

Crime and Communities

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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("crime_and_communities_data.csv")
```

```
## Parsed with column specification:
## cols(
##   .default = col_double()
## )

## See spec(...) for full column specifications.
```

```
print(dim(CC))
```

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

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

Dataset exploration

All of these variables are numerical. The summary statistics are displayed below, and these variables are a mix of percentages, counts, and counts per capita. Due to the mixed nature of these variable types, normalizing the data and mean-centering it will be best in order to factor in all variables equitably. Most of the entries (1675/1994=84%) are missing data for LEMAS predictors, so LEMAS predictors will have to be omitted. Additionally, several of the variables are goal variables, so they will be omitted as well for interest's sake.

```
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
##
##   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
```

Data Processing

Due to the LEMAS survey not being applicable to most of the datapoints, we will remove the columns where the 1675 entries have missing data. We are then left with the first 98 columns of the dataset.

```
X = X[,1:98]
X = X[!is.na(X),]
y = y[!is.na(X)]
```

Regression task

We will first split the data 75%/25% and leave the 25% as a test set for model performance comparison later.

```
smp_size <- floor(0.75 * nrow(X))
set.seed(123)
```

```

train_ind = sample(seq_len(nrow(X)), size = smp_size)

trainX = X[train_ind, ]
testX = X[-train_ind, ]
trainY = y[train_ind]
testY = y[-train_ind]

train = data.frame(trainX, "y"=trainY)
train = na.omit(train)
test = data.frame(testX, "y"=testY)
test = na.omit(test)

```

Our first step will be to build a simple multiple regression model and examine the significance of the various features. We will examine feature importances and select the most relevant/significant ones. Many of these features are highly correlated, so by including the highest significance features we are eliminating redundancy.

```

model = lm(y ~ ., data=train)
summary(model)

```

```

##
## Call:
## lm(formula = y ~ ., data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1442.59  -181.06   -40.15   125.29  2132.30
##
## Coefficients: (2 not defined because of singularities)
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    5.463e+03  3.929e+03   1.390 0.164612
## population     -1.006e-03  2.354e-03  -0.427 0.669266
## householdsize  -1.152e+02  1.375e+02  -0.838 0.402185
## racepctblack    7.608e+00  3.808e+00   1.998 0.045931 *
## racePctWhite    4.220e-01  3.635e+00   0.116 0.907605
## racePctAsian    1.479e+00  6.098e+00   0.243 0.808357
## racePctHispan  -9.677e-01  3.238e+00  -0.299 0.765104
## agePct12t21     1.151e+01  1.512e+01   0.761 0.446763
## agePct12t29    -2.967e+01  1.525e+01  -1.946 0.051879 .
## agePct16t24     1.459e+01  2.186e+01   0.667 0.504782
## agePct65up     -1.720e+01  1.267e+01  -1.358 0.174819
## numbUrban       9.986e-04  2.322e-03   0.430 0.667232
## pctUrban        8.957e-01  5.515e-01   1.624 0.104612
## medIncome      -1.549e-02  8.142e-03  -1.903 0.057286 .
## pctWwage       -1.062e+01  6.988e+00  -1.520 0.128819
## pctWFarmSelf    2.561e+01  1.854e+01   1.381 0.167497
## pctWInvInc     -3.356e+00  3.055e+00  -1.098 0.272184
## pctWSocSec      1.062e+01  6.812e+00   1.558 0.119365
## pctWPubAsst     1.685e+01  6.945e+00   2.427 0.015364 *
## pctWRetire     -1.636e+01  4.378e+00  -3.736 0.000194 ***
## medFamInc       1.341e-02  8.077e-03   1.660 0.097132 .
## perCapInc      -5.905e-03  1.845e-02  -0.320 0.748995
## whitePerCap     -3.046e-03  1.470e-02  -0.207 0.835861

```

## blackPerCap	-7.613e-04	1.193e-03	-0.638	0.523579	
## indianPerCap	-1.965e-04	5.878e-04	-0.334	0.738230	
## AsianPerCap	2.256e-03	1.145e-03	1.971	0.048966	*
## OtherPerCap	2.166e-03	1.316e-03	1.646	0.099998	.
## HispPerCap	1.355e-03	2.311e-03	0.586	0.557759	
## NumUnderPov	-9.384e-04	2.711e-03	-0.346	0.729290	
## PctPopUnderPov	-9.111e+00	5.596e+00	-1.628	0.103731	
## PctLess9thGrade	-1.845e+01	7.399e+00	-2.494	0.012745	*
## PctNotHSGrad	5.538e+00	5.772e+00	0.959	0.337503	
## PctBSorMore	-3.440e-01	4.148e+00	-0.083	0.933907	
## PctUnemployed	-4.548e+00	9.467e+00	-0.480	0.631008	
## PctEmploy	7.903e+00	6.068e+00	1.302	0.193023	
## PctEmplManu	-5.043e+00	2.524e+00	-1.998	0.045874	*
## PctEmplProfServ	-9.225e-01	3.426e+00	-0.269	0.787769	
## PctOccupManu	4.498e+00	5.436e+00	0.827	0.408174	
## PctOccupMgmtProf	7.046e+00	5.729e+00	1.230	0.218994	
## MalePctDivorce	1.479e+02	8.140e+01	1.817	0.069408	.
## MalePctNevMarr	7.221e-01	6.031e+00	0.120	0.904703	
## FemalePctDiv	9.204e+01	8.516e+01	1.081	0.279942	
## TotalPctDiv	-2.318e+02	1.645e+02	-1.409	0.159051	
## PersPerFam	-3.007e+02	4.215e+02	-0.714	0.475616	
## PctFam2Par	1.108e+01	1.019e+01	1.087	0.277125	
## PctKids2Par	-2.416e+01	8.492e+00	-2.845	0.004506	**
## PctYoungKids2Par	2.955e+00	2.782e+00	1.062	0.288449	
## PctTeen2Par	-5.993e-01	2.596e+00	-0.231	0.817474	
## PctWorkMomYoungKids	6.094e+00	3.259e+00	1.870	0.061710	.
## PctWorkMom	-1.190e+01	4.734e+00	-2.514	0.012035	*
## NumKidsBornNeverMar	-6.961e-03	4.494e-03	-1.549	0.121639	
## PctKidsBornNeverMar	4.418e+01	1.122e+01	3.939	8.60e-05	***
## NumImmig	-1.992e-04	1.189e-03	-0.168	0.866982	
## PctImmigRecent	3.208e+00	2.876e+00	1.116	0.264806	
## PctImmigRec5	-1.876e+00	3.725e+00	-0.504	0.614664	
## PctImmigRec8	3.809e-01	3.491e+00	0.109	0.913134	
## PctImmigRec10	6.210e-01	2.206e+00	0.282	0.778368	
## PctRecentImmig	-1.745e+01	5.793e+01	-0.301	0.763250	
## PctRecImmig5	3.165e+00	7.322e+01	0.043	0.965530	
## PctRecImmig8	2.376e+01	6.637e+01	0.358	0.720340	
## PctRecImmig10	-4.242e+01	3.877e+01	-1.094	0.274177	
## PctSpeakEnglOnly	-1.985e+00	3.861e+00	-0.514	0.607204	
## PctNotSpeakEnglWell	-7.040e+00	1.206e+01	-0.584	0.559432	
## PctLargHouseFam	3.408e+01	3.670e+01	0.929	0.353200	
## PctLargHouseOccup	-4.666e+01	3.953e+01	-1.180	0.238068	
## PersPerOccupHous	5.771e+02	4.951e+02	1.166	0.243997	
## PersPerOwnOccHous	1.038e+02	3.329e+02	0.312	0.755337	
## PersPerRentOccHous	-3.177e+02	1.354e+02	-2.347	0.019087	*
## PctPersOwnOccup	-3.419e+01	2.018e+01	-1.694	0.090433	.
## PctPersDenseHous	2.429e+01	8.682e+00	2.798	0.005212	**
## PctHousLess3BR	1.283e+00	2.442e+00	0.525	0.599433	
## MedNumBR	7.126e+00	3.095e+01	0.230	0.817938	
## HousVacant	1.557e-02	7.195e-03	2.164	0.030652	*
## PctHousOccup	-5.614e+00	3.061e+00	-1.834	0.066865	.
## PctHousOwnOcc	2.940e+01	2.014e+01	1.460	0.144478	
## PctVacantBoarded	1.737e+01	4.258e+00	4.080	4.75e-05	***
## PctVacMore6Mos	-2.497e+00	1.077e+00	-2.317	0.020631	*


```
## MedYrHousBuilt      -7.909e-01  1.860e+00  -0.425  0.670817
## PctHousNoPhone      1.487e-01  6.572e+00   0.023  0.981955
## PctWOFullPlumb     -1.651e+01  3.036e+01  -0.544  0.586726
## OwnOccLowQuart      1.140e-03  1.484e-03   0.769  0.442286
## OwnOccMedVal        -1.793e-04  1.789e-03  -0.100  0.920180
## OwnOccHiQuart       -9.669e-04  7.705e-04  -1.255  0.209691
## OwnOccQrange        NA          NA          NA      NA
## RentLowQ            -8.162e-01  3.154e-01  -2.588  0.009756 **
## RentMedian          -3.694e-02  5.717e-01  -0.065  0.948497
## RentHighQ           -2.372e-01  3.296e-01  -0.720  0.471839
## RentQrange          NA          NA          NA      NA
## MedRent             1.169e+00  5.011e-01   2.332  0.019846 *
## MedRentPctHousInc    1.220e+00  6.048e+00   0.202  0.840214
## MedOwnCostPctInc     -1.785e+00  6.942e+00  -0.257  0.797101
## MedOwnCostPctIncNoMtg -3.480e+01  1.021e+01  -3.409  0.000670 ***
## NumInShelters       1.508e-01  7.862e-02   1.917  0.055385 .
## NumStreet           -1.336e-02  1.666e-01  -0.080  0.936101
## PctForeignBorn       1.471e+01  7.766e+00   1.894  0.058399 .
## PctBornSameState     -5.089e-01  1.597e+00  -0.319  0.750056
## PctSameHouse85       -1.308e+00  3.069e+00  -0.426  0.669940
## PctSameCity85        1.274e+00  2.338e+00   0.545  0.585865
## PctSameState85       1.006e+00  3.717e+00   0.271  0.786653
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 361.7 on 1397 degrees of freedom
## Multiple R-squared:  0.679, Adjusted R-squared:  0.657
## F-statistic: 30.78 on 96 and 1397 DF, p-value: < 2.2e-16
```

```
library(caret)
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
importances = data.frame(varImp(model, scale=FALSE))
importances$variable = row.names(importances)

imp = importances[order(importances$Overall, decreasing=TRUE),]

head(imp, 40)
```

```
##              Overall              variable
## PctVacantBoarded 4.080452 PctVacantBoarded
## PctKidsBornNeverMar 3.938600 PctKidsBornNeverMar
## pctWRetire 3.736076 pctWRetire
## MedOwnCostPctIncNoMtg 3.409151 MedOwnCostPctIncNoMtg
## PctKids2Par 2.845005 PctKids2Par
## PctPersDenseHous 2.798061 PctPersDenseHous
## RentLowQ 2.587910 RentLowQ
## PctWorkMom 2.514401 PctWorkMom
## PctLess9thGrade 2.494044 PctLess9thGrade
```

## pctWPubAsst	2.426676	pctWPubAsst
## PersPerRentOccHous	2.346547	PersPerRentOccHous
## MedRent	2.331936	MedRent
## PctVacMore6Mos	2.317314	PctVacMore6Mos
## HousVacant	2.163754	HousVacant
## PctEmplManu	1.998331	PctEmplManu
## racepctblack	1.997806	racepctblack
## AsianPerCap	1.970603	AsianPerCap
## agePct12t29	1.945803	agePct12t29
## NumInShelters	1.917448	NumInShelters
## medIncome	1.902692	medIncome
## PctForeignBorn	1.894248	PctForeignBorn
## PctWorkMomYoungKids	1.869874	PctWorkMomYoungKids
## PctHousOccup	1.834011	PctHousOccup
## MalePctDivorce	1.817149	MalePctDivorce
## PctPersOwnOccup	1.694291	PctPersOwnOccup
## medFamInc	1.660033	medFamInc
## OtherPerCap	1.645954	OtherPerCap
## PctPopUnderPov	1.628092	PctPopUnderPov
## pctUrban	1.623950	pctUrban
## pctWSocSec	1.558400	pctWSocSec
## NumKidsBornNeverMar	1.548871	NumKidsBornNeverMar
## pctWWage	1.519674	pctWWage
## PctHousOwnOcc	1.460136	PctHousOwnOcc
## TotalPctDiv	1.409022	TotalPctDiv
## pctWFarmSelf	1.381009	pctWFarmSelf
## agePct65up	1.357572	agePct65up
## PctEmploy	1.302317	PctEmploy
## OwnOccHiQuart	1.254992	OwnOccHiQuart
## PctOccupMgmtProf	1.229760	PctOccupMgmtProf
## PctLargHouseOccup	1.180334	PctLargHouseOccup

We will choose the most important features and build our next regression models, tweaking our feature set when necessary. We will also normalize the features.

```
features = imp$variable[1:35]
train = train[, c(features, "y")]
test = test[, c(features, "y")]
library(BBmisc)
```

```
##
## Attaching package: 'BBmisc'
```

```
## The following object is masked from 'package:base':
##
## isFALSE
```

```
train = data.frame(normalize(train[,features]), "y"=train$y)
test = data.frame(normalize(test[,features]), "y"=test$y)
```

The three different types of regressions we will be using are simple linear regression, random forest regression, and ridge regression. First we will build a Random Forest regression model.

```

set.seed(123)
library(randomForest)

## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

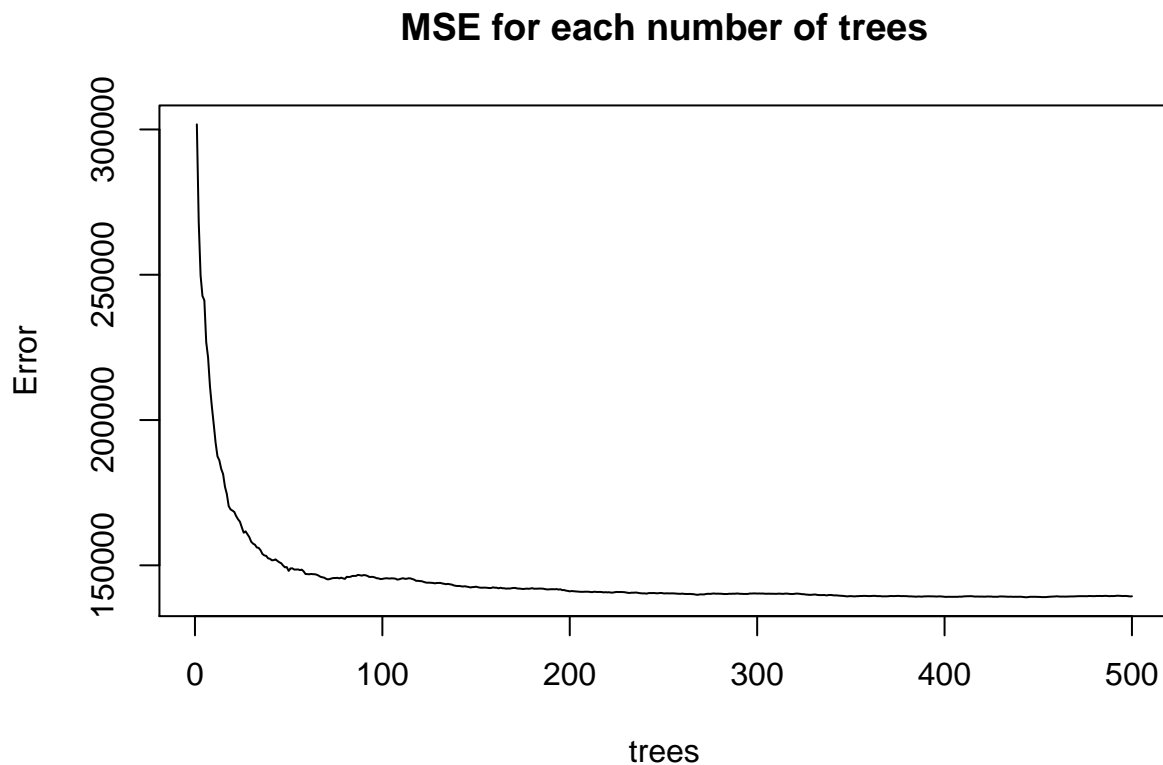
## The following object is masked from 'package:ggplot2':
##
##     margin

rf = randomForest(
  formula = y ~ .,
  data    = train
)
rf

##
## Call:
## randomForest(formula = y ~ ., data = train)
##           Type of random forest: regression
##           Number of trees: 500
## No. of variables tried at each split: 11
##
##           Mean of squared residuals: 139332.1
##           % Var explained: 63.45

plot(rf, main="MSE for each number of trees")

```



```
which.min(rf$mse)
```

```
## [1] 444
```

We can see that the MSE decreases to a certain point and then is minimized with 339 trees. We will now rebuild our model with the optimal number of trees.

```
set.seed(123)
rf = randomForest(
  formula = y ~ .,
  data    = train,
  ntree   = 339
)
rf
```

```
##
## Call:
## randomForest(formula = y ~ ., data = train, ntree = 339)
##              Type of random forest: regression
##              Number of trees: 339
## No. of variables tried at each split: 11
##
##              Mean of squared residuals: 139802.8
##              % Var explained: 63.32
```

Our next model will be a ridge regression model. We will use the glmnet package and set alpha to 0 to perform ridge regression. We will test a set of lambda values using cross validation in order to find the optimal lambda for our model.

```
library(glmnet)

## Loading required package: Matrix

## Loading required package: foreach

## Loaded glmnet 2.0-18

lambda_seq = 10^seq(2, -2, by = -.1)
ridge_cv = cv.glmnet(data.matrix(train[,features]), train$y, alpha = 0, lambda = lambda_seq)
best_lambda = ridge_cv$lambda.min
best_lambda

## [1] 0.1995262

ridge = glmnet(data.matrix(train[,features]), train$y, alpha = 0, lambda = best_lambda)
summary(ridge)

##           Length Class      Mode
## a0           1    -none-   numeric
## beta        35   dgCMatrix S4
## df           1    -none-   numeric
## dim           2    -none-   numeric
## lambda        1    -none-   numeric
## dev.ratio     1    -none-   numeric
## nulldev       1    -none-   numeric
## npasses       1    -none-   numeric
## jerr          1    -none-   numeric
## offset        1    -none-   logical
## call          5    -none-   call
## nobs          1    -none-   numeric
```

Our final regression model will be a simple multiple regression using our predictor variables.

```
linear = lm(y~., data=train)
summary(linear)

##
## Call:
## lm(formula = y ~ ., data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1422.16  -188.72   -41.62   124.75  2108.84
##
## Coefficients:
```

```
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)      599.146      9.339  64.154 < 2e-16 ***
## PctVacantBoarded    64.705     13.621   4.750 2.23e-06 ***
## PctKidsBornNeverMar 130.645     28.914   4.518 6.73e-06 ***
## pctWRetire        -83.530     16.376  -5.101 3.83e-07 ***
## MedOwnCostPctIncNoMtg -49.327     12.678  -3.891 0.000104 ***
## PctKids2Par       -193.566     45.994  -4.209 2.73e-05 ***
## PctPersDenseHous    115.455     28.416   4.063 5.10e-05 ***
## RentLowQ          -123.247     36.682  -3.360 0.000800 ***
## PctWorkMom         -61.089     26.848  -2.275 0.023026 *
## PctLess9thGrade    -72.048     22.427  -3.213 0.001344 **
## pctWPubAsst        75.723     24.146   3.136 0.001747 **
## PersPerRentOccHous  -25.266     29.236  -0.864 0.387618
## MedRent           134.922     40.468   3.334 0.000877 ***
## PctVacMore6Mos     -30.105     13.287  -2.266 0.023607 *
## HousVacant         80.441     24.126   3.334 0.000877 ***
## PctEmplManu       -28.496     12.185  -2.339 0.019488 *
## racepctblack      101.685     20.249   5.022 5.75e-07 ***
## AsianPerCap        23.001     10.606   2.169 0.030272 *
## agePct12t29       -26.163     23.403  -1.118 0.263784
## NumInShelters      75.638     34.299   2.205 0.027594 *
## medIncome         -78.555     87.198  -0.901 0.367802
## PctForeignBorn     11.639     21.666   0.537 0.591204
## PctWorkMomYoungKids  30.731     23.967   1.282 0.199970
## PctHousOccup       -18.114     13.046  -1.388 0.165201
## MalePctDivorce     161.401     49.718   3.246 0.001195 **
## PctPersOwnOccup    -186.891    109.864  -1.701 0.089134 .
## medFamInc         14.860     76.114   0.195 0.845235
## OtherPerCap        27.204     10.045   2.708 0.006845 **
## PctPopUnderPov     -83.488     32.320  -2.583 0.009887 **
## pctUrban          45.910     12.311   3.729 0.000200 ***
## pctWSocSec         42.840     39.824   1.076 0.282232
## NumKidsBornNeverMar -121.045     41.659  -2.906 0.003721 **
## pctWWage          -6.839     43.370  -0.158 0.874721
## PctHousOwnOcc      194.025    107.417   1.806 0.071081 .
## TotalPctDiv       -148.157     57.152  -2.592 0.009628 **
## pctWFarmSelf        8.712     11.872   0.734 0.463172
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 361 on 1458 degrees of freedom
## Multiple R-squared:  0.6664, Adjusted R-squared:  0.6584
## F-statistic: 83.21 on 35 and 1458 DF,  p-value: < 2.2e-16
```

We will now use these three built models and compare their performance on the test set. We will predict using the models, find the residuals, and calculate the Mean Squared Error (MSE) as our performance metric.

```
linear_pred = predict(linear, test[,features])
rf_pred = predict(rf, test[,features])
ridge_pred = predict(ridge, data.matrix(test[,features]))

mse = function(pred, actual) {
  resids = pred - actual
  sqer = resids^2
```

```

    return (mean(sqr))
}

linear_mse = mse(linear_pred, test$y)
rf_mse = mse(rf_pred, test$y)
ridge_mse = mse(ridge_pred, test$y)
mses = c("LR"=linear_mse, "RF"=rf_mse, "Ridge"=ridge_mse)
mses

```

```

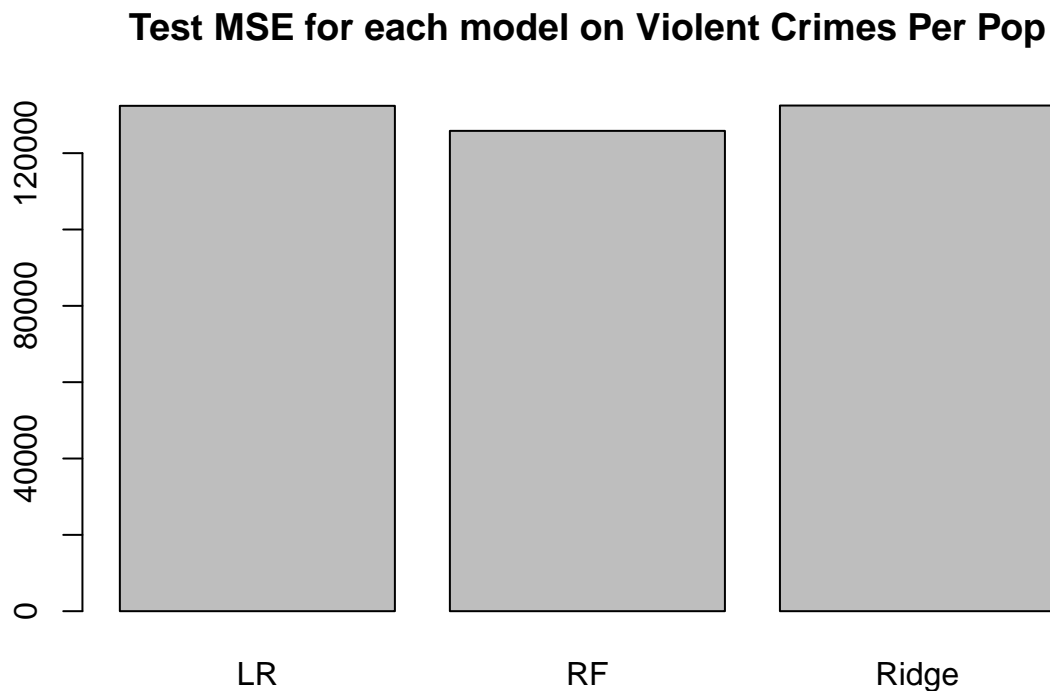
##          LR          RF          Ridge
## 132399.6 125837.6 132479.7

```

```

barplot(mses, main="Test MSE for each model on Violent Crimes Per Pop")

```



We can see that our Random Forest regression model performs best out of all 3 models on the test set. The simple linear and ridge regression models performed similarly, but in order to predict violent crimes per population we will choose to use the Random Forest regression model that we built.