

Final Project

Due 4-27-2018

Introduction

Baltimore, Maryland, just the name of the city brings to mind countless forms of illegality and the varied levels of force spent to counteract such actions. Whether it be the spike in recent carjackings from 2017 and the judicial systems lax consequences against the youth committing the crimes or Freddie Grey's death in the back seat of a police van after not being secured by officers after his arrest for possession of an illegal knife, Baltimore remains a city centered on the yin and yang between crimes committed and the response to those crimes. To help people better understand the Baltimore's crime as well as add transparency to what police officers are up against, the Baltimore Police Department released crime statistics going back to December 2011. The statistics are open for interaction in many ways including downloading as a .csv file, visualizing through plot.ly, and access through a SODA API. In addition, this dataset was made available on kaggle.com for kernels to be produced on the data. The goal of this project is better understand the behaviors associated with many different types of crimes in the city of Baltimore.

Methods

The data was downloaded as a .csv file from <https://www.kaggle.com/sohier/crime-in-baltimore> and read into R for analysis. Upon inspection, the data set contained crime and arrest records back to 12/15/2011. The set is 276,529 rows of 15 columns including: CrimeDate, Location, Description, Inside/Outside, District, Neighborhood, and Total Incidents. A little bit of exploratory data analysis was done to spur the questions the following hypotheses attempt to answer. Finally, F tests were used to determine relationships of variance as well as whether variances were equal in mean tests. T-tests were used to determine differences or equality of means after checking equality of variances. If the equal variances requirement was violated, a Wilcoxon rank sum test was used. In comparing percents, a two proportion z test was used to determine differences. Finally, in looking at multiple means, an ANOVA was used to check

differences with a Tukey HSD determining which pairs were significantly different.

	CrimeDate	CrimeTime	CrimeCode	Location	Description	Inside/Outside	Weapon
1	9/2/2017	23:30:00	3JK	4200 AUDREY AVE	ROBBERY - RESIDENCE	I	KNIFE
2	9/2/2017	23:00:00	7A	800 NEWINGTON AVE	AUTO THEFT	O	NA
3	9/2/2017	22:53:00	9S	600 RADNOR AV	SHOOTING	Outside	FIREARM
4	9/2/2017	22:50:00	4C	1800 RAMSAY ST	AGG. ASSAULT	I	OTHER
5	9/2/2017	22:31:00	4E	100 LIGHT ST	COMMON ASSAULT	O	HANDS
6	9/2/2017	22:00:00	5A	CHERRYCREST RD	BURGLARY	I	NA
7	9/2/2017	21:15:00	1F	3400 HARMONY CT	HOMICIDE	Outside	FIREARM
8	9/2/2017	21:35:00	3B	400 W LANVALE ST	ROBBERY - STREET	O	NA
9	9/2/2017	21:00:00	4C	2300 LYNDBURST AVE	AGG. ASSAULT	O	OTHER
10	9/2/2017	21:00:00	4E	1200 N ELLWOOD AVE	COMMON ASSAULT	I	HANDS
11	9/2/2017	21:00:00	4C	2300 LYNDBURST AVE	AGG. ASSAULT	O	OTHER
12	9/2/2017	20:56:00	3CF	3600 EDMONDSON AVE	ROBBERY - COMMERCIAL	I	FIREARM
13	9/2/2017	20:55:00	6C	5100 PARK HEIGHTS AVE	LARCENY	NA	NA
14	9/2/2017	20:10:00	4C	3900 GWYNNS FALLS PKWY	AGG. ASSAULT	O	OTHER
15	9/2/2017	20:00:00	6D	5500 SUMMERFIELD AVE	LARCENY FROM AUTO	O	NA

Hypotheses

Test 1: Are the number of Arson committed in one month more varied in the Winter months (December, January, and February) in comparison to the other nine months?

$$H_0 : \sigma_{Winter}^2 = \sigma_{SprSumWin}^2$$

$$H_1 : \sigma_{Winter}^2 > \sigma_{SprSumWin}^2$$

Test 2: Are there more Auto Thefts on Weekends over Weekdays?

$$H_0 : \mu_{Weekend} = \mu_{Weekday}$$

$$H_1 : \mu_{Weekend} > \mu_{Weekday}$$

Test 3: On a given night are there more shootings inside a residence than outside?

$$H_0 : M_{Inside} = M_{Outside}$$

$$H_1 : M_{Inside} < M_{Outside}$$

Test 4: On any given day, if you are assaulted, is it more likely to be a common assault?

$$H_0 : \mu_{CommonAssault} = \mu_{AggAssault}$$

$$H_1 : \mu_{CommonAssault} > \mu_{AggAssault}$$

Test 5: Is there a district with a distinctly higher number of Burglary's in the Summer months? If so, which are significantly different?

$$H_0 : \mu_{Cent} = \mu_E = \mu_{NE} = \mu_N = \mu_{NW} = \mu_{SE} = \mu_S = \mu_{SW} = \mu_W$$

$$H_1 : \text{At least one mean is different.}$$

Results

Test 1: Are the number of arson committed in one month more varied in the Winter months (December, January, and February) in comparison to the other nine months?

Data Cleaning

There were 1,464 arson recorded in this data set. When we separate them out by month, split them into Spring, Summer, and Fall (SprSumFall) and Winter divides them into a usable frame.

Statistical Test

In order to find out if the arson are more varied in a Winter month, we should use an F test to compare the variances. Now that the two groups are divided, we calculate the sample variances and degrees of freedom for each group. Finally, we find the F statistic($F = 0.5954$) for our variance pair.

Test 2: Are there more Auto Thefts on Weekends over Weekdays?

Data Cleaning

To prep the data to be worked on, we should filter down the whole table down to 28,366 robberies, carjackings, and auto thefts. Using the *wday* function from the **lubridate** package, we need a label for each day and we need to split the incidents into two data frames titled 'weekday' and 'weekend'. Once finished, we should tally up all the events grouped on Date and looked at the distributions to make sure a test on means was appropriate. With normal distributions in both plots, we can move on to check the variances of the two groups.

Statistical Test(s)

After checking the normal distributions, we should run an F test to on the variances to make sure they were not unequal. I used the F test to make sure the test statistic was under the rejection region. The F test turned up not to be statistically significant. With the variances checked, we can move forward with testing the means with a t-test.

Test 3: On a given night are there more shootings outside a residence than inside?

Data Cleaning

To begin, we trimmed the data set down to just shootings after 5 PM of each day. Upon filtering, we sum up each group of inside and outside shootings by date. After grouping on location, we look at the bar graphs to see what distribution this scenario fits.

Statistical Test

Given the fact that they were skewed right, we should use the non-parametric Wilcoxon Rank Sum test to determine if one group was shifted farther to the right than the other.

Test 4: On a given day if you are assaulted, is it more likely to be a common assault?

Data Cleaning

To arrive at probabilities of Common vs. Aggravated Assaults, we filter the crime down to those two, summed up the total incidents of each group by day and divided them by the total number of Assaults. Finally, we graphed the two distributions making sure the distributions were normally distributed.

Statistical Test

With normally distributed distributions, we take to evaluating if the mean of the probability of falling victim to a common assault was less than that of an aggravated assault. A t-test to evaluate if that was the case will suffice.

Test 5: Is there a District with a distinctly higher number of Burglary's in the Summer Months? If so, which are significantly different?

Data Cleaning

To begin, we pull out only the Summer months data for Burglaries, grouped by Month/Year, and summarized the total number of incidents. There was a District equal to 'NA' that was filtered out. After compiling all the data into a workable form, we graph the residual scatterplot, histogram of residuals, and Normal Q-Q plot. Seeing nothing remarkable, it is safe to move forward with an ANOVA.

Statistical Test

Seeing no issues with the ANOVA plots barring one outlier, we can go forward to check to see if at least one mean was different than the rest. Then, if significant we can use Tukey's post hoc test to determine pairwise differences.

Results

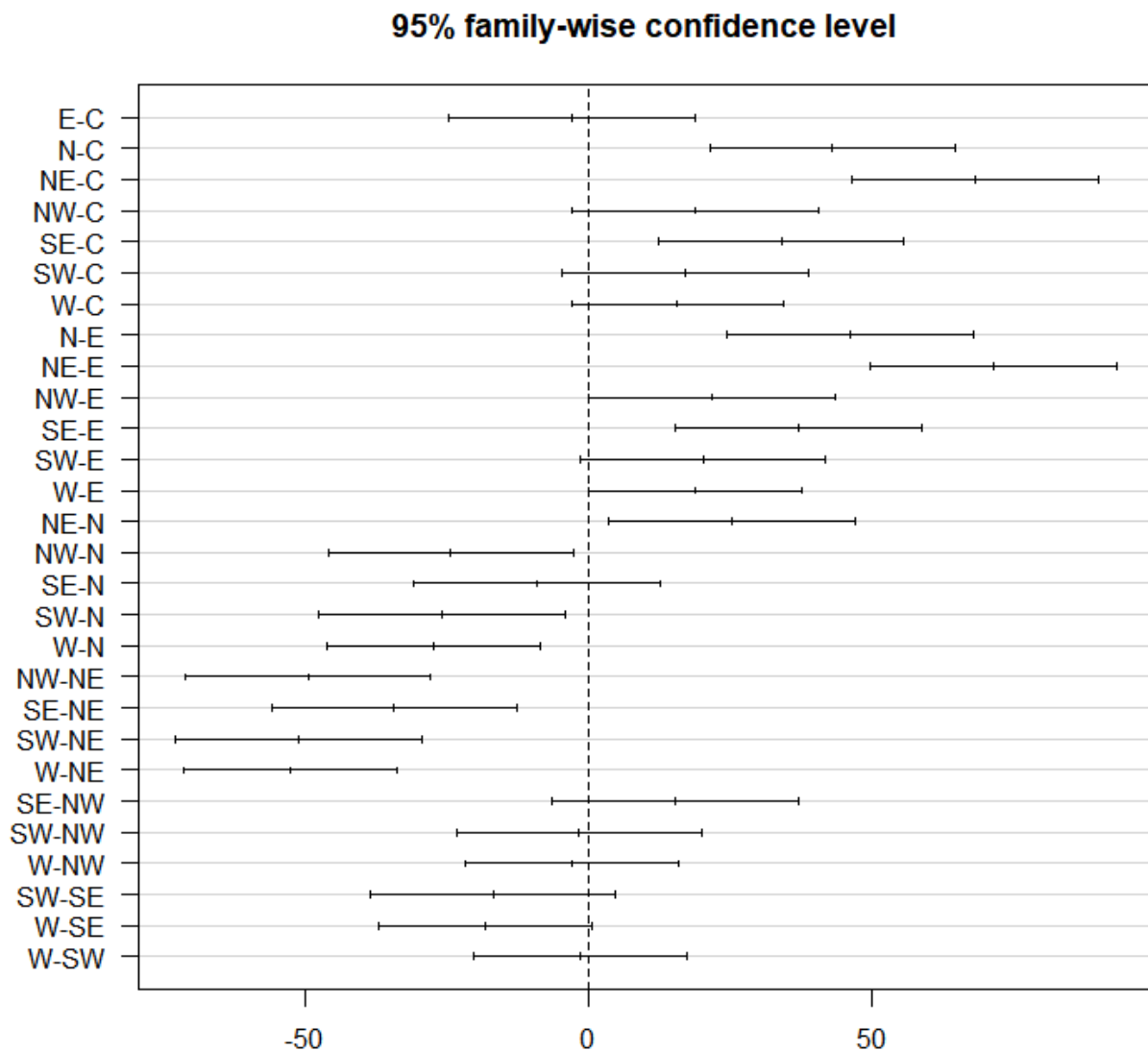
- In regards to arson and their variation in Winter months compared to the other three seasons, the F test statistic is lower than the rejection region, we did not have sufficient evidence to reject the hypothesis that the count of arson in the Winter months are different for the other three seasons. It

does not appear to show a difference in variation.

- Given that the variances were checked, we moved forward with a t-test to check the mean values of weekend auto thefts in comparison to weekday auto tests. The t-test yielded a value of -1.503. With a p-value of 0.1203, we deem this result not statistically significant at the 5% α level. We do not have proof that auto thefts increase on the weekends.
- After determining the test, I ran the Wilcoxon Tank Sum test on the data and arrived at a p-value of 3.6623×10^{-23} . Therefore, there is evidence to reject the null hypothesis that the median number of Shootings inside and outside of a building on a given night are the same. It appears there are more shootings outside a residence at night than inside.
- The results came back statistically significant with a test statistic of $\chi^2 = 8876.888$ which equates to a Z-score of $\sqrt{8876.888} = 94.217$. The p-value associated with the test statistic is 2×10^{-16} . Thus, it does appear that, if one is assaulted, they are more likely to be assaulted in the form of a Common Assault as opposed to an Aggravated Assault.
- My ANOVA came back statistically significant with an F value of 32.54. Having validated that at least one mean was different, I proceeded with a TukeyHSD to check which pairs were different. The following list reflects the hierarchy determined by the Statistically Significant pairwise differences:
 1. The Northeastern District has distinctly larger number of burglaries than all other groups.
 2. The Northwestern District has a distinctly larger number of burglaries than the Western, Northern, and Eastern.
 3. The Southern District has a distinctly larger number of burglaries in the Summer months over the Central, Eastern, and the Southwest.
 4. The Southwest District has a distinctly larger number of burglaries in the Summer months over the Eastern, Northern, and the Western districts.
 5. The Western District has a distinctly larger number of burglaries in the Summer months over the Northern and southern Districts.

6. The Northern District has a distinctly larger number of burglaries in the Summer months over the Central and Eastern Districts.

7. The Southeastern District has a distinctly larger number of burglaries in the Summer months over the Central and Eastern Districts.



Conclusion

With so much data within this data set, this analysis hardly counts as a tip of the iceberg in identifying relationships between Crime(s) in Baltimore. Going forward, more exhaustive analysis should be performed

to identify actionable trends over time that the city could remedy or capitalize on to increase quality of life for its citizens. Additionally, building a mathematical model that *explains* crime numbers in the different neighborhoods could aid the city of Baltimore. All in all, Baltimore Police Department keeping transparency at the forefront empowers citizens in and out of Baltimore to help turn around crime's hold on the city's residents.

References

City of Baltimore. (2017). BPDPart1VictimBasedCrimeData [Data file]. Retrieved from <https://www.kaggle.com/sohier/crime-in-baltimore/data>.

Initial Analysis

Kyle Ligon

Read the data in and library calls

```
library(tidyverse)
library(zoo)
library(lubridate)
library(gridExtra)

crime <- read_csv("BPD_Part_1_Victim_Based_Crime_Data.csv", progress = FALSE)
```

Looking at the data

```
head(crime)

## # A tibble: 6 x 15
##   CrimeDate CrimeTime CrimeCode Location      Description `Inside/Outside`
##   <chr>      <time>      <chr>      <chr>      <chr>          <chr>
## 1 9/2/2017  23:30      3JK      4200 AUDRE~ ROBBERY - RE~ I
## 2 9/2/2017  23:00      7A       800 NEWING~ AUTO THEFT  0
## 3 9/2/2017  22:53      9S       600 RADNOR~ SHOOTING    Outside
## 4 9/2/2017  22:50      4C       1800 RAMSA~ AGG. ASSAULT I
## 5 9/2/2017  22:31      4E       100 LIGHT ~ COMMON ASSAU~ 0
## 6 9/2/2017  22:00      5A      CHERRYCRE~ BURGLARY    I
## # ... with 9 more variables: Weapon <chr>, Post <int>, District <chr>,
## #   Neighborhood <chr>, Longitude <dbl>, Latitude <dbl>, `Location
## #   1` <chr>, Premise <chr>, `Total Incidents` <int>

names(crime)

## [1] "CrimeDate"      "CrimeTime"      "CrimeCode"
## [4] "Location"       "Description"     "Inside/Outside"
## [7] "Weapon"         "Post"           "District"
## [10] "Neighborhood"   "Longitude"       "Latitude"
## [13] "Location 1"     "Premise"         "Total Incidents"
```

Looks like we have information about the crime, where it happened, when it happened, what happened in the form of Description, and the responding Post.

Counting up the Number of Crimes

```
descCounts <- crime %>%
  group_by(Description) %>%
  tally() %>%
  arrange(desc(n))

descCounts

## # A tibble: 15 x 2
##   Description      n
##   <chr>          <int>
```

```
## 1 LARCENY 60528
## 2 COMMON ASSAULT 45518
## 3 BURGLARY 42538
## 4 LARCENY FROM AUTO 36295
## 5 AGG. ASSAULT 27513
## 6 AUTO THEFT 26838
## 7 ROBBERY - STREET 17691
## 8 ROBBERY - COMMERCIAL 4141
## 9 ASSAULT BY THREAT 3503
## 10 SHOOTING 2910
## 11 ROBBERY - RESIDENCE 2866
## 12 RAPE 1637
## 13 HOMICIDE 1559
## 14 ROBBERY - CARJACKING 1528
## 15 ARSON 1464
```

Counting up Where the Crimes Occurred

```
hoodCounts <- crime %>%
  group_by(Neighborhood) %>%
  tally() %>%
  arrange(desc(n))
head(hoodCounts)
```

```
## # A tibble: 6 x 2
##   Neighborhood      n
##   <chr>          <int>
## 1 Downtown      9048
## 2 Frankford     6642
## 3 Belair-Edison 5977
## 4 Brooklyn     4516
## 5 Cherry Hill   4086
## 6 Sandtown-Winchester 4026
```

Let's focus on Arsons. Particularly, let's see if the number of Arsons committed in one month are more varied in the winter months than in the other nine months of the year. For this I will:

- Summarize the number of arsons by month
- Run an F test on number of arsons between the two groups
- Write a conclusion for the test

1) Are the distributions of arsons in the winter months less varied than other 9 months?

```
arsons <- crime %>%
  filter(Description == "ARSON")
head(arsons)
```

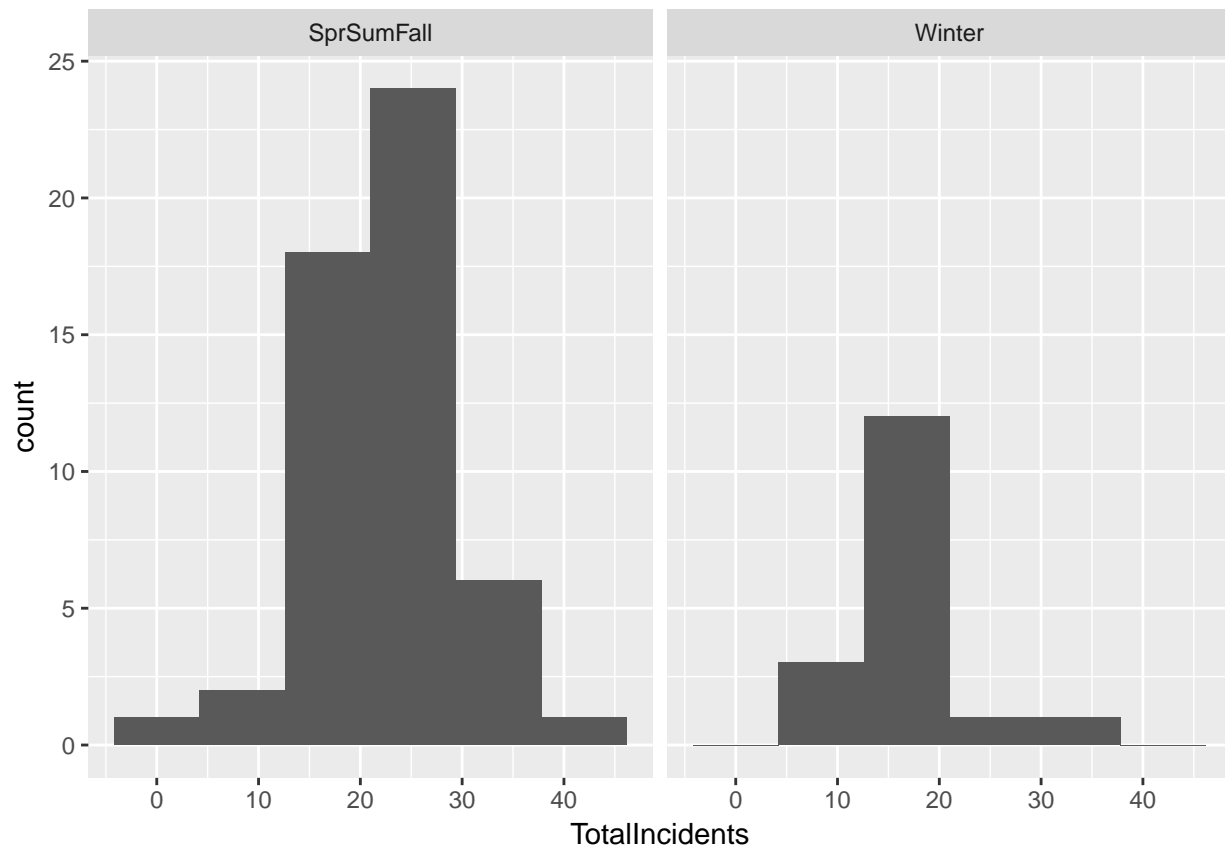
```
## # A tibble: 6 x 15
##   CrimeDate CrimeTime CrimeCode Location Description `Inside/Outside`
##   <chr>      <time>    <chr>   <chr>      <chr>      <chr>
## 1 9/1/2017  22:00      8A0     300 N FREMON~ ARSON      I
## 2 8/30/2017 22:00      8H     2600 FLORA ST ARSON      <NA>
```

```
## 3 8/30/2017 19:30      8H      3700 CLIFTMO~ ARSON      0
## 4 8/30/2017 15:26      8AV     4600 PARK HE~ ARSON      I
## 5 8/29/2017 03:30      8H      800 RAPPOLLA~ ARSON     <NA>
## 6 8/28/2017 06:50      8H      3300 TIVOLY ~ ARSON      0
## # ... with 9 more variables: Weapon <chr>, Post <int>, District <chr>,
## #   Neighborhood <chr>, Longitude <dbl>, Latitude <dbl>, `Location
## #   1` <chr>, Premise <chr>, `Total Incidents` <int>
```

Checking the dimensions of the new frame

```
dim(arsons)
```

```
## [1] 1464    15
```



With “normal” distributions, we will proceed with the hypotheses.

Hypotheses: $H_0: \text{var_Winter} = \text{var_SprSumFall}$ $H_1: \text{var_Winter} < \text{var_SprSumFall}$

Variance of the Winter Months

```
#degrees of freedom for W
arsons_grouped %>% filter(WinterBin == "Winter") %>% tally() - 1
```

```
##      n
## 1 16
```

```
var_W
```

```
## # A tibble: 1 x 1
##   Variance
##     <dbl>
```

```
## 1      27.3
```

Variance of the Other Months

```
arsons_grouped %>% filter(WinterBin != "Winter") %>% tally() - 1
```

```
##      n
```

```
## 1 51
```

```
var_SSF
```

```
## # A tibble: 1 x 1
```

```
##   Variance
```

```
##   <dbl>
```

```
## 1      45.9
```

Test Statistic for F Test

```
f <- as.numeric(round(var_W/var_SSF, 4))
```

```
f
```

```
## [1] 0.5945
```

Rejection Region

```
qf(0.975, 16, 51)
```

```
## [1] 2.075301
```

```
f < qf(0.025, 16, 51)
```

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

```
f > qf(0.975, 16, 51)
```

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

Since our F Test Statistic is not larger and not smaller than the F Stat for alpha, we do not have enough evidence to reject the null hypothesis that the variances are equal. It does not appear that the the Winter months experience a less varied number of arsons than the other 9 months.

2) Are there more Auto Thefts on Weekends over Weekdays?

```
auto_thefts <- crime %>%  
  filter(Description %in% c("ROBBERY - CARJACKING", "AUTO THEFT"))  
head(auto_thefts)
```

```
## # A tibble: 6 x 15
```

```
##   CrimeDate CrimeTime CrimeCode Location      Description `Inside/Outside`
```

```
##   <chr>      <time>    <chr>    <chr>      <chr>      <chr>
```

```
## 1 9/2/2017  23:00      7A       800 NEWINGTO~ AUTO THEFT  0
```

```
## 2 9/2/2017  08:00      7A       4700 HOMESDA~ AUTO THEFT  I
```

```
## 3 9/2/2017  02:00      7C       1500 RUSSELL~ AUTO THEFT  0
```

```
## 4 9/1/2017  22:30      7A       300 E LORRAI~ AUTO THEFT  0
```

```
## 5 9/1/2017  21:30      7A       3500 CHESTER~ AUTO THEFT  0
```

```
## 6 9/1/2017  20:45      7A       OSTEND ST & ~ AUTO THEFT  0
```

```
## # ... with 9 more variables: Weapon <chr>, Post <int>, District <chr>,  
## #   Neighborhood <chr>, Longitude <dbl>, Latitude <dbl>, `Location`
```

```
## #   1` <chr>, Premise <chr>, `Total Incidents` <int>
```

```

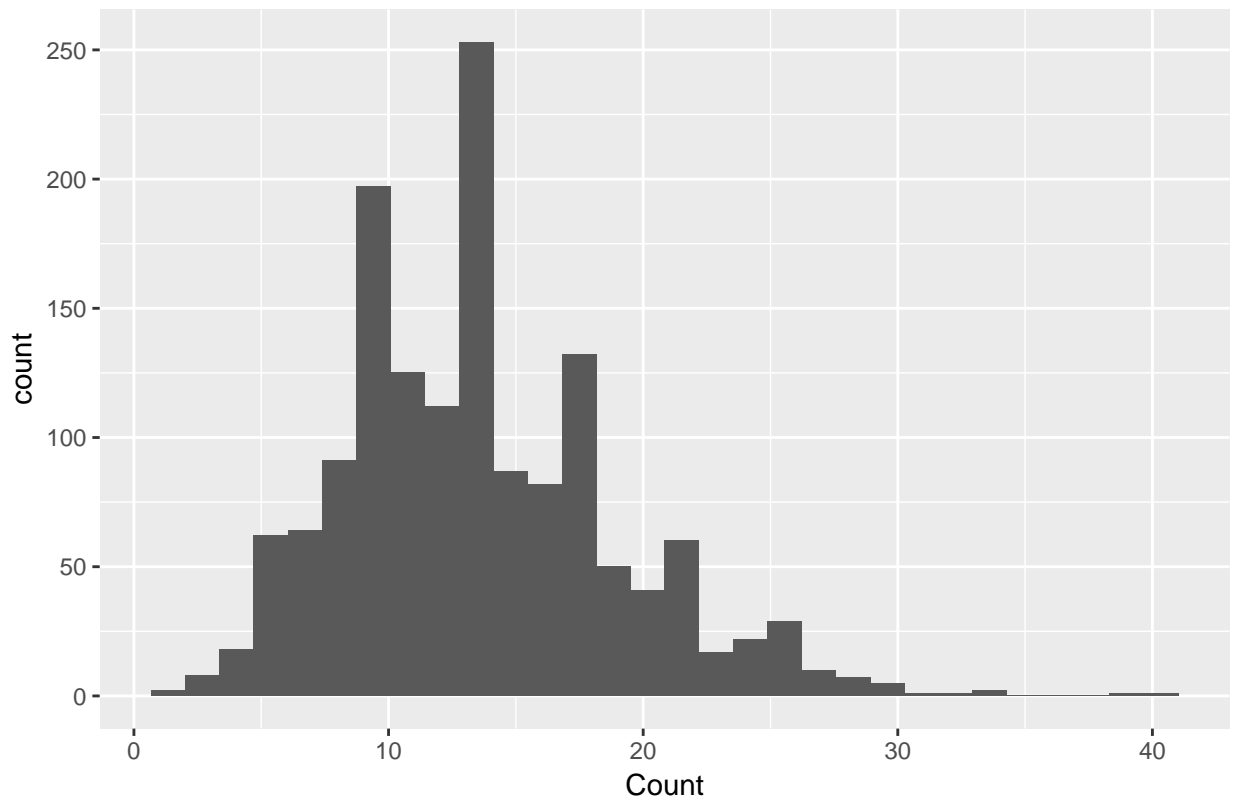
at_form <- auto_thefts %>%
  mutate(CrimeDate= as.Date(CrimeDate, format = "%m/%d/%Y"),
         DateName = wday(CrimeDate, label = TRUE))
weekend <- at_form %>%
  filter(DateName %in% c("Sat", "Sun")) %>%
  group_by(CrimeDate, DateName) %>%
  summarize(Count = sum(`Total Incidents`))

weekday <- at_form %>%
  filter(!(DateName %in% c("Sat", "Sun"))) %>%
  group_by(CrimeDate, DateName) %>%
  summarize(Count = sum(`Total Incidents`))

ggplot(data = weekday, aes(x = Count)) + geom_histogram() + ggtitle("Weekday Distribution")

```

Weekday Distribution

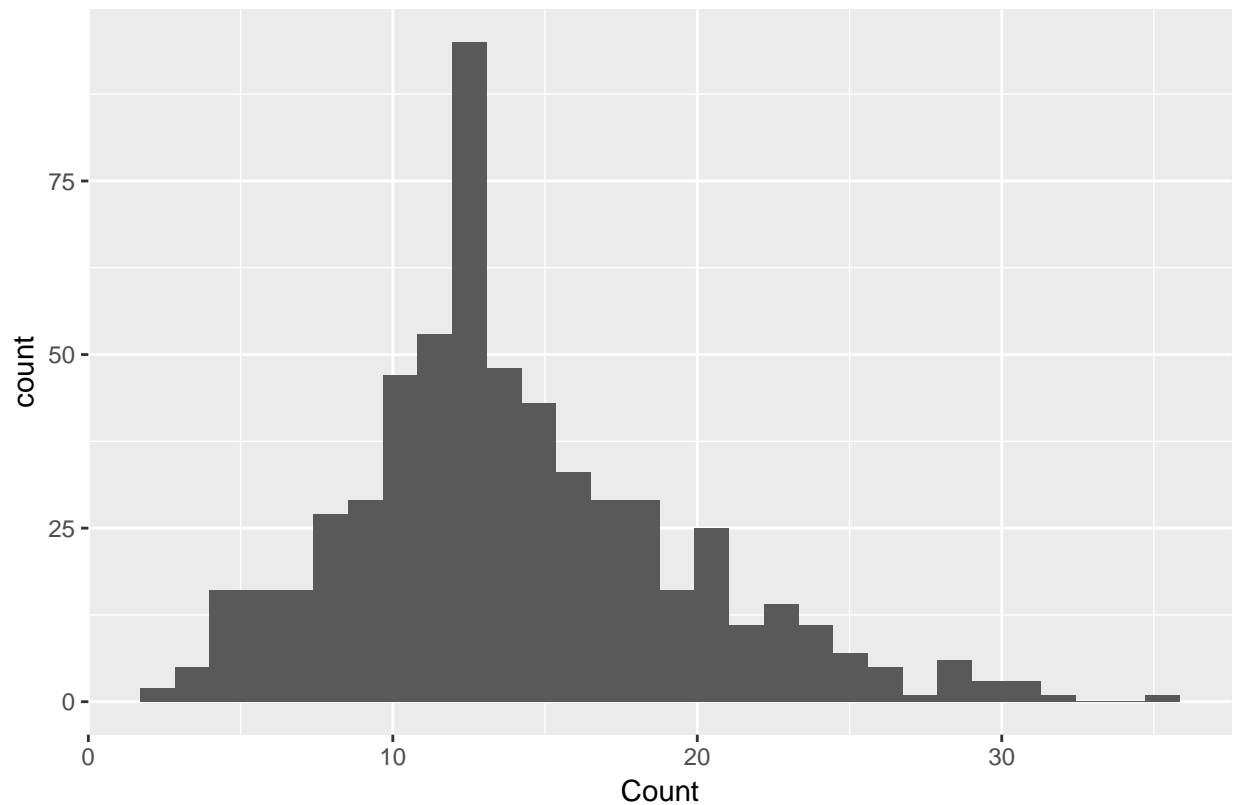


```

ggplot(data = weekend, aes(x = Count)) + geom_histogram() + ggtitle("Weekend Distribution")

```

Weekend Distribution



With our data cleaned, we can now go about testing to see if the mean of the weekend set is larger than the mean of the weekday set. But first... equal variance check. Which, is just an F test:

H_0: Var_Weekday = var_Weekend H_1: var_Weekday < var_weekend

```
#Weekday Variance
var(weekday$Count)
```

```
## [1] 28.16756
```

```
#df of Weekday
nrow(weekday)-1
```

```
## [1] 1479
```

```
#Weekend Variance
var(weekend$Count)
```

```
## [1] 30.29062
```

```
#df of Weekends
nrow(weekend)-1
```

```
## [1] 591
```

Test Statistic

```
f_w <- var(weekday$Count)/var(weekend$Count)
f_w
```

```
## [1] 0.9299104
```

Rejection Region:

```
up <- qf(0.975, 1479, 591)
up
```

```
## [1] 1.146795
```

```
dwn <- qf(0.025, 1479, 591)
dwn
```

```
## [1] 0.8754564
```

```
f_w > up
```

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

```
f_w < dwn
```

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

Conclusion: Since our F Stat was less than the upper rejection region and more than the lower rejection region, we do not have enough evidence to reject the hypothesis that the variances are equal. It does not appear that the variances are different. Now we can test the means.

Hypotheses: H_0 : mean_weekday = mean_weekend H_1 : mean_weekday < mean_weekend

Test Statistic:

```
t.test(x = weekday$Count, y = weekend$Count)
```

```
##
```

```
## Welch Two Sample t-test
```

```
##
```

```
## data: weekday$Count and weekend$Count
```

```
## t = -1.5301, df = 1054.2, p-value = 0.1263
```

```
## alternative hypothesis: true difference in means is not equal to 0
```

```
## 95 percent confidence interval:
```

```
## -0.9252956 0.1144848
```

```
## sample estimates:
```

```
## mean of x mean of y
```

```
## 13.57432 13.97973
```

Rejection Region

```
lower <- qt(0.05, 2070)
lower
```

```
## [1] -1.64559
```

```
-1.5301 < lower
```

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

Conclusion: Since -1.5301 is greater than our rejection region, we do not have enough proof to reject our null hypothesis that the means are the same. It does not appear that there are more Auto thefts on weekends in comparison to weekdays.

3) On a given night are there more shootings inside a residence than outside?

```
shootings <- crime %>%
# mutate(CrimeTime = strptime(CrimeTime, format = "%H:%M")) %>%
```

```

filter(Description == "SHOOTING", CrimeTime > "17:00") %>%
group_by(CrimeDate, `Inside/Outside`) %>%
summarize(Count = sum(`Total Incidents`))
head(shootings)

```

```

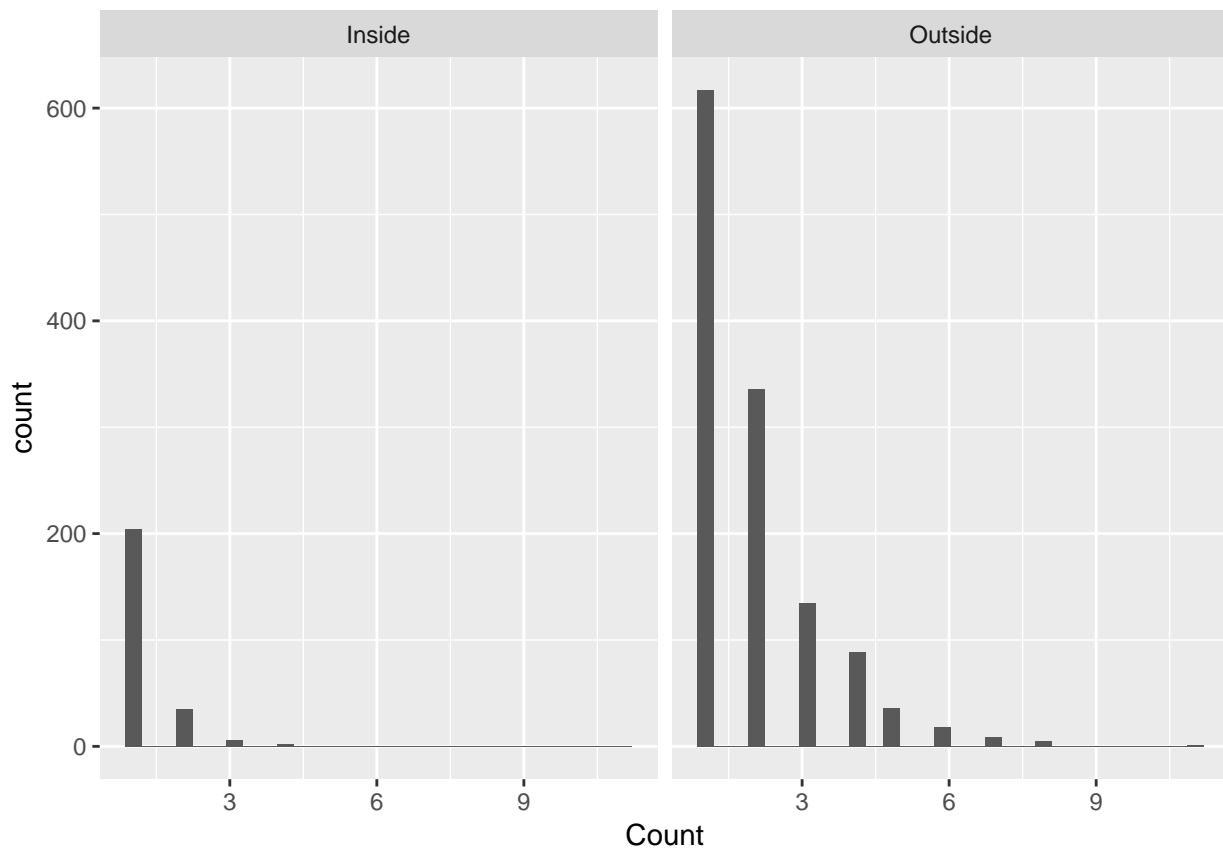
## # A tibble: 6 x 3
## # Groups:   CrimeDate [5]
##   CrimeDate `Inside/Outside` Count
##   <chr>      <chr>          <int>
## 1 1/1/2012   Outside              1
## 2 1/1/2013   Inside               1
## 3 1/1/2013   Outside              1
## 4 1/1/2014   Outside              2
## 5 1/1/2015   Outside              1
## 6 1/1/2016   Outside              3

```

```
dim(shootings)
```

```
## [1] 1493    3
```

```
ggplot(shootings, aes(x = Count)) + geom_histogram() + facet_grid(~ `Inside/Outside`)
```



With non-normal distributions, our route that we should run down is to check to see if the medians are different between the two groups. Using the Wilcoxon Rank Sum test, we'll see what if the outside median is larger than the inside median.

Hypothesis: $H_0: M_{\text{Inside}} = M_{\text{Outside}}$ $H_1: M_{\text{Inside}} > M_{\text{Outside}}$


```
w <- wilcox.test(Count ~ `Inside/Outside`, data = shootings, alternative = "greater")
```

Test Statistic

```
w$statistic
```

```
##      W  
## 98797
```

Rejection Region

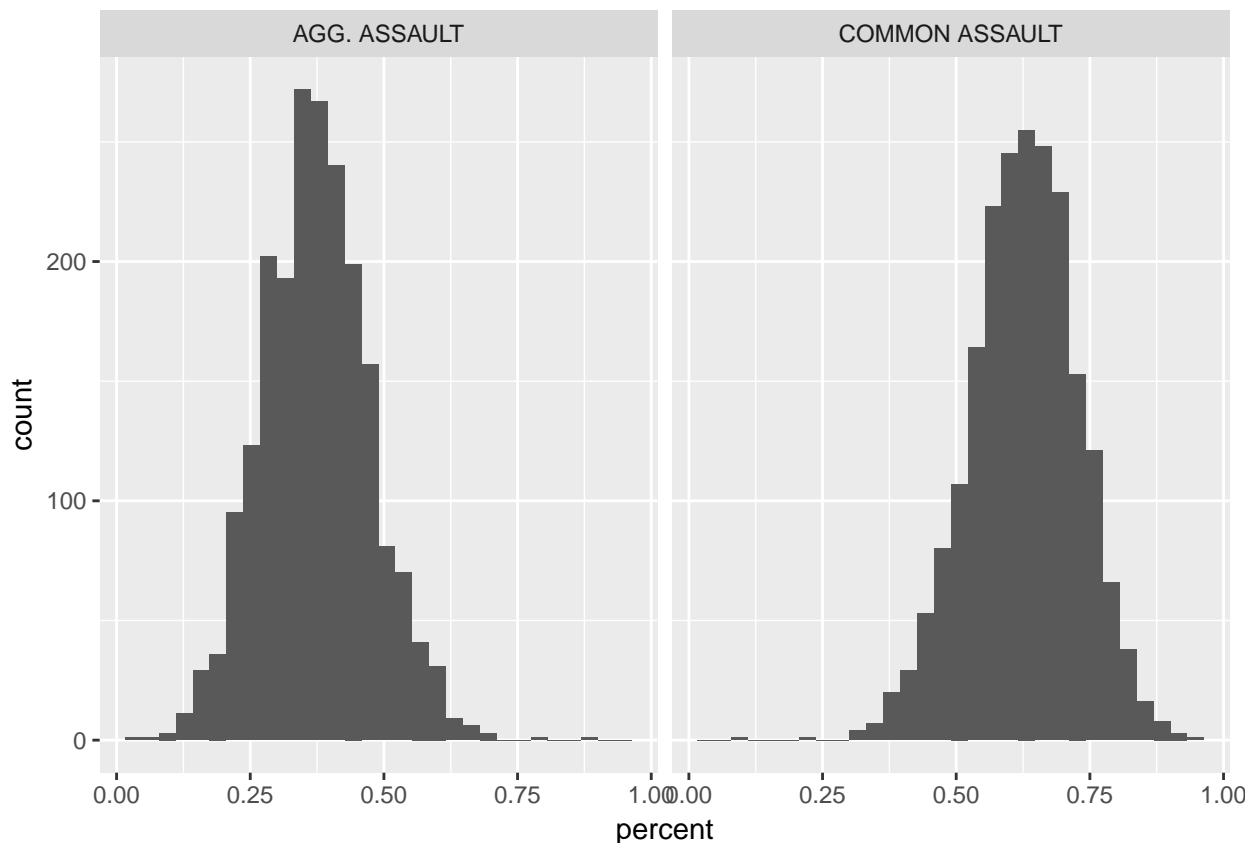
```
## [1] FALSE
```

Conclusion/Interpretation: Since our p-value is greater than 0.05, we do not have enough evidence to reject the null hypothesis that the Medians are the same. It does not appear there are more shootings inside a residence than outside.

4) On a given day if you are assaulted, is it more likely to be a common assault?

Hypotheses: H_0 : Mean_aggAssault = Mean_CommonAssault H_1 : Mean_aggAssault < Mean_CommonAssault

```
assaults <- crime %>%  
  filter(Description %in% c("AGG. ASSAULT", "COMMON ASSAULT")) %>%  
  select(CrimeDate, Description, `Total Incidents`) %>%  
  group_by(CrimeDate, Description) %>%  
  summarize(Total = sum(`Total Incidents`)) %>%  
  ungroup()  
  
day_merge <- assaults %>%  
  group_by(CrimeDate) %>%  
  summarize(Count = sum(Total))  
  
assaults <- assaults %>%  
  group_by(CrimeDate) %>%  
  left_join(day_merge) %>%  
  mutate(percent = Total/Count) %>%  
  ungroup() %>%  
  mutate(CrimeDate = as.Date(CrimeDate, format = "%m/%d/%Y")) %>%  
  arrange(desc(CrimeDate))  
  
ggplot(data = assaults, aes(x = percent)) + geom_histogram() + facet_grid(~Description)
```



```
assaults_split <- t.test(formula = percent ~ Description, data = assaults, alternative = "less")
```

Test Statistic/p-value

```
assaults_split$statistic
```

```
##          t
## -80.19273
```

```
assaults_split$p.value
```

```
## [1] 0
```

Conclusion: Since our p-value is less than 0.05, we have sufficient evidence to reject the null hypothesis that the means are the same. It appears that the Mean percent of the Aggravated Assault group is less than the Mean percent of the Common Assault.

5) Is there a District with a distinctly higher number of Burglary's in the Summer Months? If so, which are significantly different?

H₀: means are all the same H₁: at least one mean is different

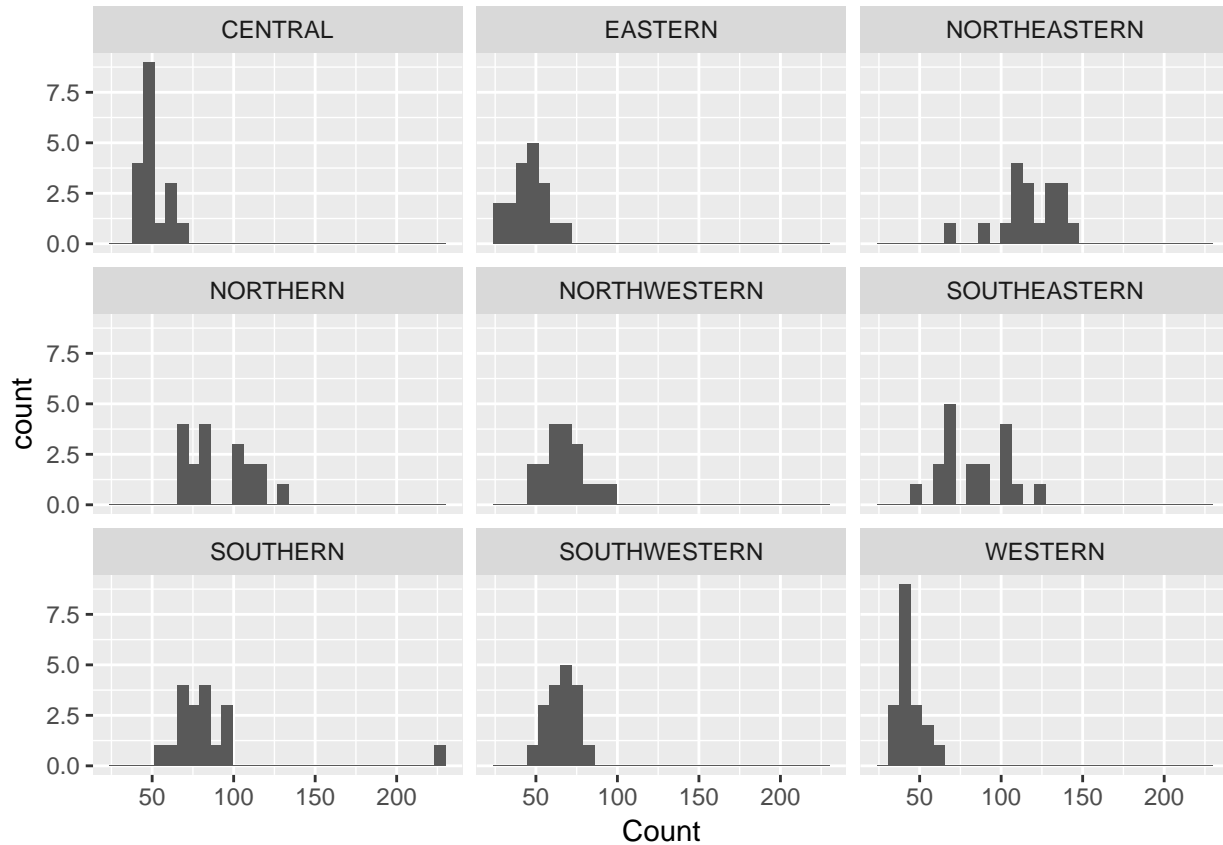
```
summer_burglaries <- crime %>%
  filter(substr(CrimeDate, 1,1) %in% c('6','7','8'), Description == "BURGLARY") %>%
  mutate(CrimeDate <- as.Date(CrimeDate, format = "%m/%d/%Y")) %>%
  mutate(YearMon = as.yearmon(CrimeDate, "%m/%d/%Y")) %>%
  group_by(District, YearMon) %>%
  summarize(Count = sum(`Total Incidents`)) %>%
```

```

    filter(District != "NA") %>%
    ungroup()

ggplot(data= summer_burglaries, aes(x = Count)) + geom_histogram() + facet_wrap(~ District)

```



Test Choice: Since there is a mess of distributions that appear to fit an ANOVA model, I'll use the ANOVA test to see if there's one mean that's different.

```

summer_burglaries <- summer_burglaries %>%
  mutate(District = as.factor(District))

sum_burg_anova_check <- aov(Count ~ District, data = summer_burglaries)

y <- quantile(sum_burg_anova_check$residuals[!is.na(sum_burg_anova_check$residuals)], c(0.25, 0.75))
x <- qnorm(c(0.25, 0.75))
slope = diff(y)/diff(x)
int <- y[1L] - slope*x[1L]

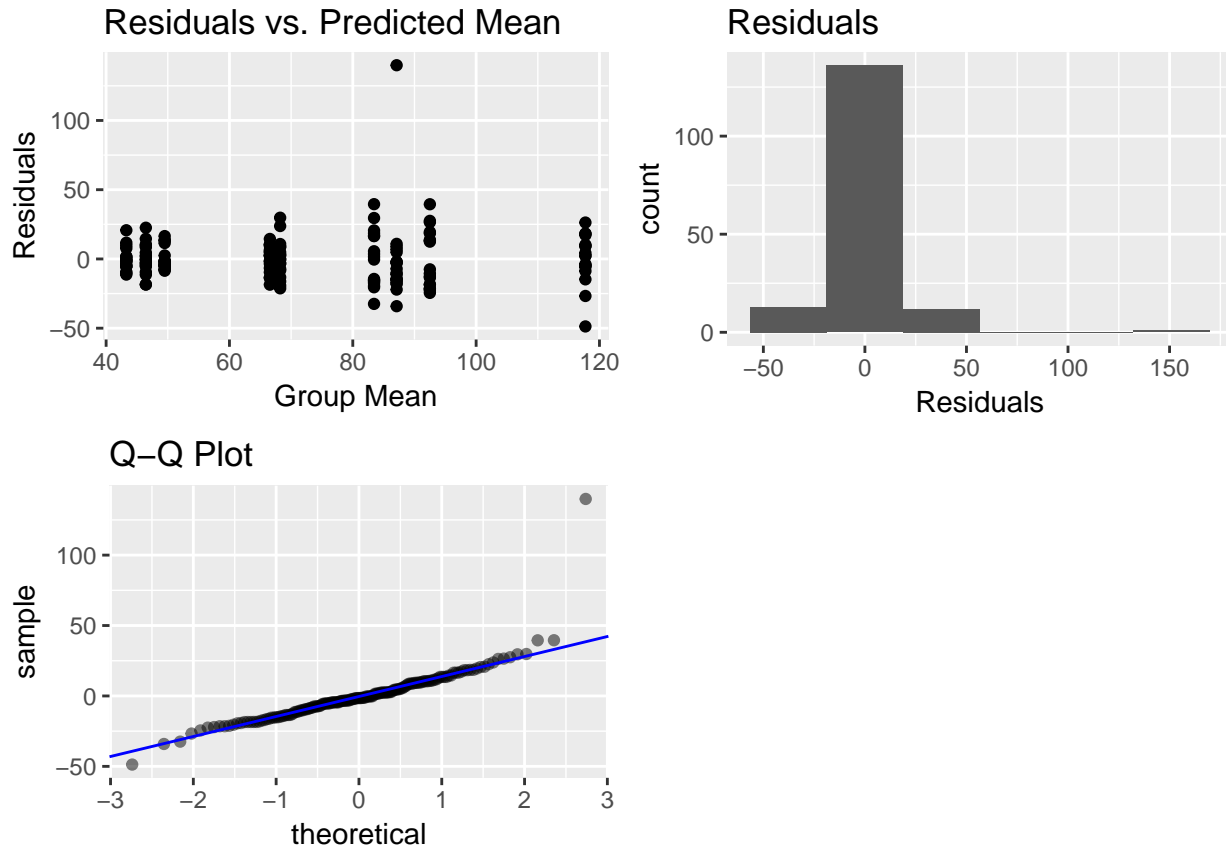
norm_res <- ggplot(data = sum_burg_anova_check, aes(x = sum_burg_anova_check$residuals)) + geom_histogram()

resid_jitter <- ggplot(data = sum_burg_anova_check, aes(x = sum_burg_anova_check$fitted.values, y = sum_burg_anova_check$residuals)) + geom_jitter()

```

```
qq <- ggplot(data = sum_burg_anova_check) + stat_qq(aes(sample = sum_burg_anova_check$residuals), alpha = 0.5) +
  geom_abline(slope = slope, intercept = int, color = "blue") + ggtitle("Q-Q Plot")

res_sum <- as.table(summary(sum_burg_anova_check$residuals), nrow = 2, ncol = 6)
grid.arrange(resid_jitter, norm_res, qq, nrow = 2, ncol = 2)
```



Checking ANOVA/Test Statistic/p-value

```
summary(sum_burg_anova_check)
```

```
##           Df Sum Sq Mean Sq F value Pr(>F)
## District    8  88078   11010   32.54 <2e-16 ***
## Residuals  153  51772     338
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Since our p-value is considerably less than 0.05, we can conclude that it appears that one mean is different than the other. We will proceed with Tukey's HSD to show which district is different from another.

```
thsd_sum_burg <- TukeyHSD(sum_burg_anova_check)
thsd_sum_burg
```

```
##      Tukey multiple comparisons of means
##      95% family-wise confidence level
##
## Fit: aov(formula = Count ~ District, data = summer_burglaries)
##
```

## \$District		diff	lwr	upr	p adj
## EASTERN-CENTRAL	-3.055556	-22.3503538	16.239243	0.9998975	
## NORTHEASTERN-CENTRAL	68.222222	48.9274240	87.517020	0.0000000	
## NORTHERN-CENTRAL	43.000000	23.7052018	62.294798	0.0000000	
## NORTHWESTERN-CENTRAL	18.722222	-0.5725760	38.017020	0.0647509	
## SOUTHEASTERN-CENTRAL	33.944444	14.6496462	53.239243	0.0000046	
## SOUTHERN-CENTRAL	37.611111	18.3163129	56.905909	0.0000003	
## SOUTHWESTERN-CENTRAL	17.055556	-2.2392427	36.350354	0.1295154	
## WESTERN-CENTRAL	-6.222222	-25.5170205	13.072576	0.9839710	
## NORTHEASTERN-EASTERN	71.277778	51.9829795	90.572576	0.0000000	
## NORTHERN-EASTERN	46.055556	26.7607573	65.350354	0.0000000	
## NORTHWESTERN-EASTERN	21.777778	2.4829795	41.072576	0.0145920	
## SOUTHEASTERN-EASTERN	37.000000	17.7052018	56.294798	0.0000004	
## SOUTHERN-EASTERN	40.666667	21.3718684	59.961465	0.0000000	
## SOUTHWESTERN-EASTERN	20.111111	0.8163129	39.405909	0.0340026	
## WESTERN-EASTERN	-3.166667	-22.4614649	16.128132	0.9998657	
## NORTHERN-NORTHEASTERN	-25.222222	-44.5170205	-5.927424	0.0020286	
## NORTHWESTERN-NORTHEASTERN	-49.500000	-68.7947982	-30.205202	0.0000000	
## SOUTHEASTERN-NORTHEASTERN	-34.277778	-53.5725760	-14.982980	0.0000036	
## SOUTHERN-NORTHEASTERN	-30.611111	-49.9059094	-11.316313	0.0000556	
## SOUTHWESTERN-NORTHEASTERN	-51.166667	-70.4614649	-31.871868	0.0000000	
## WESTERN-NORTHEASTERN	-74.444444	-93.7392427	-55.149646	0.0000000	
## NORTHWESTERN-NORTHERN	-24.277778	-43.5725760	-4.982980	0.0035837	
## SOUTHEASTERN-NORTHERN	-9.055556	-28.3503538	10.239243	0.8645865	
## SOUTHERN-NORTHERN	-5.388889	-24.6836871	13.905909	0.9937698	
## SOUTHWESTERN-NORTHERN	-25.944444	-45.2392427	-6.649646	0.0012955	
## WESTERN-NORTHERN	-49.222222	-68.5170205	-29.927424	0.0000000	
## SOUTHEASTERN-NORTHWESTERN	15.222222	-4.0725760	34.517020	0.2488070	
## SOUTHERN-NORTHWESTERN	18.888889	-0.4059094	38.183687	0.0601195	
## SOUTHWESTERN-NORTHWESTERN	-1.666667	-20.9614649	17.628132	0.9999991	
## WESTERN-NORTHWESTERN	-24.944444	-44.2392427	-5.649646	0.0024032	
## SOUTHERN-SOUTHEASTERN	3.666667	-15.6281316	22.961465	0.9995979	
## SOUTHWESTERN-SOUTHEASTERN	-16.888889	-36.1836871	2.405909	0.1381106	
## WESTERN-SOUTHEASTERN	-40.166667	-59.4614649	-20.871868	0.0000000	
## SOUTHWESTERN-SOUTHERN	-20.555556	-39.8503538	-1.260757	0.0273407	
## WESTERN-SOUTHERN	-43.833333	-63.1281316	-24.538535	0.0000000	
## WESTERN-SOUTHWESTERN	-23.277778	-42.5725760	-3.982980	0.0064007	

- The Northeastern District has distinctly larger number of burglaries than all other groups.
- The Northwestern District has a distinctly larger number of burglaries than the Western, Northern, and Eastern.
- The Southern District has a distinctly larger number of burglaries in the Summer months over the Central, Eastern, and the Southwest.
- The Southwest District has a distinctly larger number of burglaries in the Summer months over the Eastern, Northern, and the Western districts.
- The Western District has a distinctly larger number of burglaries in the Summer months over the Northern and southern Districts.
- The Northern District has a distinctly larger number of burglaries in the Summer months over the Central and Eastern Districts.
- The Southeastern District has a distinctly larger number of burglaries in the Summer months over the

Central and Eastern Districts.