



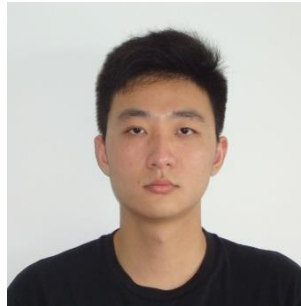
Crime Analysis of Chicago in 2015



Team member



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Overview



262893 obs. of 22 variables

ID, Case.Number, **Date**, Block, IUCR, **Primary.Type**, **Description**, **Location.Description**, **Arrest**, Domestic, Beat, District, Ward, Community.Area, **FBI.Code**, X.Coordinate, Y.Coordinate, Year, Updated.On, **Latitude**, **Longitude**, Location

259807 obs. of 22 variables

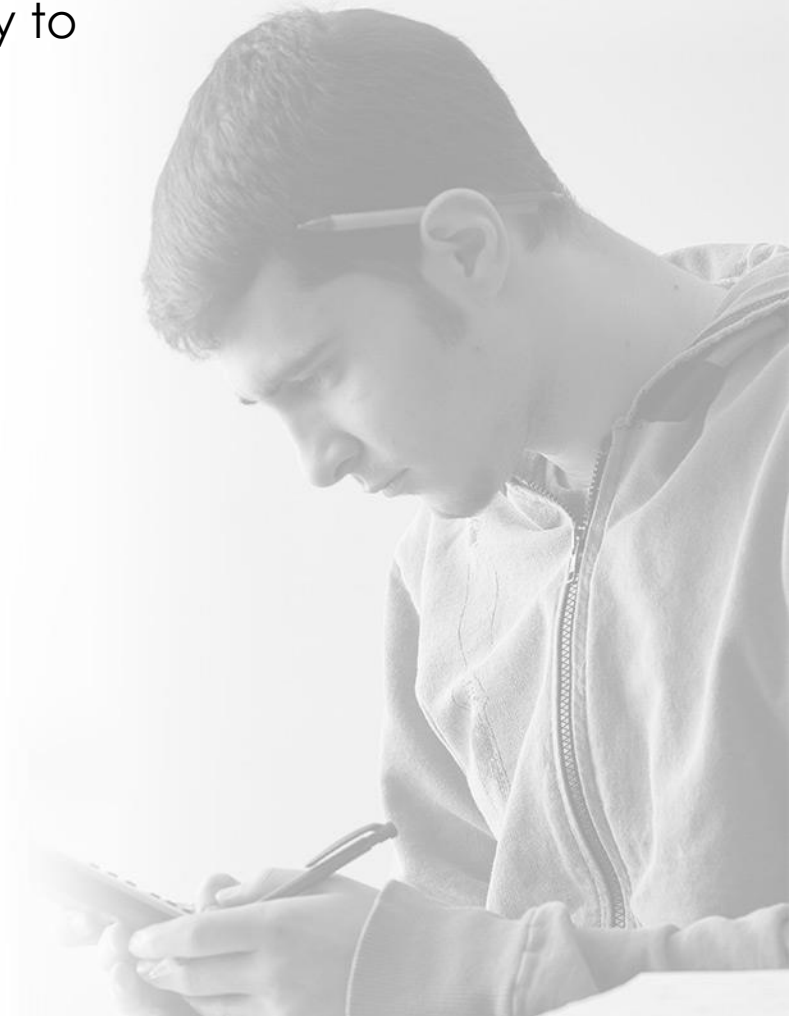
01/18/2015 04:00:00 PM

| date_month | date_day | date_year | time_hour | time_minute | time_second |
|------------|----------|-----------|-----------|-------------|-------------|
| 1 | 18 | 2015 | 16 | 0 | 0 |



As citizens or tourists, what should they care for?

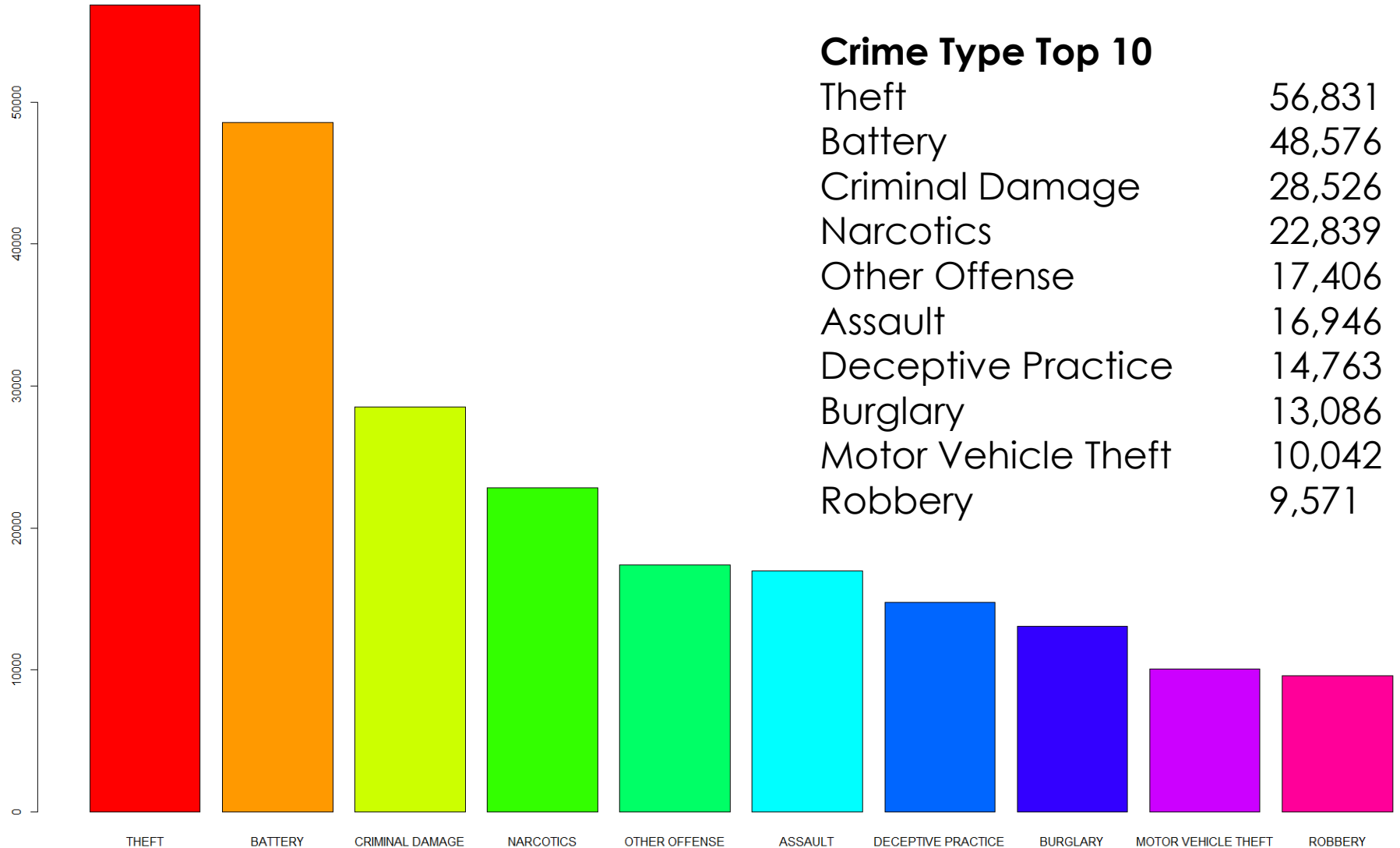
- Which kind of crime has the most frequency to happen?
- Theft or Robbery...?
- Which area of Chicago has the most crime rate?
- Downtown or countryside?
- What time has the most crime rate?
- Day or night?



Crime Type



Crime Type



Crime Type Top 10

| | |
|---------------------|--------|
| Theft | 56,831 |
| Battery | 48,576 |
| Criminal Damage | 28,526 |
| Narcotics | 22,839 |
| Other Offense | 17,406 |
| Assault | 16,946 |
| Deceptive Practice | 14,763 |
| Burglary | 13,086 |
| Motor Vehicle Theft | 10,042 |
| Robbery | 9,571 |

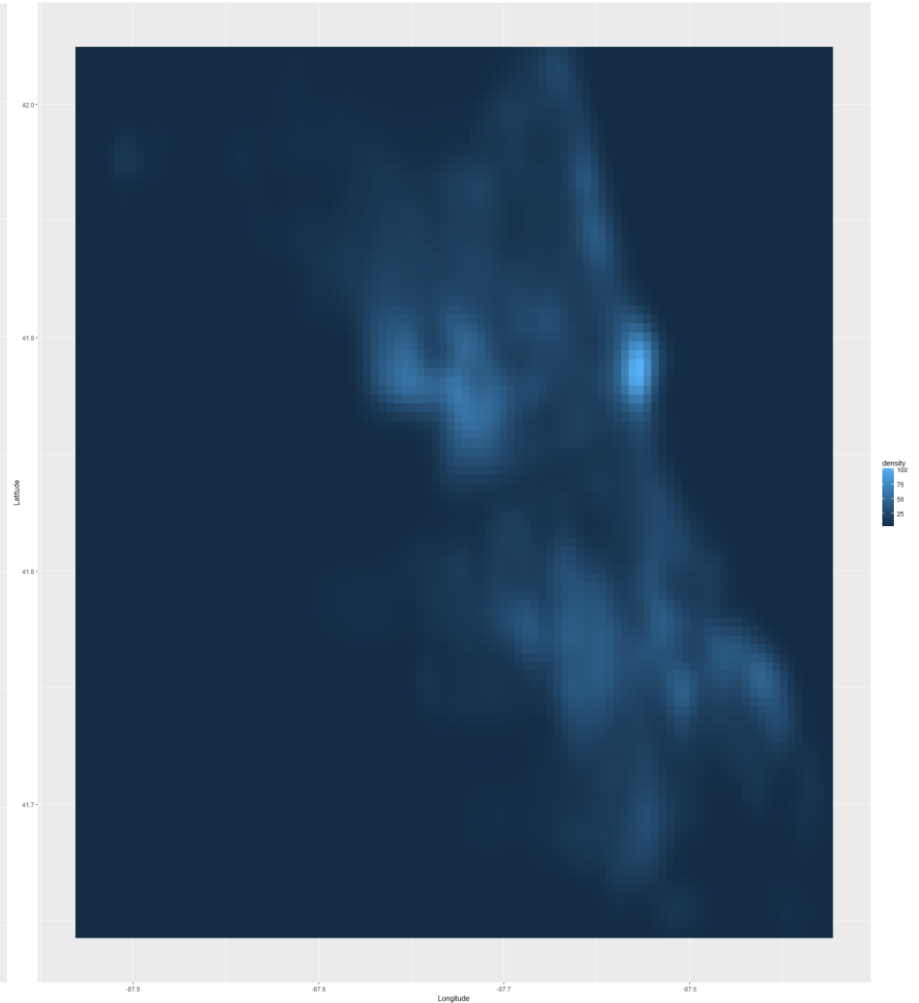
Crime



Point Map



Raster Map



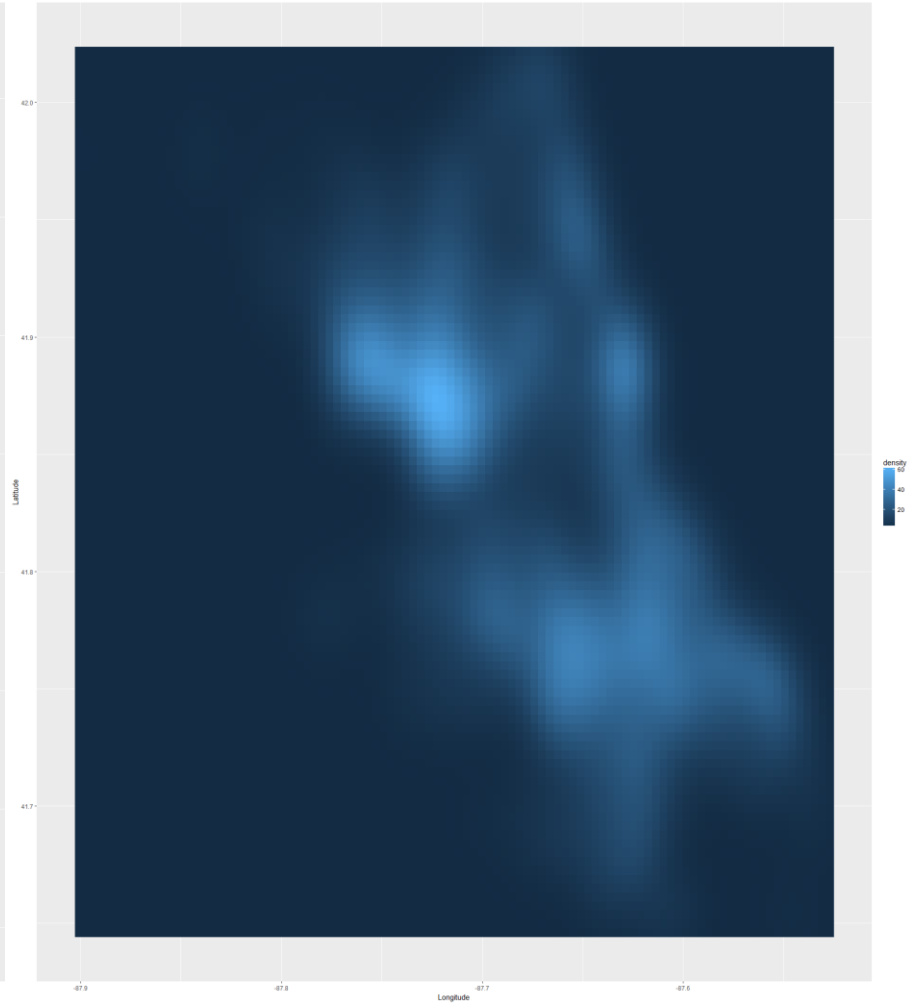
Robbery



Point Map



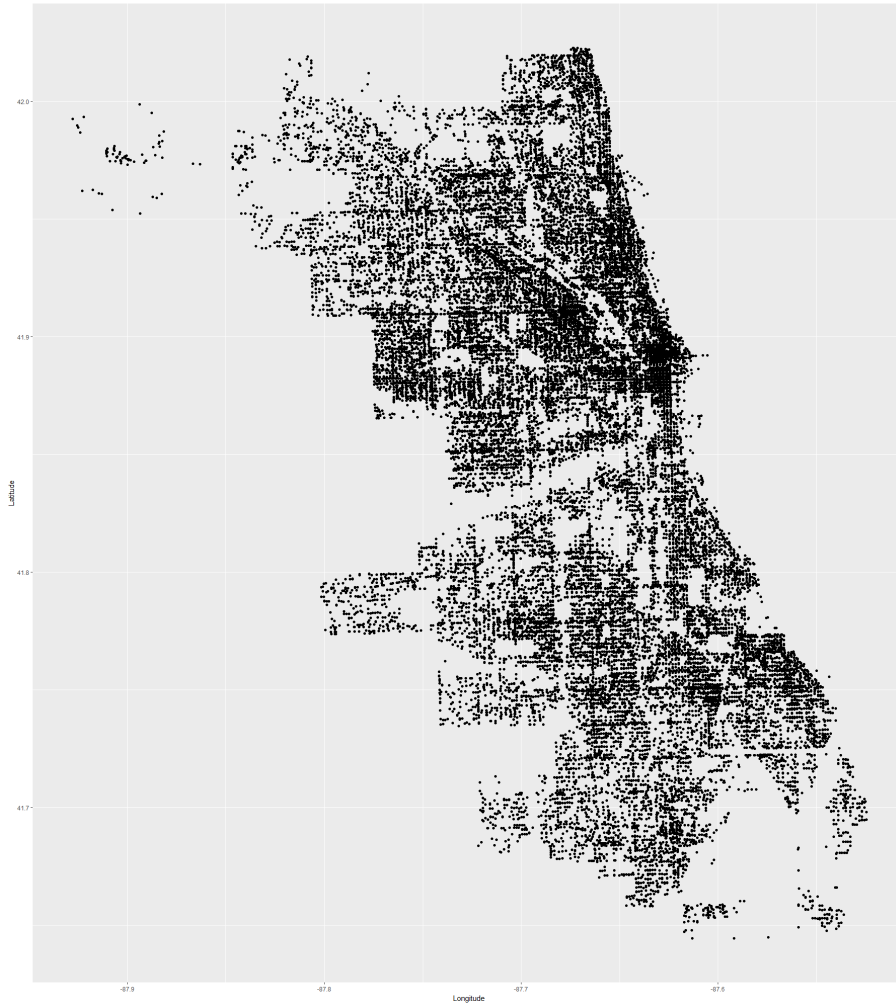
Raster Map



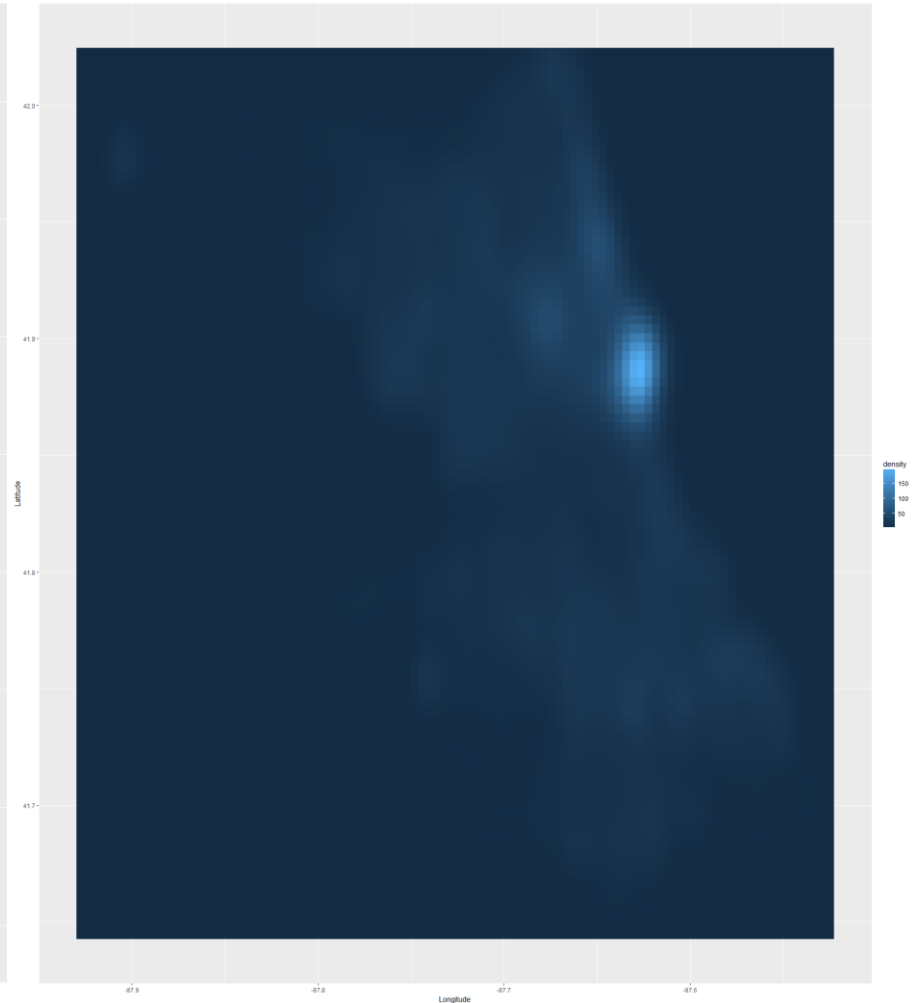
Theft



Point Map



Raster Map



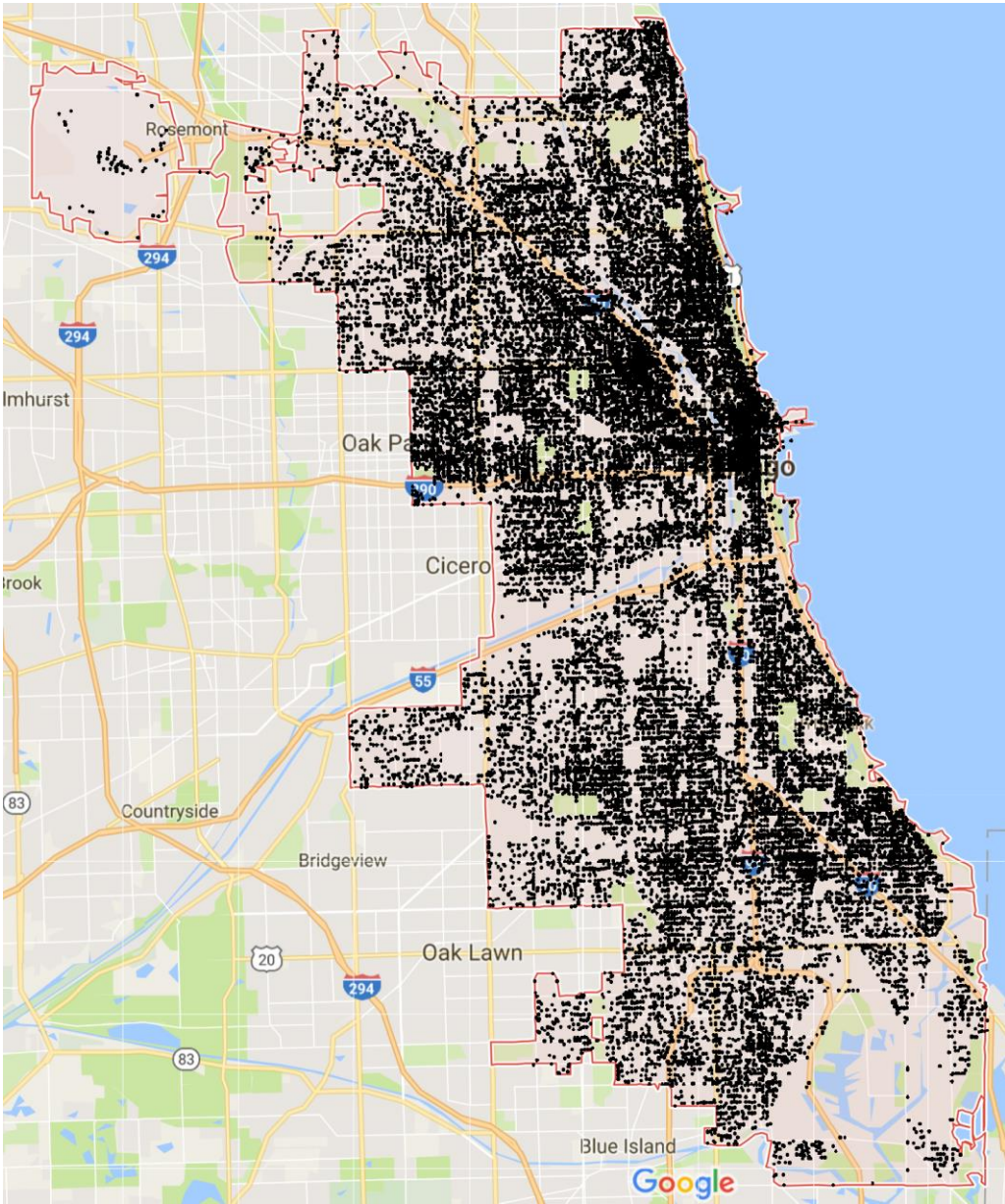
Theft

We want to pay more attention on **theft**

Theft Point on Google Map

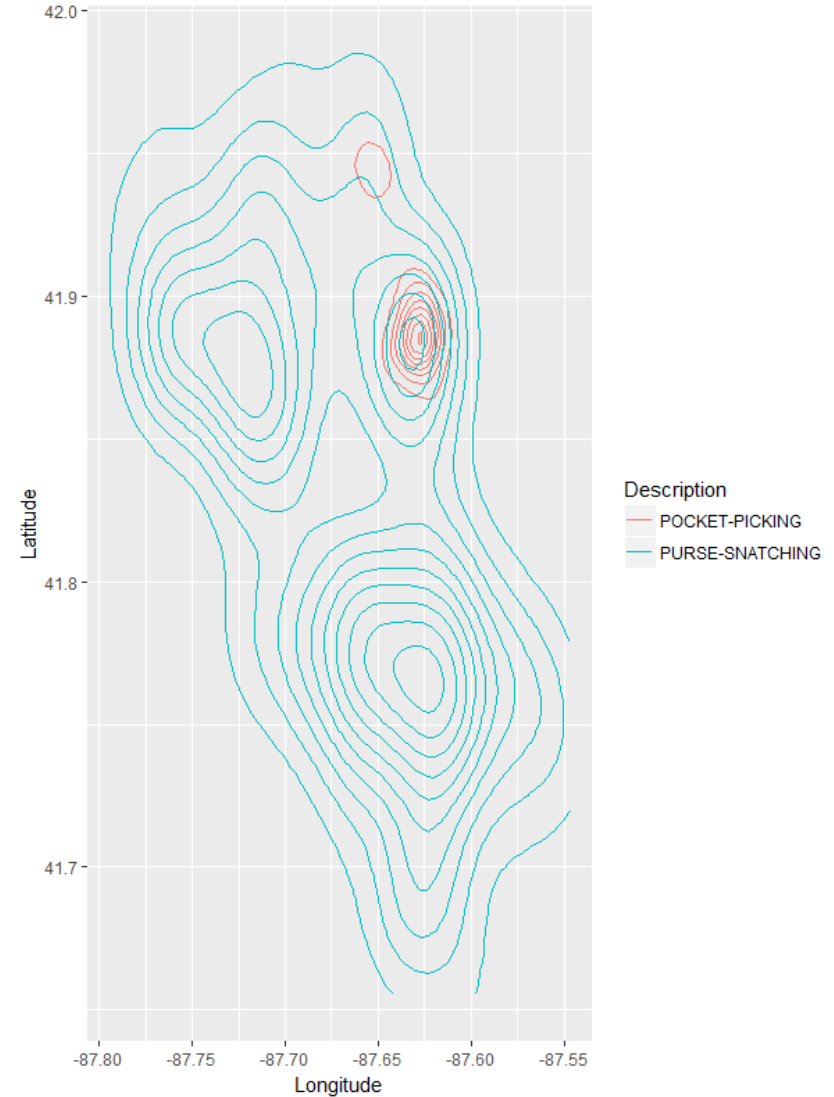
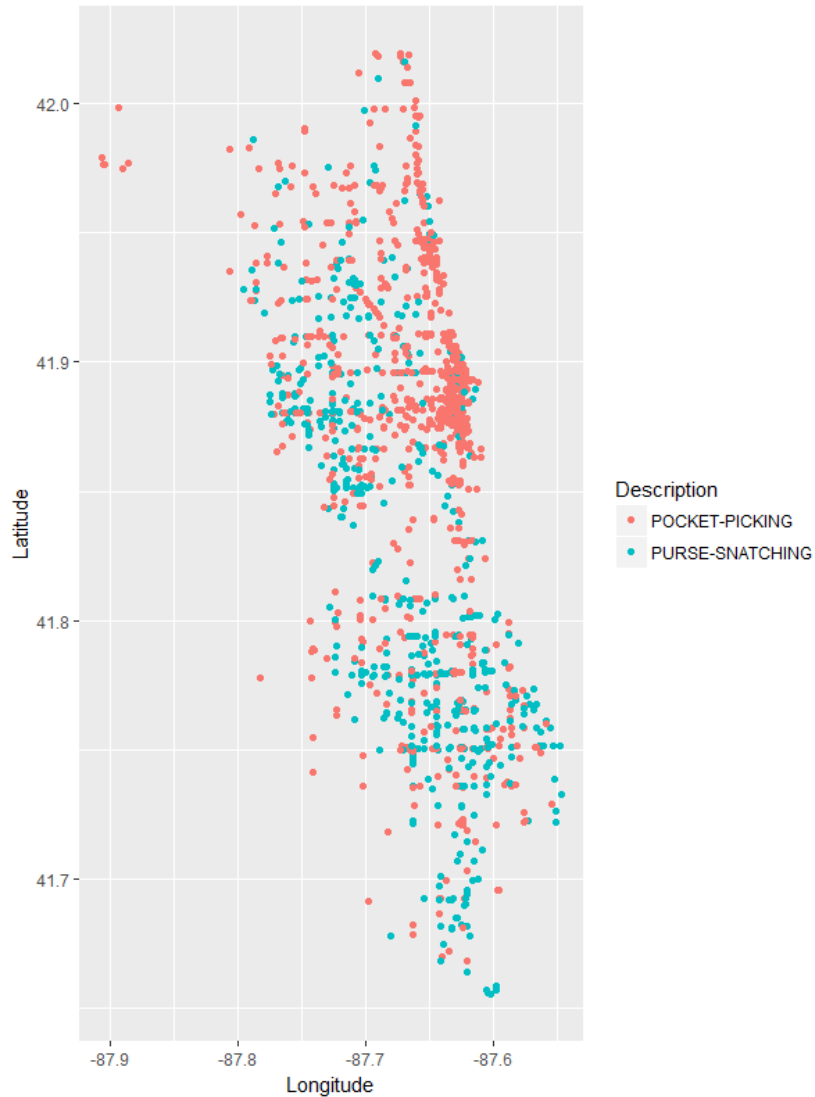
More:
Downtown Area

Less:
Highway,
Park,
River,
Lake,
Airport



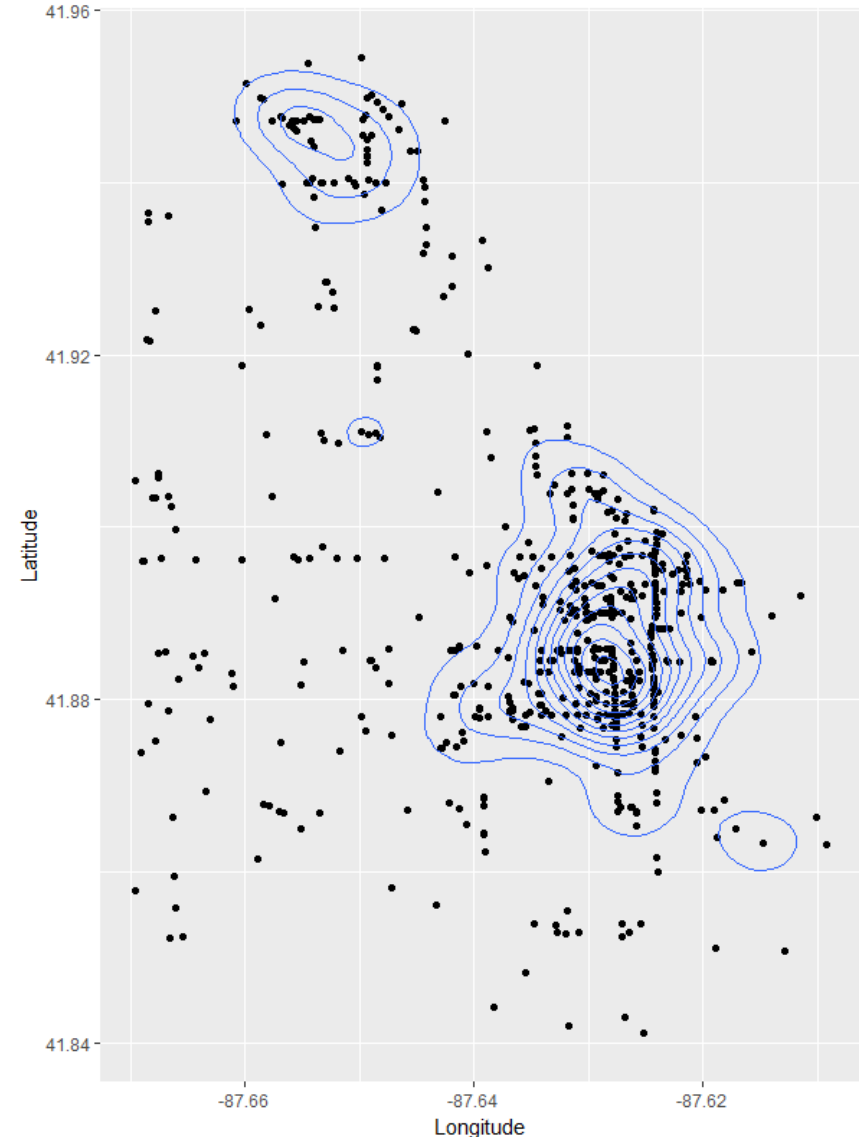
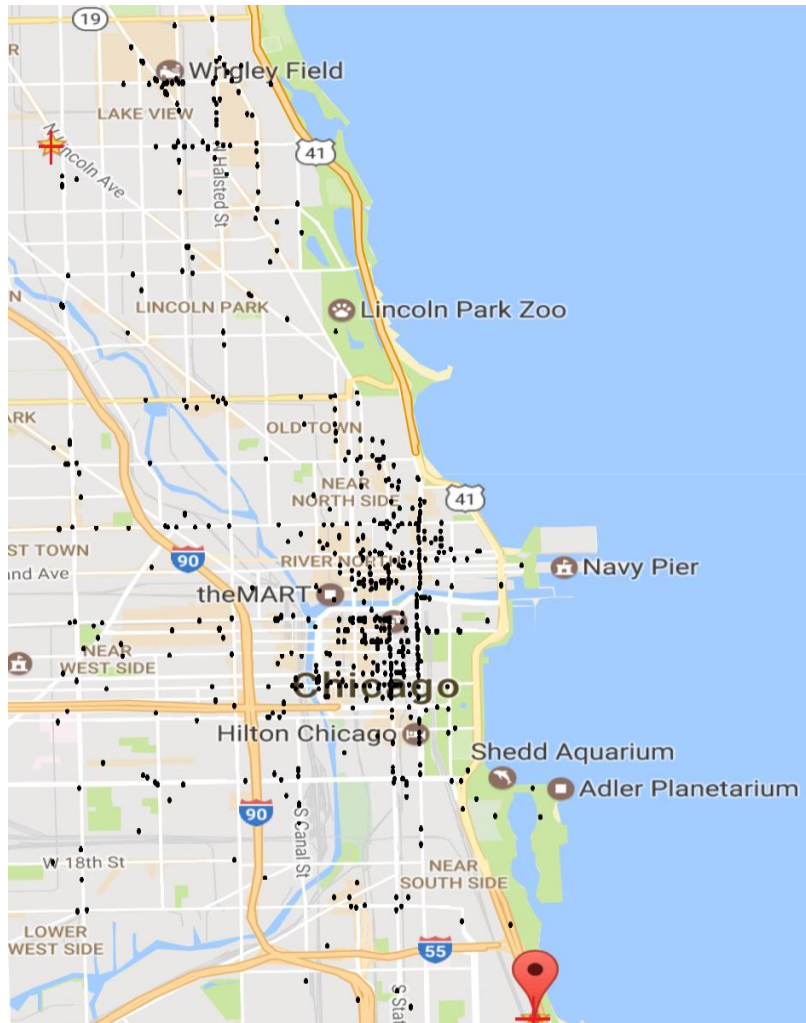


Theft: Pocket-Picking & Purse-Snatching

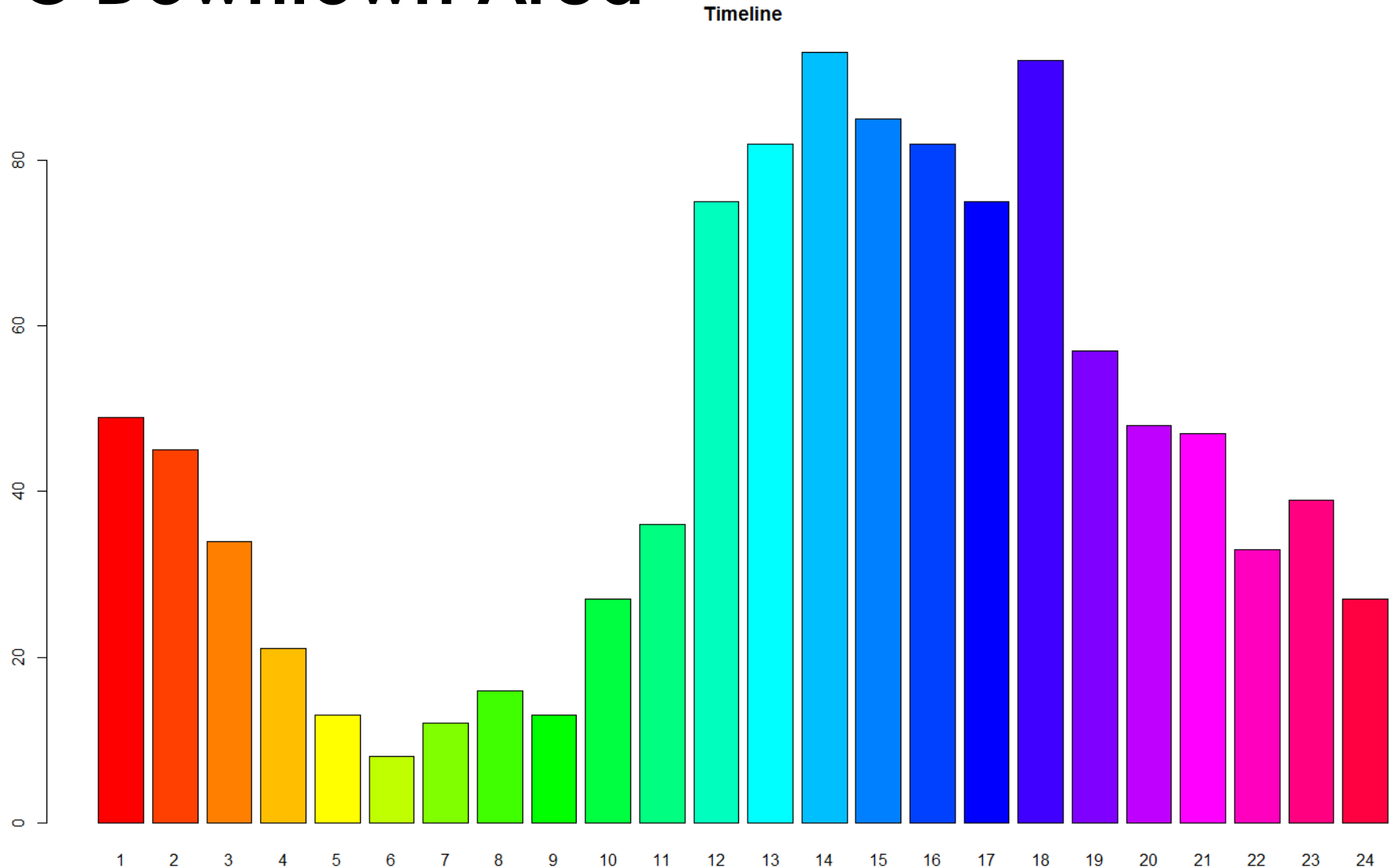




Theft: Pocket-Picking & Purse-Snatching @ Downtown Area



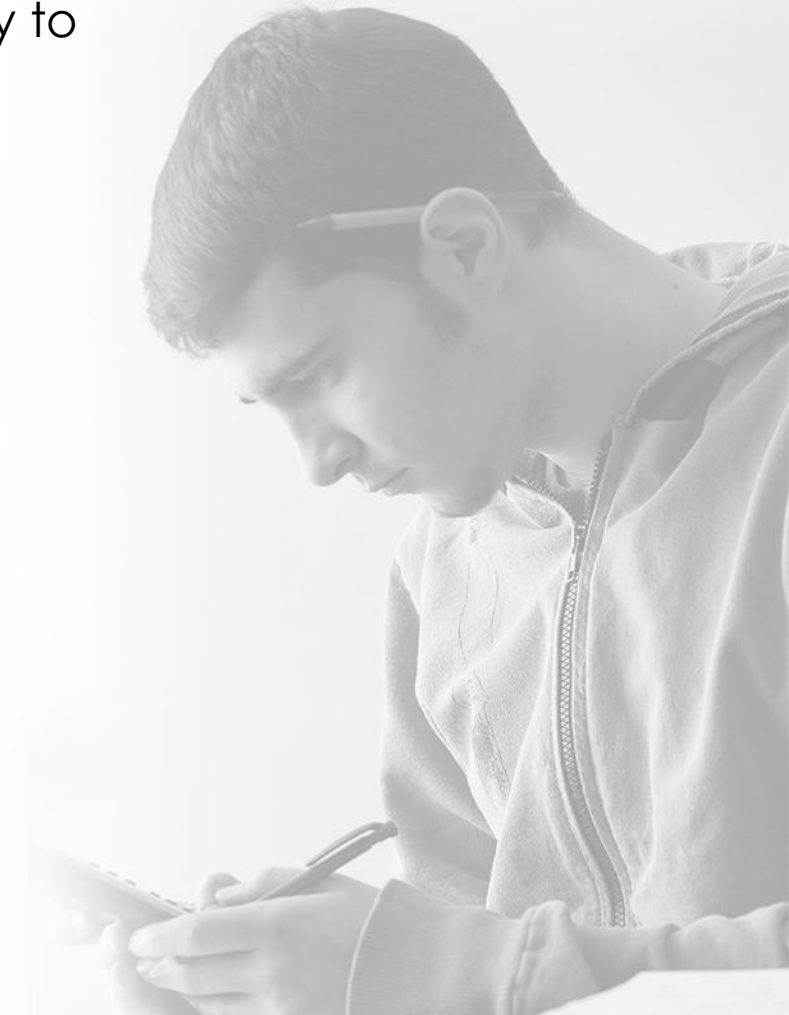
Theft: Pocket-Picking & Purse-Snatching @ Downtown Area





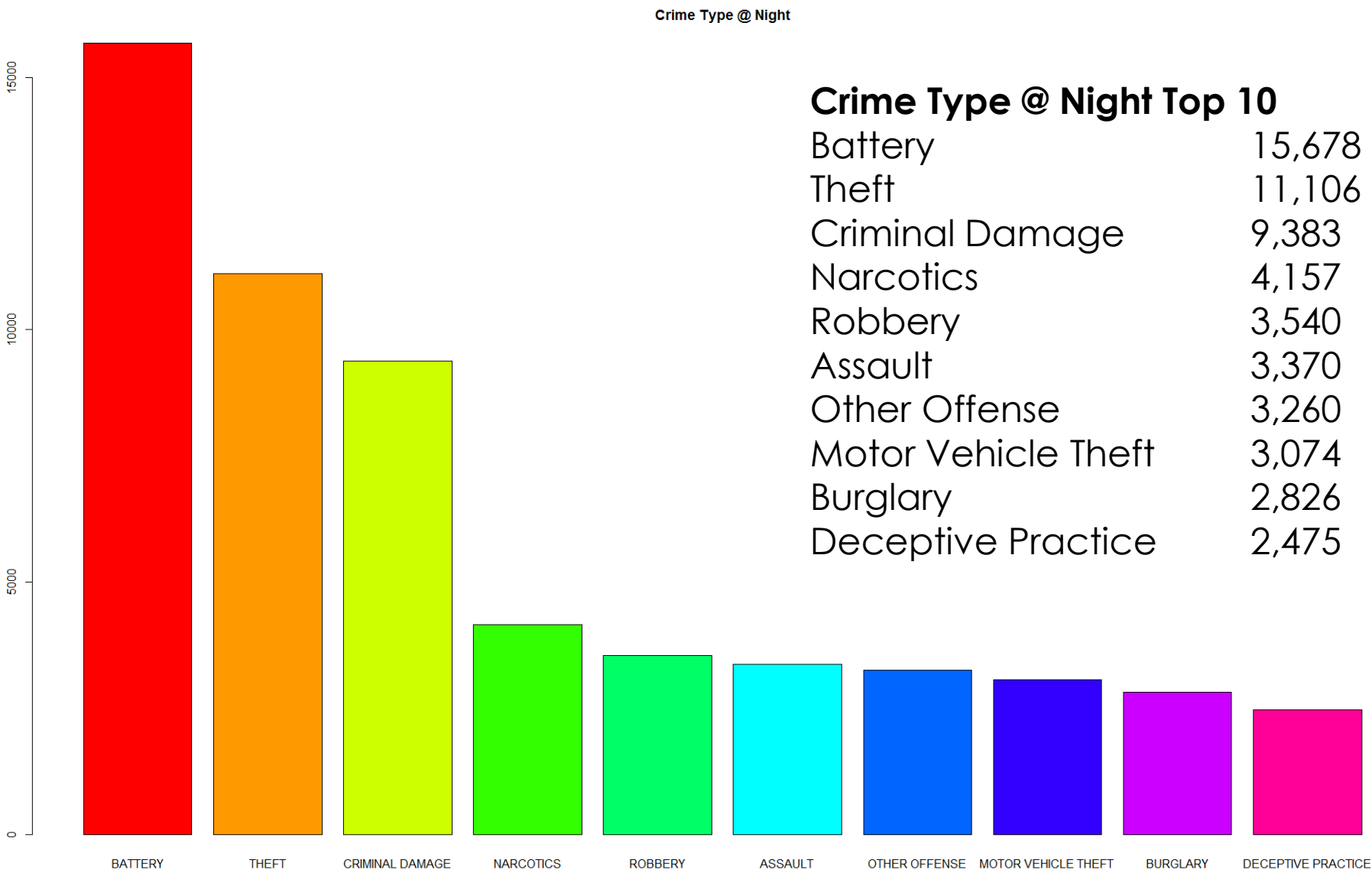
As police department, what should they care for?

- Which kind of crime has the most frequency to happen at night?
- Battery...?
- Has gun?
- Yes or no?
- How should they patrol?
- Which area and what is the center point?





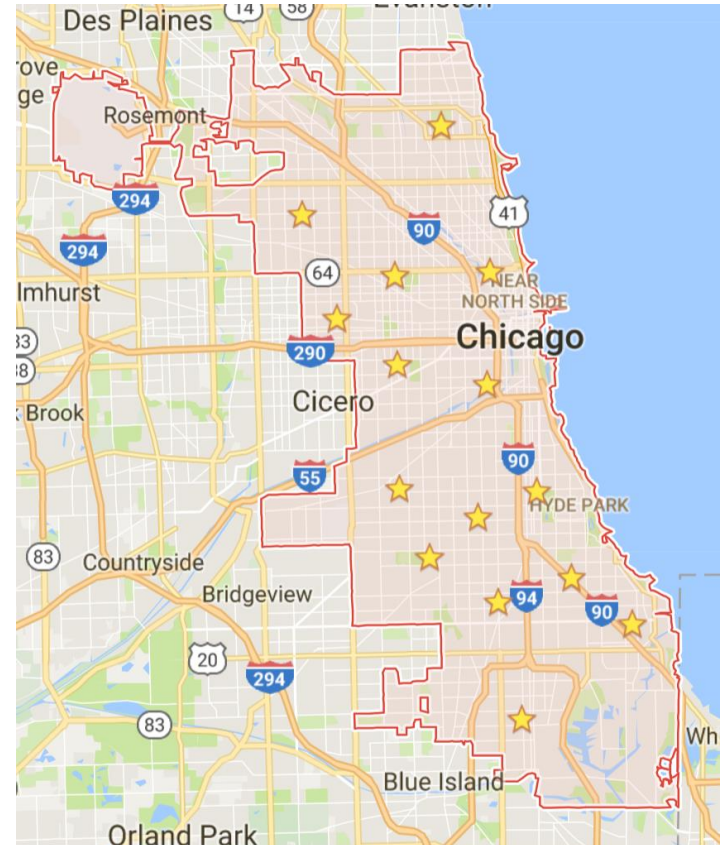
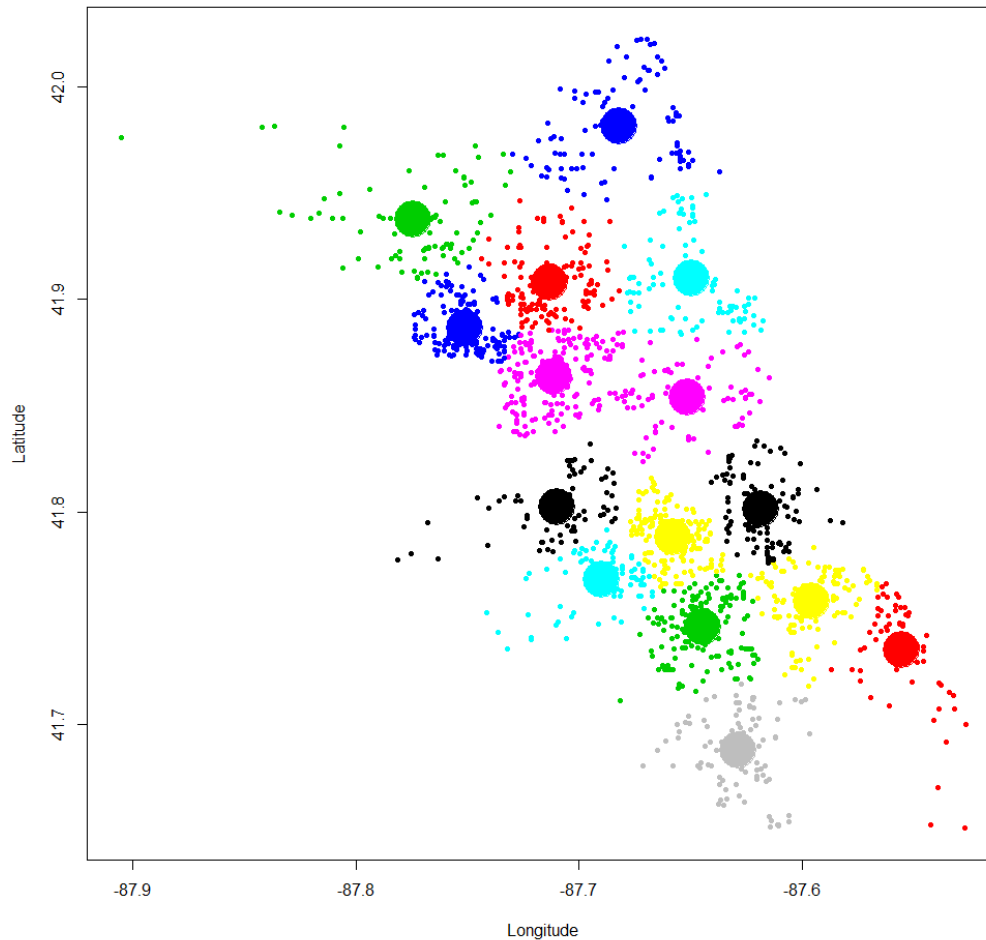
Crime Type @ Night (10pm-6am)



Battery w/ Gun @ Night

Use k-means to find the center points with Latitude and Longitude (k=15).

Battery w/ Gun @ Night

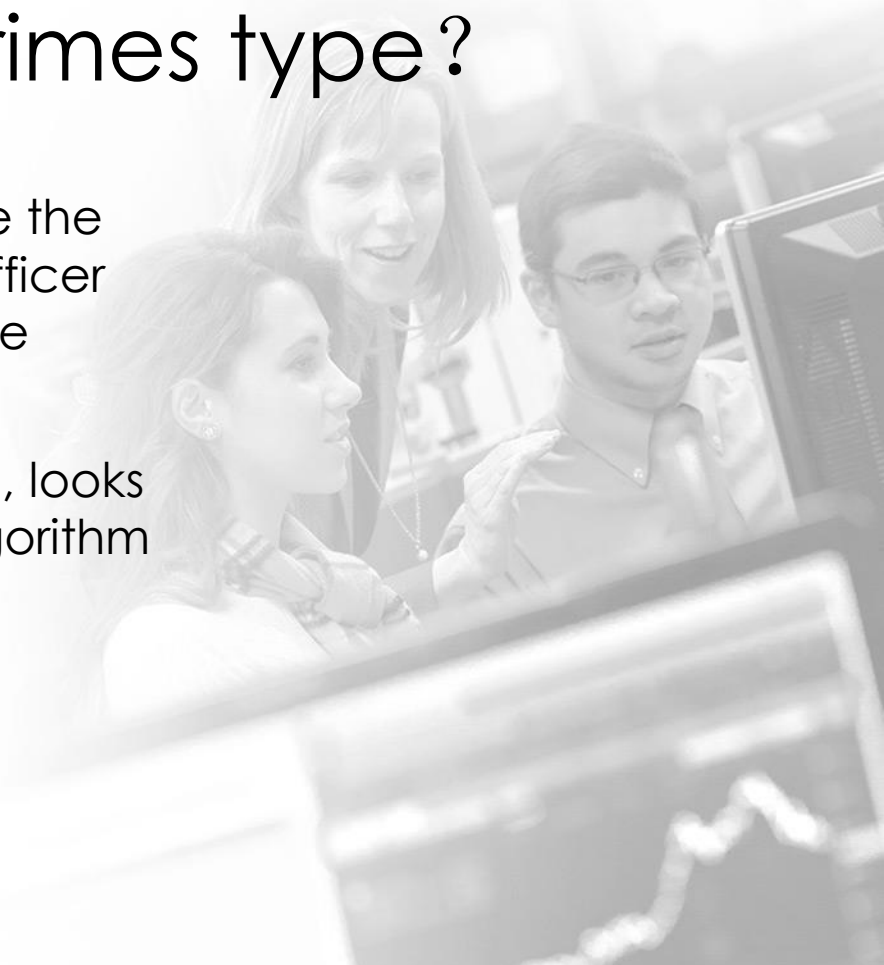




Information for police from this data

Can we predict the crimes type?

- If we can predict the crime type before the police get to the scene of crime, the officer can be prepared which can reduce the danger.
- We have Latitude, Longitude and date, looks like we can use *k*-Nearest Neighbor Algorithm to predict the crimes types.





Use k-nearest neighbor to predict the crime type with Latitude and Longitude (k=50) .

| | Actual | | | | | | | | | | | | | |
|----------------------------------|--------|---------|---------|---------------------|----------|----------------------------------|------------|-----------|----------------------------|--------------|------------------|-------|-------------------|-----|
| Predict | ARSON | ASSAULT | BATTERY | CRIM SEXUAL ASSAULT | HOMICIDE | INTERFERENCE WITH PUBLIC OFFICER | KIDNAPPING | OBSCENITY | OFFENSE INVOLVING CHILDREN | PROSTITUTION | PUBLIC INDECENCY | THEFT | WEAPONS VIOLATION | |
| ARSON | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | |
| ASSAULT | 0 | 5 | 14 | | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 14 | 1 | |
| BATTERY | 54 | 2226 | 6569 | | 141 | 71 | 198 | 28 | 2 | 286 | 69 | 2 | 3820 | 507 |
| CRIM SEXUAL ASSAULT | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| HOMICIDE | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| INTERFERENCE WITH PUBLIC OFFICER | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| KIDNAPPING | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| OBSCENITY | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| OFFENSE INVOLVING CHILDREN | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| PROSTITUTION | 1 | 12 | 46 | | 2 | 0 | 2 | 2 | 0 | 2 | 159 | 0 | 30 | 2 |
| PUBLIC INDECENCY | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| THEFT | 21 | 1150 | 3042 | | 97 | 23 | 84 | 14 | 3 | 133 | 43 | 1 | 7554 | 156 |
| WEAPONS VIOLATION | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |

Because the amount of **Battery** and **Theft** type are much more than other crime types, no matter where the crimes happen, it will be highly likely predicted as **Battery** or **Theft**.



Use k-nearest neighbor to predict the crime type with Latitude, Longitude and date (k=50).

| | Actual | | | | | | | | | | | | |
|----------------------------------|--------|---------|---------|---------------------|----------|----------------------------------|------------|-----------|----------------------------|--------------|------------------|-------|-------------------|
| Predict | ARSON | ASSAULT | BATTERY | CRIM SEXUAL ASSAULT | HOMICIDE | INTERFERENCE WITH PUBLIC OFFICER | KIDNAPPING | OBSCENITY | OFFENSE INVOLVING CHILDREN | PROSTITUTION | PUBLIC INDECENCY | THEFT | WEAPONS VIOLATION |
| ARSON | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ASSAULT | 0 | 10 | 14 | | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 12 | 0 |
| BATTERY | 65 | 2029 | 6173 | | 154 | 68 | 216 | 29 | 1 | 241 | 162 | 1 | 3792 |
| CRIM SEXUAL ASSAULT | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 513 |
| HOMICIDE | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| INTERFERENCE WITH PUBLIC OFFICER | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| KIDNAPPING | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| OBSCENITY | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| OFFENSE INVOLVING CHILDREN | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| PROSTITUTION | 0 | 10 | 23 | | 1 | 2 | 3 | 0 | 0 | 66 | 0 | 22 | 3 |
| PUBLIC INDECENCY | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| THEFT | 11 | 1344 | 3461 | | 84 | 24 | 66 | 15 | 4 | 180 | 42 | 2 | 7592 |
| WEAPONS VIOLATION | 0 | 0 | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

This time I use normalized Latitude, Longitude and date to predict the crime type. But the **Battery** and **Theft** type still dominate the prediction, no matter where and when the crimes happen, it still will be highly likely predicted as **Battery** or **Theft**.



Use weighted k-nearest neighbor to predict the crime type with Latitude, Longitude and date (k=50).

| Predict | Actual | | | | | | | | | | | | | |
|----------------------------------|--------|---------|---------|---------------------|----------|----------------------------------|------------|-----------|----------------------------|--------------|------------------|-------|-------------------|--|
| | ARSON | ASSAULT | BATTERY | CRIM SEXUAL ASSAULT | HOMICIDE | INTERFERENCE WITH PUBLIC OFFICER | KIDNAPPING | OBSCENITY | OFFENSE INVOLVING CHILDREN | PROSTITUTION | PUBLIC INDECENCY | THEFT | WEAPONS VIOLATION | |
| ARSON | 0 | 0 | 57 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 0 | |
| ASSAULT | 0 | 90 | 1932 | | 0 | 0 | 0 | 0 | 0 | 15 | 0 | 1355 | 1 | |
| BATTERY | 0 | 193 | 6004 | | 0 | 0 | 0 | 0 | 0 | 40 | 0 | 3430 | 4 | |
| CRIM SEXUAL ASSAULT | 0 | 7 | 159 | | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 73 | 0 | |
| HOMICIDE | 0 | 2 | 65 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 0 | |
| INTERFERENCE WITH PUBLIC OFFICER | 0 | 7 | 202 | | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 72 | 1 | |
| KIDNAPPING | 0 | 0 | 26 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 0 | |
| OBSCENITY | 0 | 1 | 1 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | |
| OFFENSE INVOLVING CHILDREN | 0 | 9 | 244 | | 0 | 0 | 0 | 0 | 7 | 0 | 0 | 161 | 0 | |
| PROSTITUTION | 0 | 3 | 98 | | 0 | 0 | 0 | 0 | 0 | 131 | 0 | 39 | 0 | |
| PUBLIC INDECENCY | 0 | 0 | 1 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | |
| THEFT | 0 | 159 | 3672 | | 0 | 0 | 0 | 0 | 0 | 31 | 0 | 7549 | 7 | |
| WEAPONS VIOLATION | 0 | 17 | 476 | | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 169 | 1 | |

The weighted k-nearest neighbor Algorithm still can't make any improvement. The **Battery** and **Theft** type still dominate the prediction.



What if we remove Battery and Theft type.

- Since Battery and theft are not serious crimes, what if we remove these two type and choose some serious crimes with close amount?
- I chose **ASSAULT, BURGLARY, DECEPTIVE PRACTICE, MOTOR VEHICLE THEFT, OTHER OFFENSE** and **ROBBERY**. These six types have similar amount.





Use weighted k-nearest neighbor to predict the crime type among six different types (remove Battery and Theft) with Latitude, Longitude and date(k=50).

| Predict | Actual | | | | | |
|---------------------|---------|----------|--------------------|---------------------|---------------|---------|
| | ASSAULT | BURGLARY | DECEPTIVE PRACTICE | MOTOR VEHICLE THEFT | OTHER OFFENSE | ROBBERY |
| ASSAULT | 1112 | 317 | 586 | 186 | 954 | 173 |
| BURGLARY | 675 | 536 | 521 | 197 | 590 | 125 |
| DECEPTIVE PRACTICE | 485 | 238 | 1438 | 130 | 544 | 88 |
| MOTOR VEHICLE THEFT | 515 | 236 | 309 | 290 | 462 | 151 |
| OTHER OFFENSE | 978 | 343 | 757 | 194 | 1122 | 168 |
| ROBBERY | 568 | 226 | 264 | 166 | 437 | 282 |

This one is much better than the former results.

Measure the performance and decide K value

Use average correct rate to measure the performance.

$$\text{Correct rate} = \frac{n_{\text{correct prediction in one type}}}{n_{\text{all prediction in one type}}}$$

| | Actual | | | | | |
|---------------------|---------|----------|--------------------|---------------------|---------------|---------|
| Predict | ASSAULT | BURGLARY | DECEPTIVE PRACTICE | MOTOR VEHICLE THEFT | OTHER OFFENSE | ROBBERY |
| ASSAULT | 1112 | 317 | 586 | 186 | 954 | 173 |
| BURGLARY | 675 | 536 | 521 | 197 | 590 | 125 |
| DECEPTIVE PRACTICE | 485 | 238 | 1438 | 130 | 544 | 88 |
| MOTOR VEHICLE THEFT | 515 | 236 | 309 | 290 | 462 | 151 |
| OTHER OFFENSE | 978 | 343 | 757 | 194 | 1122 | 168 |
| ROBBERY | 568 | 226 | 264 | 166 | 437 | 282 |

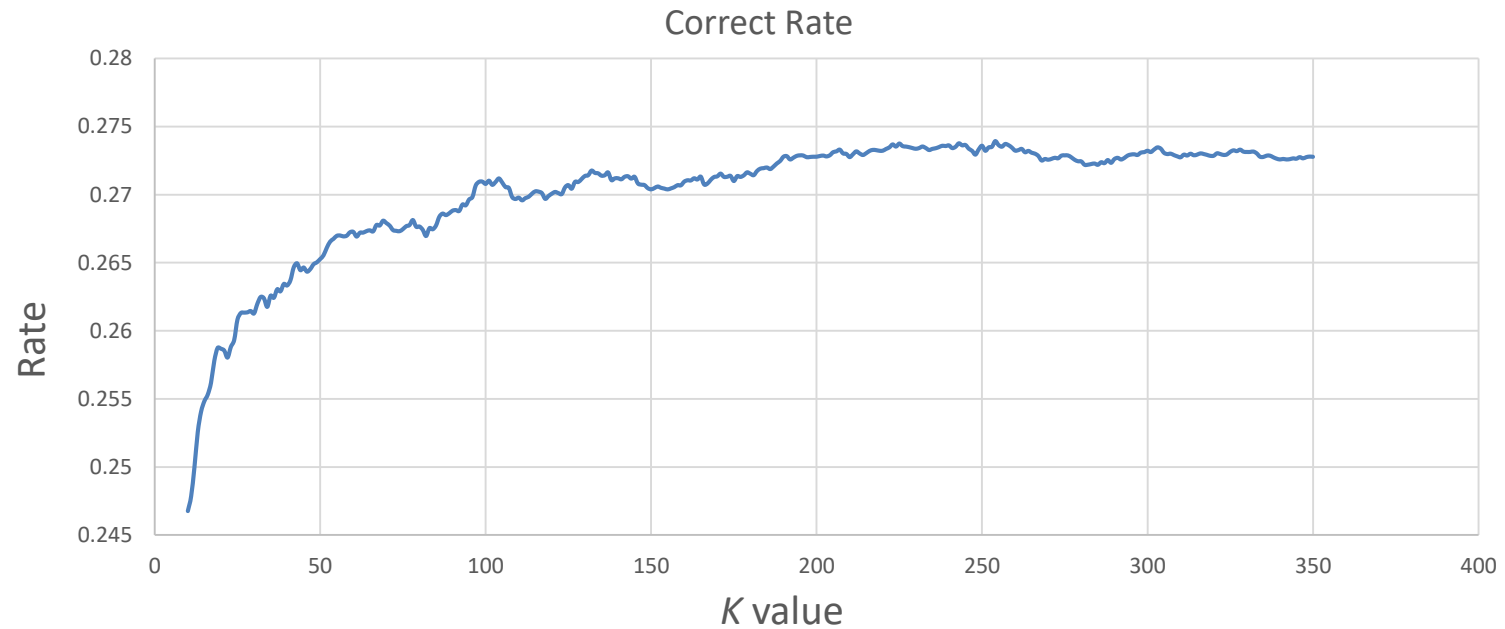
Correct predictions in
Deceptive Practice type

All predictions in
Deceptive Practice
type

Average correct rate = average(correct rate)

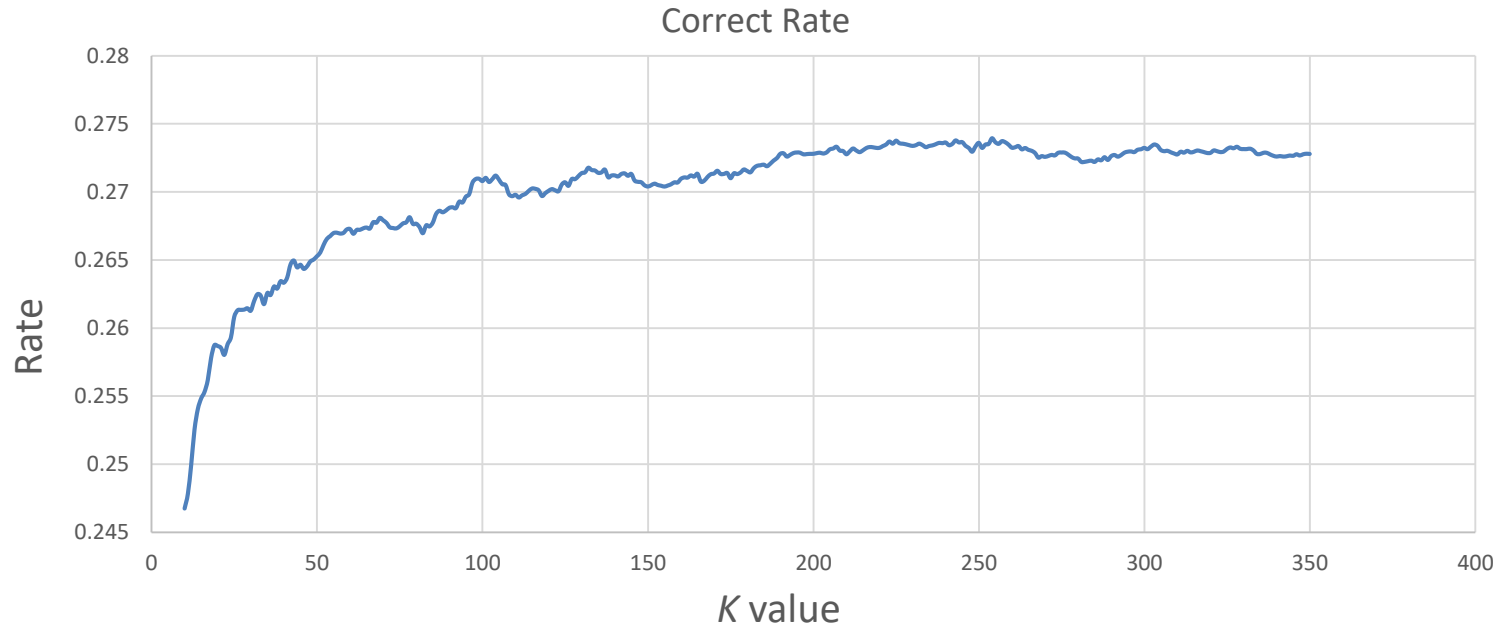
Measure the performance and decide K value

Decide the K value based on the performance.



Calculate the correct rate when K vary from 10 to 350.

Good model or bad model



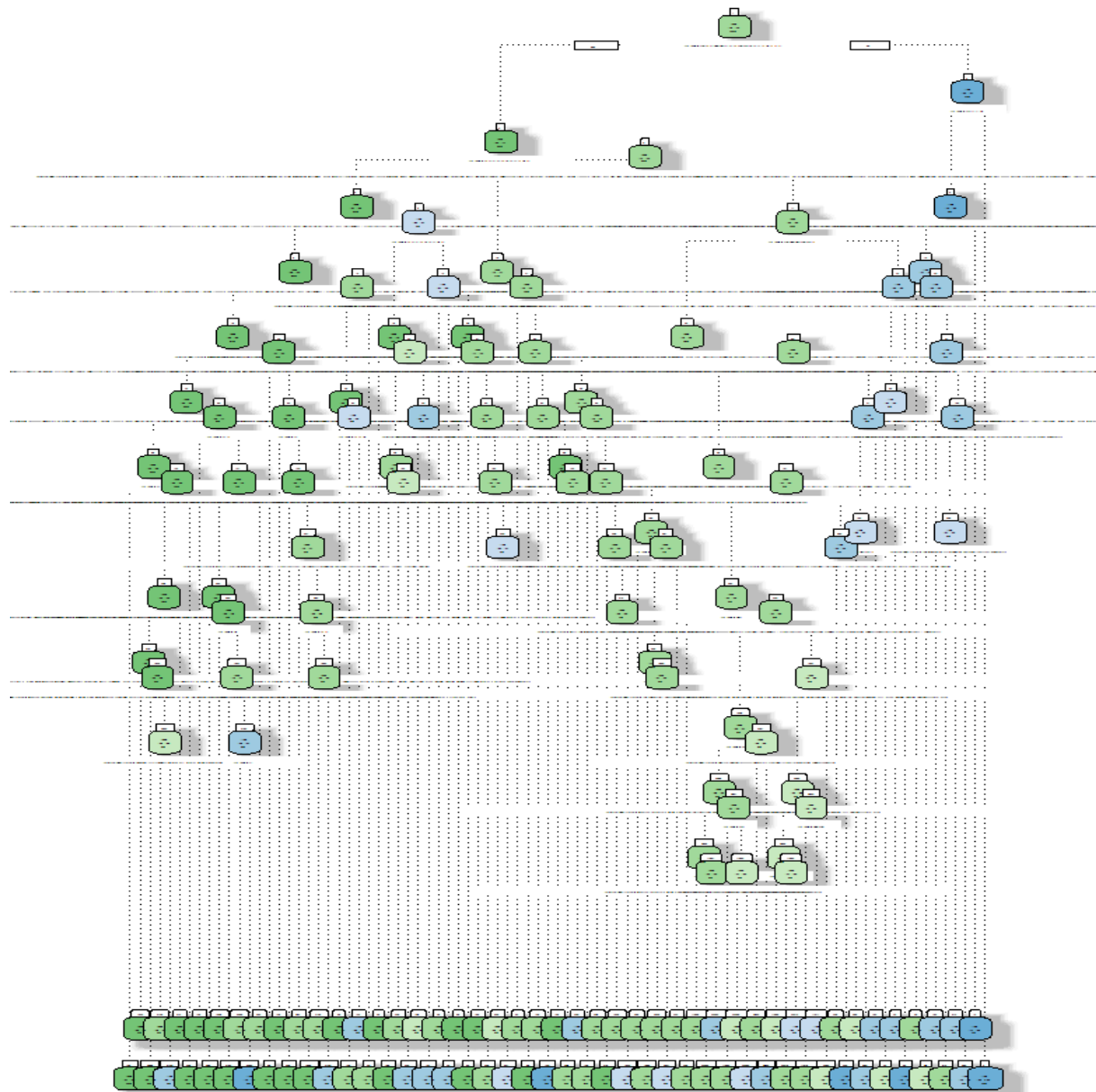
The max correct rate is around 27.5%. Which means this model only has about one fourth chance to get a correct prediction.

Unfortunately, this model is not a good model and may be *K*-nn is not useful on this dataset.



If a new case is reported, can police catch the suspect?

- The data contains primary type and location of the crimes, when a new case is reported, the police can use this model to know the arrested rate of the specified crime type. If the chance of catching the suspect is high, the police can use more force to catch the suspect in the short time.





Filtered Data

118,626 records

```
> table(dataset$FBI.Code)
```

| | | | | | | | | | | | | | | | |
|------|------|------|-------|-----|------|----|----|-------|------|------|-------|------|------|------|-------|
| 04A | 04B | 08A | 08B | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 18 | 26 | 3 | 5 | 6 |
| 2867 | 4669 | 6073 | 23962 | 414 | 3054 | 4 | 24 | 16757 | 2104 | 1161 | 17250 | 2151 | 6649 | 4855 | 26632 |

```
> table(dataset$Primary.Type)
```

| | | | | | | | | |
|-----------|--------------|----------|----------|--------|----------|-----------|-----------|----------|
| ASSAULT | BATTERY | BURGLARY | CRIMINAL | DAMAGE | CRIMINAL | TRESPASS | DECEPTIVE | PRACTICE |
| 8940 | 28631 | 4855 | | 16757 | | 1816 | | 3496 |
| NARCOTICS | PROSTITUTION | ROBBERY | | THEFT | WEAPONS | VIOLATION | | |
| 17585 | 1161 | 6649 | | 26632 | | 2104 | | |

```
> table(dataset$Location.Description)
```

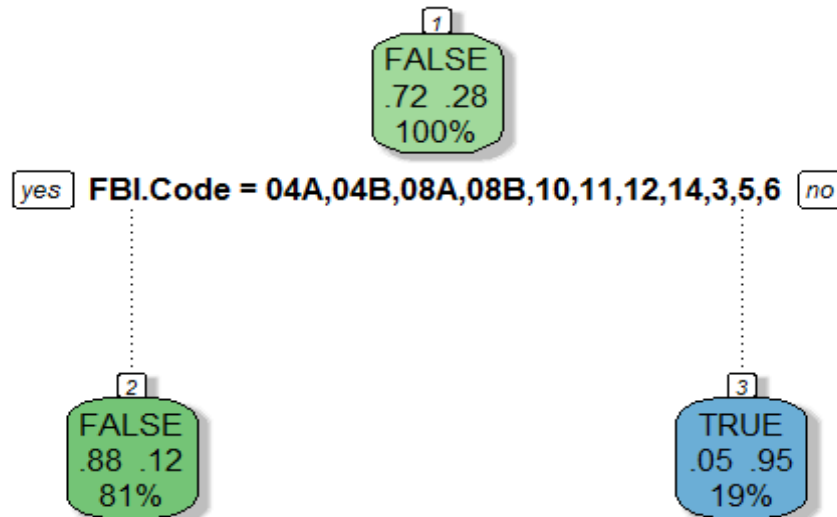
| | | | |
|-----------|---------|---------------------------|------------------------|
| APARTMENT | PARKING | LOT/GARAGE (NON. RESID.) | RESTAURANT |
| 30482 | | 6476 | 4755 |
| SIDEWALK | | STREET | VEHICLE NON-COMMERCIAL |
| 25298 | | 47606 | 4009 |



| CRIME CATEGORIES (NIBRS CODE) | UNIFORM CRIME REPORTING (UCR) CODE AND DESCRIPTION |
|--|--|
| ALL CRIME | INCLUDES ALL CRIME CATEGORIES |
| INDEX CRIME DEFINITION: MORE SERIOUS OFFENSES. | <u>INCLUDES THE FOLLOWING CRIME CATEGORIES (SEE BELOW)</u> HOMICIDE 1ST & 2ND DEGREE (01A) (INDEX) CRIMINAL SEXUAL ASSAULT (02) (INDEX) ROBBERY (03) (INDEX) AGGRAVATED ASSAULT (04A) (INDEX) AGGRAVATED BATTERY (04B) (INDEX) BURGLARY (05) (INDEX) LARCENY (06) (INDEX) MOTOR VEHICLE THEFT (07) (INDEX) ARSON (09) (INDEX) |
| NON-INDEX CRIME DEFINITION: LESS SERIOUS OFFENSES. | <u>INCLUDES THE FOLLOWING CRIME CATEGORIES (SEE BELOW)</u> INVOLUNTARY MANSLAUGHTER (01B) SIMPLE ASSAULT (08A) SIMPLE BATTERY (08B) FORGERY & COUNTERFEITING (10) FRAUD (11) EMBEZZLEMENT (12) STOLEN PROPERTY (13) VANDALISM (14) WEAPONS VIOLATION (15) PROSTITUTION (16) CRIMINAL SEXUAL ABUSE (17) DRUG ABUSE (18) GAMBLING (19) OFFENSES AGAINST FAMILY (20) LIQUOR LICENSE (22) DISORDERLY CONDUCT (24) MISC NON-INDEX OFFENSE (26) |
| VIOLENT CRIME DEFINITION: CRIME RELATED TO VIOLENCE | <u>INCLUDES THE FOLLOWING CRIME CATEGORIES (SEE BELOW)</u> HOMICIDE 1ST & 2ND DEGREE (01A) (INDEX) CRIMINAL SEXUAL ASSAULT (02) (INDEX) ROBBERY (03) (INDEX) AGGRAVATED ASSAULT (04A) (INDEX) AGGRAVATED BATTERY (04B) (INDEX) |
| PROPERTY CRIME DEFINITION: CRIME RELATED TO PROPERTY | <u>INCLUDES THE FOLLOWING CRIME CATEGORIES (SEE BELOW)</u> BURGLARY (05) (INDEX) LARCENY (06) (INDEX) MOTOR VEHICLE THEFT (07) (INDEX) ARSON (09) (INDEX) |

Rpart without using parameter

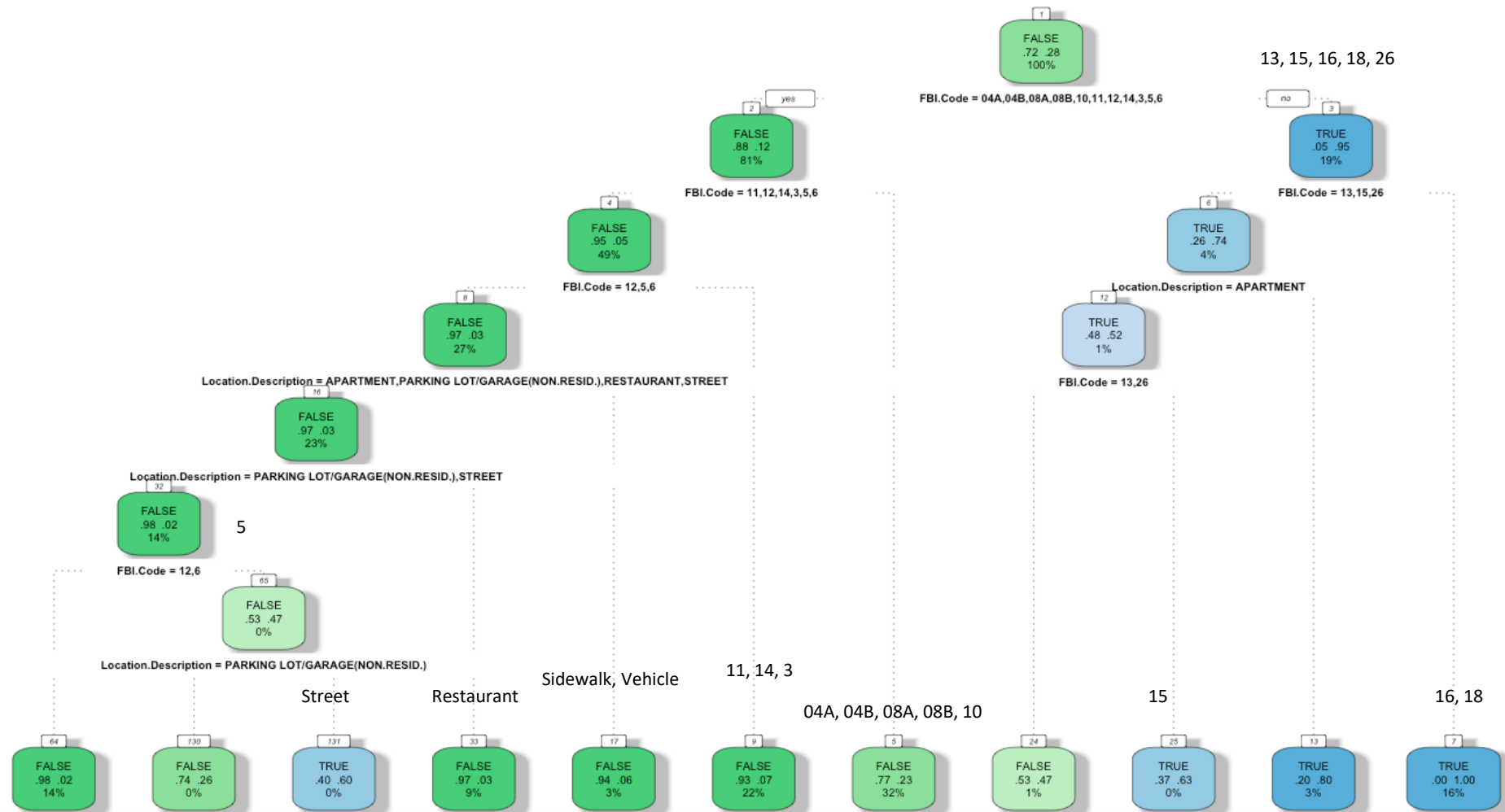
```
mytree <- rpart(Arrest~Location.Description+FBI.Code,  
  data = dataset, method = "class")
```





```
mytree <- rpart(Arrest~Location.Description+FBI.Code, data =  
  dataset, method = "class", control = rpart.control(minbucket  
  = 9, cp=0.00001))
```

- minbucket: the minimum number of observations in any terminal <leaf> node.
- cp : complexity parameter.





Statistical Results

- Arrest rate is low, only 19% are caught in most common type.
- Only 2% of Theft & Embezzlement are caught.
- The crimes happened in restaurant mostly can't catch the criminal suspect.
- Nearly all suspects of the Narcotics & Prostitution are caught.

Summary



STEVENS
INSTITUTE *of* TECHNOLOGY
THE INNOVATION UNIVERSITY®

Thank you!

