uk road safety

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```
#install.packages('stats19')
library(stats19)
```

```
## Warning: package 'stats19' was built under R version 3.6.3
```

```
## Data provided under OGL v3.0. Cite the source and link to:
## www.nationalarchives.gov.uk/doc/open-government-licence/version/3/
```

```
library(ggplot2)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
#install.packages('sugrrants')

library(sugrrants)
```

```
## Warning: package 'sugrrants' was built under R version 3.6.3
```

```
## Getting data for 3 years (2016 2017 & 2018) for accidents, vehicles  & casualities




# d16 = "casualtiestRoadSafetyData_Accidents_2016"
# dl_stats19(file_name = paste0(d17, ".zip"))
# crashes_2017_raw = read_accidents(year = 2017,
#                                   filename = "Acc.csv")
#
# dl_stats19(year = 2017, type = "vehicles", ask = FALSE)
# vehicles_2017_raw = read_vehicles(year = 2017)
#
#
# crashes = list()
# vehicles = list()
# casualties = list()
#
# for (i in seq(1:2))
# {
#   file = "casualtiestRoadSafetyData_Accidents_"
#   year = 2015 + i
#   file_name = paste0(file, year, '.zip')
#   filename = paste0(file, year, '.csv')
#   dl_stats19(file_name = file_name)
#   crashes_raw = read_accidents(year = year, filename = filename)
#   crashes[i] = format_accidents(crashes_raw)
#   dl_stats19(year = year, type = "vehicles", ask = FALSE)
#   vehicles_raw= read_vehicles(year = year)
#   vehicles[i]  = format_vehicles(vehicles_raw)
#   dl_stats19(year = year, type = "casualties", ask = FALSE)
#   casualties_raw= read_casualties(year = year)
#   casualties[i]= format_casualties(casualties_raw)
# }
#
#
# head(crashes[1])
```

```
casualties_2016 <- read.csv('../dataset/dftRoadSafetyData_Casualties_2016.csv')
casualties_2017 <- read.csv('../dataset/dftRoadSafetyData_Casualties_2017.csv')
casualties_2018 <- read.csv('../dataset/dftRoadSafetyData_Casualties_2018.csv')

#dim(casualties_2016)
#dim(casualties_2017)
#dim(casualties_2018)

colnames(casualties_2016) <- c("Accident_Index",
                               "Vehicle_Reference",
                               "Casualty_Reference",
                               "Casualty_Class",
                               "Sex_of_Casualty",
                               "Age_of_Casualty",
                               "Age_Band_of_Casualty",
                               "Casualty_Severity",
                               "Pedestrian_Location",
                               "Pedestrian_Movement",
                               "Car_Passenger",
                               "Bus_or_Coach_Passenger",
                               "Pedestrian_Road_Maintenance_Worker",
                               "Casualty_Type",
                               "Casualty_Home_Area_Type",
                               "Casualty_IMD_Decile")

colnames(casualties_2017) <- colnames(casualties_2016)
colnames(casualties_2018) <- colnames(casualties_2016)
```

```
casualties_2016$Year <- 2016
casualties_2017$Year <- 2017
casualties_2018$Year <- 2018

casualties <- rbind(casualties_2016, casualties_2017, casualties_2018)

#glimpse(casualties)

# casualties <- casualties[(casualties$Vehicle_Reference != -1 & casualties$Vehicle_Reference
!= 999 &
#               casualties$Casualty_Reference != -1 & casualties$Casualty_Reference != 991 &
#               casualties$Casualty_Class != -1 &
#               casualties$Sex_of_Casualty != -1 &
#               casualties$Age_of_Casualty != -1 &
#               casualties$Age_Band_of_Casualty != -1 &
#               casualties$Casualty_Severity != -1  &
#               casualties$Pedestrian_Location != -1  &
#               casualties$Pedestrian_Movement != -1 &
#               casualties$Car_Passenger != -1 &
#               casualties$Bus_or_Coach_Passenger != -1 &
#               casualties$Pedestrian_Road_Maintenance_Worker != -1 &
#               casualties$Casualty_Type != -1 &
#               casualties$Casualty_Home_Area_Type != -1 &
#               casualties$Casualty_IMD_Decile != -1), ]


#unique(casualties$Casualty_Type)

casualties[-6] <- lapply(casualties[-6], factor)

glimpse(casualties)
```

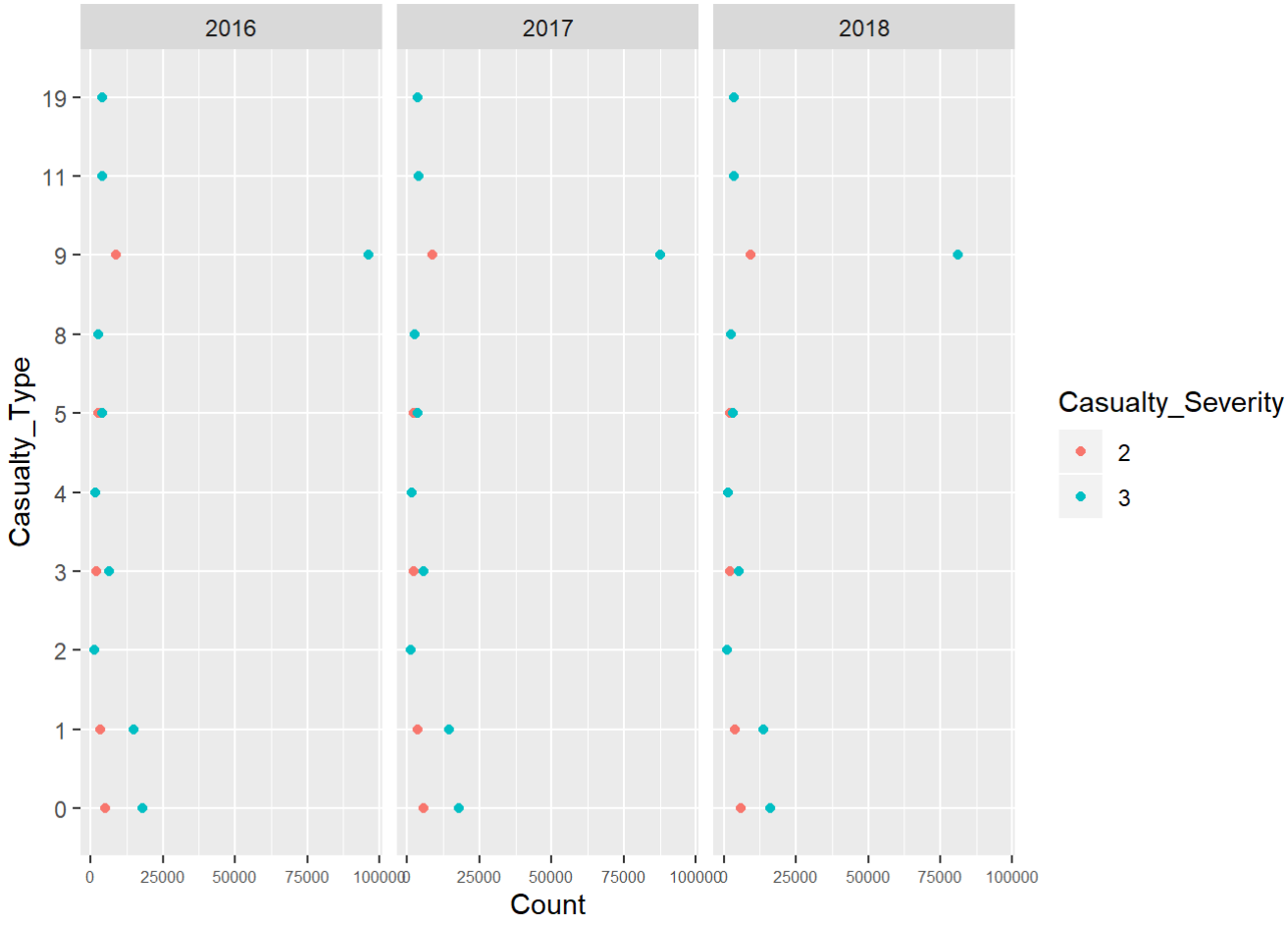
```
## Observations: 512,974
## Variables: 17
## $ Accident_Index                   <fct> 2016010000005, 201601000000...
## $ Vehicle_Reference                <fct> 2, 1, 1, 1, 2, 1, 1, 2, 1, ...
## $ Casualty_Reference               <fct> 1, 1, 1, 1, 1, 1, 1, 1, 1, ...
## $ Casualty_Class                   <fct> 1, 1, 1, 2, 1, 1, 3, 1, 1, ...
## $ Sex_of_Casualty                  <fct> 1, 2, 1, 2, 1, 2, 2, 2, 1, ...
## $ Age_of_Casualty                  <int> 23, 36, 24, 59, 28, 30, 33,...
## $ Age_Band_of_Casualty             <fct> 5, 7, 5, 9, 6, 6, 6, 6, 5, ...
## $ Casualty_Severity                <fct> 3, 3, 3, 3, 3, 3, 3, 3, 3, ...
## $ Pedestrian_Location              <fct> 0, 0, 0, 0, 0, 0, 5, 0, 0, ...
## $ Pedestrian_Movement              <fct> 0, 0, 0, 0, 0, 0, 1, 0, 0, ...
## $ Car_Passenger                    <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
## $ Bus_or_Coach_Passenger           <fct> 0, 0, 0, 3, 0, 0, 0, 0, 0, ...
## $ Pedestrian_Road_Maintenance_Worker <fct> 0, 0, 0, 0, 0, 0, 2, 0, 0, ...
## $ Casualty_Type                    <fct> 2, 9, 9, 11, 1, 9, 0, 9, 4,...
## $ Casualty_Home_Area_Type          <fct> 1, 1, 1, 1, 1, 1, 1, 1, 1, ...
## $ Casualty_IMD_Decile              <fct> 4, 10, 8, 4, 6, 3, 1, 7, -1...
## $ Year                             <fct> 2016, 2016, 2016, 2016, 201...
```

```
#write.csv(casualties, '../dataset/dftRoadSafetyData_Casualties.csv')
```

```
table(casualties$Casualty_Type)
```

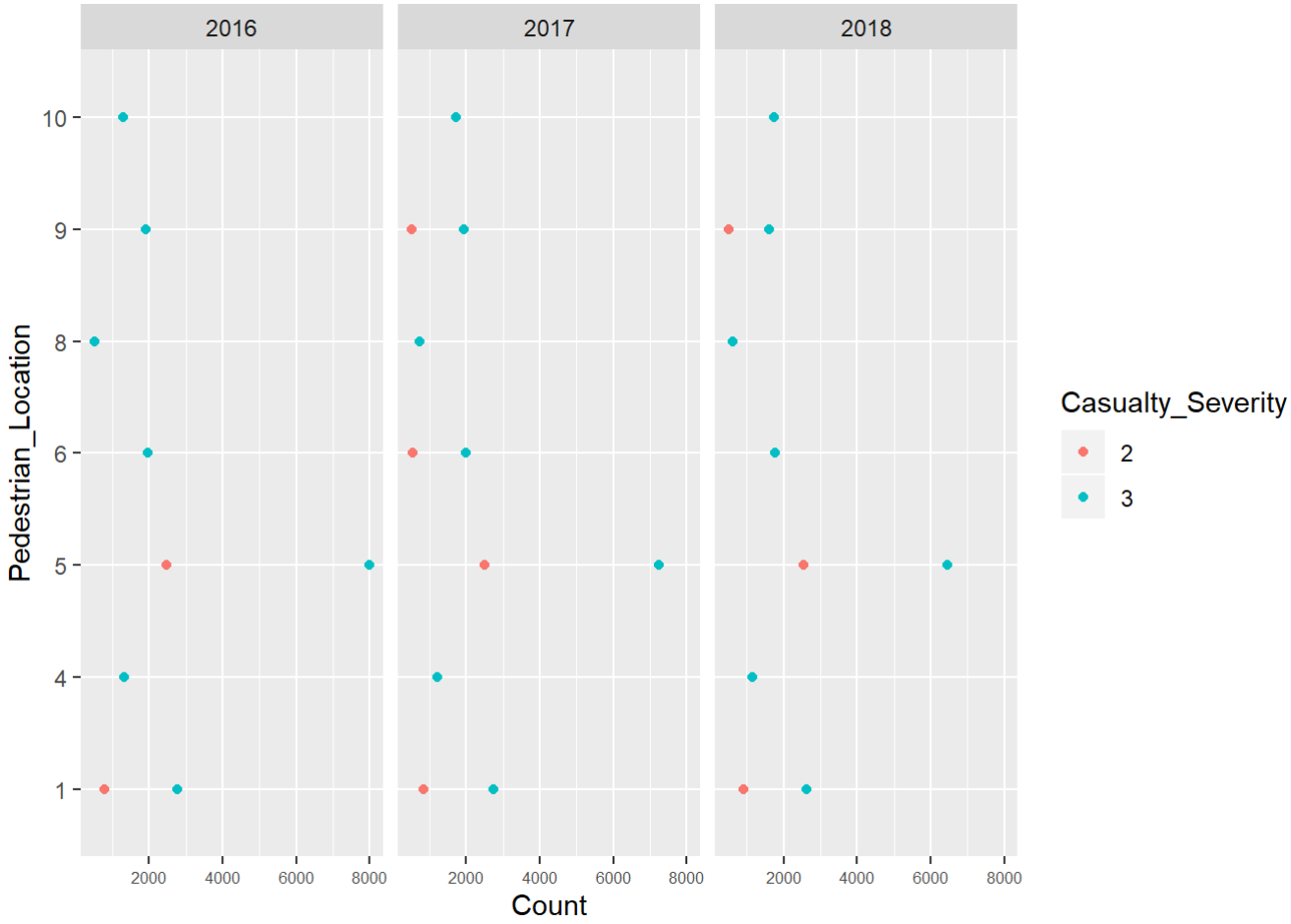
```
##
##     -1      0      1      2      3      4      5      8      9     10
##     10  69787  54348   4902  23695   6444  18247   8263 293844   1000
##     11     16     17     18     19     20     21     22     23     90
##  12283    254    290     34  12583    926   2097    599    156   1812
##     97     98
##    713    687
```

```
casualty_type <- casualties[casualties$Casualty_Type != -1, ] %>%
            group_by(Casualty_Type, Casualty_Severity, Year) %>%
            summarise(Count = n())

#sort(casualty_type$Count)

top_casualty_type <- casualty_type[casualty_type$Count > 1000, ]



ggplot(data=top_casualty_type, aes(x=Casualty_Type, y=Count, color=Casualty_Severity)) +
  geom_point() +
  facet_wrap(~Year) +
  coord_flip() +
  theme(axis.text.x = element_text(size=6))
```



-We can see over the year most casualties are of type 9, 0 & 1 which represent Car occupant, Pedestrian & Cyclist respectively. -type 8 which represent taxi, have low casualties but again we are not aware of the actual number of taxi on roads.

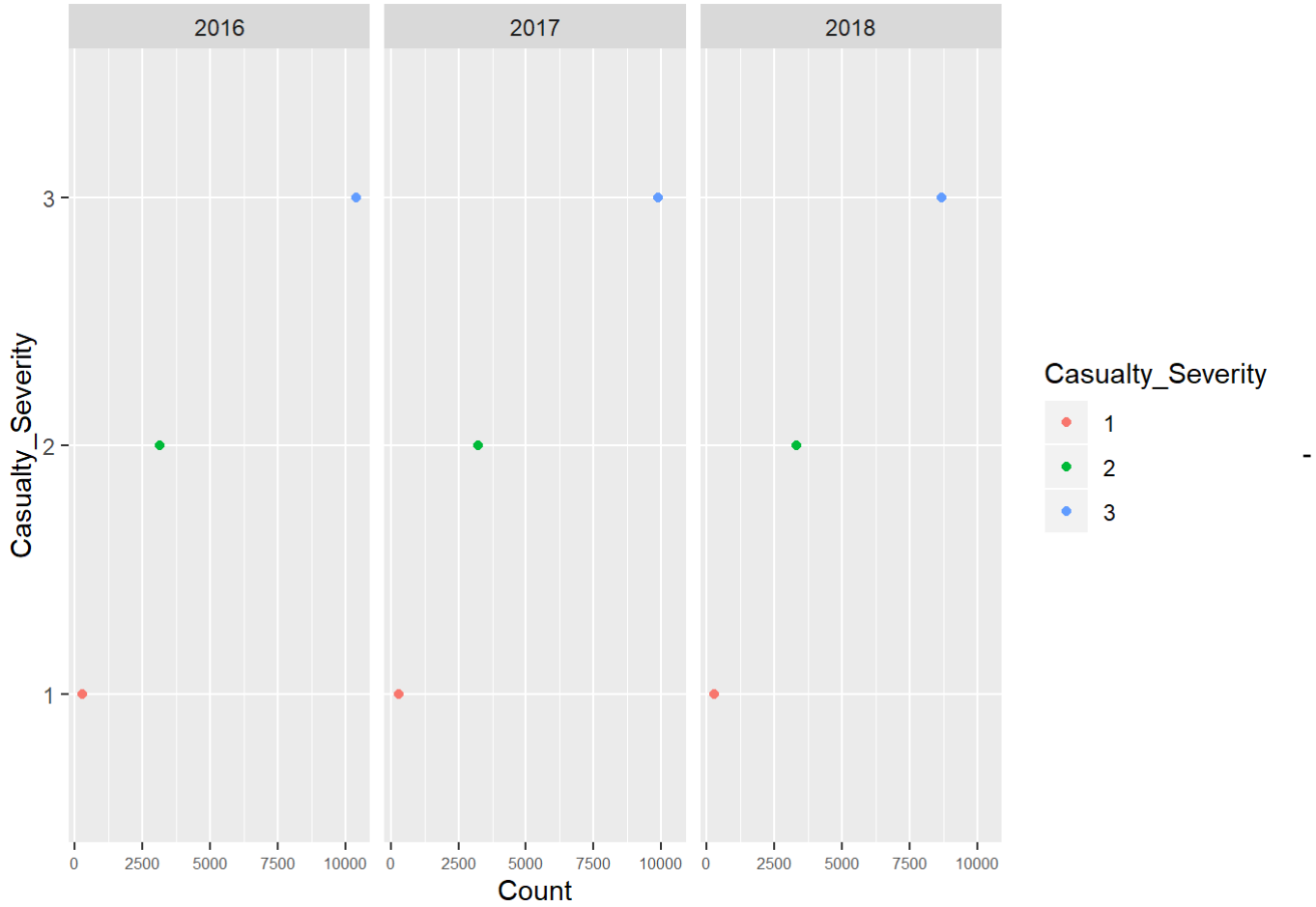
```
## Pedestrain Casualties Cases

#table(casualties$Pedestrian_Location)

t = (casualties$Casualty_Type  == 0 & casualties$Pedestrian_Location != -1)

pedestrian_casualties <- casualties[t, ] %>%
            group_by(Pedestrian_Location, Casualty_Severity, Year) %>%
            summarise(Count = n())

#pedestrian_casualties[pedestrian_casualties$Casualty_Severity == 1, ]

ggplot(data=pedestrian_casualties[pedestrian_casualties$Count > 500, ], aes(x=Pedestrian_Loca
tion, y=Count, color=Casualty_Severity)) +
  geom_point() +
  facet_wrap(~Year) +
  coord_flip() +
  theme(axis.text.x = element_text(size=6))
```



-The below graph show the location with with pedestrain casualty count more than 500. -Most of the pedestrian have slight severity. -While cases for location at 1, 5 which is “Crossing on pedestrian crossing facility” & “In carriageway, crossing elsewhere” have some serious severity cases. -It may suggest that people are being irresponsible and not using pedestrain crossing for case 5.

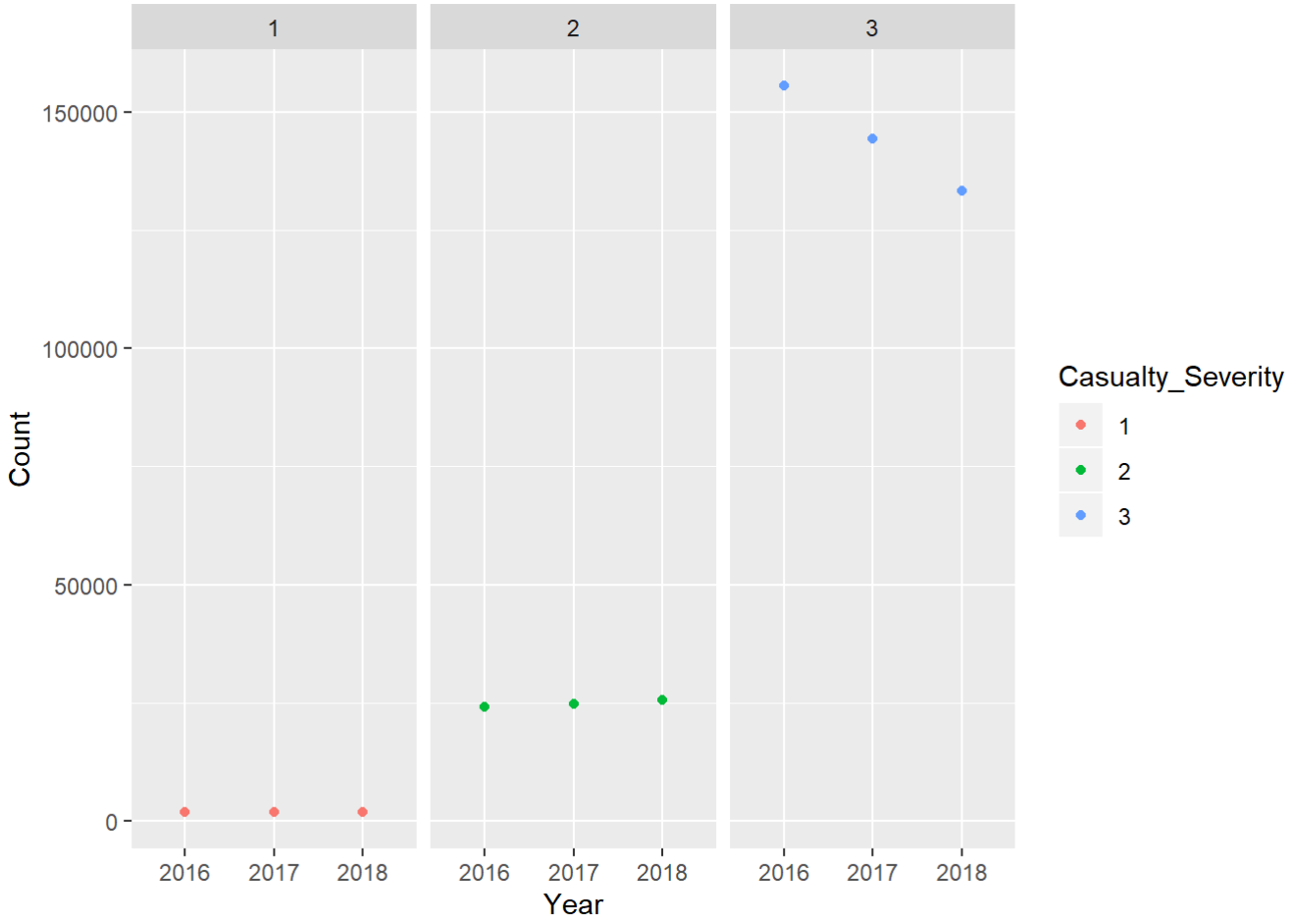
-Then there are some cases at location 6 which is “On footway or verge” suggest drivers are being irresponsible. -cases at location 9 which is In carriageway, not crossing. So it is similar to case 5.

```
## Pedestrain in Carriageway Casualties Cases
pedestrain_in_carriageway <- pedestrian_casualties[(pedestrian_casualties$Pedestrian_Location
== 9 |
                       pedestrian_casualties$Pedestrian_Location == 5 |
                       pedestrian_casualties$Pedestrian_Location == 8), ]


pedestrain_in_carriageway <- pedestrain_in_carriageway %>%
            group_by(Casualty_Severity, Year) %>%
            summarise(Count = sum(Count))

ggplot(data=pedestrain_in_carriageway, aes(x=Casualty_Severity, y=Count, color=Casualty_Sever
ity)) +
  geom_point() +
  facet_wrap(~Year) +
  coord_flip() +
  theme(axis.text.x = element_text(size=6))
```



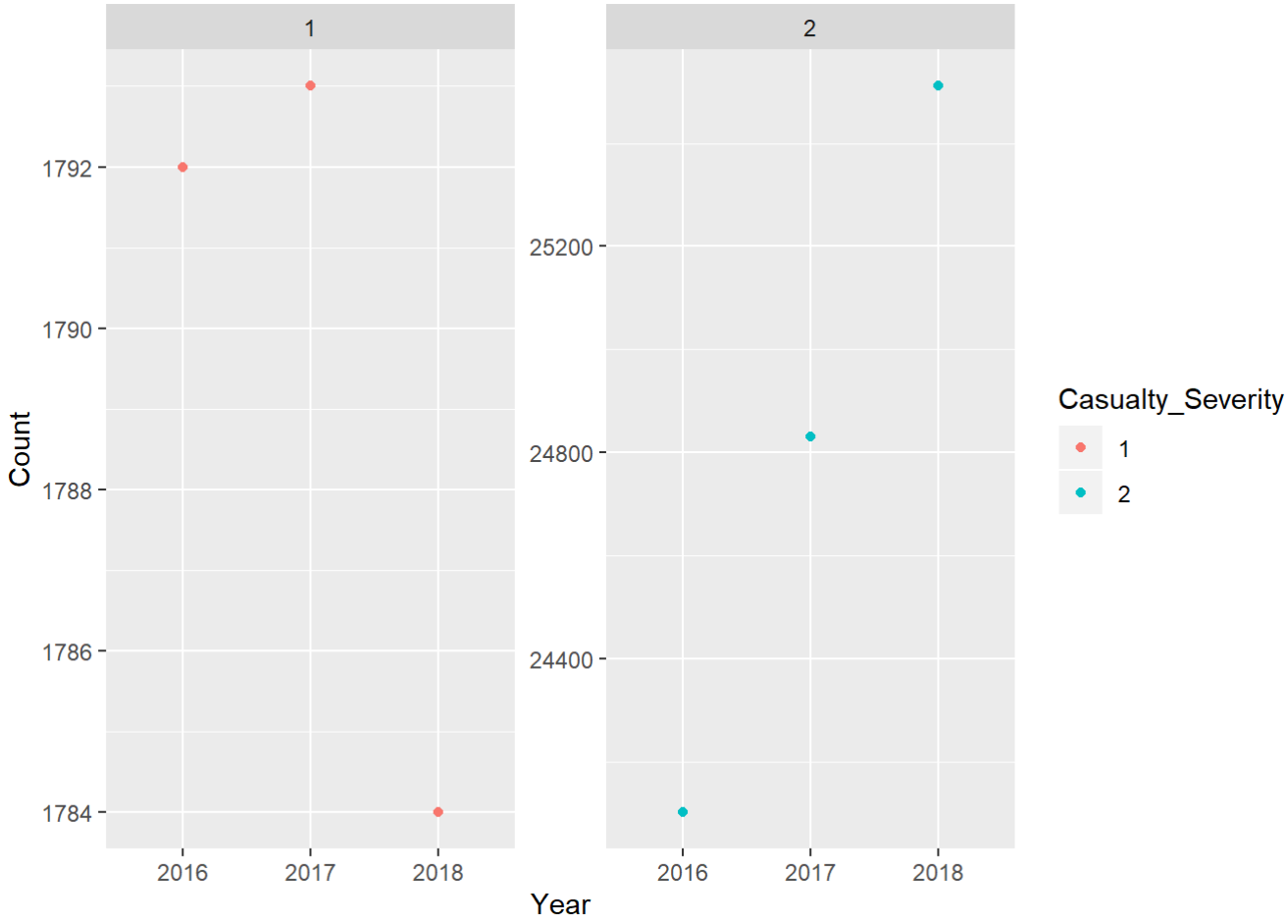
Fatal & serious Casualties count have not improved much perhaps serious cases have slightly increase over year. -Slight casualties case count have improved over year.

```
#unique(casualties$Casualty_Severity)

severity <- casualties %>%
            group_by(Casualty_Severity, Year) %>%
            summarise(Count = n())

ggplot(data=severity, aes(x=Year, y=Count, color=Casualty_Severity)) +
  geom_point() +
  facet_wrap(~Casualty_Severity)
```



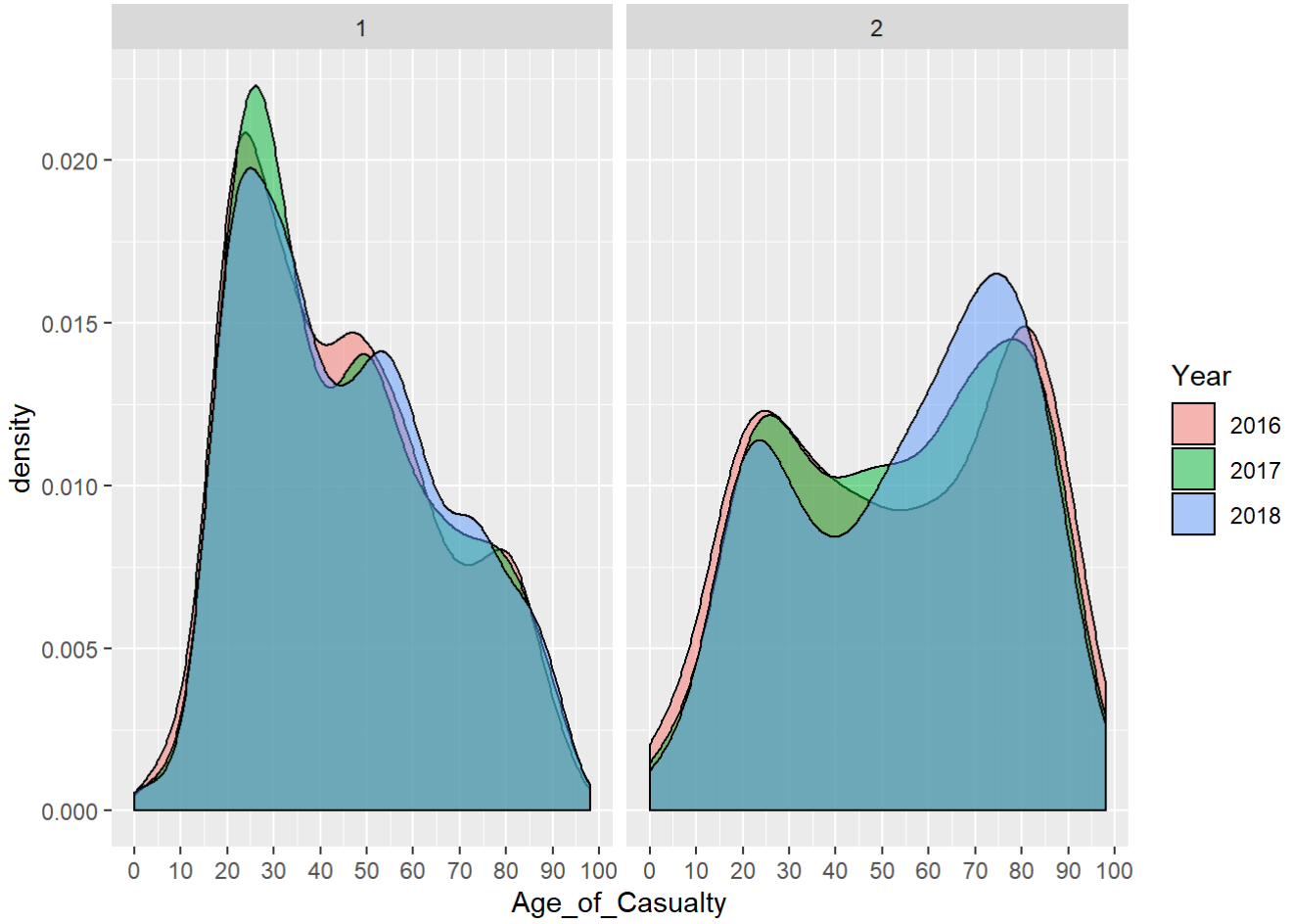
Severities type 1 & 2 are almost same over year 2016 to 2018 but there has been decrease in type 3 over the years. 1 - Fatal, 2 - Serious, 3 - Slight

```
## Considering fatal & serious cases
ggplot(data=severity[severity$Casualty_Severity != 3, ], aes(x=Year, y=Count, color=Casualty_
Severity)) +
  geom_point() +
  facet_wrap(~Casualty_Severity, scales = "free")
```



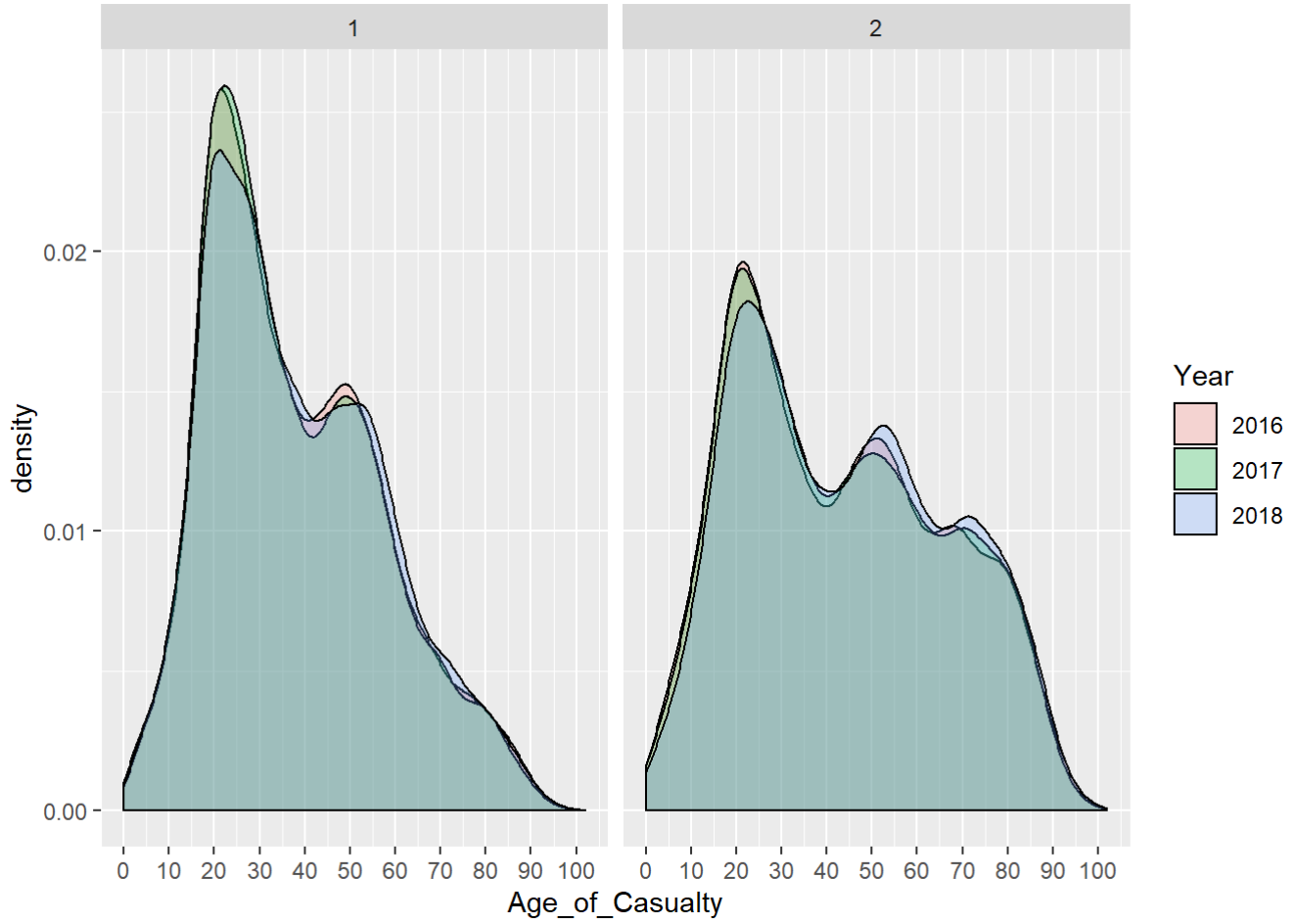
While consdering just the carriage way for pedesterian we notice similar trend, fatal cases have not imporved much and there is increase in serious cases over the year.

```
#rm(list=c('fatalities'))

## Fatal Cases
fatalities <- casualties[casualties$Casualty_Severity == 1, ]
fatalities <- fatalities[fatalities$Sex_of_Casualty != -1, ]

ggplot(data=fatalities[fatalities$Age_of_Casualty != -1, ], aes(x=Age_of_Casualty)) +
  geom_density(aes(fill=Year), alpha=0.5) +
  scale_x_continuous(breaks = seq(0,100,10)) +
  facet_wrap(~Sex_of_Casualty)
```



-Fatal casualties are higest among yonger male which reduces with age. -For female fatalties is high for yonger female which slight decrease for age group till aound 50, and then its again high for age 60 to aroud 90. -There has been a similar trend over the year.

```
## Serious Severity Cases
serious_severity <- casualties[casualties$Casualty_Severity == 2, ]

serious_severity <- serious_severity[serious_severity$Sex_of_Casualty != -1, ]

ggplot(data=serious_severity[serious_severity$Age_of_Casualty != -1, ], aes(x=Age_of_Casualt
y)) +
  geom_density(aes(fill=Year), alpha=0.25) +
  scale_x_continuous(breaks = seq(0,100,10)) +
  facet_wrap(~Sex_of_Casualty)
```




```
length(unique(casualties$Accident_Index))
```

```
## [1] 389238
```

-Similar to fatal casualties, serious severity case are higest among yonger male which reduces with age. -For female serious severity is high for yonger female, but after age 30 it reduces with age. -There has been a similar trend over the year.

-Either there are more number of younger population on the road or there is more casualties among this age.

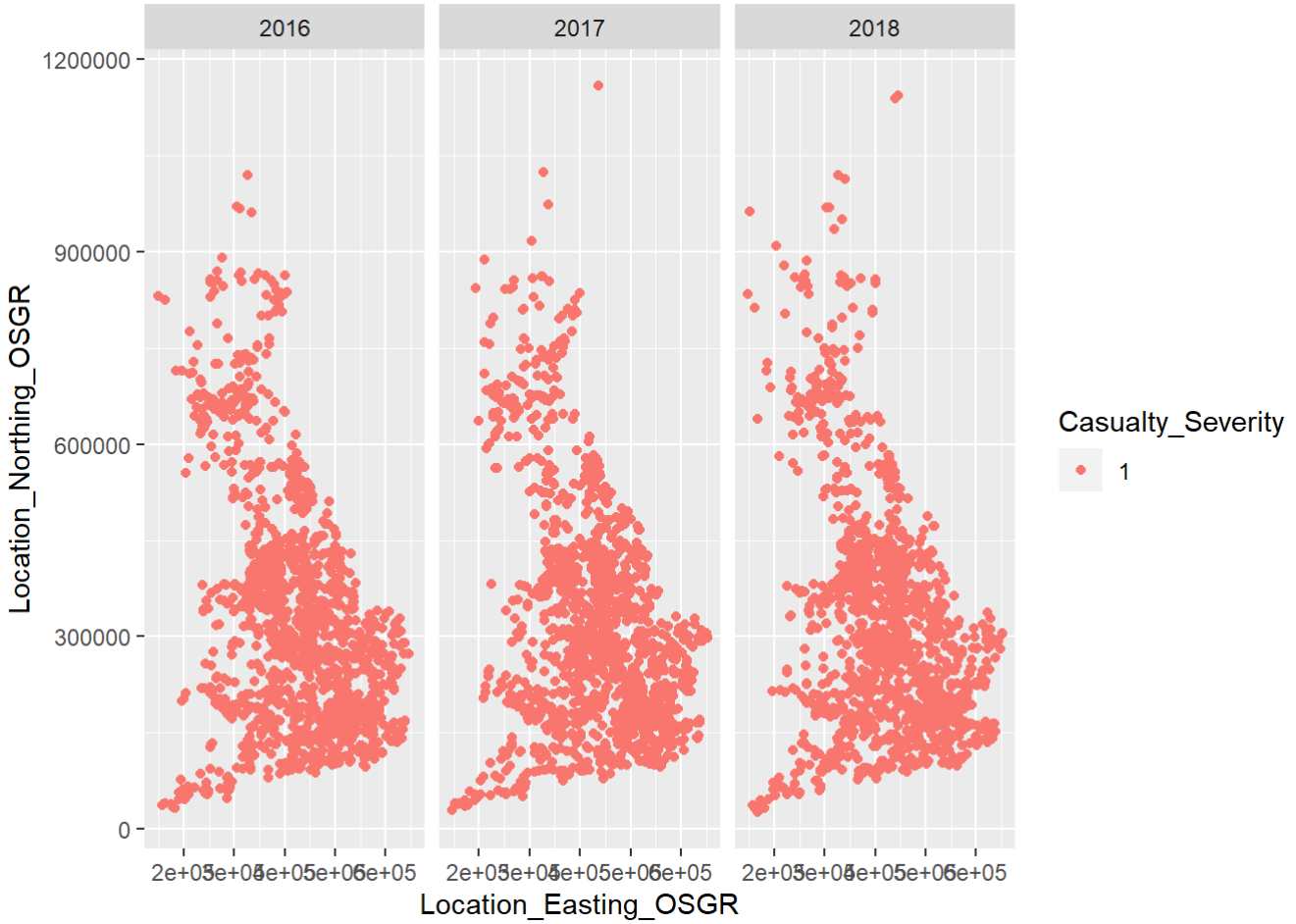
```
accidents_2016 <- read.csv('../dataset/dftRoadSafetyData_Accidents_2016.csv')
accidents_2017 <- read.csv('../dataset/dftRoadSafetyData_Accidents_2017.csv')
accidents_2018 <- read.csv('../dataset/dftRoadSafetyData_Accidents_2018.csv')


#dim(accidents_2016)[1] + dim(accidents_2017)[1] + dim(accidents_2018)[1]

colnames(accidents_2017) <- colnames(accidents_2016)
colnames(accidents_2018) <- colnames(accidents_2016)


accidents_2016$Year <- 2016
accidents_2017$Year <- 2017
accidents_2018$Year <- 2018

accidents_2016$Date <- as.Date(accidents_2016$Date, "%d-%m-%Y")
accidents_2017$Date <- as.Date(accidents_2017$Date, "%d/%m/%Y")
accidents_2018$Date <- as.Date(accidents_2018$Date, "%d/%m/%Y")


#sum(is.na(accidents_2018$Time))

accidents <- rbind(accidents_2016, accidents_2017, accidents_2018)
```

```
## Getting location of the accidents
accident_location <- accidents %>%
                        select(Accident_Index, Location_Easting_OSGR, Location_Northing_OSGR)



## Adding location to casualties data
casualties_location <- merge(casualties, accident_location, by="Accident_Index")

dim(casualties_location)
```

```
## [1] 512913     19
```

```
ggplot(data=casualties_location[casualties_location$Casualty_Severity == 1, ], aes(x=Location
_Easting_OSGR, y=Location_Northing_OSGR)) +
        geom_point(aes(color=Casualty_Severity)) +
          facet_wrap(~Year)
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```

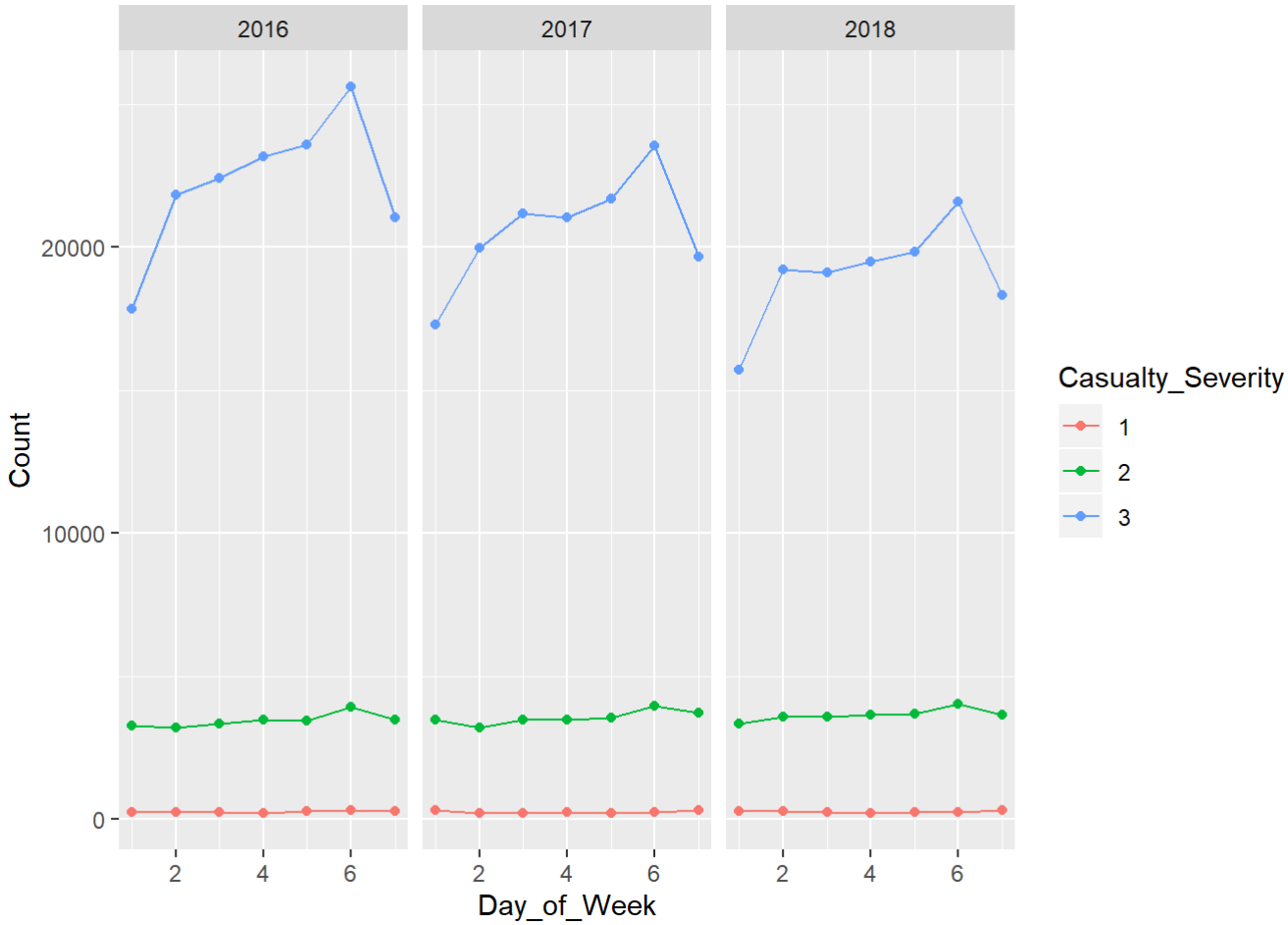



```
accident_time <- accidents %>%
                      select(Accident_Index, Date, Day_of_Week, Time)

accident_time$Hour <- as.factor(as.integer(format(strptime(accident_time$Time,"%H:%M"),'%H'
)))
accident_time$Day <- as.factor(as.integer(format(as.Date(accident_time$Date, "%Y-%m-%d"), "%
d")))
accident_time$Month <- as.factor(as.integer(format(as.Date(accident_time$Date, "%Y-%m-%d"),
"%m")))

accident_time$Quarter <- as.factor(ifelse(as.integer(accident_time$Month) > 9, 4,
                                  ifelse(as.integer(accident_time$Month) > 6, 3,
                                         ifelse(as.integer(accident_time$Month) > 3, 2, 1
))))


glimpse(accident_time)
```

```
## Observations: 389,238
## Variables: 8
## $ Accident_Index <fct> 2016010000005, 2016010000006, 2016010000008, 20...
## $ Date           <date> 2016-11-01, 2016-11-01, 2016-11-01, 2016-11-01...
## $ Day_of_Week    <int> 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,...
## $ Time           <fct> 02:30, 00:37, 01:25, 09:15, 07:53, 09:29, 08:53...
## $ Hour           <fct> 2, 0, 1, 9, 7, 9, 8, 10, 9, 9, 9, 10, 8, 8, 9, ...
## $ Day            <fct> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,...
## $ Month          <fct> 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11,...
## $ Quarter        <fct> 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,...
```

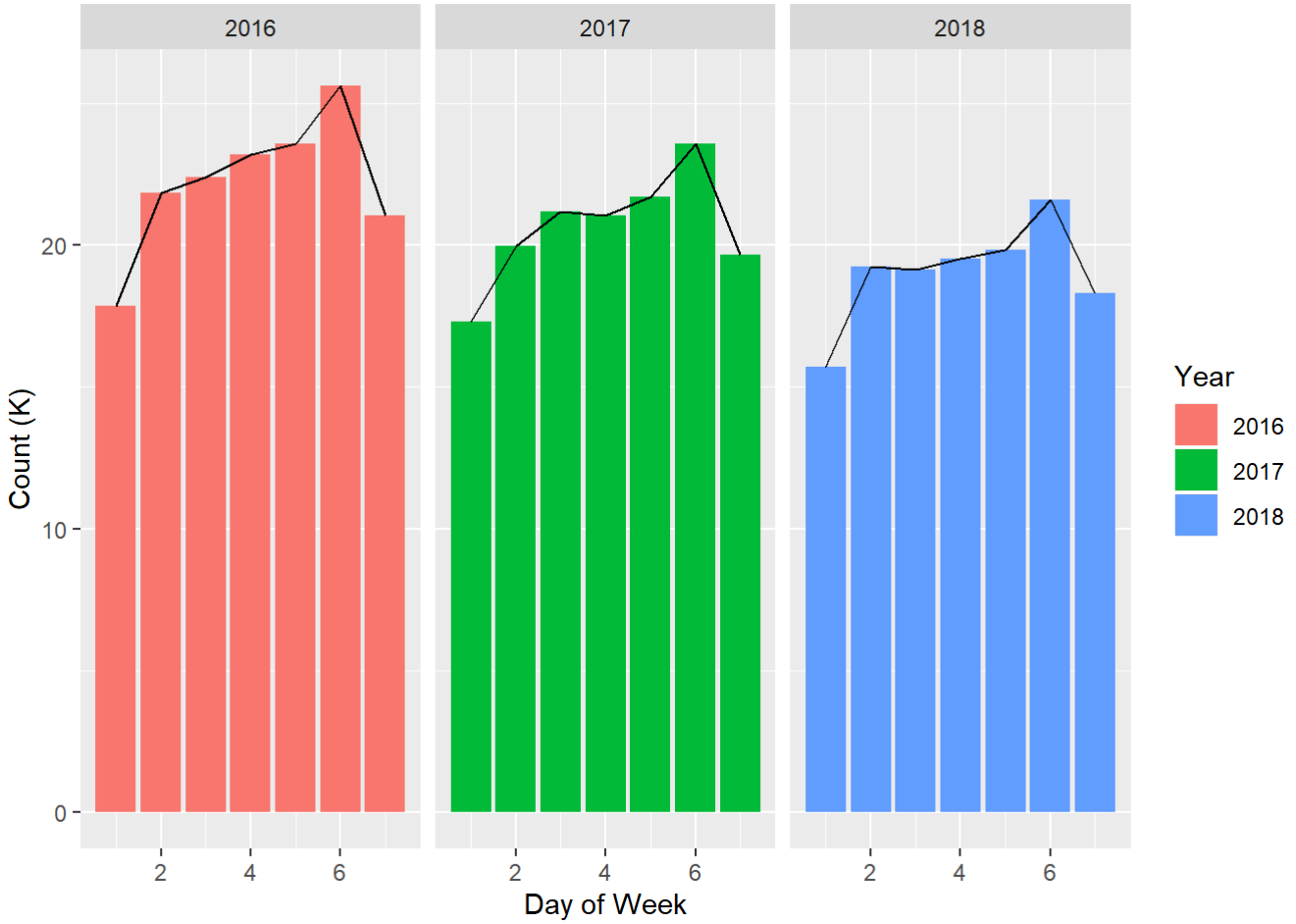
```
#head(accident_time[20:30, ])
#dim(accident_time)
accident_time <- na.omit(accident_time)



casualties_time <- merge(casualties, accident_time, by="Accident_Index")
```

```
## Casualties by week
casualties_week <- casualties_time %>%
                    group_by(Casualty_Severity, Day_of_Week, Year) %>%
                    summarise(Count=n())


ggplot(data=casualties_week, aes(x=Day_of_Week, y=Count, color=Casualty_Severity)) +
        geom_point() +
        geom_line() +
        facet_wrap(~Year)
```

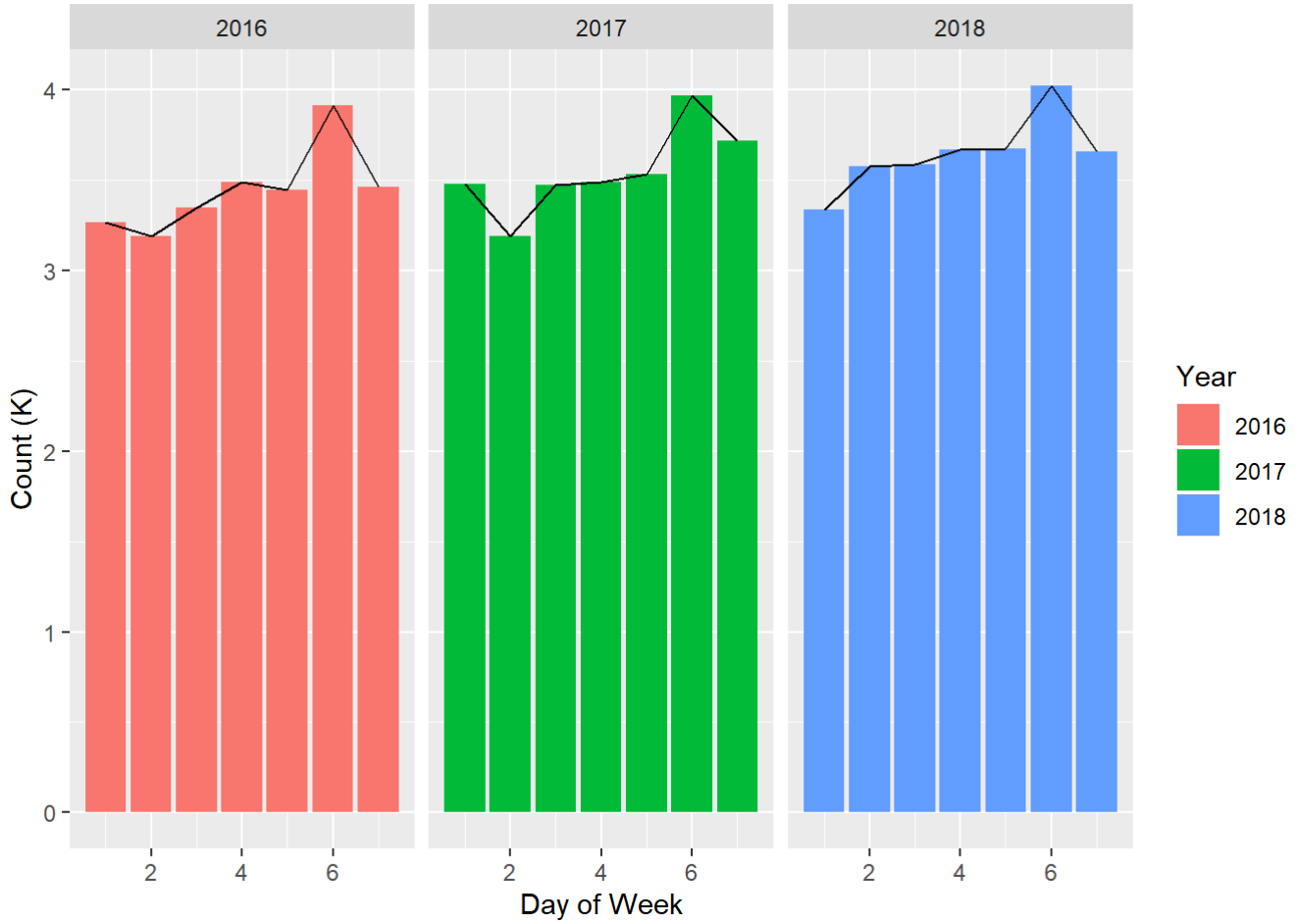


Severity 3 (slight) cases increase from day 1 (sunday) till day 6 (friday) which is highest and saturday have low such cases as compared to other days except sunday.

```
## Severity 3 - slight
#ggplot(data=casualties_week[casualties_week$Casualty_Severity == 3, ], aes(x=Day_of_Week, y=
Count)) +
#        geom_point() +
#        geom_line() +
#        facet_wrap(~Year)


ggplot(data=casualties_week[casualties_week$Casualty_Severity == 3, ], aes(x=Day_of_Week, y=C
ount/1000)) +
        geom_bar(stat = 'identity', aes(fill=Year)) +
        geom_line() +
        facet_wrap(~Year) +
        xlab('Day of Week') +
        ylab('Count (K)')
```

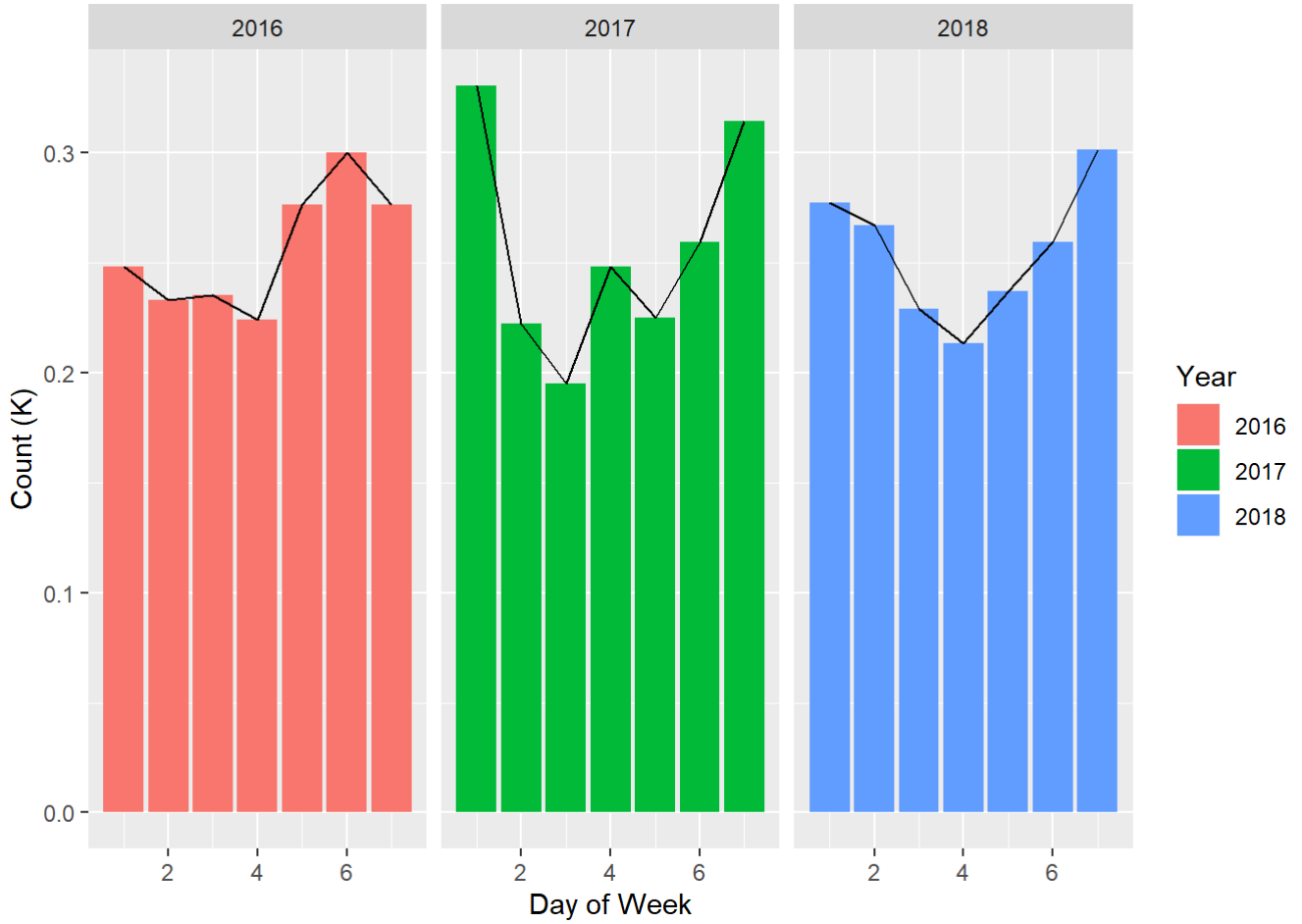



```
## Severity 2 - serious case

ggplot(data=casualties_week[casualties_week$Casualty_Severity == 2, ], aes(x=Day_of_Week, y=C
ount/1000)) +
        geom_bar(stat = 'identity', aes(fill=Year)) +
        geom_line() +
        facet_wrap(~Year) +
        xlab('Day of Week') +
        ylab('Count (K)')
```



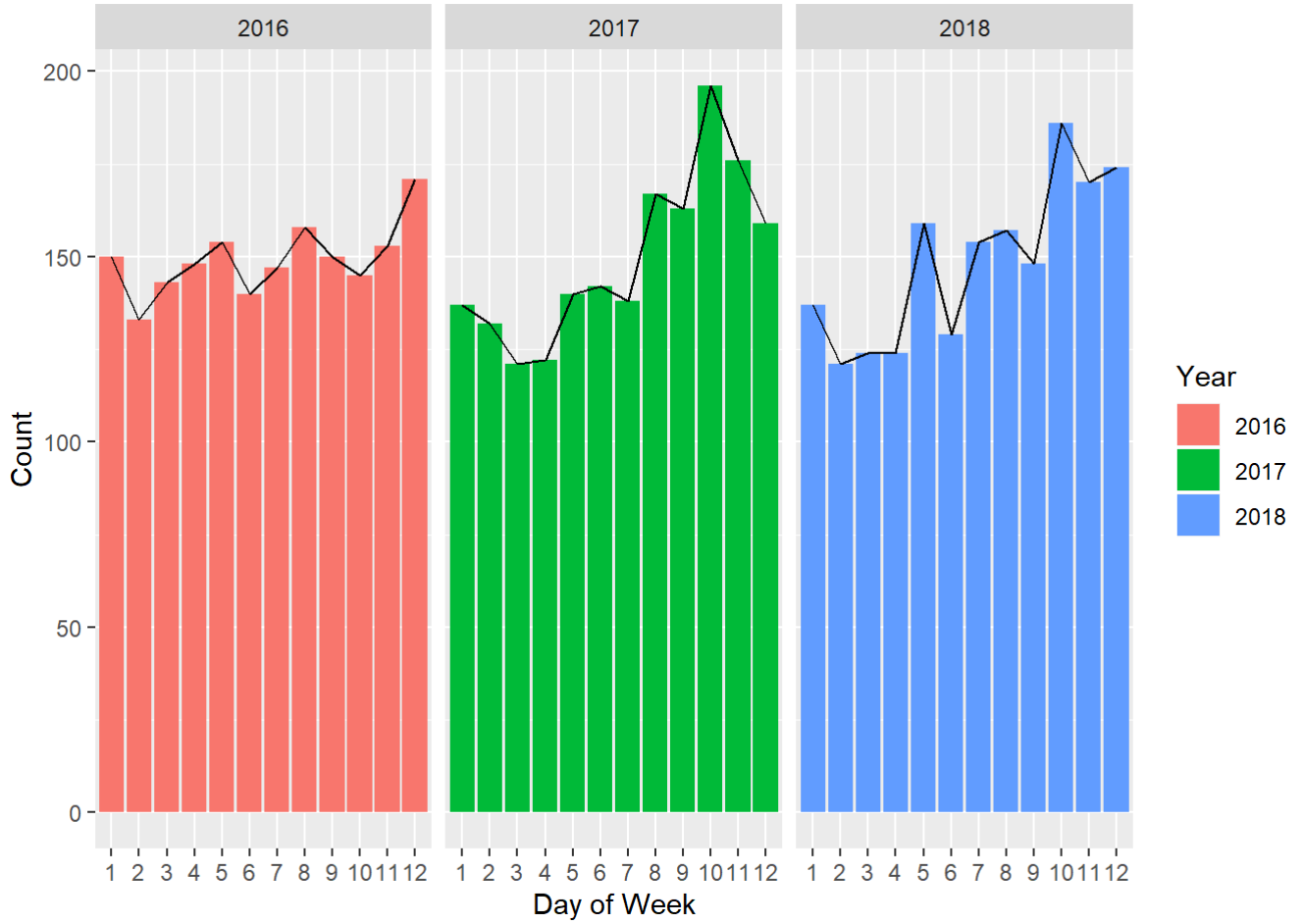
Severity 2 (serious) have similar monday to friday increasing trend. friday with higest count.

```
## Severity 1 - fatal

ggplot(data=casualties_week[casualties_week$Casualty_Severity == 1, ], aes(x=Day_of_Week, y=C
ount/1000)) +
        geom_bar(stat = 'identity', aes(fill=Year)) +
        geom_line() +
        facet_wrap(~Year) +
        xlab('Day of Week') +
        ylab('Count (K)')
```



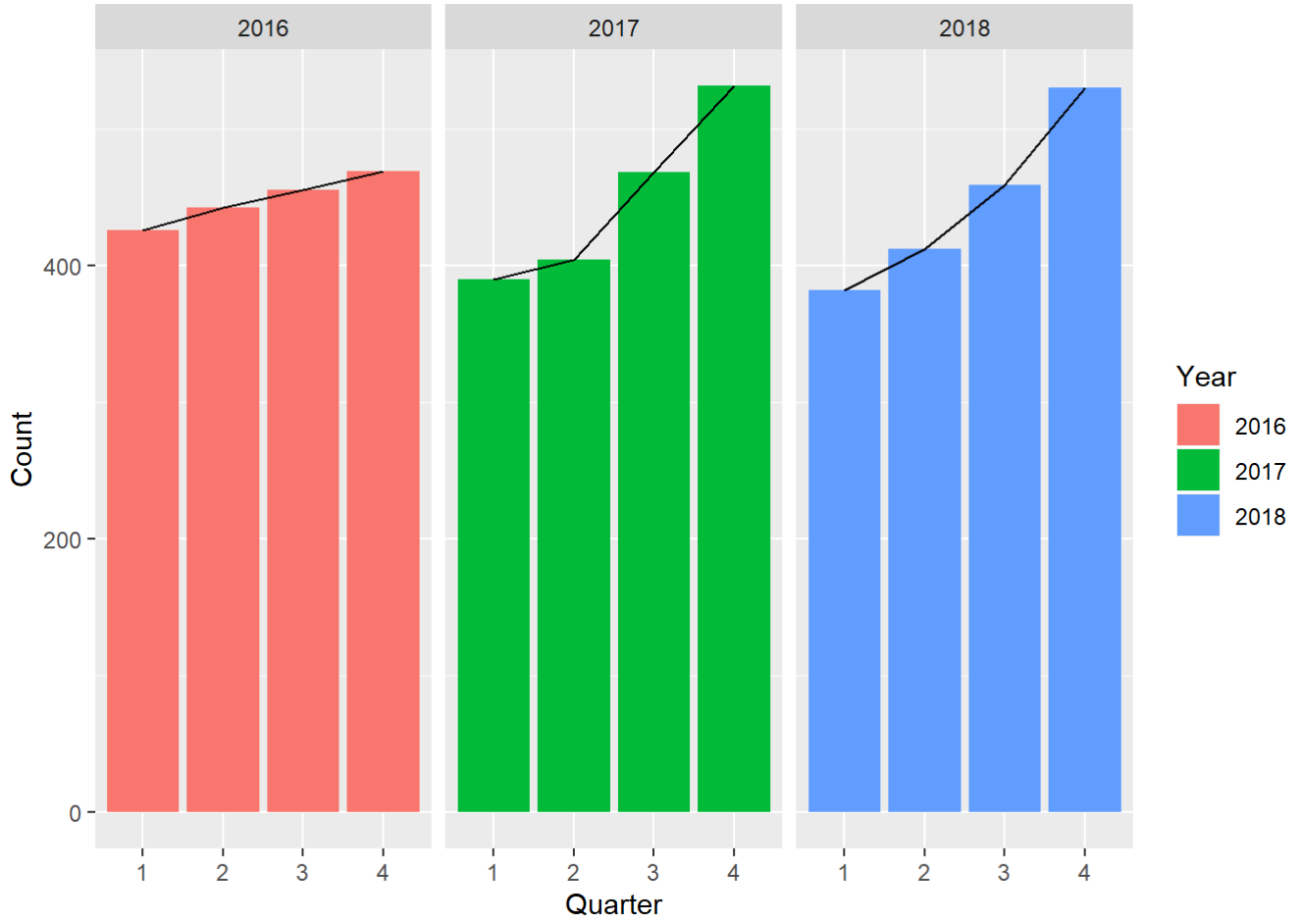
Severity 3 (fatal) cases are higher on sunday and saturday except 2016 year where thrusday, friday and saturday have higher count.

```
casualties_month <- casualties_time %>%
                    group_by(Casualty_Severity, Month, Year) %>%
                    summarise(Count=n())


#casualties_month$Month <- as.integer(casualties_month$Month)
#                                     labels = c("1", "2", "3", "4", "5", "6", "7", "8", "9",
 "10", "11", "12"),
#                                     levels=c("1", "2", "3", "4", "5", "6", "7", "8", "9", "1
0", "11", "12"))

# ggplot(data=casualties_month[casualties_month$Casualty_Severity == 1, ], aes(x=Month, y=Cou
nt, group=Year)) +
#         geom_point() +
#         geom_line() +
#         facet_wrap(~Year)



ggplot(data=casualties_month[casualties_month$Casualty_Severity == 1, ], aes(x=Month, y=Coun
t, group=Year)) +
        geom_bar(stat = 'identity', aes(fill=Year)) +
        geom_line() +
        facet_wrap(~Year) +
        xlab('Day of Week') +
        ylab('Count')
```



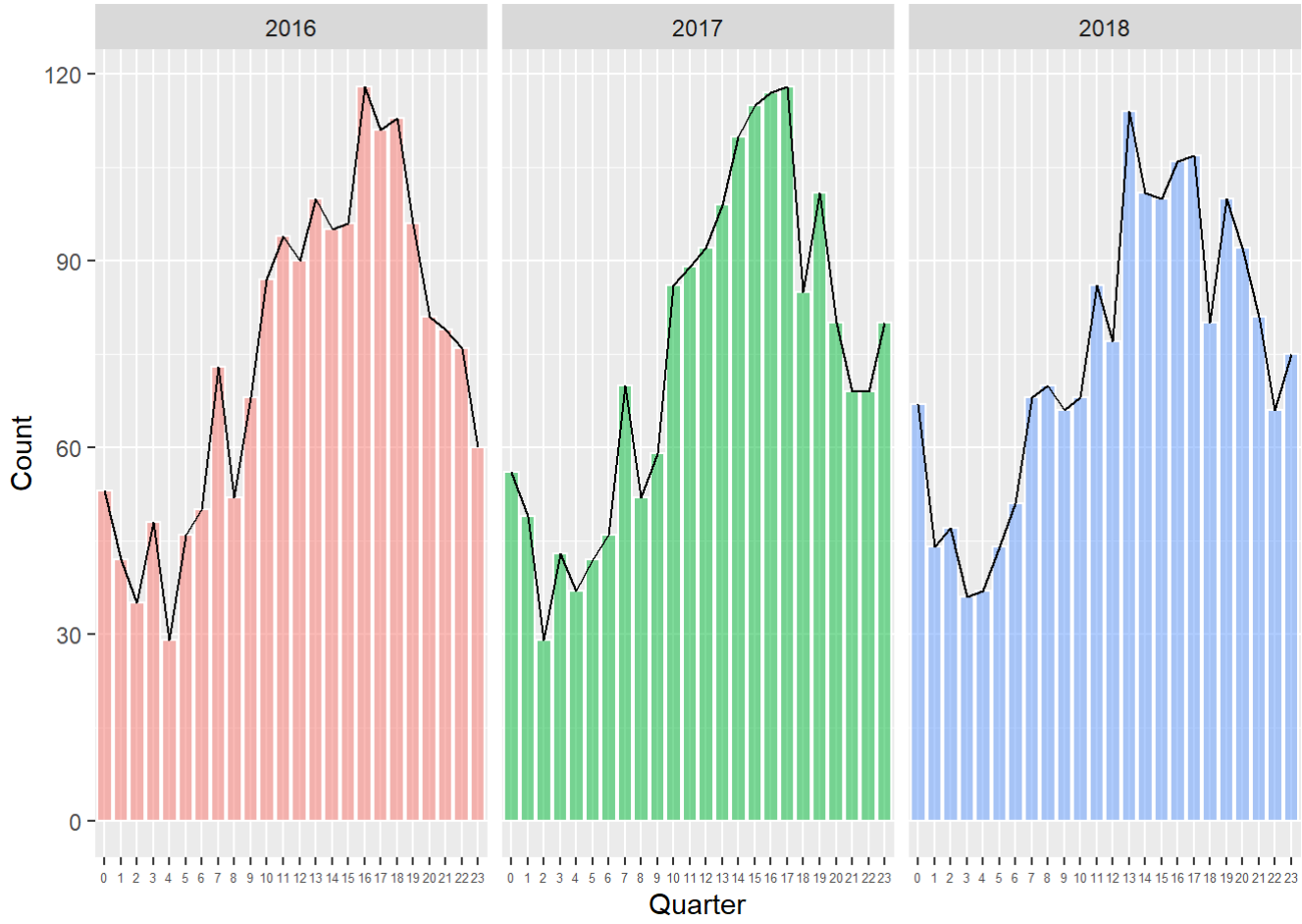
There is an increaing trend from month January to December. Though there are few month with lower count in between.

```
casualties_quarter <- casualties_time %>%
                    group_by(Casualty_Severity, Quarter, Year) %>%
                    summarise(Count=n())

#casualties_quarter <- na.omit(casualties_quarter)
#glimpse(casualties_quarter)
#casualties_quarter$Quarter <- as.integer(casualties_quarter$Quarter)



# ggplot(data=casualties_quarter[casualties_quarter$Casualty_Severity == 1, ], aes(x=Quarter,
y=Count, group=Year)) +
#         geom_point() +
#         geom_line() +
#         facet_wrap(~Year)

ggplot(data=casualties_quarter[casualties_quarter$Casualty_Severity == 1, ], aes(x=Quarter, y
=Count, group=Year)) +
        geom_bar(stat = 'identity', aes(fill=Year)) +
        geom_line() +
        facet_wrap(~Year) +
        xlab('Quarter') +
        ylab('Count')
```



Over the year, There is an increasing trend for the fatalities case for 1st to 4th quarter. For first quarter of year the count for fatalities have decreased over the but this is opposite for last 2 quarters.

```
casualties_hour <- casualties_time %>%
                   group_by(Casualty_Severity, Hour, Year) %>%
                   summarise(Count=n())

casualties_hour <- na.omit(casualties_hour)

# ggplot(data=casualties_hour[casualties_hour$Casualty_Severity == 1, ], aes(x=Hour, y=Count,
group=Year)) +
#         geom_point() +
#         geom_line() +
#         facet_wrap(~Year) +
#         theme(axis.text.x=element_text(size=6))


ggplot(data=casualties_hour[casualties_hour$Casualty_Severity == 1, ], aes(x=Hour, y=Count, g
roup=Year)) +
        geom_bar(stat = 'identity', aes(fill=Year), colour="white", alpha=0.5) +
        geom_line() +
        facet_wrap(~Year) +
        xlab('Quarter') +
        ylab('Count') +
        theme(legend.position = "none",
              axis.text.x=element_text(size=5))
```



There is a increasing trend from around 2am to 5pm over the year. There is a peak from 2 to 7 pm. Night time after 7 till 12 have more count of fatalities than after 12 till 5-6 pm. May be there are less number of cars and pedestrian then.

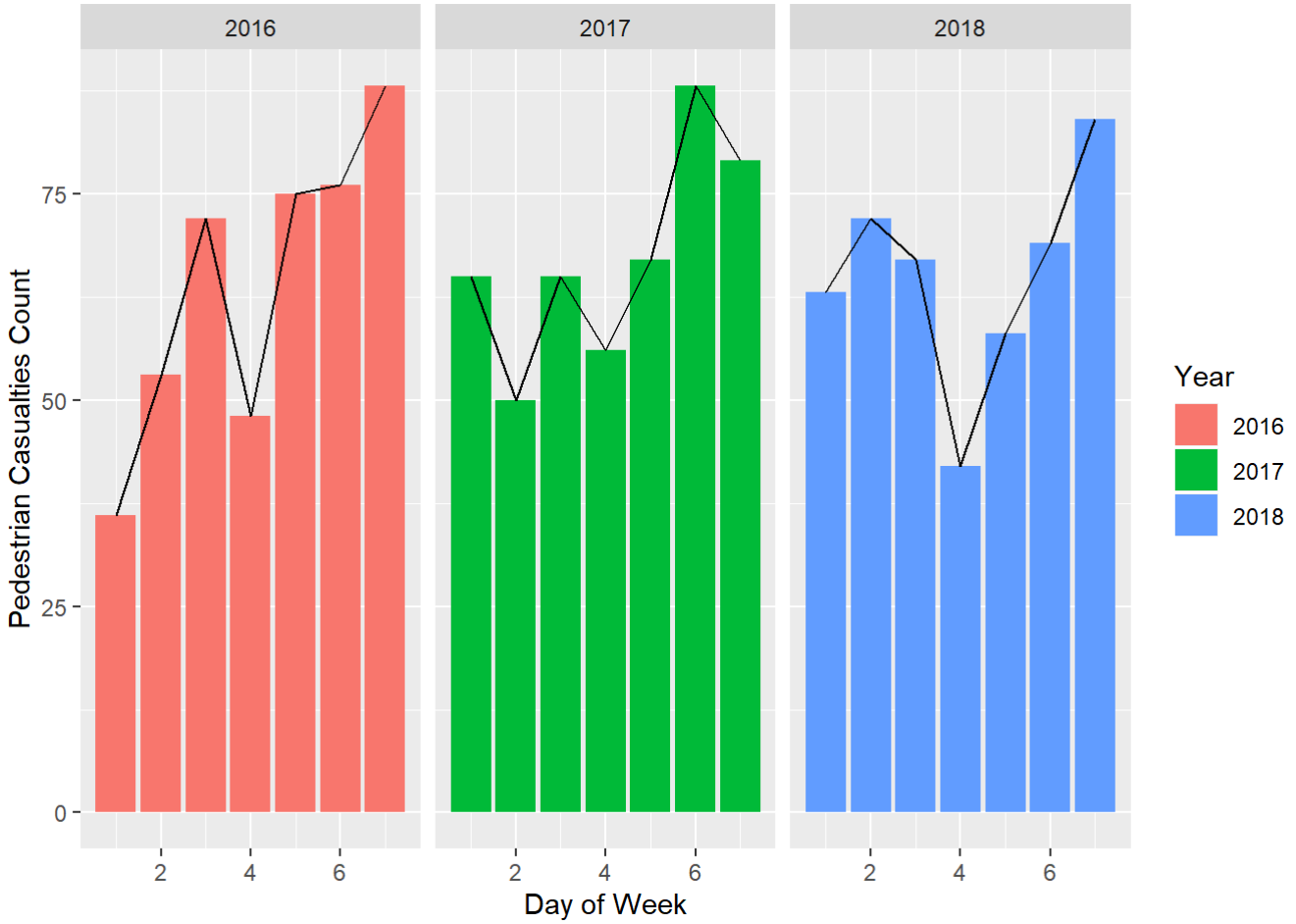
There is a sudden rise at 7 am. May be because of increase in buses and cars on road.

Pedestrian Fatalities Analysis

```
t = (casualties_time$Casualty_Type  == 0)
pedestrian_casualties_by_week <- casualties_time[t, ] %>%
                                 group_by(Casualty_Severity, Day_of_Week, Year) %>%
                                 summarise(Count=n())
dim(casualties_time[t, ])
```

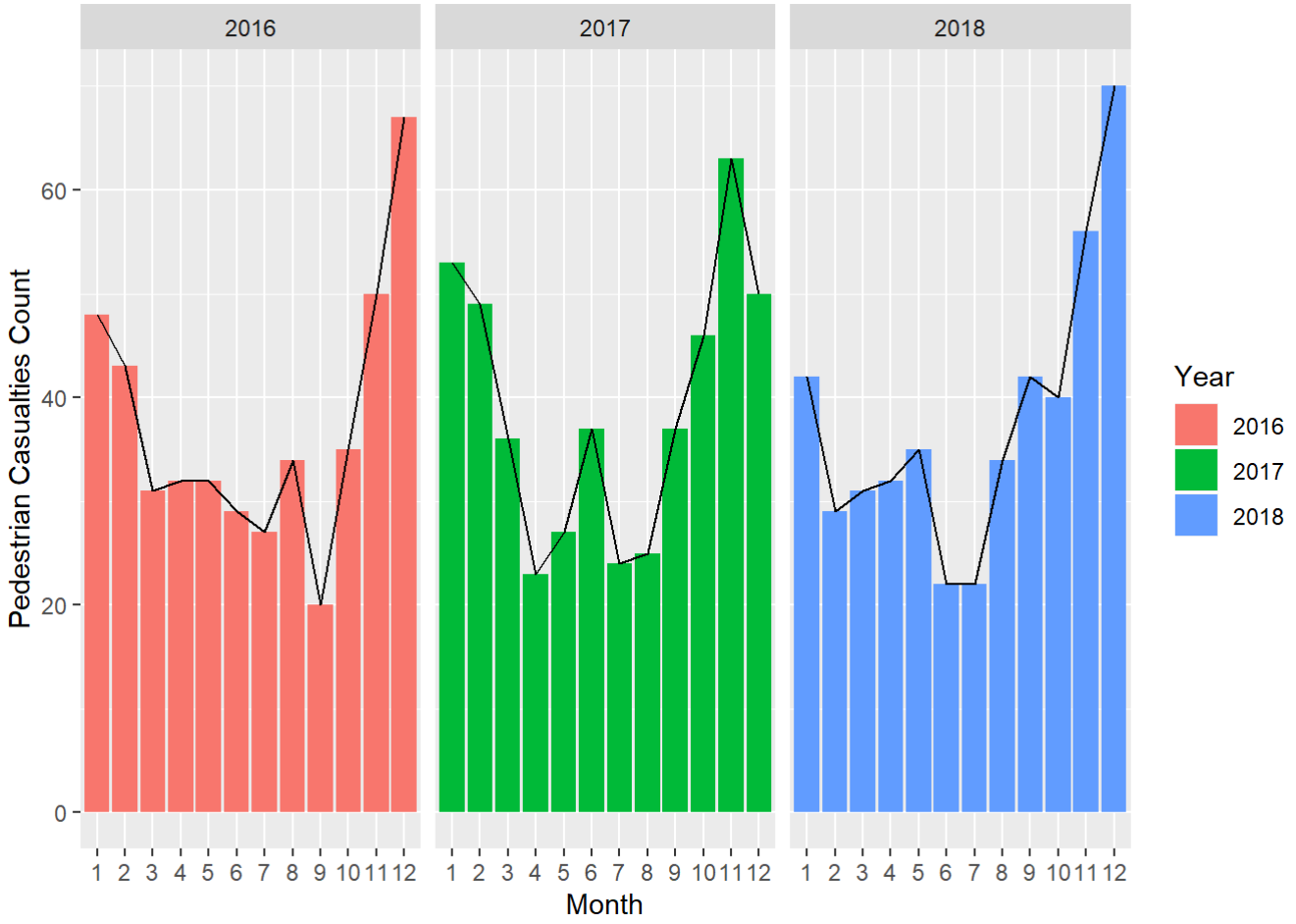
```
## [1] 69779    24
```

```
ggplot(data=pedestrian_casualties_by_week[pedestrian_casualties_by_week$Casualty_Severity ==
1, ], aes(x=Day_of_Week, y=Count)) +
        geom_bar(stat = 'identity', aes(fill=Year)) +
        geom_line() +
        facet_wrap(~Year) +
        xlab('Day of Week') +
        ylab('Pedestrian Casualties Count')
```



Severity 3 (fatal) cases are higher on sunday and saturday except 2016 year where thrusday, friday and saturday have higher count.

```
pedestrian_casualties_by_month <- casualties_time[t, ] %>%
                    group_by(Casualty_Severity, Month, Year) %>%
                    summarise(Count=n())

ggplot(data=pedestrian_casualties_by_month[pedestrian_casualties_by_month$Casualty_Severity =
= 1, ], aes(x=Month, y=Count, group=Year)) +
        geom_bar(stat = 'identity', aes(fill=Year)) +
        geom_line() +
        facet_wrap(~Year) +
        xlab('Month') +
        ylab('Pedestrian Casualties Count')
```

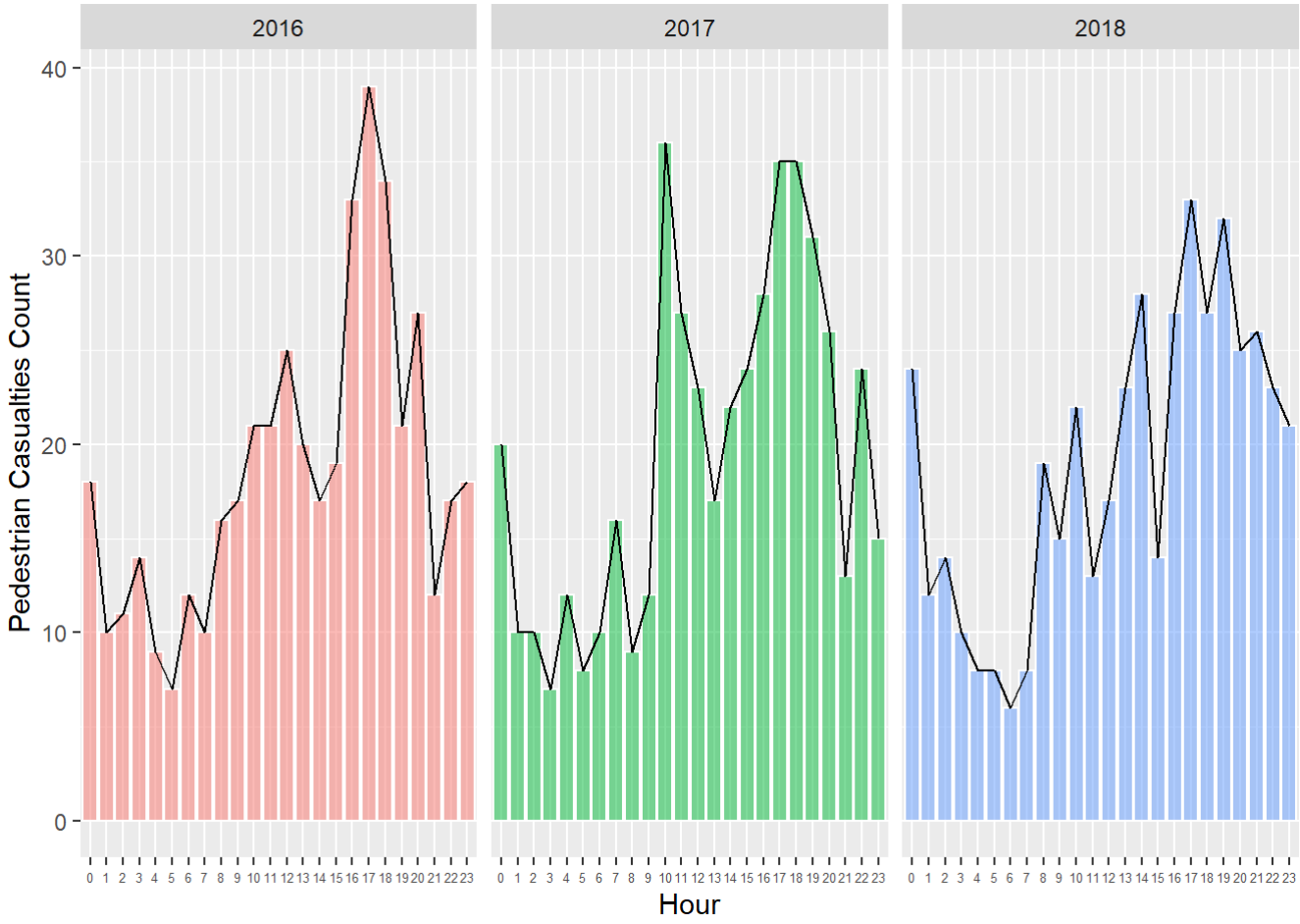


There is an increaing trend from month January to December. Though there are few month with lower count in between.

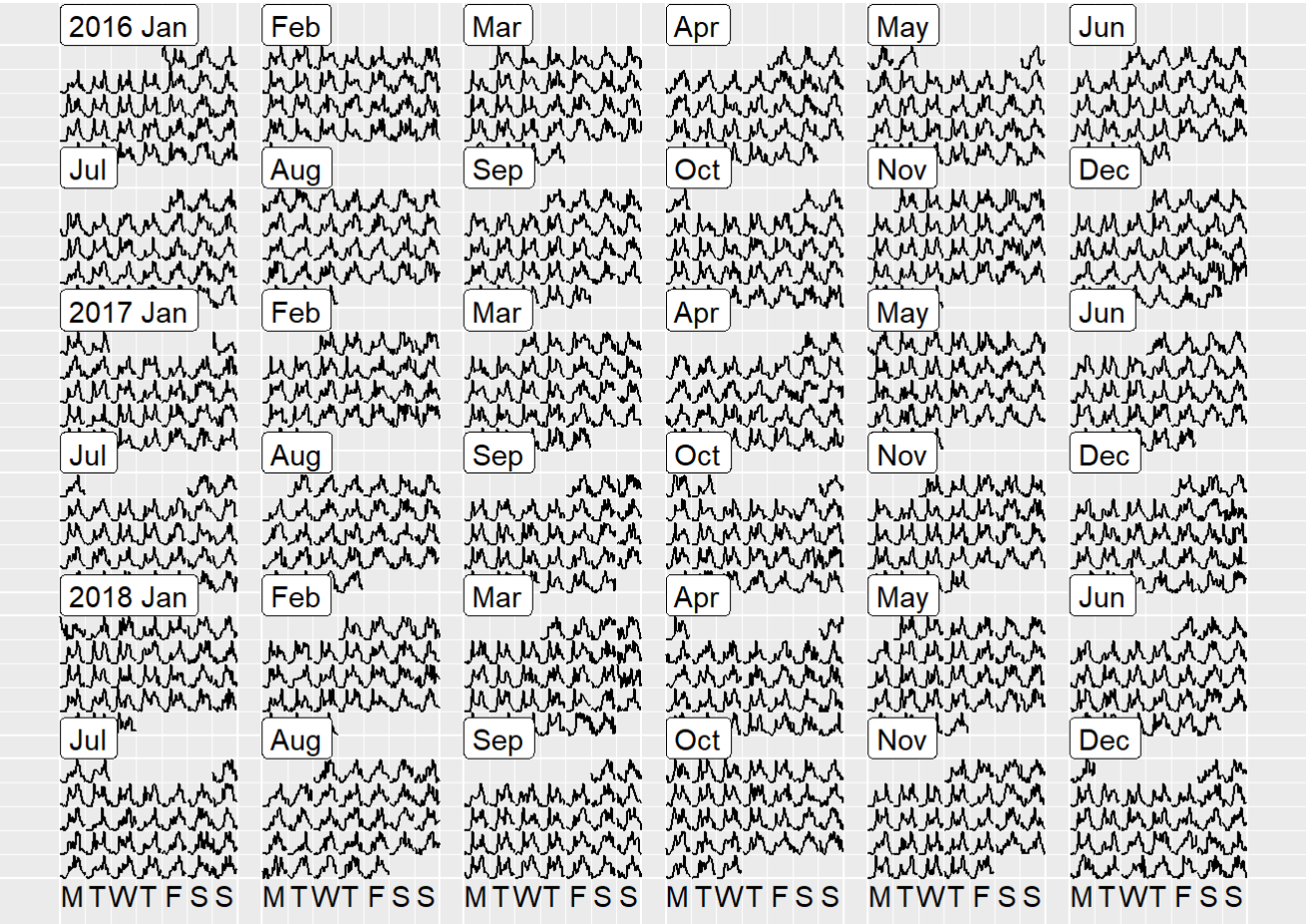
```
pedestrian_casualties_by_quarter <- casualties_time[t, ] %>%
                    group_by(Casualty_Severity, Quarter, Year) %>%
                    summarise(Count=n())

ggplot(data=pedestrian_casualties_by_quarter[pedestrian_casualties_by_quarter$Casualty_Severi
ty == 1, ], aes(x=Quarter, y=Count, group=Year)) +
        geom_bar(stat = 'identity', aes(fill=Year)) +
        geom_line() +
        facet_wrap(~Year) +
        xlab('Quarter') +
        ylab('Pedestrian Casualties Count')
```

Over the year, There is an increasing trend for the fatalities case for 1st to 4th quarter. For first quarter of year the count for fatalities have decreased over the but this is opposite for last 2 quarters.

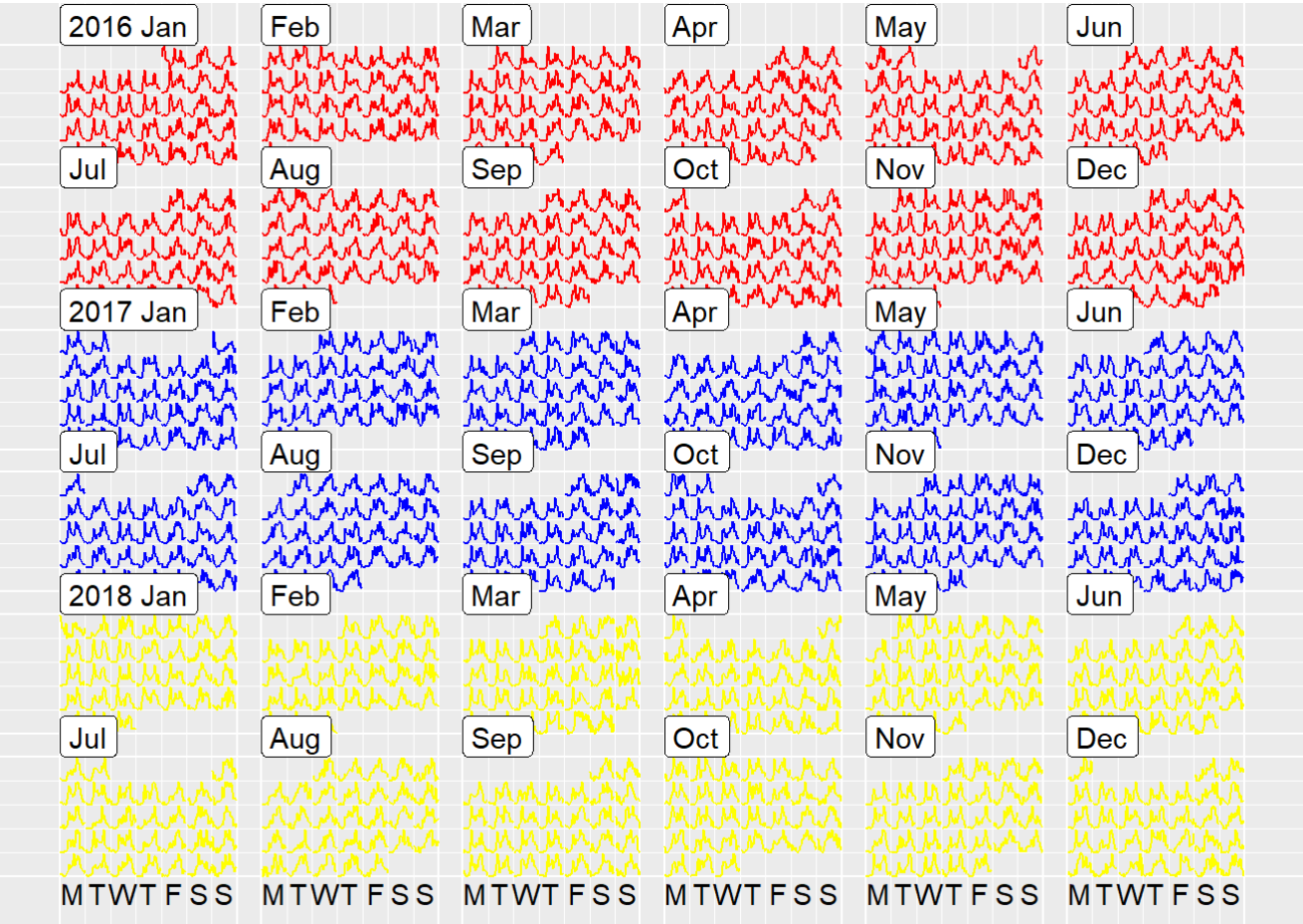
```
pedestrian_casualties_by_hour <- casualties_time[t, ] %>%
                    group_by(Casualty_Severity, Hour, Year) %>%
                    summarise(Count=n())

# ggplot(data=casualties_hour[casualties_hour$Casualty_Severity == 1, ], aes(x=Hour, y=Count,
group=Year)) +
#         geom_point() +
#         geom_line() +
#         facet_wrap(~Year) +
#         theme(axis.text.x=element_text(size=6))


ggplot(data=pedestrian_casualties_by_hour[pedestrian_casualties_by_hour$Casualty_Severity ==
1, ], aes(x=Hour, y=Count, group=1)) +
        geom_bar(stat = 'identity', aes(fill=Year), colour="white", alpha=0.5) +
        geom_line() +
        facet_wrap(~Year) +
        xlab('Hour') +
        ylab('Pedestrian Casualties Count') +
        theme(legend.position = "none",
              axis.text.x=element_text(size=5))
```




```
pedestrian_casualties_count <- casualties_time %>%
                               group_by(Date, Hour) %>%
                               summarise(Count=n())

#sum(is.na(pedestrian_casualties_hourly_count$Hour))


#head(casualties_hourly_count)


#casualties_calendar <- merge(casualties_time, casualties_hourly_count, by=c('Date', 'Hour'))

calendar_mm_df <- pedestrian_casualties_count %>%
                frame_calendar(x=Hour,
                               y=Count,
                               date = Date,
                               calendar = "monthly")


p1 <- calendar_mm_df %>%
  ggplot(aes(x = .Hour, y = .Count, group = Date)) +
  geom_line()

prettify(p1)
```


2016 Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
2017 Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
2018 Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
M T W T F S S

```
#head(casualties_time)
y <- c(casualties_time$Year == 2018)
c <- y & t
pedestrian_casualties_mm_count <- casualties_time %>%
                              group_by(Date, Year, Hour) %>%
                              summarise(Count=n())

#sum(is.na(pedestrian_casualties_hourly_count$Hour))


#head(casualties_hourly_count)


#casualties_calendar <- merge(casualties_time, casualties_hourly_count, by=c('Date', 'Hour'))

calendar_mm_df <- pedestrian_casualties_mm_count %>%
                frame_calendar(x=Hour,
                               y=Count,
                               date = Date)


p1 <- ggplot(calendar_mm_df) +
  geom_line(data=filter(calendar_mm_df, Year == 2016), aes(x = .Hour, y = .Count, group = Dat
e), color='red') +
  geom_line(data=filter(calendar_mm_df, Year == 2017), aes(x = .Hour, y = .Count, group = Dat
e), color='blue') +
  geom_line(data=filter(calendar_mm_df, Year == 2018), aes(x = .Hour, y = .Count, group = Dat
e), color='yellow')

prettify(p1)
```




```
library('ggplot2')
#install.packages("forecast")
library('forecast')
```

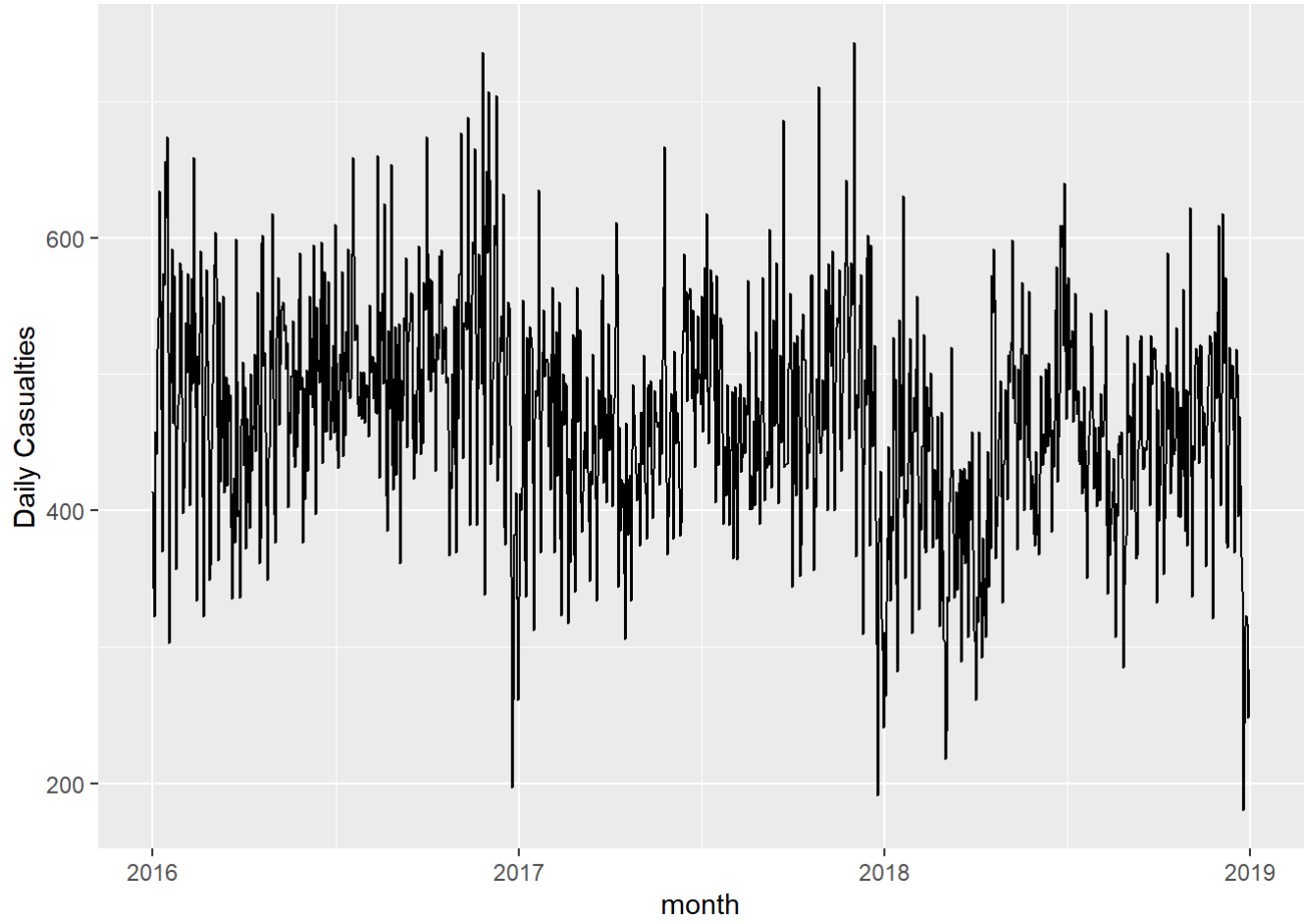
```
## Warning: package 'forecast' was built under R version 3.6.3
```

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

```
library('tseries')
```

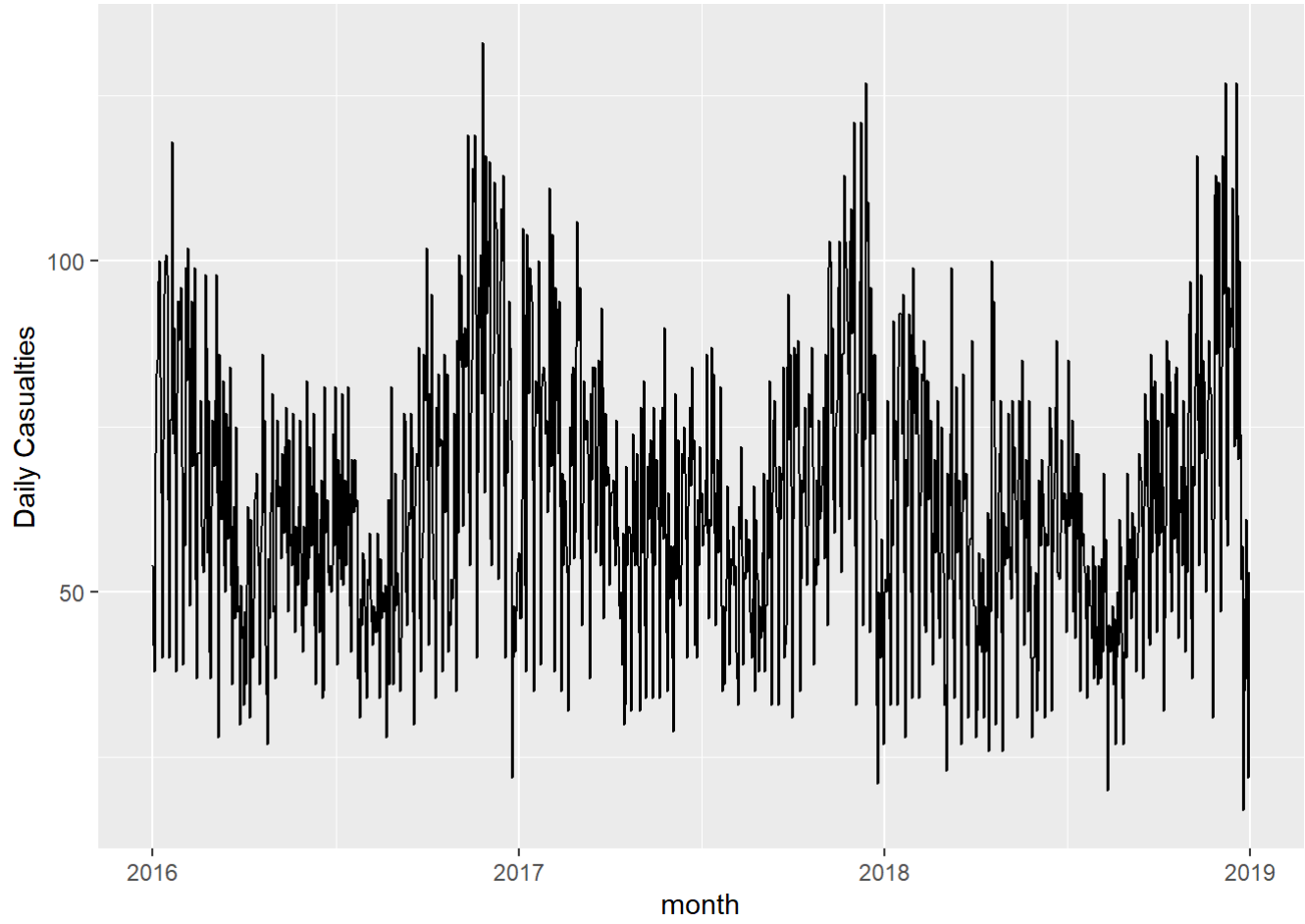
```
## Warning: package 'tseries' was built under R version 3.6.3
```

```
casualties_monthly_trend <- casualties_time %>%
                            group_by(Date,Year, Month) %>%
                            summarize(Count=n())

ggplot(casualties_monthly_trend, aes(Date, Count)) + geom_line() + scale_x_date('month')  + y
lab("Daily Casualties") +
            xlab("")
```



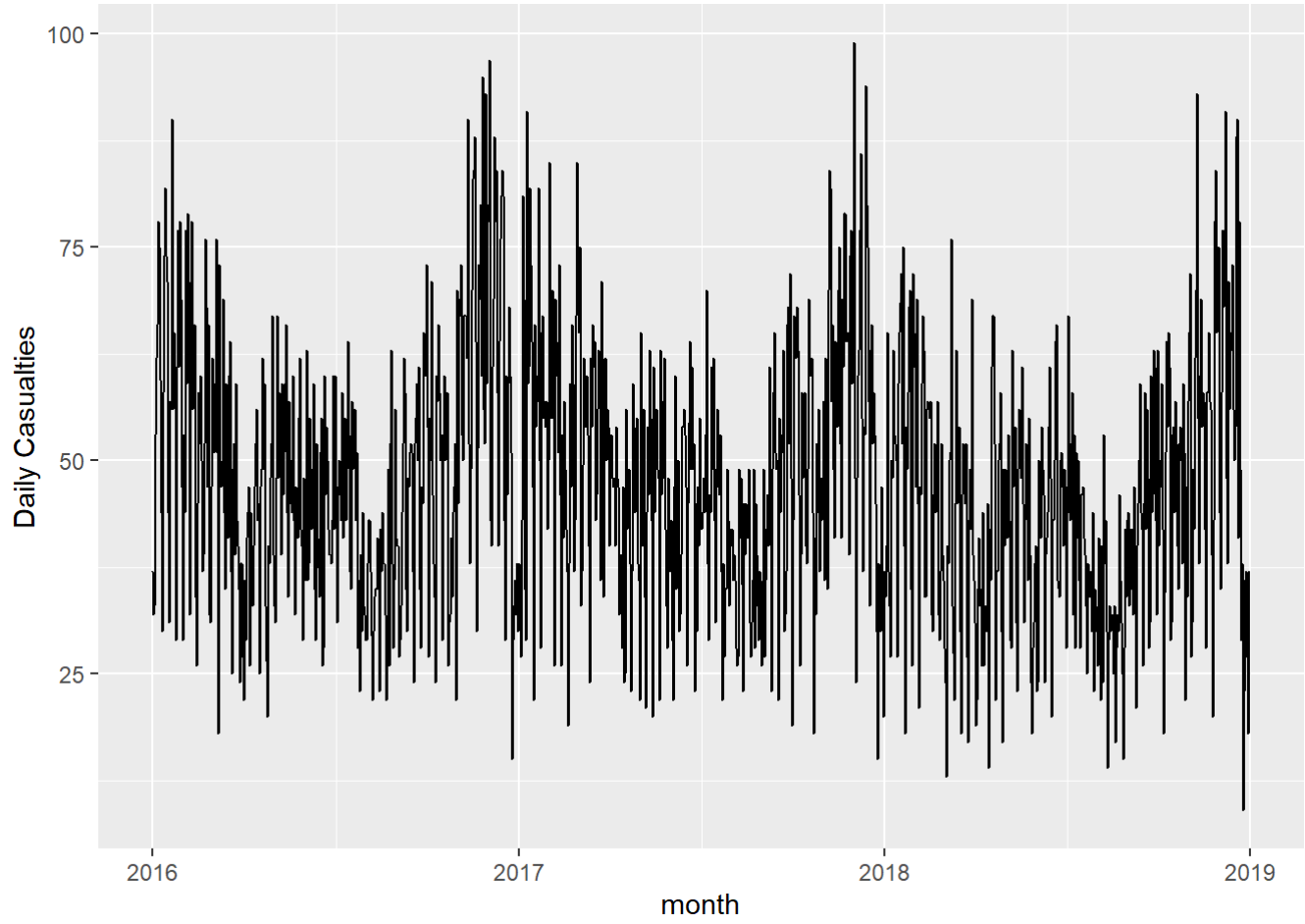
There is no trend as such but there may be some seasonality.

```
r <- casualties_time$Casualty_Type == 0
casualties_monthly_trend <- casualties_time[r, ] %>%
                            group_by(Date,Year, Month) %>%
                            summarize(Count=n())

ggplot(casualties_monthly_trend, aes(Date, Count)) + geom_line() + scale_x_date('month')  + y
lab("Daily Casualties") +
           xlab("")
```



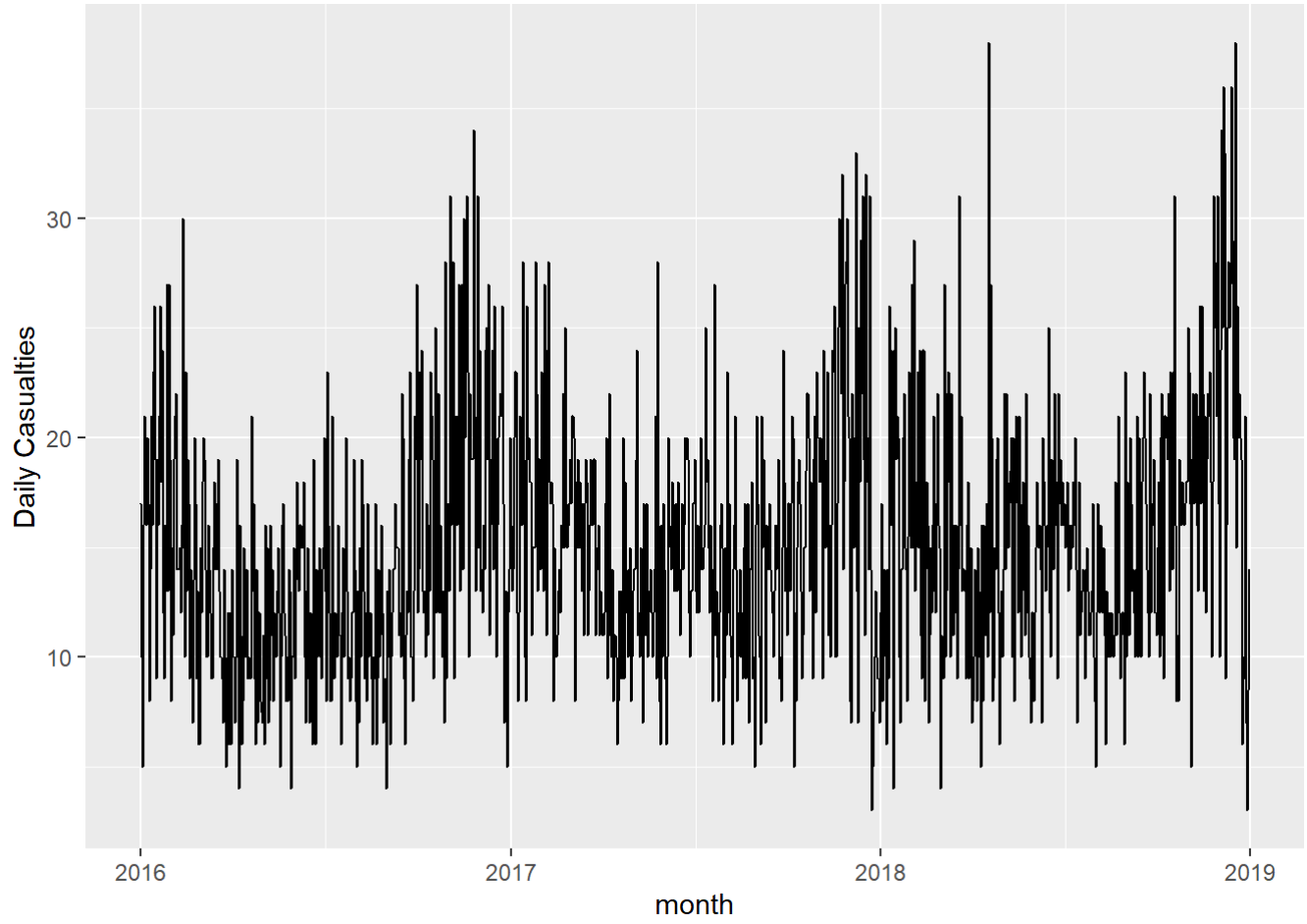
Case for pedestrian is quite similar to overall casualties.

```
r <- casualties_time$Casualty_Type == 0 & casualties_time$Casualty_Severity == 3
severity_3_monthly_trend <- casualties_time[r, ] %>%
                            group_by(Date,Year, Month) %>%
                            summarize(Count=n())

ggplot(severity_3_monthly_trend, aes(Date, Count)) + geom_line() + scale_x_date('month')  + y
lab("Daily Casualties") +
            xlab("")
```



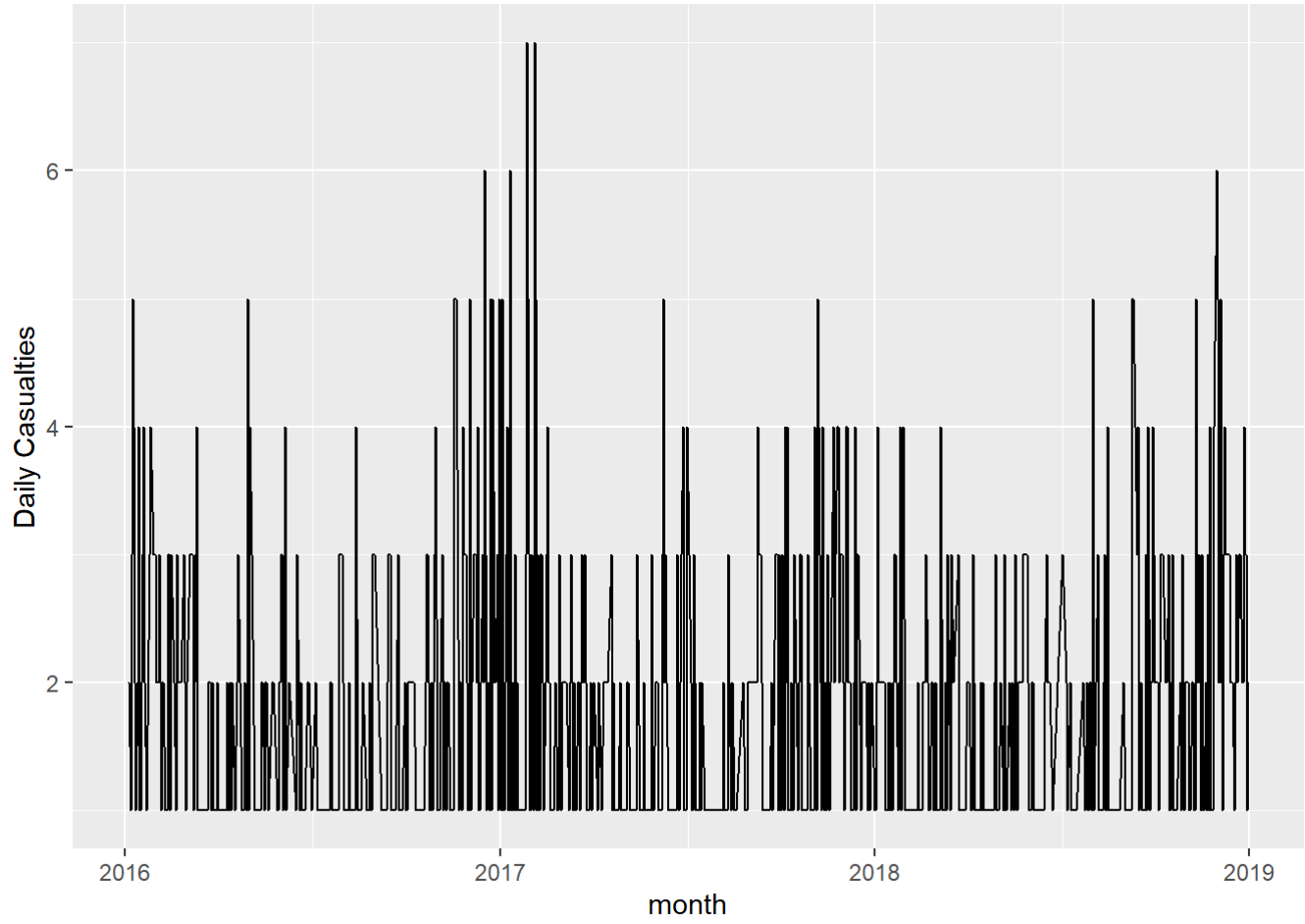
Pedestrain case with severity 3 have mean of around 50 cases daily for 1st quarter which decreases till 3rd quarter and then increase for 4th for all year 2016-2018. There seems to be a seasonal trend here.

```
r <- casualties_time$Casualty_Type == 0 & casualties_time$Casualty_Severity == 2
severity_2_monthly_trend <- casualties_time[r, ] %>%
                              group_by(Date,Year, Month) %>%
                              summarize(Count=n())



ggplot(severity_2_monthly_trend, aes(Date, Count)) + geom_line() + scale_x_date('month')  + y
lab("Daily Casualties") +
            xlab("")
```



Creating a u-shape seasonal trend every year. Pedestrain case with severity 2 have mean of around 15 cases daily for 1st quarter which decreases till 2nd quarter and then start increasing from 3rd for all year 2016-2018.There seems to be a seasonal trend here.

```
r <- casualties_time$Casualty_Type == 0 & casualties_time$Casualty_Severity == 1
severity_1_monthly_trend <- casualties_time[r, ] %>%
                              group_by(Date,Year, Month) %>%
                              summarize(Count=n())



ggplot(severity_1_monthly_trend, aes(Date, Count)) + geom_line() + scale_x_date('month')  + y
lab("Daily Casualties") +
            xlab("")
```

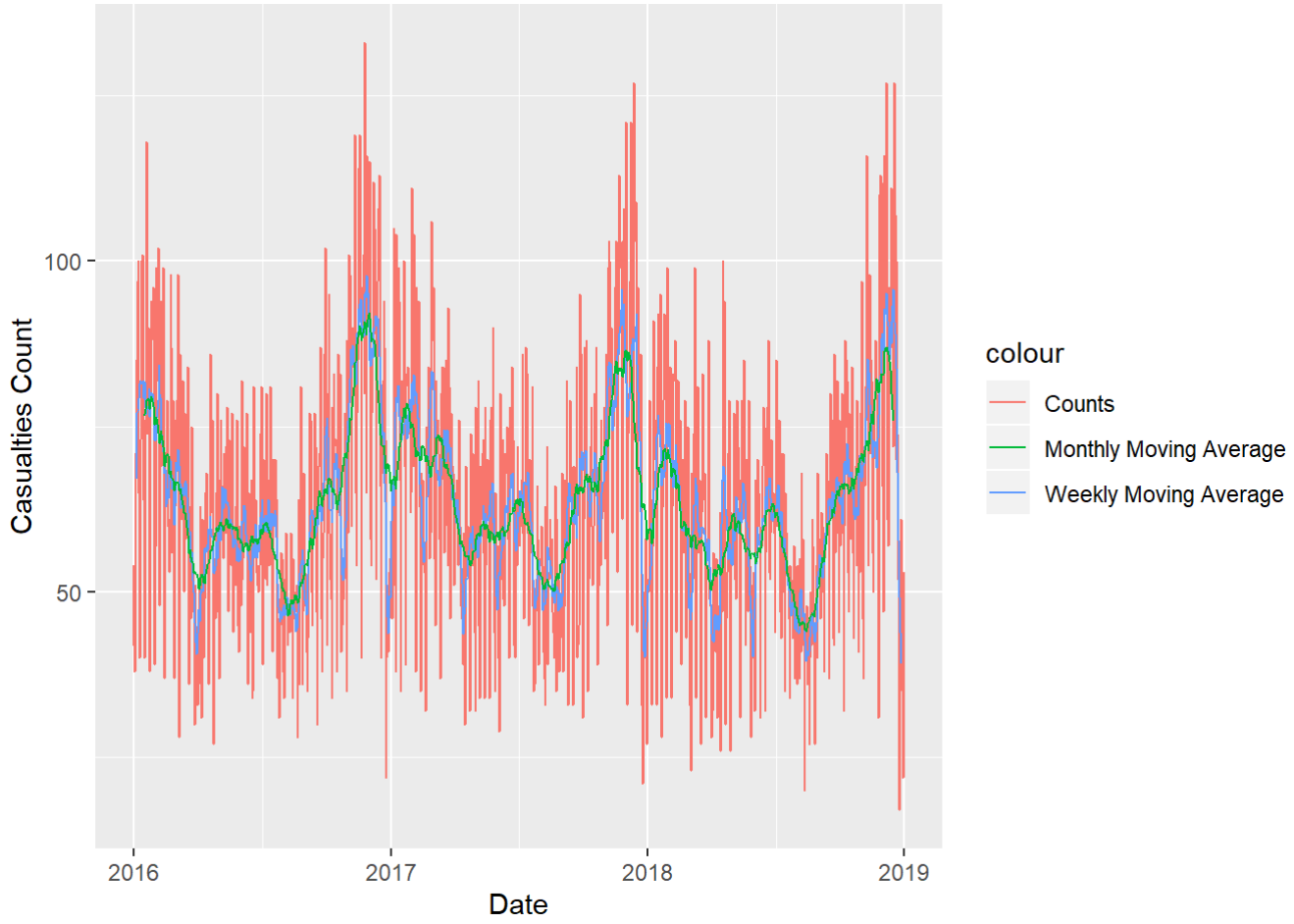


Similar to case 2, Creating a u-shape seasonal trend every year. Pedestrain case with severity 1 have mean of around 2 cases daily for 1st quarter which decreases till 2nd quarter and then start increasing from 3rd for all year 2016-2018.There seems to be a seasonal trend here.

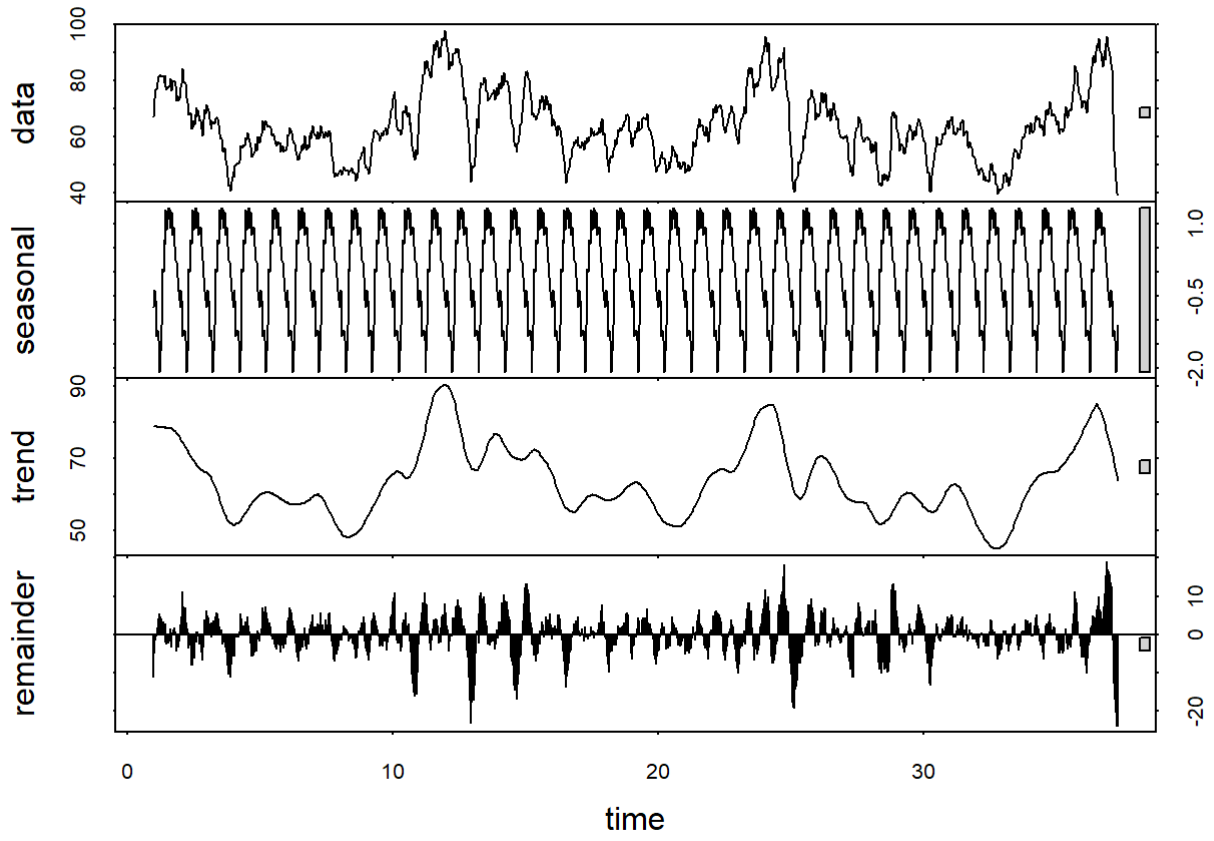
```
casualties_monthly_trend$Count_MA <- ma(casualties_monthly_trend$Count, order=7)
casualties_monthly_trend$Count_MA30 <- ma(casualties_monthly_trend$Count, order=30)

# ggplot(casualties_monthly_trend, aes(Date, Count)) + geom_line() + scale_x_date('month')  +
ylab("Daily Casualties") +
#             xlab("")

ggplot() +
  geom_line(data = casualties_monthly_trend, aes(x = Date, y = Count, colour = "Counts")) +
  geom_line(data = casualties_monthly_trend, aes(x = Date, y = Count_MA,   colour = "Weekly M
oving Average"))  +
  geom_line(data = casualties_monthly_trend, aes(x = Date, y = Count_MA30, colour = "Monthly
 Moving Average"))  +
  ylab('Casualties Count')
```

```
## Warning: Removed 6 rows containing missing values (geom_path).
```

```
## Warning: Removed 30 rows containing missing values (geom_path).
```




```
count_ma = ts(na.omit(casualties_monthly_trend$Count_MA), frequency=30)
decomp <- stl(count_ma, s.window = 'periodic')
decomp_count <- seasadj(decomp)
plot(decomp)
```

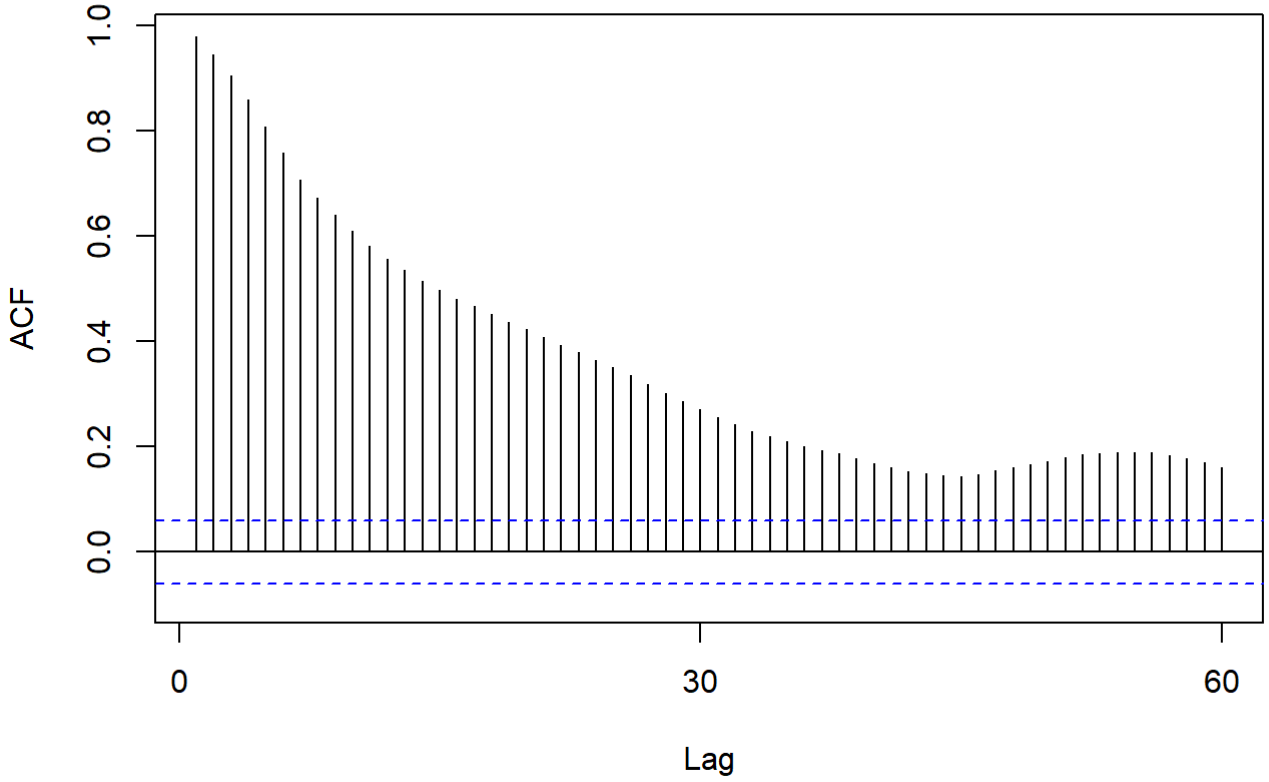



```
adf.test(count_ma, alternative = "stationary")
```

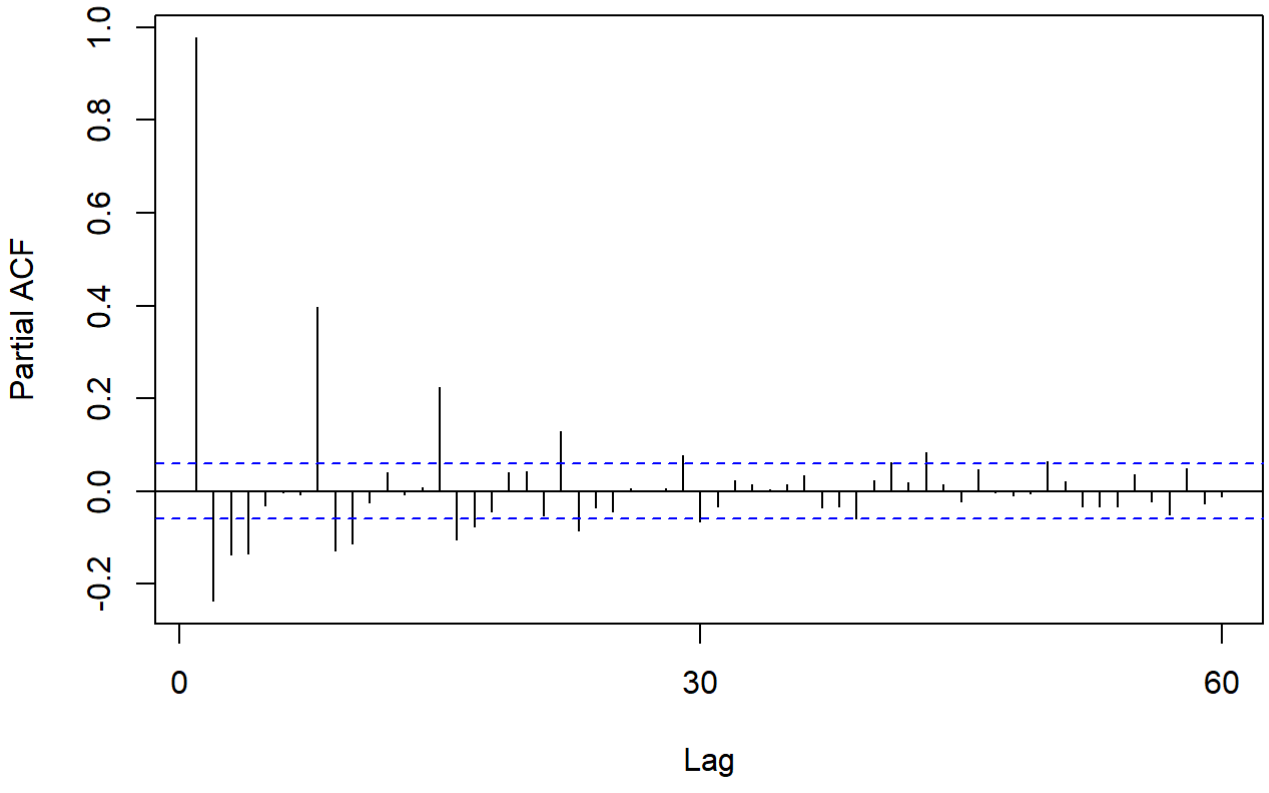
```
## Warning in adf.test(count_ma, alternative = "stationary"): p-value smaller
## than printed p-value
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  count_ma
## Dickey-Fuller = -4.8602, Lag order = 10, p-value = 0.01
## alternative hypothesis: stationary
```

```
Acf(count_ma, main='')
```




```
Pacf(count_ma, main='')
```



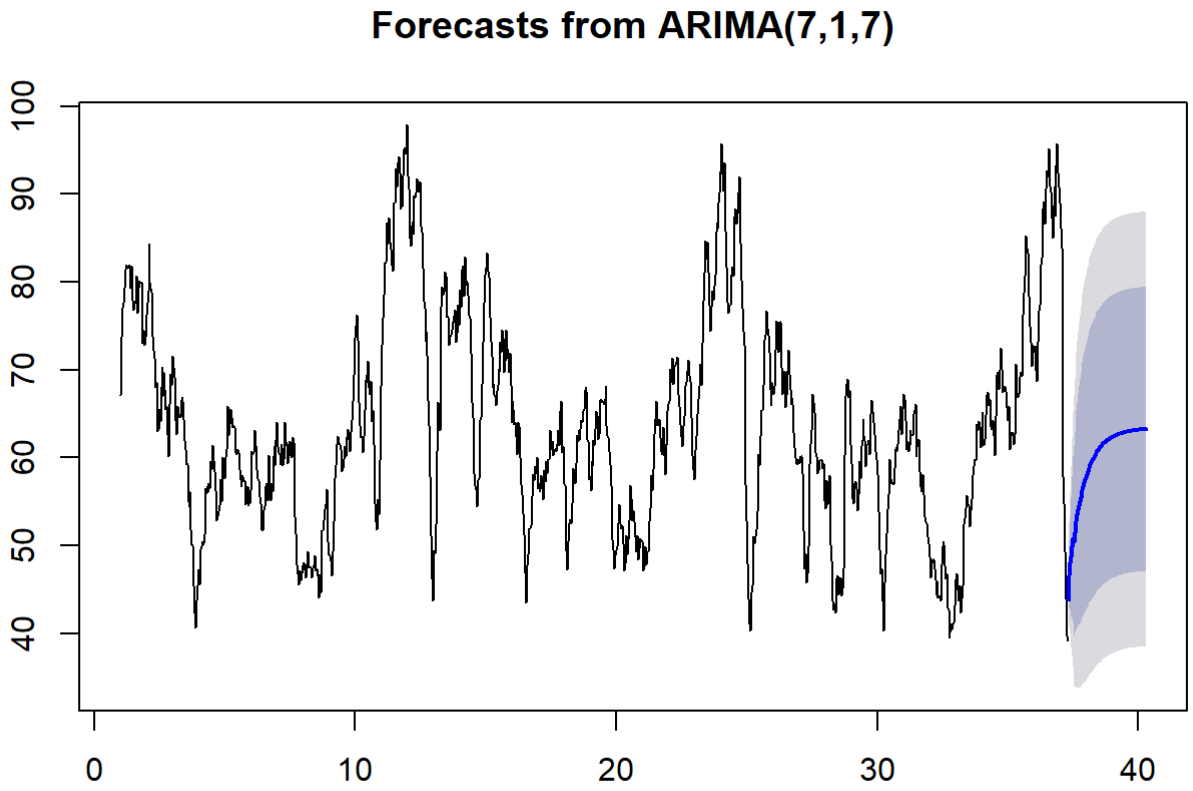
```
model_1 = arima(count_ma, order=c(1,1,7))
model_1
```

```
##
## Call:
## arima(x = count_ma, order = c(1, 1, 7))
##
## Coefficients:
##          ar1     ma1     ma2     ma3     ma4     ma5     ma6      ma7
##       0.0647  0.2638  0.2106  0.2106  0.1793  0.1749  0.2350  -0.7049
## s.e.  0.0520  0.0409  0.0389  0.0334  0.0314  0.0365  0.0305   0.0367
##
## sigma^2 estimated as 3.407:  log likelihood = -2220.79,  aic = 4459.57
```

```
model_2 = arima(count_ma, order=c(7,1,7))
model_2
```

```
##
## Call:
## arima(x = count_ma, order = c(7, 1, 7))
##
## Coefficients:
##          ar1     ar2     ar3     ar4      ar5     ar6     ar7     ma1
##       0.2824  0.1527  0.1591  0.0629  -0.0088  0.1001  0.0878  0.0305
## s.e.  0.0347  0.0328  0.0359  0.0372   0.0336  0.0338  0.0343  0.0171
##           ma2      ma3      ma4      ma5     ma6      ma7
##       -0.0151  -0.0363  -0.0457  -0.0052  0.0263  -0.9545
## s.e.   0.0117   0.0144   0.0183   0.0144  0.0114   0.0174
##
## sigma^2 estimated as 3.284:  log likelihood = -2205.61,  aic = 4441.23
```

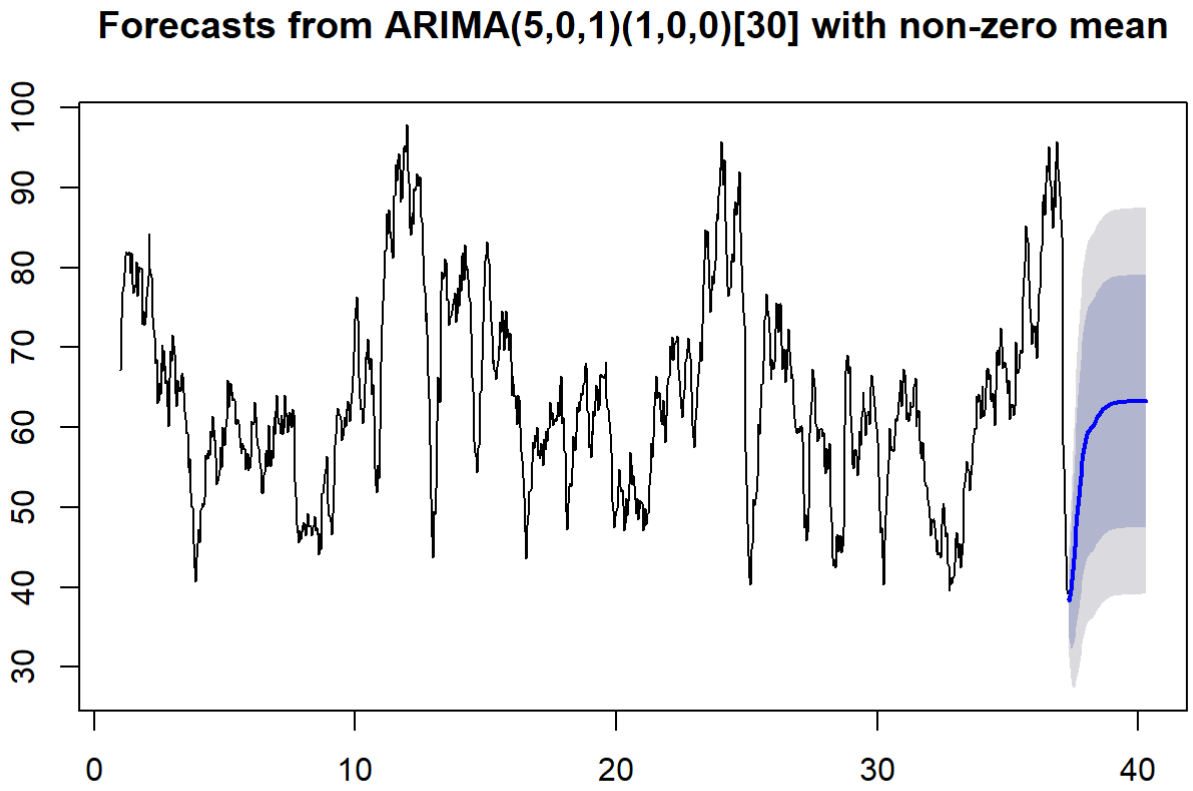
```
fcast <- forecast(model_2, h=90)
plot(fcast)
```




```
 fit_w_seasonality = auto.arima(count_ma, seasonal=TRUE)
fit_w_seasonality
```

```
## Series: count_ma
## ARIMA(5,0,1)(1,0,0)[30] with non-zero mean
##
## Coefficients:
##          ar1     ar2      ar3      ar4      ar5     ma1    sar1     mean
##       0.3518  0.8657  -0.0341  -0.0253  -0.2246  0.8220  0.0357  63.3053
## s.e.  0.0481  0.0554   0.0411   0.0329   0.0298  0.0405  0.0318   1.9528
##
## sigma^2 estimated as 5.293:  log likelihood=-2452.72
## AIC=4923.43   AICc=4923.6   BIC=4968.38
```

```
f_cast <- forecast(fit_w_seasonality, h=90)
plot(f_cast)
```


Forecasts from ARIMA(5,0,1)(1,0,0)[30] with non-zero mean
100
90
80
70
60
50
40
30
0
10
20
30
40