.830	Max. : 84.67	Max. : 50.03	Max. : 62.67
##				
##	PctOccupManu	PctOccupMgmtProf	MalePctDivorce	MalePctNevMarr
##	Min. : 1.370	Min. : 6.48	Min. : 2.130	Min. : 12.06
##	1st Qu.: 9.072	1st Qu.: 21.92	1st Qu.: 7.162	1st Qu.: 25.41
##	Median : 13.040	Median : 26.30	Median : 9.240	Median : 29.00
##	Mean : 13.747	Mean : 28.25	Mean : 9.180	Mean : 30.67
##	3rd Qu.: 17.465	3rd Qu.: 32.89	3rd Qu.: 11.110	3rd Qu.: 33.47
##	Max. : 44.270	Max. : 64.97	Max. : 19.090	Max. : 76.32
##				
##	FemalePctDiv	TotalPctDiv	PersPerFam	PctFam2Par
##	Min. : 3.35	Min. : 2.83	Min. : 2.290	Min. : 32.24
##	1st Qu.: 9.94	1st Qu.: 8.64	1st Qu.: 2.990	1st Qu.: 67.67
##	Median : 12.63	Median : 11.04	Median : 3.095	Median : 74.77
##	Mean : 12.40	Mean : 10.88	Mean : 3.129	Mean : 73.90
##	3rd Qu.: 14.80	3rd Qu.: 13.06	3rd Qu.: 3.220	3rd Qu.: 81.64
##	Max. : 23.46	Max. : 19.11	Max. : 4.640	Max. : 93.60
##				
##	PctKids2Par	PctYoungKids2Par	PctTeen2Par	PctWorkMomYoungKids
##	Min. : 26.11	Min. : 27.43	Min. : 30.64	Min. : 24.42
##	1st Qu.: 63.62	1st Qu.: 74.42	1st Qu.: 69.92	1st Qu.: 55.45
##	Median : 72.06	Median : 83.77	Median : 76.67	Median : 60.70
##	Mean : 70.91	Mean : 81.75	Mean : 75.34	Mean : 60.43
##	3rd Qu.: 79.82	3rd Qu.: 91.44	3rd Qu.: 82.52	3rd Qu.: 65.80
##	Max. : 92.58	Max. : 100.00	Max. : 97.34	Max. : 87.97
##				
##	PctWorkMom	NumKidsBornNeverMar	PctKidsBornNeverMar	NumImmig
##	Min. : 41.95	Min. : 0.0	Min. : 0.000	Min. : 20
##	1st Qu.: 64.96	1st Qu.: 146.2	1st Qu.: 1.083	1st Qu.: 407
##	Median : 69.25	Median : 361.0	Median : 2.080	Median : 1040
##	Mean : 68.80	Mean : 2041.5	Mean : 3.140	Mean : 6314
##	3rd Qu.: 73.34	3rd Qu.: 1070.2	3rd Qu.: 3.980	3rd Qu.: 3389
##	Max. : 89.37	Max. : 527557.0	Max. : 24.190	Max. : 2082931

```

##
## PctImmigRecent      PctImmigRec5      PctImmigRec8      PctImmigRec10
## Min.      : 0.000    Min.      : 0.00    Min.      : 0.00    Min.      : 0.00
## 1st Qu.: 6.942    1st Qu.:11.70    1st Qu.:17.91    1st Qu.:23.54
## Median :12.440    Median :19.64    Median :27.46    Median :35.58
## Mean      :13.734    Mean      :20.83    Mean      :28.12    Mean      :35.48
## 3rd Qu.:18.090    3rd Qu.:27.69    3rd Qu.:37.07    3rd Qu.:46.81
## Max.      :64.290    Max.      :76.16    Max.      :80.81    Max.      :88.00
##
## PctRecentImmig      PctRecImmig5      PctRecImmig8      PctRecImmig10
## Min.      : 0.000    Min.      : 0.000    Min.      : 0.000    Min.      : 0.000
## 1st Qu.: 0.180    1st Qu.: 0.290    1st Qu.: 0.410    1st Qu.: 0.540
## Median : 0.530    Median : 0.780    Median : 1.080    Median : 1.380
## Mean      : 1.149    Mean      : 1.781    Mean      : 2.424    Mean      : 3.094
## 3rd Qu.: 1.370    3rd Qu.: 2.180    3rd Qu.: 2.870    3rd Qu.: 3.680
## Max.      :13.710    Max.      :19.930    Max.      :25.340    Max.      :32.630
##
## PctSpeakEnglOnly    PctNotSpeakEnglWell    PctLargHouseFam    PctLargHouseOccup
## Min.      : 6.15    Min.      : 0.000    Min.      : 0.960    Min.      : 0.440
## 1st Qu.:83.70    1st Qu.: 0.510    1st Qu.: 3.390    1st Qu.: 2.360
## Median :91.78    Median : 0.955    Median : 4.290    Median : 3.050
## Mean      :86.55    Mean      : 2.538    Mean      : 5.465    Mean      : 3.975
## 3rd Qu.:95.41    3rd Qu.: 2.467    3rd Qu.: 5.957    3rd Qu.: 4.280
## Max.      :98.98    Max.      :38.330    Max.      :34.870    Max.      :30.870
##
## PersPerOccupHous    PersPerOwnOccHous    PersPerRentOccHous    PctPersOwnOccup
## Min.      :1.580    Min.      :1.610    Min.      :1.580    Min.      :13.93
## 1st Qu.:2.400    1st Qu.:2.540    1st Qu.:2.120    1st Qu.:56.56
## Median :2.560    Median :2.700    Median :2.290    Median :64.99
## Mean      :2.614    Mean      :2.734    Mean      :2.382    Mean      :65.50
## 3rd Qu.:2.770    3rd Qu.:2.890    3rd Qu.:2.540    3rd Qu.:75.30
## Max.      :4.520    Max.      :4.480    Max.      :4.730    Max.      :96.59
##
## PctPersDenseHous    PctHousLess3BR      MedNumBR      HousVacant
## Min.      : 0.050    Min.      : 3.06    Min.      :1.000    Min.      : 36.0
## 1st Qu.: 1.300    1st Qu.:37.93    1st Qu.:2.000    1st Qu.: 310.0
## Median : 2.470    Median :46.78    Median :3.000    Median : 582.5
## Mean      : 4.325    Mean      :45.84    Mean      :2.626    Mean      :1733.0
## 3rd Qu.: 4.920    3rd Qu.:54.09    3rd Qu.:3.000    3rd Qu.:1280.5
## Max.      :59.490    Max.      :95.34    Max.      :4.000    Max.      :172768.0
##
## PctHousOccup      PctHousOwnOcc      PctVacantBoarded    PctVacMore6Mos
## Min.      :37.47    Min.      :16.86    Min.      : 0.000    Min.      : 3.12
## 1st Qu.:90.98    1st Qu.:54.09    1st Qu.: 0.780    1st Qu.:24.74
## Median :93.98    Median :62.08    Median : 1.740    Median :34.52
## Mean      :92.71    Mean      :62.63    Mean      : 2.791    Mean      :35.15
## 3rd Qu.:95.91    3rd Qu.:71.59    3rd Qu.: 3.520    3rd Qu.:44.26
## Max.      :99.00    Max.      :96.36    Max.      :39.890    Max.      :82.13
##
## MedYrHousBuilt      PctHousNoPhone      PctWOFullPlumb      OwnOccLowQuart
## Min.      :1939    Min.      : 0.000    Min.      :0.0000    Min.      :15700
## 1st Qu.:1956    1st Qu.: 0.980    1st Qu.:0.1800    1st Qu.: 41800
## Median :1964    Median : 3.090    Median :0.3300    Median : 65900
## Mean      :1963    Mean      : 4.446    Mean      :0.4377    Mean      : 91116

```



```

## 3rd Qu.:1971    3rd Qu.: 7.080    3rd Qu.:0.5700    3rd Qu.:126800
## Max.    :1987    Max.    :23.630    Max.    :5.3300    Max.    :500001
##
## OwnOccMedVal    OwnOccHiQuart    OwnOccQrange    RentLowQ
## Min.    : 26600    Min.    : 36700    Min.    : 0    Min.    : 99.0
## 1st Qu.: 56700    1st Qu.: 74800    1st Qu.: 32925    1st Qu.: 210.0
## Median : 84600    Median :109500    Median : 44250    Median : 305.0
## Mean    :116102    Mean    :149007    Mean    : 57891    Mean    : 328.1
## 3rd Qu.:156250    3rd Qu.:192850    3rd Qu.: 67475    3rd Qu.: 420.0
## Max.    :500001    Max.    :500001    Max.    :331000    Max.    :1001.0
##
## RentMedian    RentHighQ    RentQrange    MedRent
## Min.    : 120.0    Min.    : 182.0    Min.    : 0.0    Min.    : 192.0
## 1st Qu.: 286.0    1st Qu.: 361.2    1st Qu.:139.0    1st Qu.: 363.0
## Median : 394.0    Median : 484.0    Median :173.0    Median : 467.0
## Mean    : 428.4    Mean    : 528.4    Mean    :200.3    Mean    : 502.7
## 3rd Qu.: 547.8    3rd Qu.: 667.8    3rd Qu.:241.0    3rd Qu.: 621.0
## Max.    :1001.0    Max.    :1001.0    Max.    :803.0    Max.    :1001.0
##
## MedRentPctHousInc MedOwnCostPctInc MedOwnCostPctIncNoMtg
## Min.    :14.90    Min.    :14.10    Min.    :10.10
## 1st Qu.:24.30    1st Qu.:19.10    1st Qu.:11.90
## Median :26.20    Median :21.20    Median :12.80
## Mean    :26.33    Mean    :21.21    Mean    :13.03
## 3rd Qu.:28.10    3rd Qu.:23.30    3rd Qu.:13.80
## Max.    :35.10    Max.    :32.70    Max.    :23.40
##
## NumInShelters    NumStreet    PctForeignBorn    PctBornSameState
## Min.    : 0.00    Min.    : 0.00    Min.    : 0.180    Min.    : 6.75
## 1st Qu.: 0.00    1st Qu.: 0.00    1st Qu.: 2.080    1st Qu.:48.87
## Median : 0.00    Median : 0.00    Median : 4.490    Median :62.52
## Mean    : 67.72    Mean    : 18.71    Mean    : 7.606    Mean    :60.50
## 3rd Qu.: 24.00    3rd Qu.: 1.00    3rd Qu.: 9.585    3rd Qu.:74.38
## Max.    :23383.00    Max.    :10447.00    Max.    :60.400    Max.    :93.14
##
## PctSameHouse85    PctSameCity85    PctSameState85    LemasSwornFT
## Min.    :11.83    Min.    :27.95    Min.    :32.83    Min.    : 65.0
## 1st Qu.:44.68    1st Qu.:71.92    1st Qu.:84.73    1st Qu.: 131.0
## Median :51.87    Median :79.31    Median :89.64    Median : 173.0
## Mean    :51.32    Mean    :77.11    Mean    :87.73    Mean    : 458.7
## 3rd Qu.:58.51    3rd Qu.:84.70    3rd Qu.:92.73    3rd Qu.: 314.0
## Max.    :78.56    Max.    :96.59    Max.    :99.90    Max.    :25655.0
## NA's    :1675
## LemasSwFTPerPop    LemasSwFTFieldOps    LemasSwFTFieldPerPop    LemasTotalReq
## Min.    : 29.4    Min.    : 14.0    Min.    : 19.21    Min.    : 8100
## 1st Qu.:149.1    1st Qu.: 113.5    1st Qu.:130.43    1st Qu.: 49864
## Median :196.0    Median : 152.0    Median :170.16    Median : 89205
## Mean    :248.1    Mean    : 395.9    Mean    :211.32    Mean    :240510
## 3rd Qu.:260.8    3rd Qu.: 283.0    3rd Qu.:226.81    3rd Qu.:174171
## Max.    :3437.2    Max.    :22496.0    Max.    :3290.62    Max.    :8328470
## NA's    :1675    NA's    :1675    NA's    :1675    NA's    :1675
## LemasTotReqPerPop    PolicReqPerOffic    PolicPerPop    RacialMatchCommPol
## Min.    : 2705    Min.    : 41.4    Min.    : 29.4    Min.    : 42.15
## 1st Qu.: 65486    1st Qu.: 342.9    1st Qu.:149.2    1st Qu.: 79.44

```

```

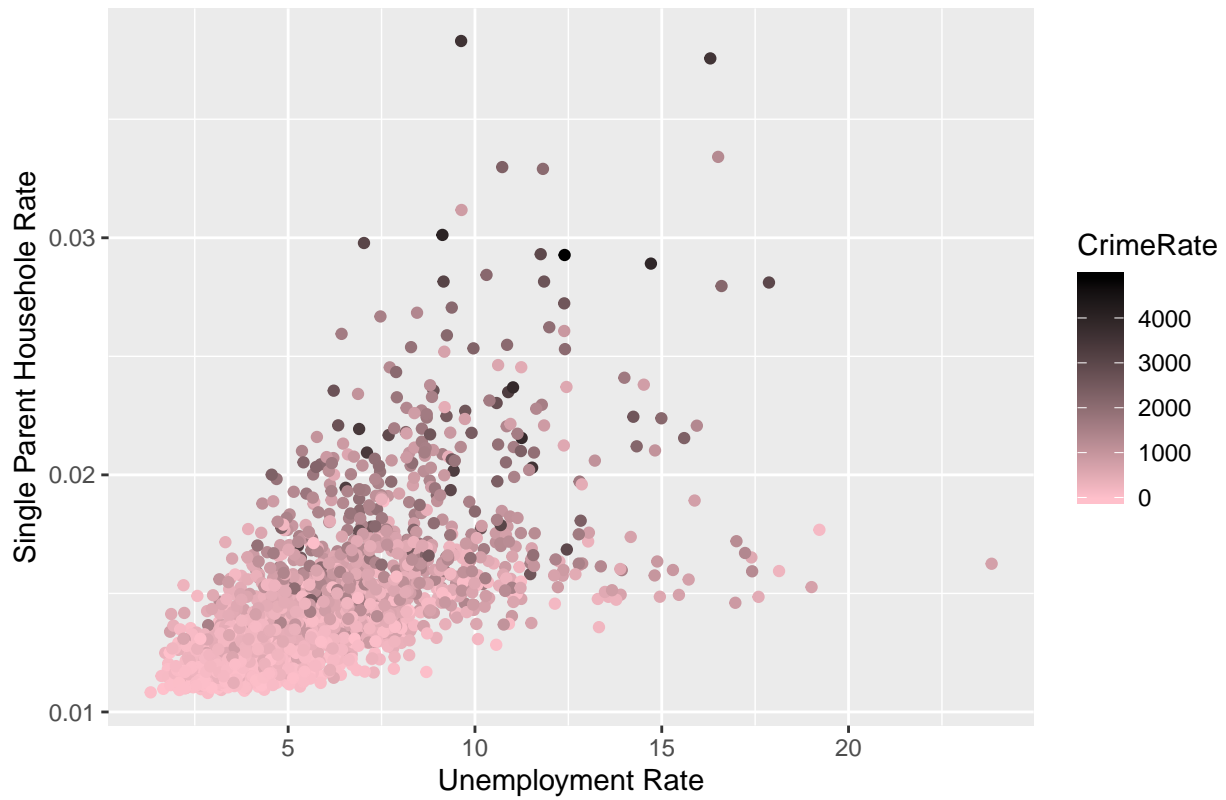
## Median : 91035   Median : 444.8   Median : 196.0   Median : 87.95
## Mean : 122280   Mean : 526.8   Mean : 248.1   Mean : 85.49
## 3rd Qu.: 131894   3rd Qu.: 646.0   3rd Qu.: 260.8   3rd Qu.: 93.62
## Max. :1926282   Max. :2162.5   Max. :3437.2   Max. :100.00
## NA's :1675     NA's :1675     NA's :1675     NA's :1675
## PctPolicWhite   PctPolicBlack   PctPolicHisp   PctPolicAsian
## Min. : 1.60     Min. : 0.000     Min. : 0.000     Min. : 0.0000
## 1st Qu.: 76.36   1st Qu.: 2.055     1st Qu.: 0.450     1st Qu.: 0.0000
## Median : 86.18   Median : 4.840     Median : 2.110     Median : 0.0000
## Mean : 82.53     Mean : 8.983     Mean : 5.683     Mean : 0.7088
## 3rd Qu.: 93.09   3rd Qu.:13.355     3rd Qu.: 6.490     3rd Qu.: 0.6650
## Max. :100.00     Max. :67.310     Max. :98.400     Max. :18.5700
## NA's :1675     NA's :1675     NA's :1675     NA's :1675
## PctPolicMinor   OfficAssgnDrugUnits   NumKindsDrugsSeiz   PolicAveOTWorked
## Min. : 0.00     Min. : 0.00     Min. : 1.000     Min. : 0.0
## 1st Qu.: 5.05     1st Qu.: 6.00     1st Qu.: 7.000     1st Qu.: 55.1
## Median :11.39     Median : 12.00     Median : 9.000     Median : 99.0
## Mean :15.20     Mean : 25.87     Mean : 8.784     Mean :119.8
## 3rd Qu.:19.68     3rd Qu.: 23.00     3rd Qu.:10.500     3rd Qu.:153.6
## Max. :98.40     Max. :1773.00     Max. :15.000     Max. :634.7
## NA's :1675     NA's :1675     NA's :1675     NA's :1675
## LandArea         PopDens         PctUsePubTrans         PolicCars
## Min. : 0.90     Min. : 10     Min. : 0.000     Min. : 20.0
## 1st Qu.: 7.40     1st Qu.: 1171     1st Qu.: 0.350     1st Qu.: 54.0
## Median : 13.70     Median : 1996     Median : 1.220     Median : 86.0
## Mean : 27.96     Mean : 2790     Mean : 3.063     Mean : 177.3
## 3rd Qu.: 25.77     3rd Qu.: 3270     3rd Qu.: 3.377     3rd Qu.: 191.0
## Max. :3569.80     Max. :44230     Max. :54.330     Max. :3187.0
## NA's :1675
## PolicOperBudg     LemasPctPolicOnPatr   LemasGangUnitDeploy
## Min. :2.380e+06     Min. :10.85     Min. : 0.000
## 1st Qu.:7.247e+06     1st Qu.:83.87     1st Qu.: 0.000
## Median :1.075e+07     Median :89.44     Median : 5.000
## Mean :2.896e+07     Mean :86.77     Mean : 4.404
## 3rd Qu.:2.047e+07     3rd Qu.:93.06     3rd Qu.:10.000
## Max. :1.617e+09     Max. :99.94     Max. :10.000
## NA's :1675     NA's :1675     NA's :1675
## LemasPctOfficDrugUn   PolicBudgPerPop
## Min. : 0.00     Min. : 15260
## 1st Qu.: 0.00     1st Qu.: 86869
## Median : 0.00     Median : 114582
## Mean : 1.01     Mean : 154590
## 3rd Qu.: 0.00     3rd Qu.: 156961
## Max. :48.44     Max. :2422367
## NA's :1675

```

## Visualization

Due to such as massive number of feature, there is no way to visualize data from every feature without dimensionality reduction. In the next coming graphs, we only examine some groups of feature that will hopefully tell us something about the data.

Crime Rate with respect to Unemployment rate and Single Parent Family F



## Missing Data Processing

check if target y contains missing data

```
any(is.na(y))
```

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

check if any of the features contains missing data

```
any(is.na(X))
```

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

Now that we have detected there is NA in some the features, we decide to replace it by the median of other existing data in that corresponding feature

```
X <- X %>% mutate_all(function(x) ifelse(is.na(x), median(x, na.rm = TRUE), x))
any(is.na(X))
```

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

## Data Normalization - Scaling

After the previous step of examination, it is obvious that many features are different in nature. For example, some features are Percentage (PctForeignBorn, PctBornSameState). Some are counts (NumInShelters, population). Some are in US Dollars (MedRent, ...). Each of the features have different range, scale, and unit. Such condition will affect how much each of the feature influence the prediction later on. Therefore, it is highly crucial that we normalize the features.

```
# X <- scale(X)
```

## Dimensionality reduction - Principal Component Analysis

Apply PCA

```
res.pca <- PCA(X = X, graph = F, ncp = 10)
```

Plot Screeplot for Eigenvalues. Due to the very high number of components (125), we only pick out the first 20

```
eig <- res.pca$eig
```

Visualize Eigen value

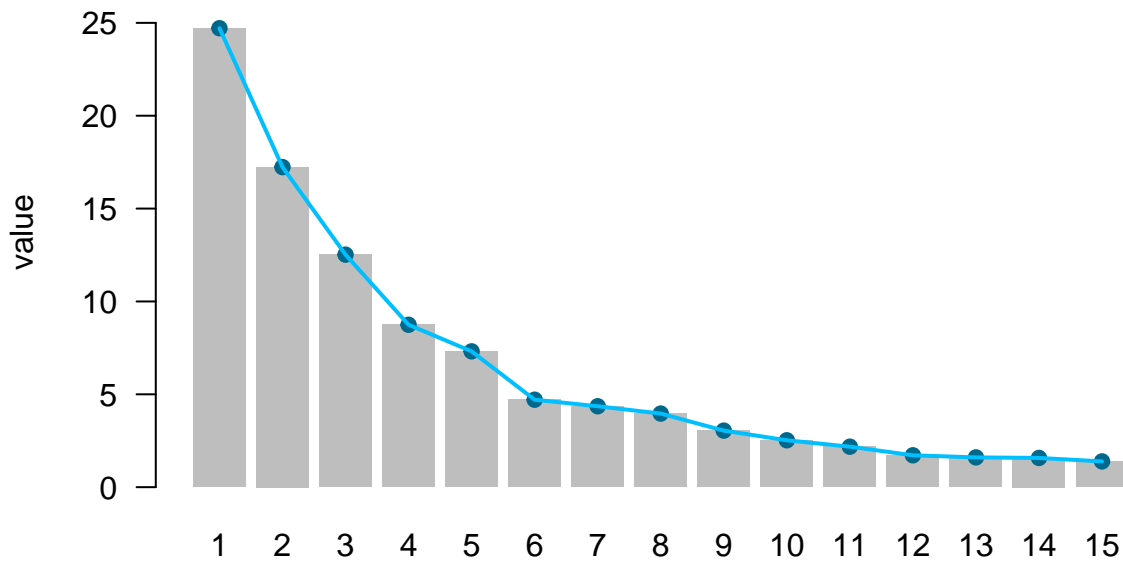
```
eigvalue <- eig[1:15, "eigenvalue"]
```

```
barchart <- barplot(eigvalue, las = 1, border = NA,
  names.arg = 1:length(eigvalue),
  ylim = c(0, 1.1 * ceiling(max(eigvalue))),
  ylab = "value",
  xlab = "Eigenvalues - how much variance the corresponding PC captures",
  main = "Scree plot")
```

```
points(barchart, eigvalue, pch = 19, col = "deepskyblue4")
```

```
lines(barchart, eigvalue, lwd = 2, col = "deepskyblue")
```

## Scree plot



### Eigenvalues – how much variance the corresponding PC captures

As you can see, each of the eigenvalue represents the amount of variance in the dataset that was captured by the corresponding PC. Also, let's examine the eigen value result overall

```
head(eig, n = 35)
```

##	eigenvalue	percentage of variance
## comp 1	24.7120404	19.9290649
## comp 2	17.2316062	13.8964566
## comp 3	12.5198102	10.0966212
## comp 4	8.7447951	7.0522541
## comp 5	7.3128094	5.8974269
## comp 6	4.7086788	3.7973216
## comp 7	4.3557958	3.5127386
## comp 8	3.9634359	3.1963193
## comp 9	3.0441163	2.4549325
## comp 10	2.5238261	2.0353436
## comp 11	2.1792252	1.7574397
## comp 12	1.7159664	1.3838439
## comp 13	1.6026493	1.2924591
## comp 14	1.5734883	1.2689422
## comp 15	1.3877036	1.1191158
## comp 16	1.3699387	1.1047893
## comp 17	1.1287800	0.9103064
## comp 18	1.1118188	0.8966281
## comp 19	1.0902493	0.8792333
## comp 20	1.0450405	0.8427746
## comp 21	0.9847874	0.7941834
## comp 22	0.9813942	0.7914469
## comp 23	0.9485897	0.7649917
## comp 24	0.9139398	0.7370482
## comp 25	0.8637256	0.6965529

## comp 26	0.8142463	0.6566503
## comp 27	0.7998861	0.6450695
## comp 28	0.7623629	0.6148088
## comp 29	0.7264818	0.5858724
## comp 30	0.6896531	0.5561718
## comp 31	0.6219795	0.5015964
## comp 32	0.5925124	0.4778326
## comp 33	0.5579743	0.4499792
## comp 34	0.5359479	0.4322160
## comp 35	0.4999603	0.4031938
##	cumulative percentage of variance	
## comp 1		19.92906
## comp 2		33.82552
## comp 3		43.92214
## comp 4		50.97440
## comp 5		56.87182
## comp 6		60.66915
## comp 7		64.18188
## comp 8		67.37820
## comp 9		69.83314
## comp 10		71.86848
## comp 11		73.62592
## comp 12		75.00976
## comp 13		76.30222
## comp 14		77.57116
## comp 15		78.69028
## comp 16		79.79507
## comp 17		80.70538
## comp 18		81.60200
## comp 19		82.48124
## comp 20		83.32401
## comp 21		84.11819
## comp 22		84.90964
## comp 23		85.67463
## comp 24		86.41168
## comp 25		87.10823
## comp 26		87.76488
## comp 27		88.40995
## comp 28		89.02476
## comp 29		89.61064
## comp 30		90.16681
## comp 31		90.66840
## comp 32		91.14624
## comp 33		91.59622
## comp 34		92.02843
## comp 35		92.43163

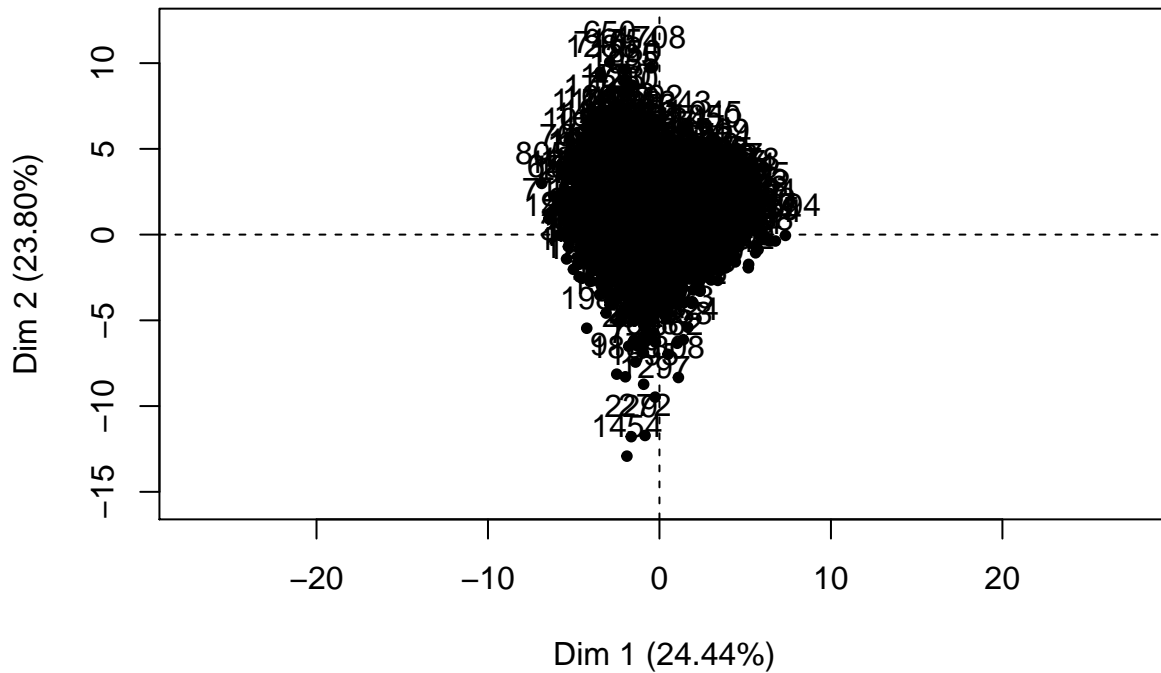
With the given information above we can choose the number of component based on:

- Elbow method: the first 6 PCs
- Kaiser's rule  $\lambda_k > 1$ : the first 20 PCs
- Jollie's rule  $\lambda_k > 0.7$ : the first 30 PCs
- A, if we wish to keep the number of PCs that accumulatively capture 70% of the variance in the data,

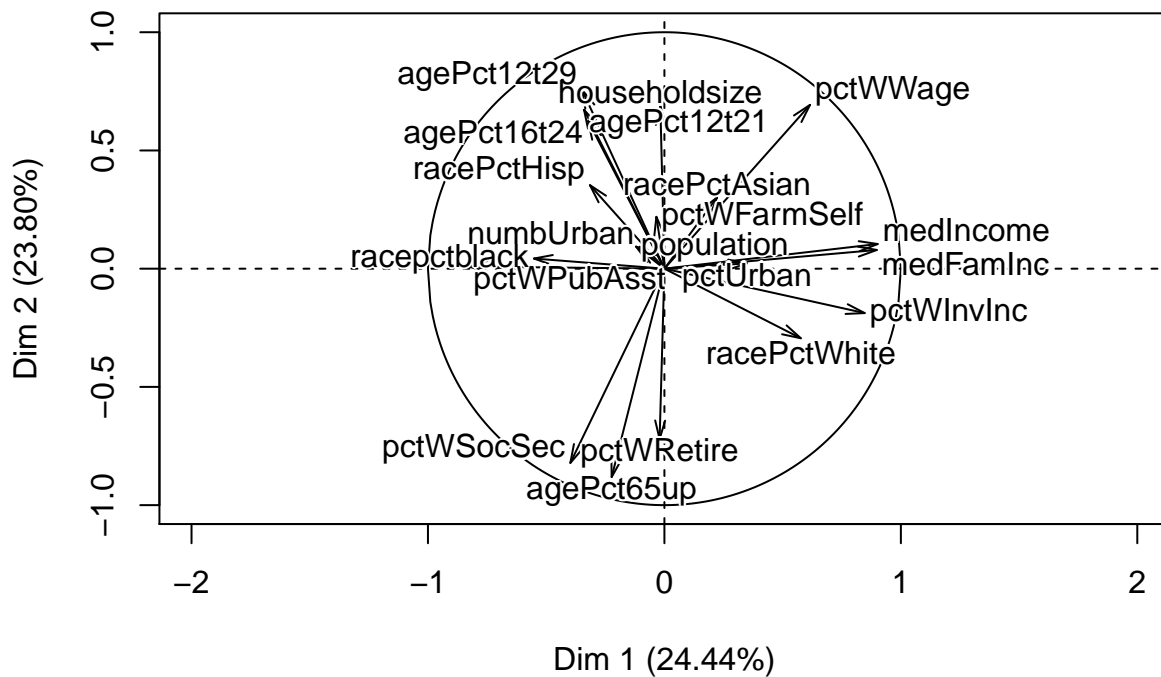
Interpretation of this plot

```
p <- PCA(X[, 1:20], graph = T)
```

### Individuals factor map (PCA)



### Variables factor map (PCA)



Question for Ryan: Now my plan is that: Keep 10 PCs only and perform regression on PCs instead of doing

so on the original data matrix. Which one of the ] “coord”, “cor”, “cos2”, “contrib” should I use?

Also, do I scale principal component again

```
# head(res.pca$var)
PCs <- res.pca$var
names(PCs) # "coord" "cor" "cos2" "contrib"

## [1] "coord" "cor" "cos2" "contrib"
PCs <- res.pca$var[["coord"]]
```

## Regression task

In this section, you should use the techniques learned in class to develop a model to predict ViolentCrimes-PerPop using the 124 features (or some subset of them) stored in **X**. Remember that you should try several different methods, and use model selection methods to determine which model is best. You should also be sure to keep a held-out test set to evaluate the performance of your model.

**YOUR CODE GOES HERE**