

# NYPD Data

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4/29/2023

## Importing the Data

We read the data directly from the below URL, and display the first rows to get an idea of the schema.

```
library(tidyverse)
```

```
## — Attaching core tidyverse packages — tidyverse 2.0.0 —
## ✓ dplyr      1.1.2      ✓ readr      2.1.4
## ✓ forcats    1.0.0      ✓ stringr    1.5.0
## ✓ ggplot2     3.4.2      ✓ tibble     3.2.1
## ✓ lubridate  1.9.2      ✓ tidyr      1.3.0
## ✓ purrr       1.0.1
## — Conflicts — tidyverse_conflicts() —
## ✗ dplyr::filter() masks stats::filter()
## ✗ dplyr::lag()     masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
url_i<-"https://data.cityofnewyork.us/api/views/833y-fsy8/rows.csv?accessType=DOWNLOAD"
```

```
d<-read.csv(url_i)
head(d)
```

	INCIDENT_...	OCCUR_...	OCCUR_...	BORO	LOC_OF_OCCUR_...	PRECI...	JURISDICTION
	<int>	<chr>	<chr>	<chr>	<chr>	<int>	
1	228798151	05/27/2021	21:30:00	QUEENS		105	
2	137471050	06/27/2014	17:40:00	BRONX		40	
3	147998800	11/21/2015	03:56:00	QUEENS		108	
4	146837977	10/09/2015	18:30:00	BRONX		44	
5	58921844	02/19/2009	22:58:00	BRONX		47	
6	219559682	10/21/2020	21:36:00	BROOKLYN		81	

6 rows | 1-8 of 22 columns

```
length(d$INCIDENT_KEY)
```

```
## [1] 27312
```

Next we check the class type of each column,

```
sapply(d,typeof)
```

```
##          INCIDENT_KEY          OCCUR_DATE          OCCUR_TIME
##          "integer"          "character"          "character"
##          BORO          LOC_OF_OCCUR_DESC          PRECINCT
##          "character"          "character"          "integer"
##          JURISDICTION_CODE          LOC_CLASSFCTN_DESC          LOCATION_DESC
##          "integer"          "character"          "character"
##          STATISTICAL_MURDER_FLAG          PERP_AGE_GROUP          PERP_SEX
##          "character"          "character"          "character"
##          PERP_RACE          VIC_AGE_GROUP          VIC_SEX
##          "character"          "character"          "character"
##          VIC_RACE          X_COORD_CD          Y_COORD_CD
##          "character"          "double"          "double"
##          Latitude          Longitude          Lon_Lat
##          "double"          "double"          "character"
```

We have to convert the dates from string to a date object

```
d['OCCUR_DATE2'] <- as.Date(d$OCCUR_DATE, "%m/%d/%Y")
head(d$OCCUR_DATE2)
```

```
## [1] "2021-05-27" "2014-06-27" "2015-11-21" "2015-10-09" "2009-02-19"
## [6] "2020-10-21"
```

We see that most of our variables are categorical, so it is better to explore by using frequencies. We can ignore the coordinates as we won't conduct a geostatistical analysis.

```
pct_na<-sapply(d,function(x){sum(is.na(x))/length(x)*100})
names <-names(d)

df<-data.frame(names,pct_na)
df
```

	names <chr>	pct_na <dbl>
INCIDENT_KEY	INCIDENT_KEY	0.000000000
OCCUR_DATE	OCCUR_DATE	0.000000000
OCCUR_TIME	OCCUR_TIME	0.000000000
BORO	BORO	0.000000000
LOC_OF_OCCUR_DESC	LOC_OF_OCCUR_DESC	0.000000000

	names <chr>	pct_na <dbl>
PRECINCT	PRECINCT	0.000000000
JURISDICTION_CODE	JURISDICTION_CODE	0.007322789
LOC_CLASSFCTN_DESC	LOC_CLASSFCTN_DESC	0.000000000
LOCATION_DESC	LOCATION_DESC	0.000000000
STATISTICAL_MURDER_FLAG	STATISTICAL_MURDER_FLAG	0.000000000
1-10 of 22 rows		Previous 1 2 3 Next

For the Categorical let's make a few frequencies

```
## [1] "OCCUR_DATE"      "OCCUR_TIME"
## [3] "BORO"            "LOC_OF_OCCUR_DESC"
## [5] "LOC_CLASSFCTN_DESC" "LOCATION_DESC"
## [7] "STATISTICAL_MURDER_FLAG" "PERP_AGE_GROUP"
## [9] "PERP_SEX"        "PERP_RACE"
## [11] "VIC_AGE_GROUP"    "VIC_SEX"
## [13] "VIC_RACE"        "Lon_Lat"
```

```
## Warning: `as.tibble()` was deprecated in tibble 2.0.0.
## i Please use `as_tibble()` instead.
## i The signature and semantics have changed, see `?as_tibble`.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```

## # A tibble: 5 × 2
##   x          n
##   <chr>      <dbl>
## 1 BRONX      0.291
## 2 BROOKLYN   0.400
## 3 MANHATTAN  0.131
## 4 QUEENS     0.150
## 5 STATEN ISLAND 0.0284
## # A tibble: 3 × 2
##   x          n
##   <chr>      <dbl>
## 1 ""         0.937
## 2 "INSIDE"   0.00886
## 3 "OUTSIDE"  0.0540
## # A tibble: 10 × 2
##   x          n
##   <chr>      <dbl>
## 1 ""         0.937
## 2 "COMMERCIAL" 0.00366
## 3 "DWELLING"   0.00465
## 4 "HOUSING"    0.0103
## 5 "OTHER"      0.00114
## 6 "PARKING LOT" 0.000256
## 7 "PLAYGROUND" 0.00110
## 8 "STREET"     0.0404
## 9 "TRANSIT"    0.000549
## 10 "VEHICLE"   0.000842
## # A tibble: 41 × 2
##   x          n
##   <chr>      <dbl>
## 1 ""         0.548
## 2 "(null)"    0.0358
## 3 "ATM"       0.0000366
## 4 "BANK"      0.000110
## 5 "BAR/NIGHT CLUB" 0.0230
## 6 "BEAUTY/NAIL SALON" 0.00410
## 7 "CANDY STORE"    0.000256
## 8 "CHAIN STORE"    0.000183
## 9 "CHECK CASH"     0.0000366
## 10 "CLOTHING BOUTIQUE" 0.000513
## # i 31 more rows
## # A tibble: 2 × 2
##   x          n
##   <chr> <dbl>
## 1 false 0.807
## 2 true  0.193
## # A tibble: 11 × 2
##   x          n
##   <chr>      <dbl>
## 1 ""         0.342
## 2 "(null)"    0.0234
## 3 "<18"      0.0583

```

```

## 4 "1020"      0.0000366
## 5 "18-24"     0.228
## 6 "224"       0.0000366
## 7 "25-44"     0.208
## 8 "45-64"     0.0226
## 9 "65+"       0.00220
## 10 "940"      0.0000366
## 11 "UNKNOWN"  0.115
## # A tibble: 5 × 2
##   x          n
##   <chr>      <dbl>
## 1 ""          0.341
## 2 "(null)"    0.0234
## 3 "F"         0.0155
## 4 "M"         0.565
## 5 "U"         0.0549
## # A tibble: 9 × 2
##   x          n
##   <chr>      <dbl>
## 1 ""          0.341
## 2 "(null)"    0.0234
## 3 "AMERICAN INDIAN/ALASKAN NATIVE" 0.0000732
## 4 "ASIAN / PACIFIC ISLANDER"        0.00564
## 5 "BLACK"                            0.419
## 6 "BLACK HISPANIC"                  0.0481
## 7 "UNKNOWN"                         0.0672
## 8 "WHITE"                           0.0104
## 9 "WHITE HISPANIC"                  0.0857
## # A tibble: 7 × 2
##   x          n
##   <chr>      <dbl>
## 1 <18      0.104
## 2 1022     0.0000366
## 3 18-24    0.369
## 4 25-44    0.450
## 5 45-64    0.0682
## 6 65+      0.00663
## 7 UNKNOWN 0.00223
## # A tibble: 3 × 2
##   x          n
##   <chr>      <dbl>
## 1 F         0.0957
## 2 M         0.904
## 3 U         0.000403
## # A tibble: 7 × 2
##   x          n
##   <chr>      <dbl>
## 1 AMERICAN INDIAN/ALASKAN NATIVE 0.000366
## 2 ASIAN / PACIFIC ISLANDER        0.0148
## 3 BLACK                            0.712
## 4 BLACK HISPANIC                  0.0969
## 5 UNKNOWN                         0.00242

```

```
## 6 WHITE 0.0256
## 7 WHITE HISPANIC 0.148
```

```
##  BORO      LOC_OF_OCCUR_DESC LOC_CLASSFCTN_DESC LOCATION_DESC
## x character,5 character,3      character,10      character,41
## n numeric,5  numeric,3        numeric,10      numeric,41
##  STATISTICAL_MURDER_FLAG PERP_AGE_GROUP PERP_SEX    PERP_RACE    VIC_AGE_GROUP
## x character,2              character,11   character,5   character,9   character,7
## n numeric,2                numeric,11    numeric,5     numeric,9     numeric,7
##  VIC_SEX    VIC_RACE
## x character,3 character,7
## n numeric,3  numeric,7
```

1.- We see that LOC\_OF\_OCCUR\_DESC, LOC\_CLASSFCTN\_DESC have 93% missing so we can't use those columns. 2.- Sex of the perpetrator is empty for 36%, but it is safe to impute M 3.- Sex of the victim has no missing values and 90% is male.

So we see an obvious pattern, that males are way overrepresented as victims and perpetrators in this type of violent crime. Which matches our intuition

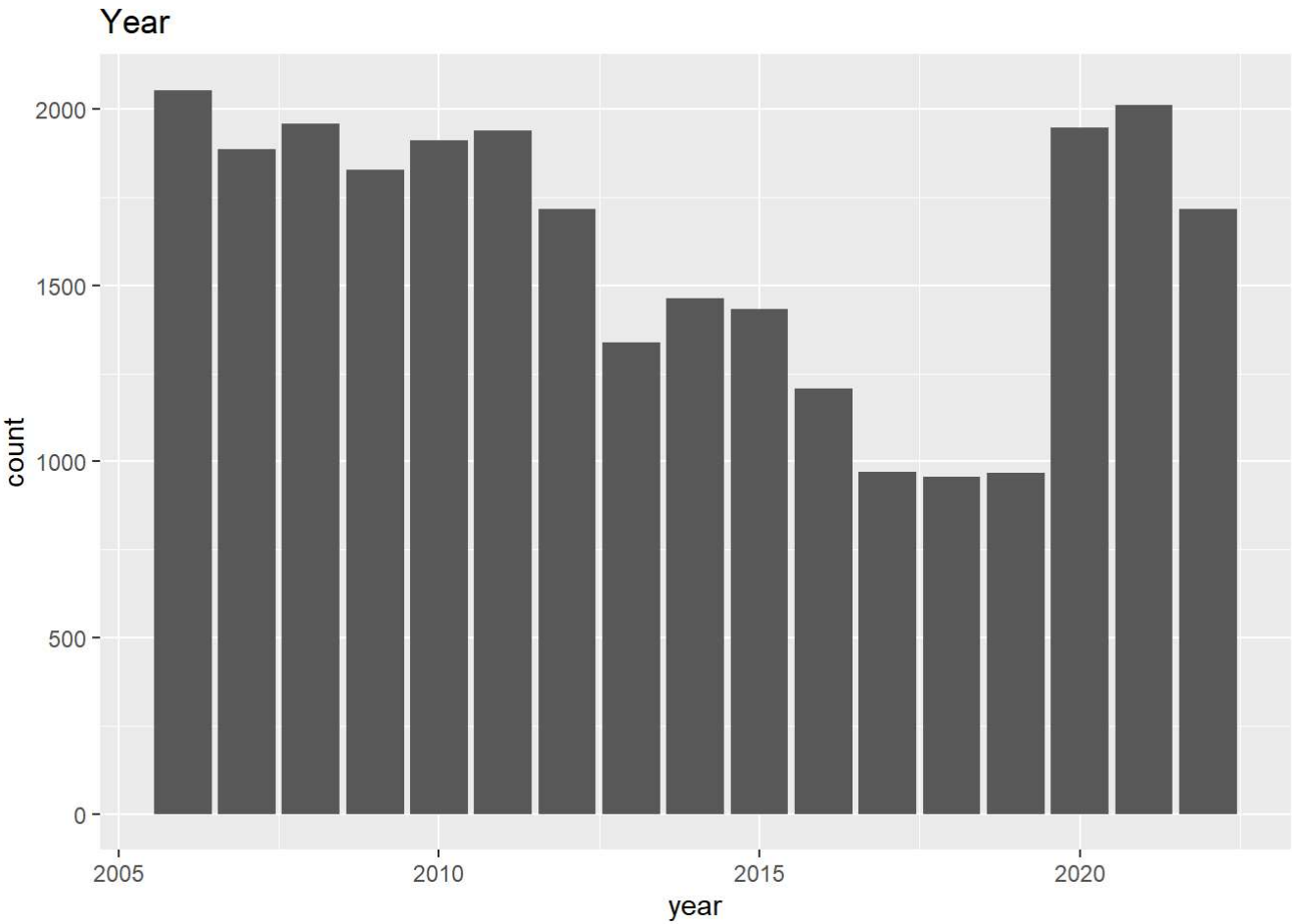
## Graphical Presentation of frequencies

Lets se the Frequencies Graphically

```
library(ggplot2)
ggplot(data=data)+geom_bar(aes(x=BORO))+ggtitle("Borough")
ggplot(data=data)+geom_bar(aes(x=PERP_AGE_GROUP))+ggtitle("Perpetrator Age Group")

ggplot(data=data)+geom_bar(aes(x=PERP_RACE))+ggtitle("Perpetrator Race")+coord_flip()

ggplot(data=data)+geom_bar(aes(x=VIC_RACE))+ggtitle("Victim Race")+coord_flip()
```

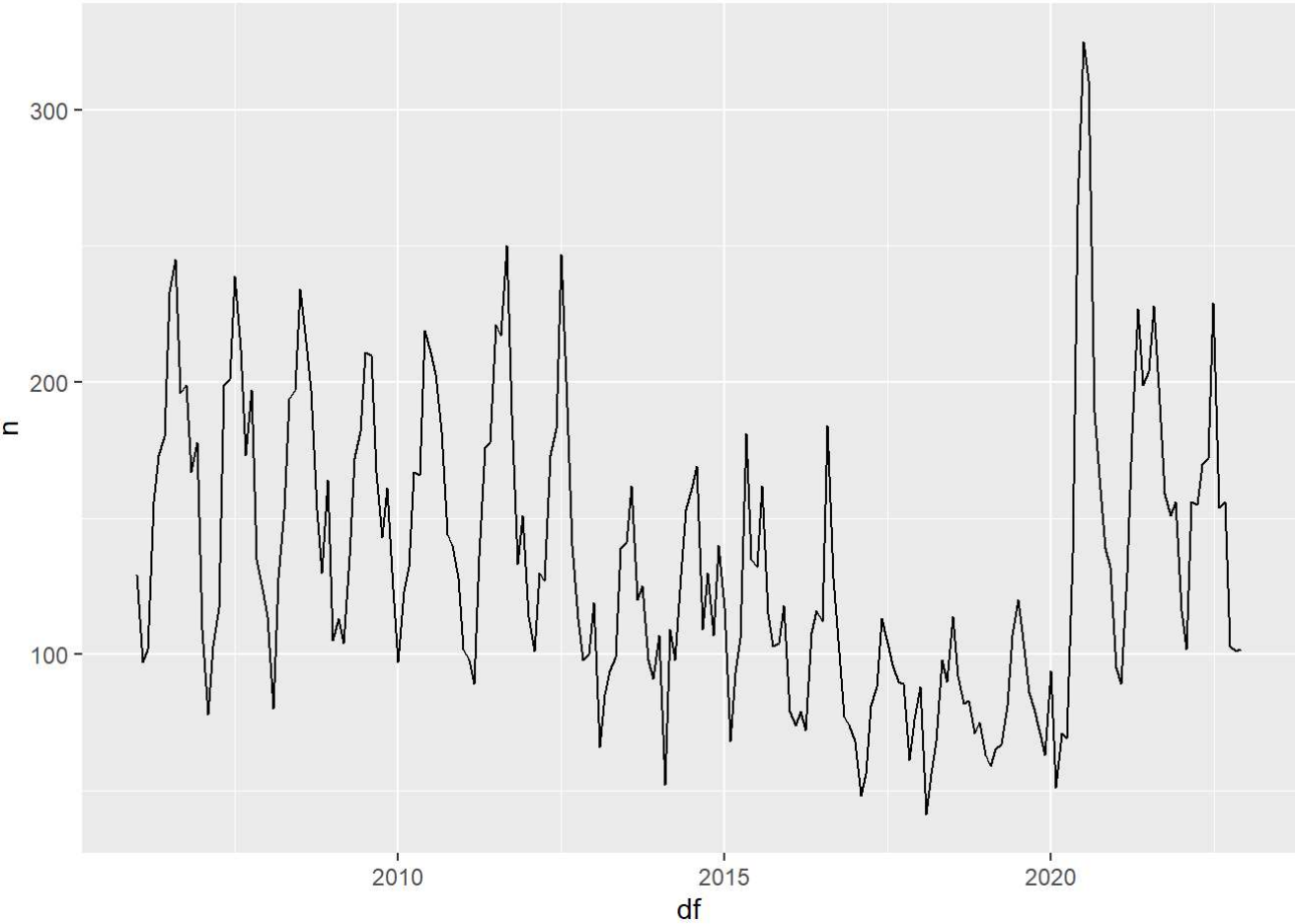


# Seasonality

Lets group the events by month and see if there are any patterns

df	n
<date>	<int>
2006-01-01	129
2006-02-01	97
2006-03-01	102
2006-04-01	156
2006-05-01	173
2006-06-01	180

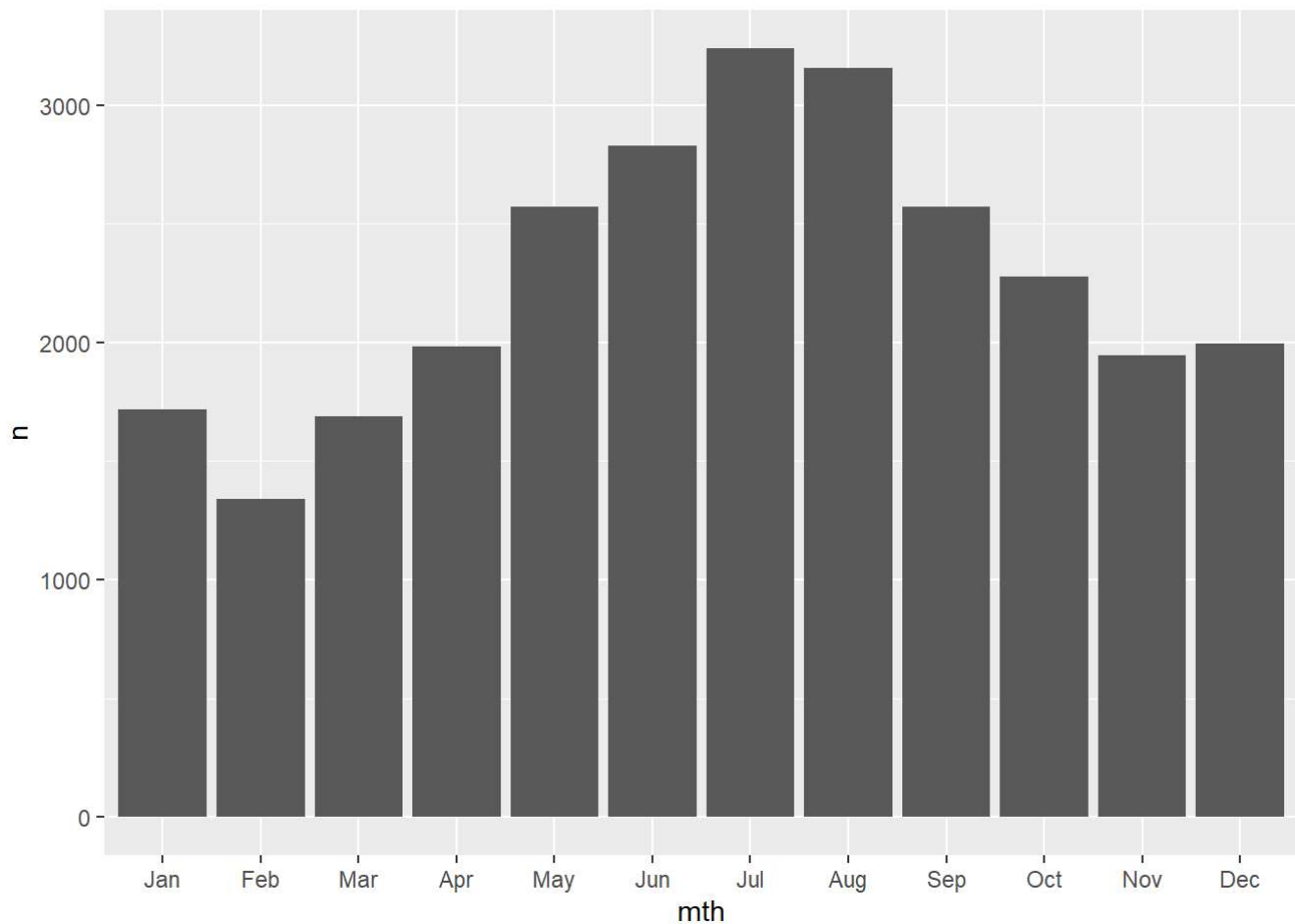
6 rows



mth	n
<ord>	<int>
Jan	1716
Feb	1340
Mar	1688
Apr	1983
May	2571
Jun	2829

6 rows





And we see a spike in Summer.

We see a clear Seasonality Patter.

## Test Seasonality

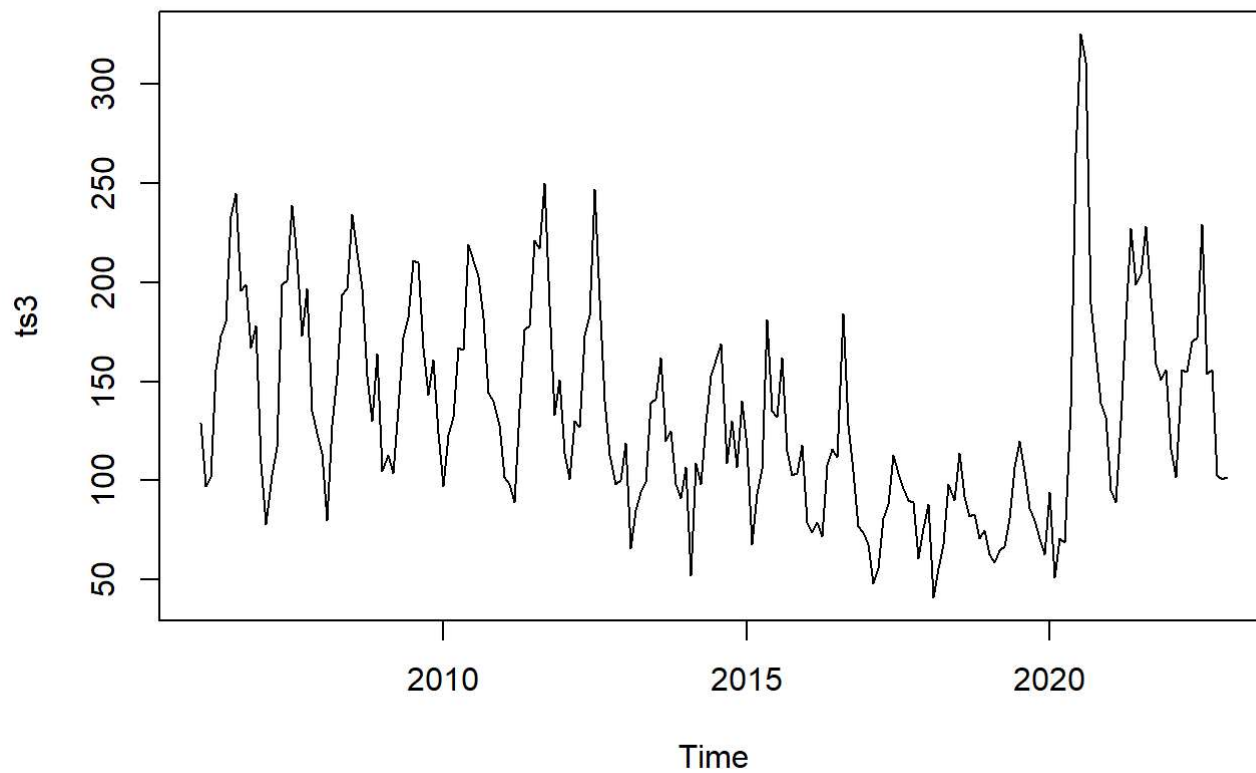
We will try to figure out the seasonality

```
ts2<- d %>%
  group_by(df ) %>%
  summarise( n = n())
head(ts2)
```

	df <date>	n <int>
	2006-01-01	129
	2006-02-01	97
	2006-03-01	102
	2006-04-01	156
	2006-05-01	173
	2006-06-01	180

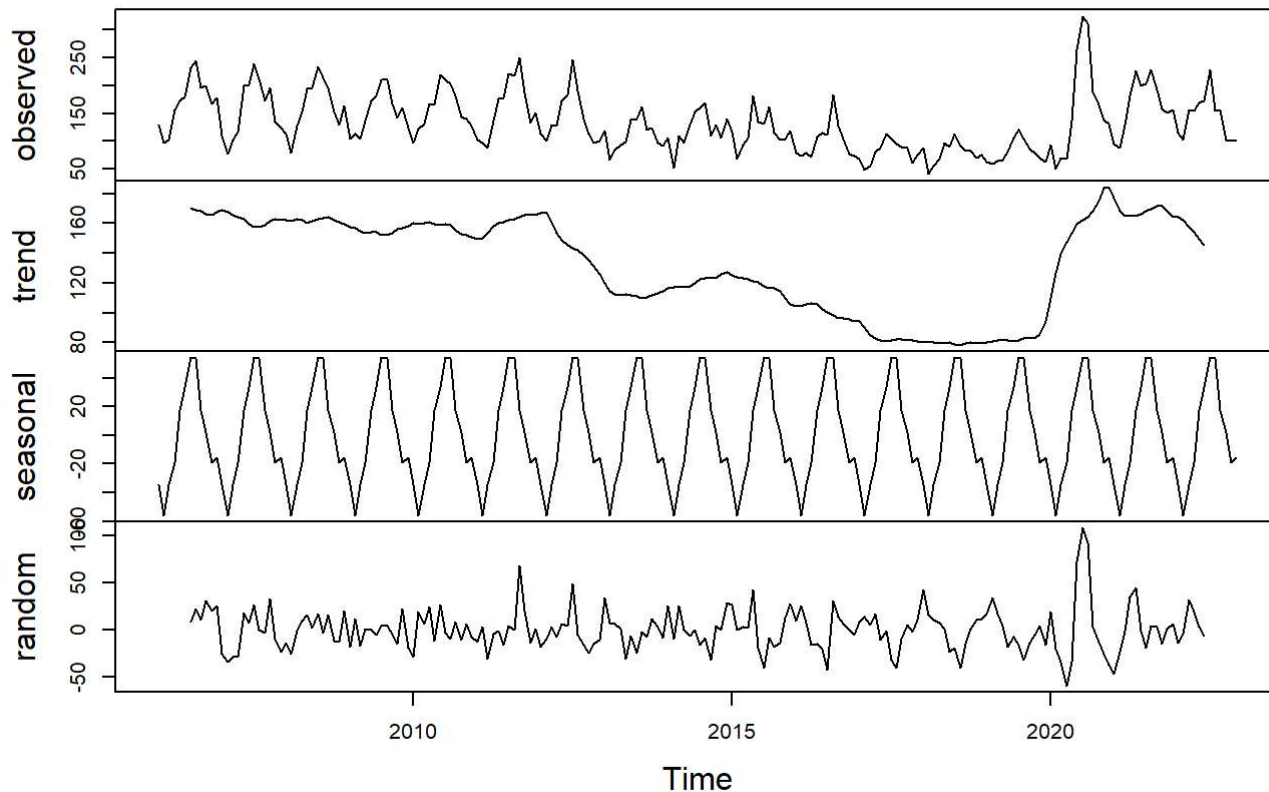
6 rows

```
ts3<-ts(ts2$n,frequency = 12,start=c(2006,1))  
plot(ts3)
```



```
ts_components <- decompose(ts3)  
plot(ts_components)
```

## Decomposition of additive time series



```
summary(ts_components)
```

```
##           Length Class  Mode
## x           204    ts    numeric
## seasonal    204    ts    numeric
## trend       204    ts    numeric
## random      204    ts    numeric
## figure       12  -none- numeric
## type         1  -none- character
```

Notice in trend the the downward slope and the structural breakdown due to COVID which caused a sharp increase and brought us back to pre 2010 levels. We see a strong seasonality component

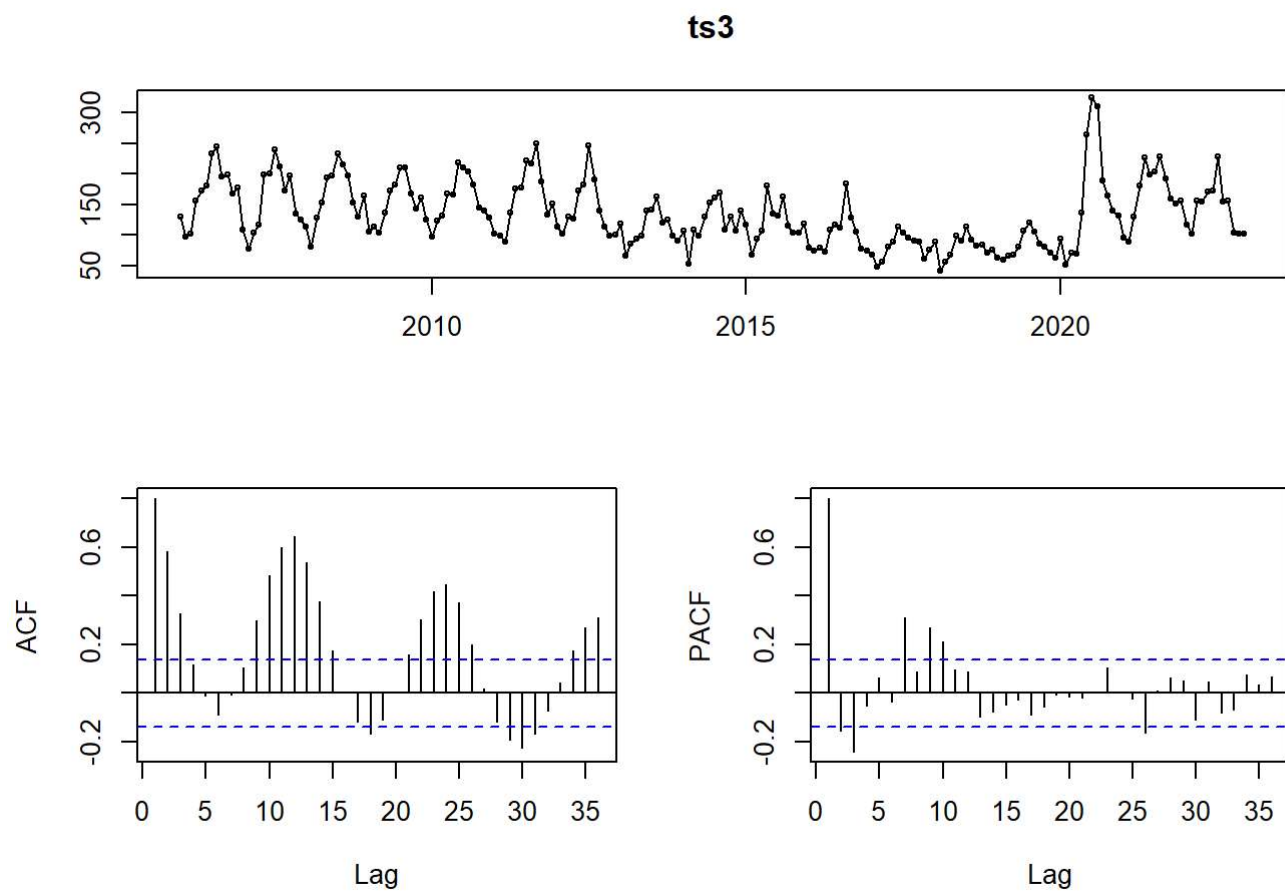
Below, we fit an arima model and we can see that the seasonal components

```
###
```

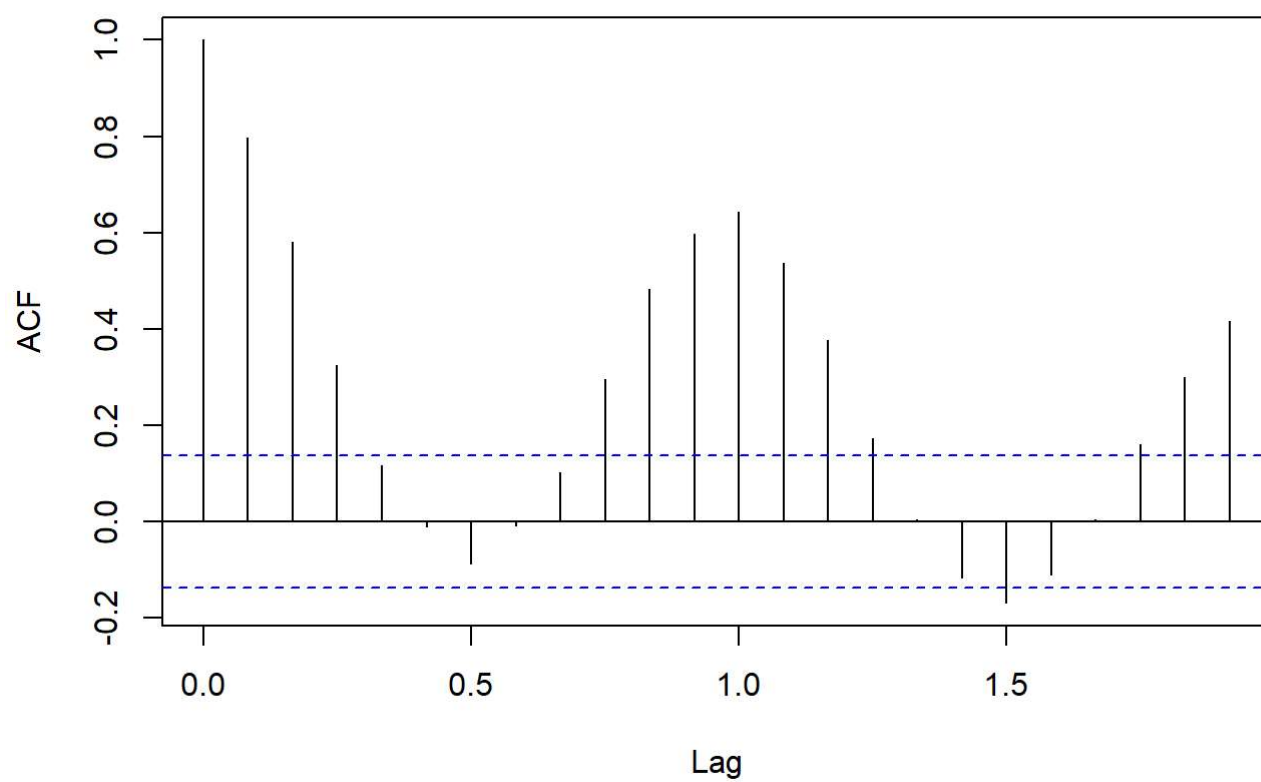
```
library(forecast)
```

```
## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo
```

```
tsdisplay(ts3)
```

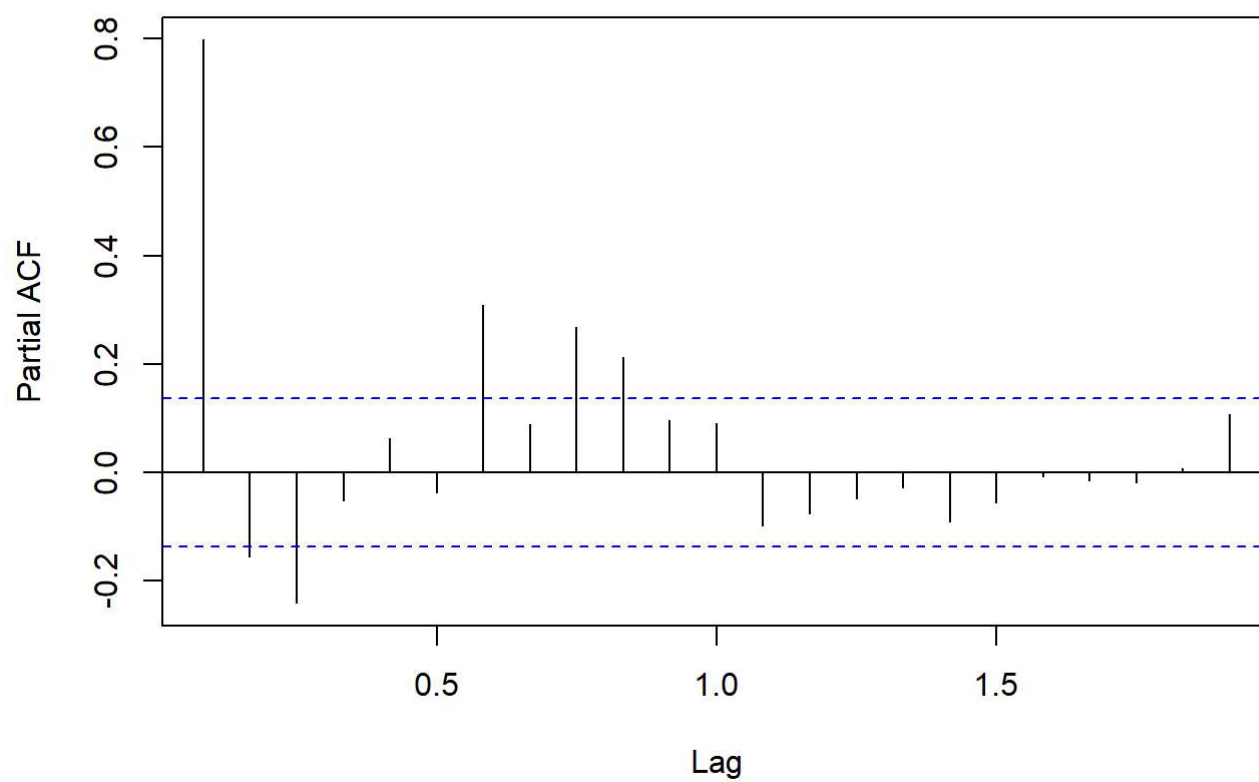


```
plot(acf(ts3))
```

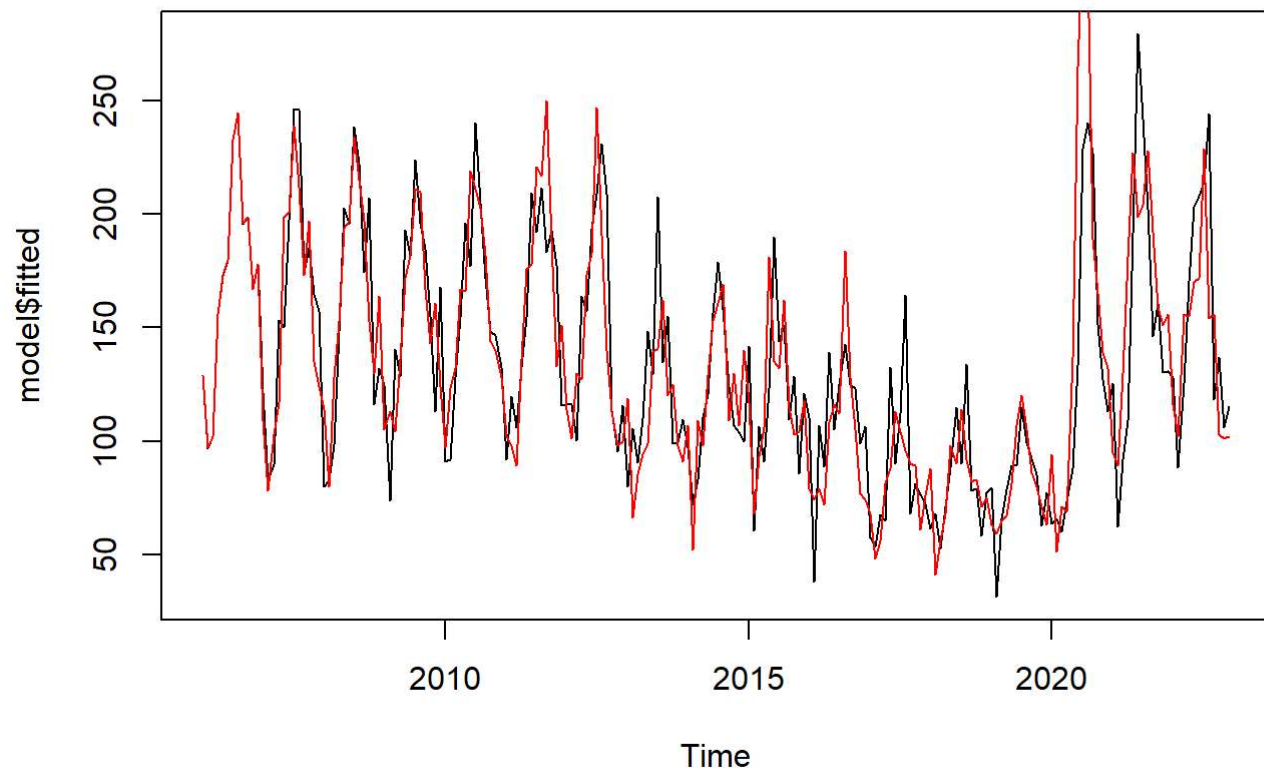
**Series ts3**

```
plot(pacf(ts3))
```

### Series ts3

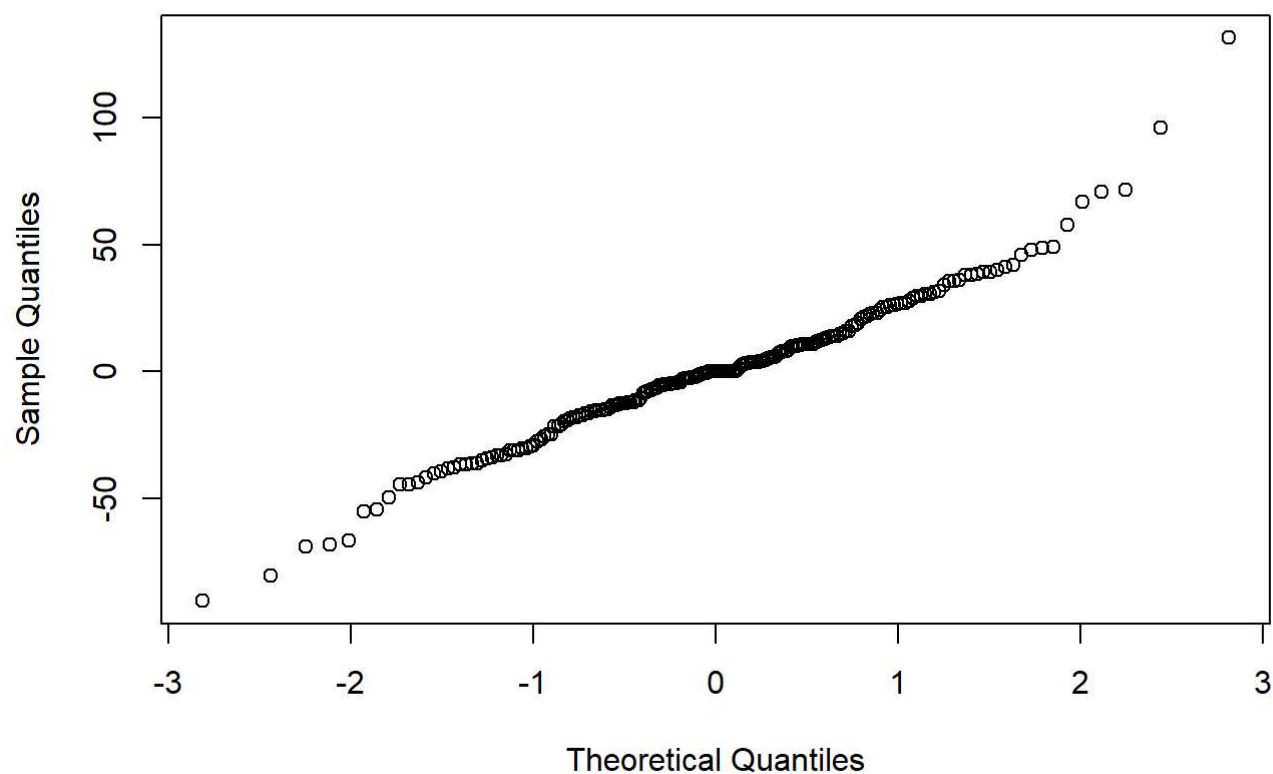


```
model<-auto.arima(ts3,seasonal = TRUE)
plot(model$fitted)
lines(ts3, col='red')
```



```
qqnorm(model$residuals)
```

## Normal Q-Q Plot



```
summary(model)
```

```
## Series: ts3
## ARIMA(1,0,0)(1,1,0)[12] with drift
##
## Coefficients:
##          ar1      sar1      drift
##      0.6803  -0.3835  -0.1351
## s.e.  0.0532   0.0689   0.4114
##
## sigma^2 = 917.1: log likelihood = -927.02
## AIC=1862.04  AICc=1862.25  BIC=1875.07
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -0.02437165 29.14876 21.3069 -2.240472 16.99186 0.767672
##              ACF1
## Training set -0.08032225
```