Analysis of mass shootings in the USA between 1966 and 2017

Introduction

Ce document est une présentation de plusieurs analyses faites sur un jeu de données présentant les fusillades de masses de 1966 à 2017. Aucune conclusion définitive ne pourra être tirer de ces analyses car le jeu de données ne compte qu'un nombre limité de variables et que d'autres variables non présentes peuvent influer sur les corrélations relevées.

Cependant ce document exposent des pistes d'études relevantes à explorer pour mieux comprendre les causes des fusillades.

2) Etude des variables qualitatives

Genre: Analyse Individuelle

```
head(shootings.Gender)
```

Proportions et fréquences

```
## # A tibble: 3 x 5
##   Gender      n ShootingsPct Shootings Label
##   <chr>   <int>        <dbl>     <int> <chr>
## 1 male      284       0.904        284 90.4%
## 2 female      5       0.0159         5 1.6%
## 3 <NA>       25       0.0796        25 8.0%
```

Nous voyons que les hommes sont à l'origine de la quasi totalité des fusillades présentes dans ce jeu de données.

```
ggplot(shootings.Gender, aes(x="", y=ShootingsPct, fill=Gender))+
  geom_bar(width = 1, stat = "identity") +
  coord_polar("y", start=0) +
  theme(axis.text.x=element_blank()) +
  geom_text(aes(x=1, y = cumsum(ShootingsPct) - ShootingsPct/3, label=Label)) +
  ggtitle("US Shootings Frequencies By Gender")
```

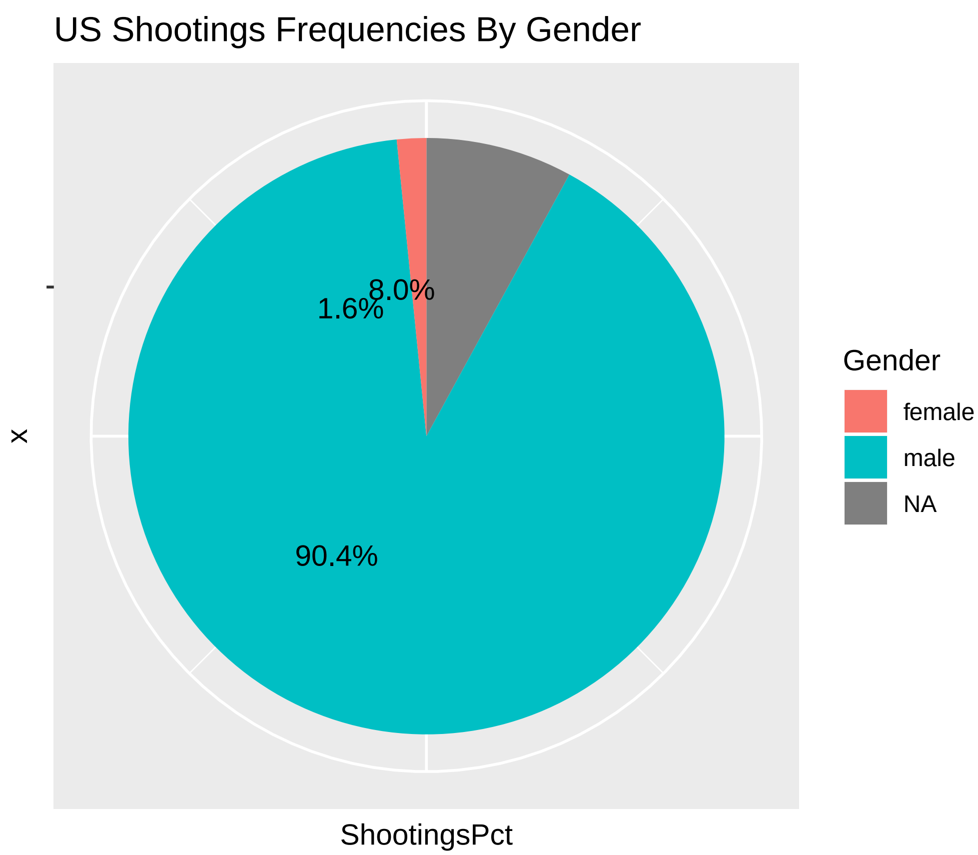


Diagramme circulaire

Test de chiralité de qualité d'ajustement

Pour le test suivant, nous avons voulu savoir si la distribution des fusillades était uniforme selon le genre.

```
shootings.Gender.ChiTest
```

```
##
##  Chi-squared test for given probabilities
##
## data:  shootings.Gender$Shootings
## X-squared = 462.81, df = 2, p-value < 2.2e-16
```

La p-value donnée par ce test est bien inférieure à 0.05, notre seuil d'erreur. Donc nous rejetons l'hypothèse que la distribution des fusillades par genre est uniforme.

Cause: Analyse Individuelle

```
head(shootings.Cause[order(shootings.Cause$ShootingsPct, decreasing = TRUE),])
```

Proportions et fréquences

```
## # A tibble: 6 x 5
##   Cause                 n ShootingsPct Shootings Label
##   <chr>             <int>        <dbl>     <int> <chr>
## 1 <NA>                 81        0.258        81 26%
## 2 psycho               64        0.204        64 20%
## 3 terrorism            61        0.194        61 19%
## 4 anger                44        0.140        44 14%
```

```
## 5 frustration         18       0.0573        18 6%
## 6 domestic dispute    13       0.0414        13 4%
```

Nous voyons que la première raison connue de commencer une fusillade est un trouble mental.

```
ggplot(shootings.Cause,
       aes(x = reorder(Cause, -ShootingsPct),
           y = ShootingsPct)) +
  geom_bar(stat = "identity",
           fill = "lightblue",
           color = "black") +
  geom_text(aes(label = Label),
            hjust = -0.15) +
  scale_y_continuous(labels = percent) +
  labs(x = "Cause",
       y = "Percent",
       title  = "US Shootings Frequencies By Cause") +
  coord_flip()
```

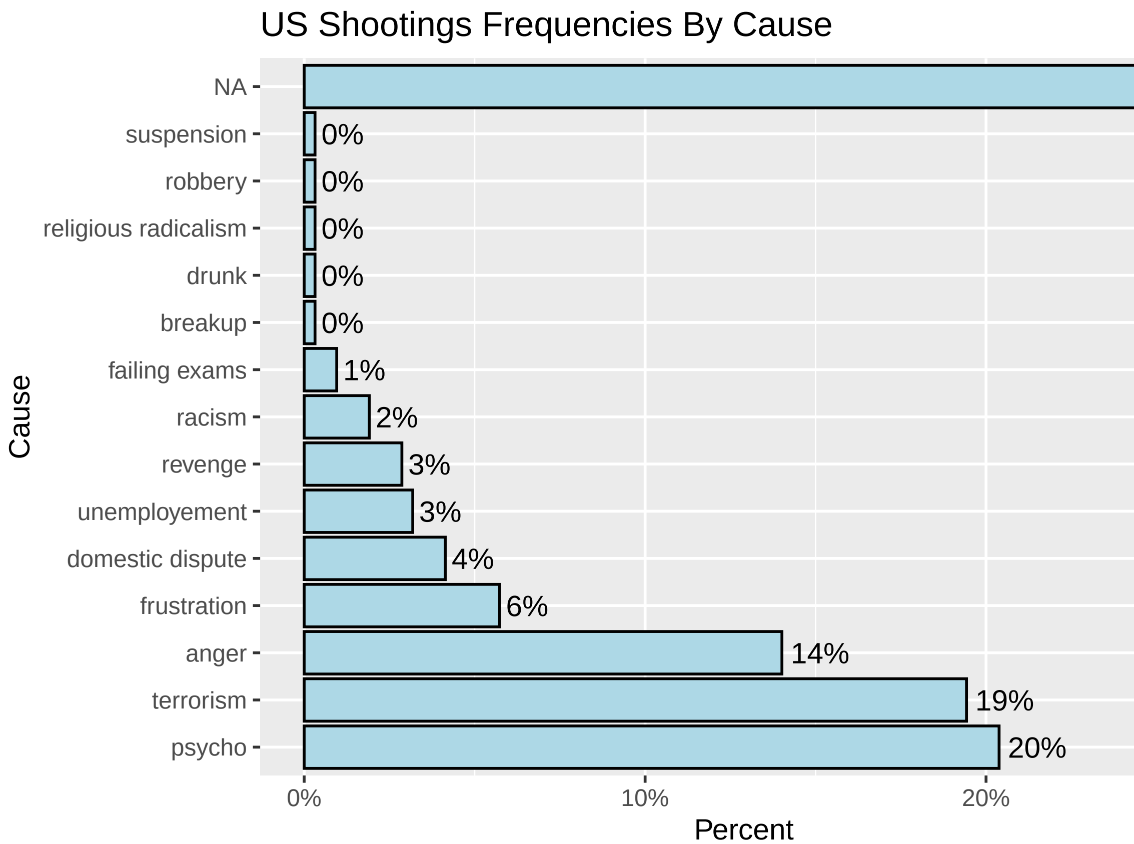


Diagramme en batons

Test de chiralité de qualité d'ajustement

Pour le test suivant, nous avons voulu savoir si la distribution des fusillades était uniforme selon la cause.

```
shootings.Cause.ChiTest
```

```
##
##  Chi-squared test for given probabilities
##
```

```
## data:  shootings.Cause$Shootings
## X-squared = 499.92, df = 14, p-value < 2.2e-16
```

La p-value donnée par ce test est bien inférieure à 0.05, notre seuil d'erreur. Donc nous rejetons l'hypothèse que la distribution des fusillades par genre est uniforme.

Cause et genre: analyse

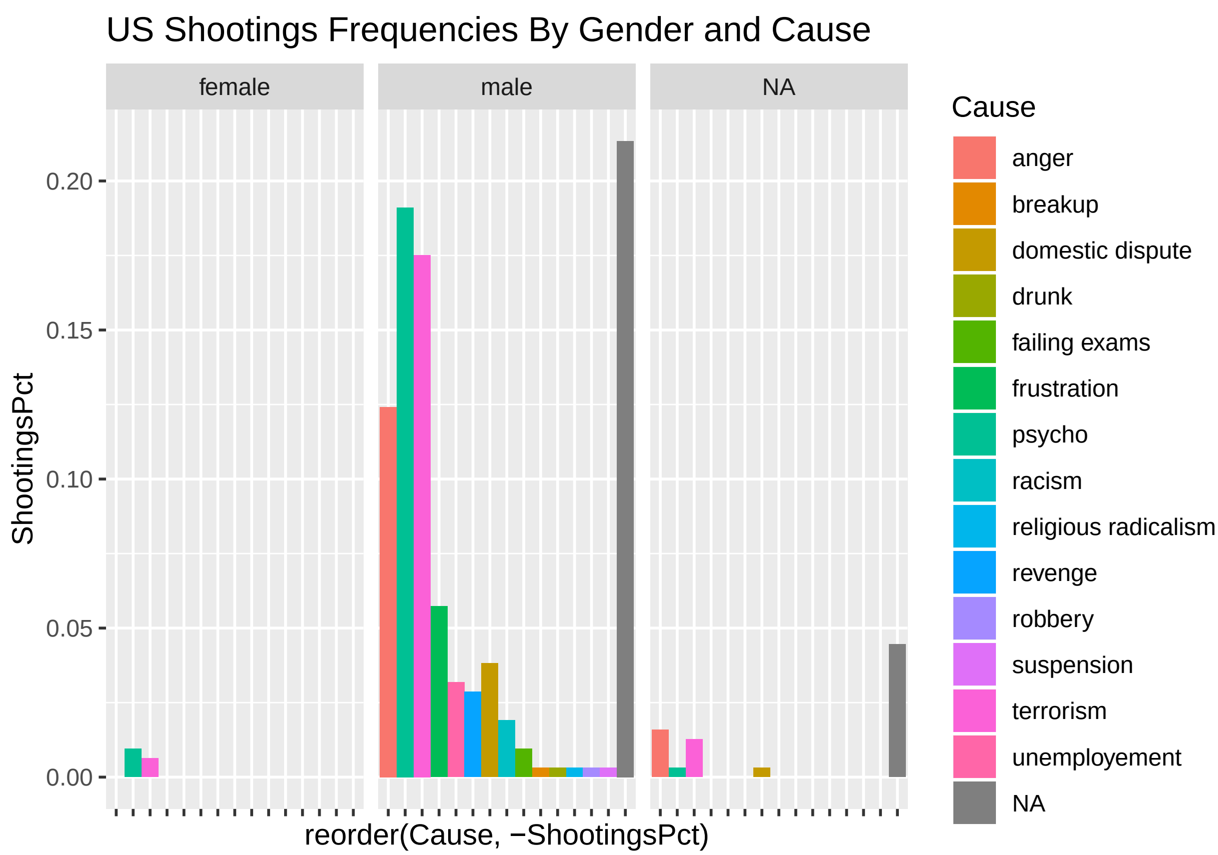
```r
shootings.CauseGender <- shootings %>%
  dplyr::group_by(.dots=c("Cause","Gender")) %>%
  dplyr::count() %>%
  dplyr::ungroup() %>%
  dplyr::mutate(ShootingsPct=`n`/sum(`n`)) %>%
  dplyr::mutate(Shootings=`n`)
shootings.CauseGender$Label <- scales::percent(shootings.CauseGender$ShootingsPct)

# Chi Squared test of goodness fit to a uniform distribution

shootings.CauseGender.ChiTest <- chisq.test(table(shootings$Cause, shootings$Gender))
```

```
## Warning in chisq.test(table(shootings$Cause, shootings$Gender)): Chi-squared
## approximation may be incorrect
```

```r
ggplot(shootings.CauseGender, aes(x=reorder(Cause, -ShootingsPct), y=ShootingsPct, fill=Cause))+
  geom_bar(width = 1, stat = "identity") +
  theme(axis.text.x=element_blank()) +
  ggtitle("US Shootings Frequencies By Gender and Cause") +
  facet_wrap(~Gender)
```



Graphique

```
shootings.CauseGender.ChiTest
```

Test de chiralité d'indépendance

```
##
##  Pearson's Chi-squared test
##
## data:  table(shootings$Cause, shootings$Gender)
## X-squared = 4.5614, df = 13, p-value = 0.9836
```

Le test de chiralité si dessus semble valider l'indépendance entre le genre de la personne. Cependant la non normalité des données et le fort manque de données pour les femmes peuvent biaiser ce test.

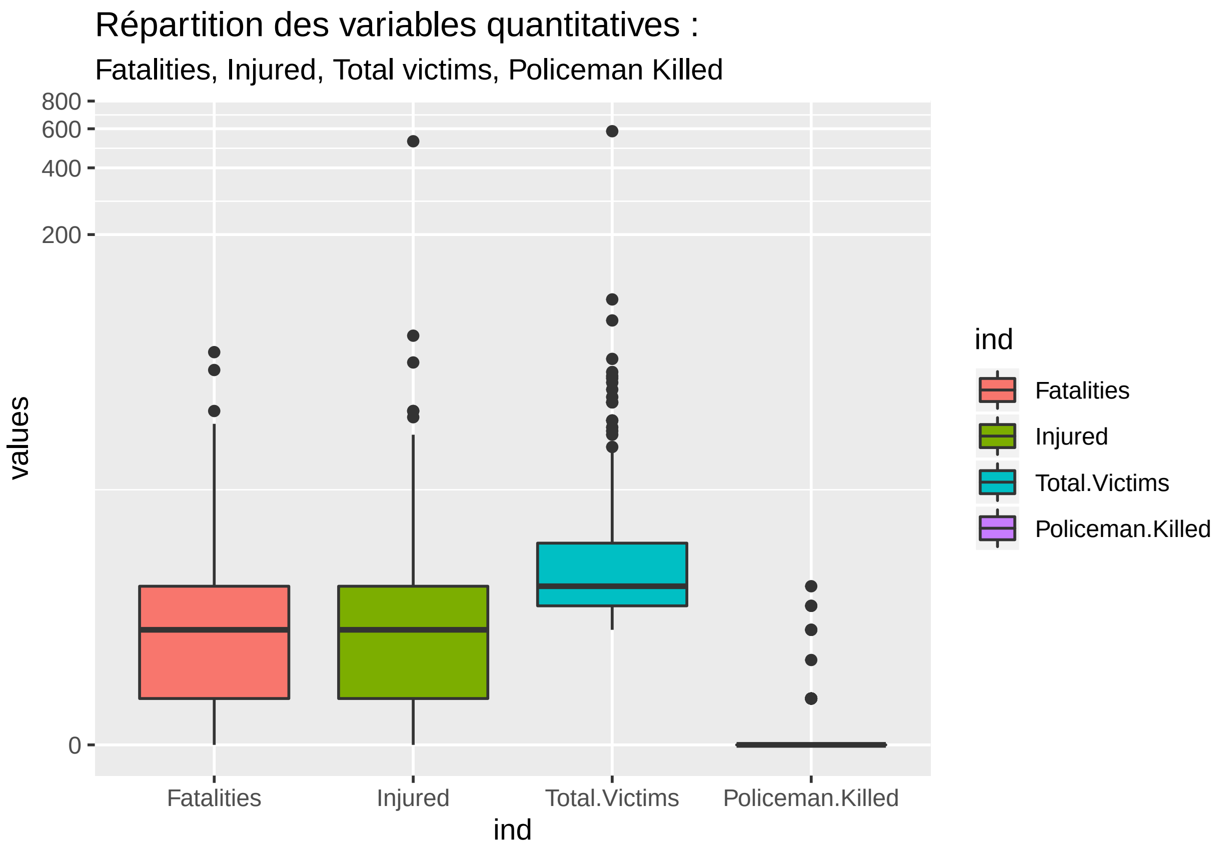
3) Etude des variables quantitatives

3.1)

```
ggplot(stack(shootings.quantitative[,-c(5,6)]), aes(x = ind, y = values, fill = ind)) +
  geom_boxplot() + scale_y_continuous(trans='pseudo_log') +
  ggtitle("Répartition des variables quantitatives :", "Fatalities, Injured, Total victims, Policeman K
```

Boxplots

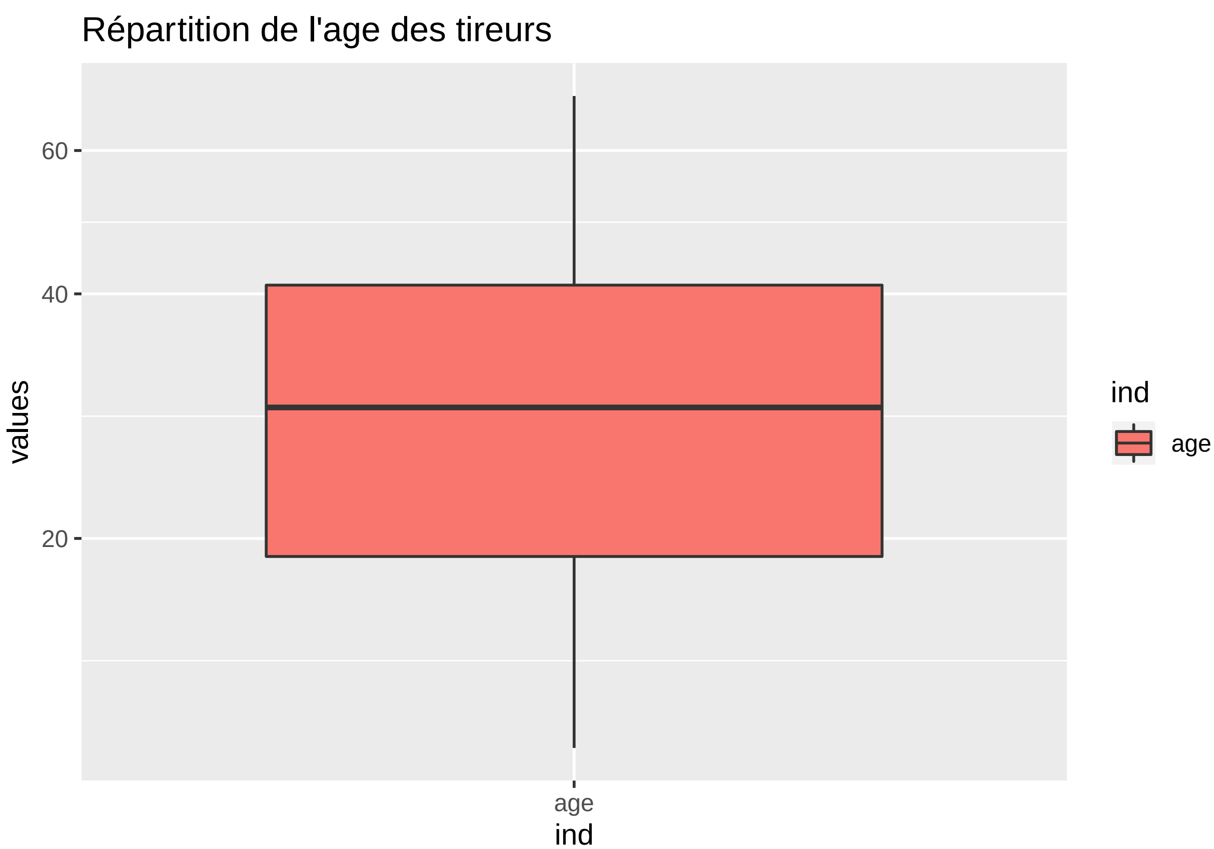
```
## Warning: Removed 6 rows containing non-finite values (stat_boxplot).
```



Le boxplot pour l'age est fait séparément :

```
ggplot(stack(shootings.ages), aes(x = ind, y = values, fill = ind)) +
  geom_boxplot() + scale_y_continuous(trans='pseudo_log') +
  ggtitle("Répartition de l'age des tireurs")
```

```
## Warning: Removed 449 rows containing non-finite values (stat_boxplot).
```




```
summary(shootings.quantitative$Fatalities)
```

Nombre de mort

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   1.000   3.000   4.379   5.000  59.000
```

```
CI(shootings.quantitative$Fatalities, ci=0.95)
```

```
##    upper     mean    lower
## 5.025635 4.378981 3.732327
```

```
fatalities_outliers <- boxplot.stats(shootings.quantitative$Fatalities)$out
fatalities_outliers_row <- which(shootings.quantitative$Fatalities %in% c(fatalities_outliers))

shootings[fatalities_outliers_row,]
```

```
## # A tibble: 17 x 26
##       S. Title Location State Incident.Area Open.Close.Loca~ Target Cause
##    <dbl> <chr> <chr>    <chr> <chr>         <chr>            <chr>  <chr>
##  1     1 Texa~ Sutherl~ Texas place of wor~ close            random <NA>
##  2     4 Las ~ Las Veg~ Neva~ event         open             random <NA>
##  3    14 Orla~ Orlando  Flor~ place of ent~ close            random <NA>
##  4    81 San ~ San Ber~ Cali~ event         close            random terr~
##  5   164 Wash~ Washing~ Dist~ <NA>          close            random terr~
##  6   177 Sand~ Newtown  Conn~ <NA>          <NA>             famil~ terr~
##  7   183 Auro~ Aurora   Colo~ place of ent~ close            random terr~
##  8   202 Fort~ Fort Ho~ Texas millitary fa~ close            random terr~
```

```
##  9   203 Bing~ Bingham~ New ~ association   close            random terr~
## 10   221 Virg~ Blacksb~ Virg~ university    close            random terr~
## 11   250 Colu~ Littlet~ Colo~ high school   close            stude~ terr~
## 12   288 Luby~ Killeen  Texas restaurant    open             random unem~
## 13   291 GMAC~ Jackson~ Flor~ <NA>          close            random psyc~
## 14   303 Post~ Edmond   Okla~ administrati~ close            cowor~ <NA>
## 15   307 McDo~ San Ysi~ Cali~ restaurant    close            random psyc~
## 16   311 Wah ~ Seattle  Wash~ place of ent~ close            random terr~
## 17   323 Univ~ Austin   Texas university    close            random terr~
## # ... with 18 more variables: Summary <chr>, Fatalities <dbl>, Injured <dbl>,
## #   Total.victims <dbl>, Policeman.Killed <dbl>, Age <dbl>, Weapon.Type <chr>,
## #   Mental.Health.Issues <chr>, Race <chr>, Gender <chr>, Latitude <dbl>,
## #   Longitude <dbl>, Age2 <dbl>, AverageAge <dbl>, Day <chr>, Month <chr>,
## #   Year <dbl>, Ten.Casualities.Min <dbl>
```

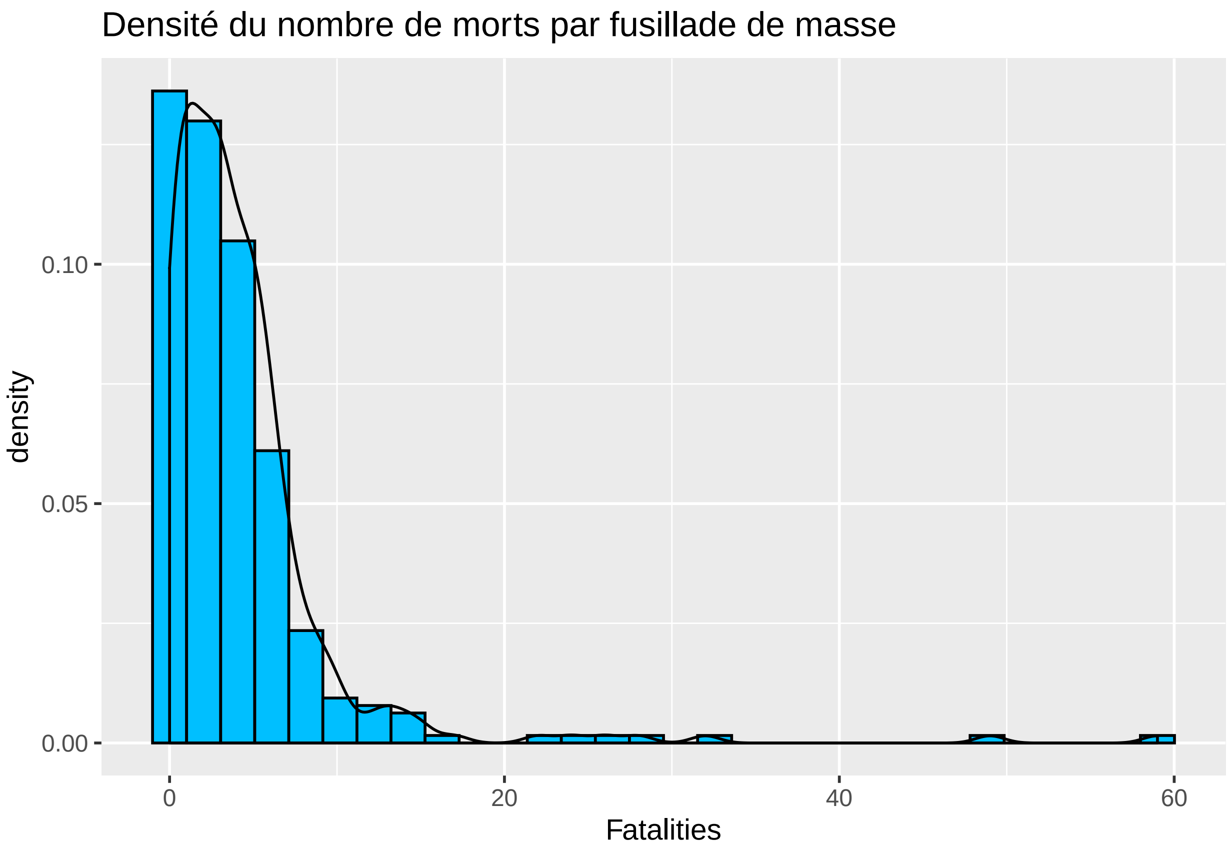
```
shapiro.test(shootings.quantitative$Fatalities)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  shootings.quantitative$Fatalities
## W = 0.57015, p-value < 2.2e-16
```

On peux assumer que la loi n'est pas normale car le test de shapiro effectué" sur notre échantillon nous retourne une p-value inférieure à 0.05

```
ggplot(shootings.quantitative, aes(x=shootings.quantitative$Fatalities)) +
  geom_histogram(aes(y = ..density..), colour = "black", fill="deepskyblue") +
  geom_density() +
  xlab("Fatalities") +
  ggtitle("Densité du nombre de morts par fusillade de masse")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



On remarque que la distribution ressemble à une loi exponentielle, pour le tester on va utiliser un test “goodness of fit”

```
## Warning in ks.test(shootings.quantitative$Fatalities, "pexp", fit$estimate):
## ties should not be present for the Kolmogorov-Smirnov test
```

```
##
##  One-sample Kolmogorov-Smirnov test
##
## data:  shootings.quantitative$Fatalities
## D = 0.13057, p-value = 4.478e-05
## alternative hypothesis: two-sided
```

```
summary(shootings.quantitative$Injured)
```

Nombre de blessés

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    1.00    3.00    6.15    5.00  527.00
```

```
CI(shootings.quantitative$Injured, ci=0.95)
```

```
##    upper     mean    lower
## 9.512986 6.149682 2.786377
```

L’intervale de confiance est de [9.512986; 2.786377] avec une moyenne de 6.149682

```
injured_outliers <- boxplot.stats(shootings.quantitative$Injured)$out
injured_outliers_row <- which(shootings.quantitative$Injured %in% c(injured_outliers))
```

```r
shootings[injured_outliers_row,]
```

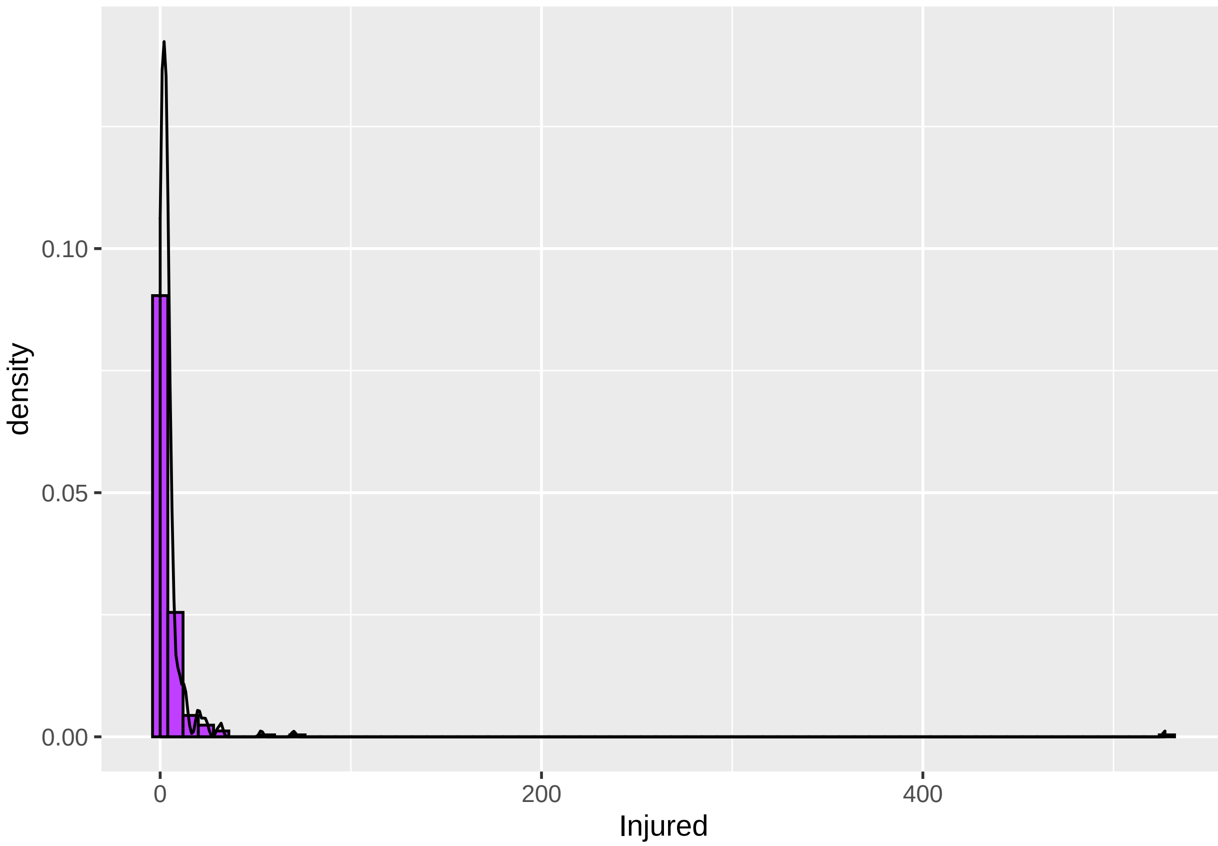
```
## # A tibble: 27 x 26
##       S. Title Location State Incident.Area Open.Close.Loca~ Target Cause
##    <dbl> <chr> <chr>    <chr> <chr>         <chr>            <chr>  <chr>
##  1     1 Texa~ Sutherl~ Texas place of wor~ close            random <NA>
##  2     4 Las ~ Las Veg~ Neva~ event         open             random <NA>
##  3    14 Orla~ Orlando  Flor~ place of ent~ close            random <NA>
##  4    52 Exce~ Hesston  Kans~ company       close            random <NA>
##  5    81 San ~ San Ber~ Cali~ event         close            random terr~
##  6   155 Isla~ Santa B~ Cali~ <NA>          <NA>             random psyc~
##  7   157 Fort~ Fort Ho~ Texas millitary fa~ open             polic~ psyc~
##  8   180 The ~ Miami    Flor~ place of ent~ close            random terr~
##  9   183 Auro~ Aurora   Colo~ place of ent~ close            random terr~
## 10   197 Tucs~ Tucson   Ariz~ <NA>          open             congr~ terr~
## # ... with 17 more rows, and 18 more variables: Summary <chr>,
## #   Fatalities <dbl>, Injured <dbl>, Total.victims <dbl>,
## #   Policeman.Killed <dbl>, Age <dbl>, Weapon.Type <chr>,
## #   Mental.Health.Issues <chr>, Race <chr>, Gender <chr>, Latitude <dbl>,
## #   Longitude <dbl>, Age2 <dbl>, AverageAge <dbl>, Day <chr>, Month <chr>,
## #   Year <dbl>, Ten.Casualities.Min <dbl>
```

```r
shapiro.test(shootings.quantitative$Injured)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  shootings.quantitative$Injured
## W = 0.11136, p-value < 2.2e-16
```

On peux assumer que la loi n'est pas normale car p-value < 0.05

```r
ggplot(shootings.quantitative, aes(x=Injured)) +
  geom_histogram(aes(y = ..density..), colour = "black", fill="darkorchid1", binwidth = 8) +
  geom_density()
```



On remarque que la distribution ressemble à une loi exponentielle, pour le tester on va utiliser un test “goodness of fit”

```
## Warning in ks.test(shootings.quantitative$Injured, "pexp", fit$estimate): ties
## should not be present for the Kolmogorov-Smirnov test
```

```
##
##  One-sample Kolmogorov-Smirnov test
##
## data:  shootings.quantitative$Injured
## D = 0.24475, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

```r
summary(shootings.quantitative$Total.Victims)
```

Nombre total de victimes

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    3.00    4.00    5.00   10.18    8.00  585.00
```

```r
CI(shootings.quantitative$Total.Victims, ci=0.95)
```

```
##     upper      mean     lower
## 13.971588 10.184713  6.397839
```

```r
victims_outliers <- boxplot.stats(shootings.quantitative$Total.Victims)$out
victims_outliers_row <- which(shootings.quantitative$Total.Victims %in% c(victims_outliers))
shootings[victims_outliers_row,]
```

```
## # A tibble: 36 x 26
##       S. Title Location State Incident.Area Open.Close.Loca~ Target Cause
##    <dbl> <chr> <chr>    <chr> <chr>         <chr>            <chr>  <chr>
##  1     1 Texa~ Sutherl~ Texas place of wor~ close            random <NA>
##  2     4 Las ~ Las Veg~ Neva~ event         open             random <NA>
##  3    13 Dall~ Dallas   Texas protest       open             police raci~
##  4    14 Orla~ Orlando  Flor~ place of ent~ close            random <NA>
##  5    52 Exce~ Hesston  Kans~ company       close            random <NA>
##  6    81 San ~ San Ber~ Cali~ event         close            random terr~
##  7    93 Umpq~ Roseburg Oreg~ university    close            stude~ terr~
##  8   155 Isla~ Santa B~ Cali~ <NA>          <NA>             random psyc~
##  9   157 Fort~ Fort Ho~ Texas millitary fa~ open             polic~ psyc~
## 10   164 Wash~ Washing~ Dist~ <NA>          close            random terr~
## # ... with 26 more rows, and 18 more variables: Summary <chr>,
## #   Fatalities <dbl>, Injured <dbl>, Total.victims <dbl>,
## #   Policeman.Killed <dbl>, Age <dbl>, Weapon.Type <chr>,
## #   Mental.Health.Issues <chr>, Race <chr>, Gender <chr>, Latitude <dbl>,
## #   Longitude <dbl>, Age2 <dbl>, AverageAge <dbl>, Day <chr>, Month <chr>,
## #   Year <dbl>, Ten.Casualities.Min <dbl>
```

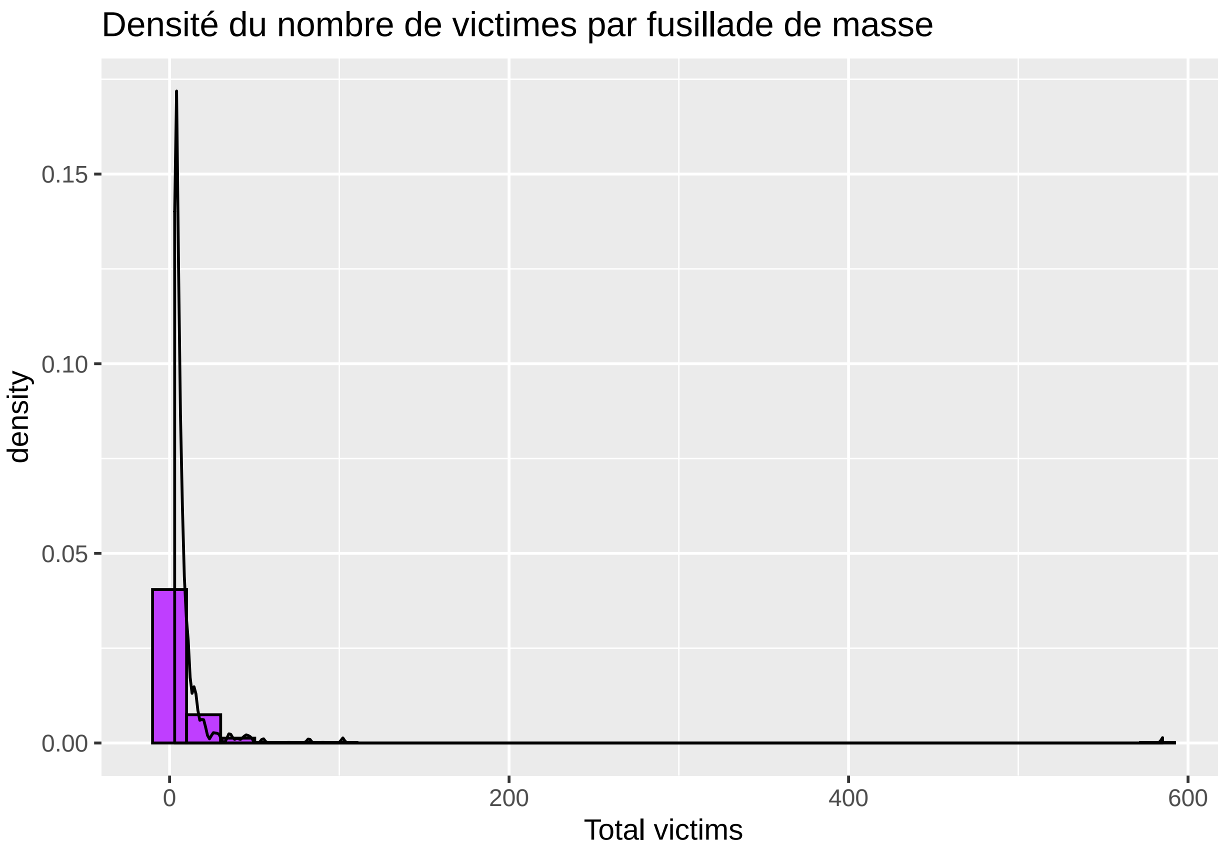
```r
shapiro.test(shootings.quantitative$Total.Victims)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  shootings.quantitative$Total.Victims
## W = 0.13555, p-value < 2.2e-16
```

On peux assumer que la loi n'est pas normale car p-value <= 0.05

```r
ggplot(shootings.quantitative, aes(x=Total.Victims)) +
  geom_histogram(aes(y = ..density..), colour = "black", fill="darkorchid1") +
  geom_density() +
  xlab("Total victims") +
  ggtitle("Densité du nombre de victimes par fusillade de masse")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



On remarque que la distribution ressemble à une loi exponentielle, pour le tester on va utiliser un test "goodness of fit"

```
## Warning in ks.test(shootings.quantitative$Total.Victims, "pexp", fit$estimate):
## ties should not be present for the Kolmogorov-Smirnov test
```

```
##
##  One-sample Kolmogorov-Smirnov test
##
## data:  shootings.quantitative$Total.Victims
## D = 0.25514, p-value < 2.2e-16
## alternative hypothesis: two-sided
```

```
summary(shootings.quantitative$Policeman.Killed)
```

Nombre de policier tués

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  0.0000  0.0000  0.0000  0.1104  0.0000  5.0000       6
```

```
CI(shootings.quantitative$Policeman.Killed, ci=0.95)
```

```
## upper  mean lower
##    NA    NA    NA
```

```
policemans_outliers <- boxplot.stats(shootings.quantitative$Policeman.Killed)$out
policemans_outliers_row <- which(shootings.quantitative$Policeman.Killed %in% c(policemans_outliers))
shootings[policemans_outliers_row,]
```

```
## # A tibble: 17 x 26
##       S. Title Location State Incident.Area Open.Close.Loca~ Target Cause
##    <dbl> <chr> <chr>    <chr> <chr>         <chr>            <chr>  <chr>
##  1     4 Las ~ Las Veg~ Neva~ event         open             random <NA>
##  2     8 Rura~ Kirkers~ Ohio  hospital      close            cowor~ <NA>
##  3    12 Bato~ Baton R~ Loui~ <NA>          open             police <NA>
##  4    13 Dall~ Dallas   Texas protest       open             police raci~
##  5    50 Wood~ Woodbri~ Virg~ home          open             random <NA>
##  6    59 Iuka~ Iuka     Miss~ home          open             polic~ dome~
##  7    83 Plan~ Colorad~ Colo~ street        close            random <NA>
##  8   126 Litt~ Little ~ New ~ <NA>          close            polic~ psyc~
##  9   153 Nell~ Las Veg~ Neva~ restaurant;s~ close            polic~ psyc~
## 10   157 Fort~ Fort Ho~ Texas millitary fa~ open             polic~ psyc~
## 11   162 Los ~ Los Ang~ Cali~ airport       open             tsa o~ anger
## 12   174 Los ~ Irvine   Cali~ <NA>          <NA>             cowor~ anger
## 13   201 Park~ Lakewood Wash~ restaurant    close            polic~ reve~
## 14   257 Calt~ Orange   Cali~ company       close            ex-co~ unem~
## 15   260 R.E.~ Aiken    Sout~ company       <NA>             ex-co~ unem~
## 16   297 Come~ Chicago  Illi~ <NA>          <NA>             random terr~
## 17   320 New ~ New Orl~ Loui~ <NA>          close            random psyc~
## # ... with 18 more variables: Summary <chr>, Fatalities <dbl>, Injured <dbl>,
## #   Total.victims <dbl>, Policeman.Killed <dbl>, Age <dbl>, Weapon.Type <chr>,
## #   Mental.Health.Issues <chr>, Race <chr>, Gender <chr>, Latitude <dbl>,
## #   Longitude <dbl>, Age2 <dbl>, AverageAge <dbl>, Day <chr>, Month <chr>,
## #   Year <dbl>, Ten.Casualities.Min <dbl>
```

```r
shapiro.test(shootings.quantitative$Policeman.Killed)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  shootings.quantitative$Policeman.Killed
## W = 0.20313, p-value < 2.2e-16
```

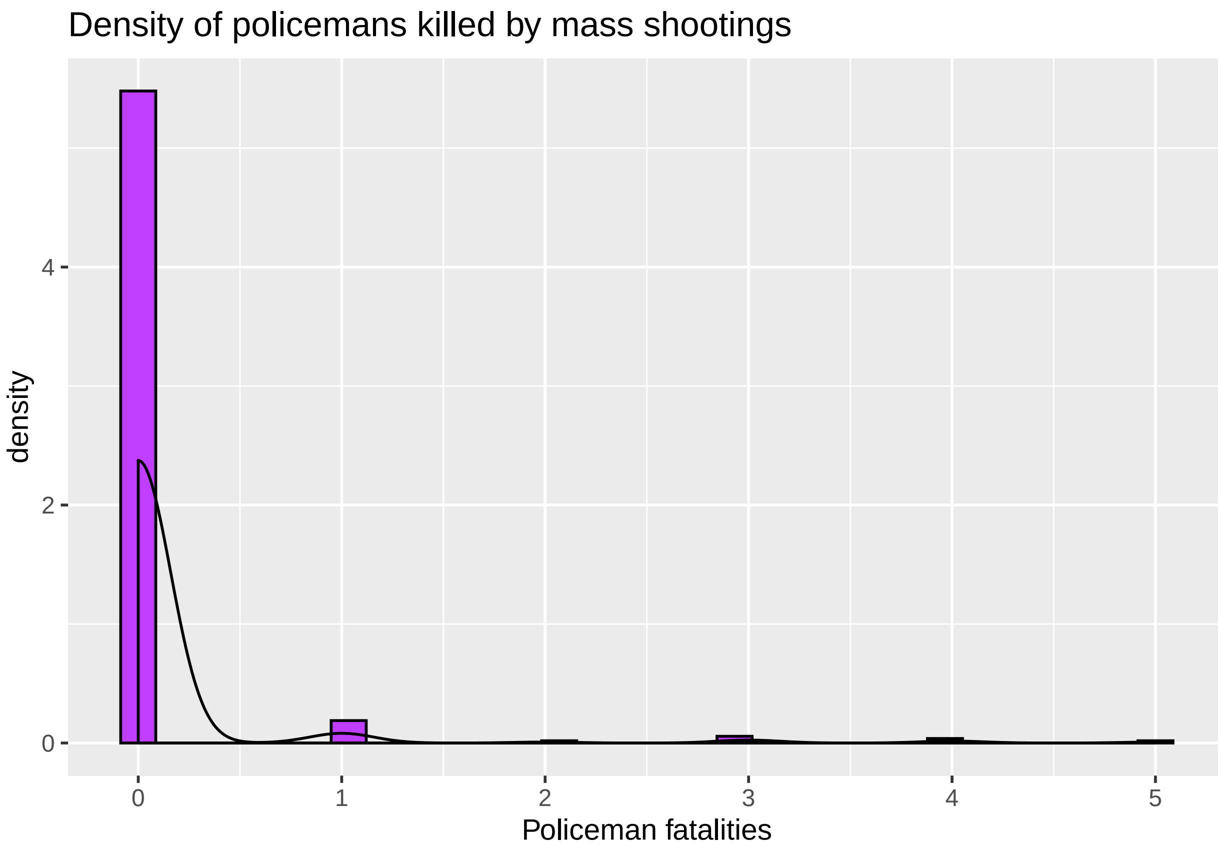
On peux assumer que la loi n'est pas normale car p-value <= 0.05

```r
ggplot(shootings.quantitative, aes(x=Policeman.Killed)) +
  geom_histogram(aes(y = ..density..), colour = "black", fill="darkorchid1") +
  geom_density() +
  xlab("Policeman fatalities") +
  ggtitle("Density of policemans killed by mass shootings")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 6 rows containing non-finite values (stat_bin).
```

```
## Warning: Removed 6 rows containing non-finite values (stat_density).
```




```
summary(shootings.ages$age)
```

Age

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   11.00   19.00   29.00   31.41   41.00   70.00     449
```

```
shootings.ages$age <- as.numeric(shootings.ages$age)
CI(shootings.ages$age, ci=0.95)
```

```
## upper  mean lower
##    NA    NA    NA
```

```
ages_outliers <- boxplot.stats(shootings.ages$age)$out
ages_outliers_row <- which(shootings.ages %in% c(ages_outliers))
shootings[ages_outliers_row,]
```

```
## # A tibble: 0 x 26
## # ... with 26 variables: S. <dbl>, Title <chr>, Location <chr>, State <chr>,
## #   Incident.Area <chr>, Open.Close.Location <chr>, Target <chr>, Cause <chr>,
## #   Summary <chr>, Fatalities <dbl>, Injured <dbl>, Total.victims <dbl>,
## #   Policeman.Killed <dbl>, Age <dbl>, Weapon.Type <chr>,
## #   Mental.Health.Issues <chr>, Race <chr>, Gender <chr>, Latitude <dbl>,
## #   Longitude <dbl>, Age2 <dbl>, AverageAge <dbl>, Day <chr>, Month <chr>,
## #   Year <dbl>, Ten.Casualities.Min <dbl>
```

Age n'a pas d'outliers

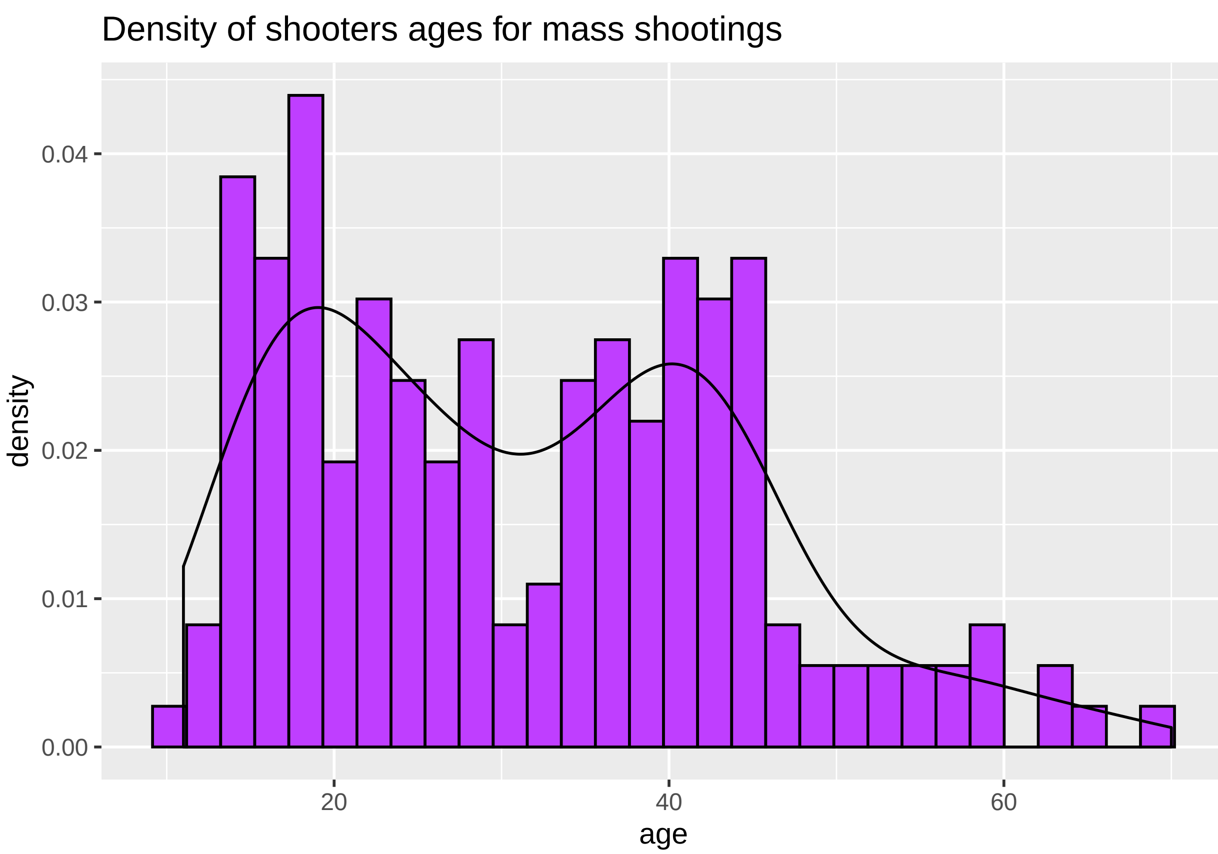
```r
shapiro.test(shootings.ages$age)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  shootings.ages$age
## W = 0.94885, p-value = 4.726e-06
```

On peux assumer que la loi n'est pas normale car p-value <= 0.05

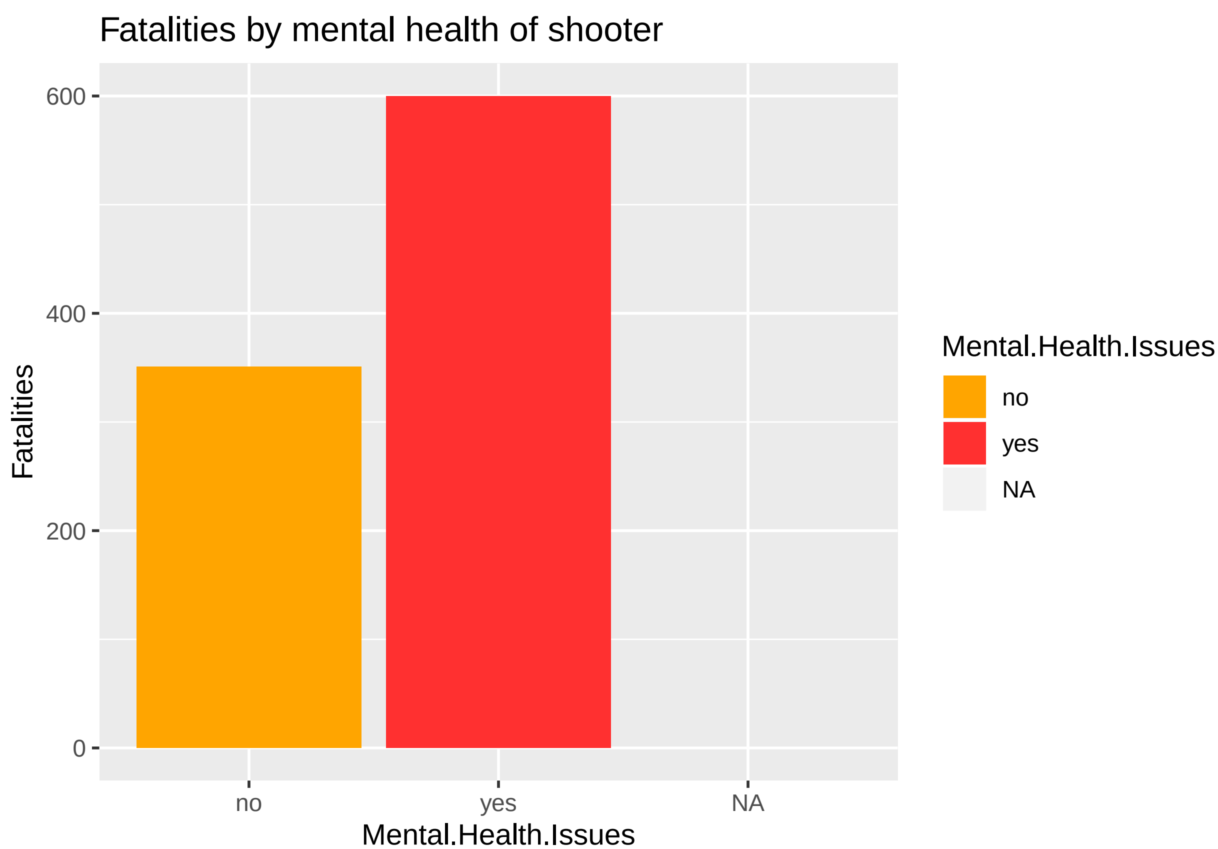
```r
ggplot(shootings.ages, aes(x=age)) +
  geom_histogram(aes(y = ..density..), colour = "black", fill="darkorchid1") +
  geom_density() +
  ggtitle("Density of shooters ages for mass shootings")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 449 rows containing non-finite values (stat_bin).
## Warning: Removed 449 rows containing non-finite values (stat_density).
```

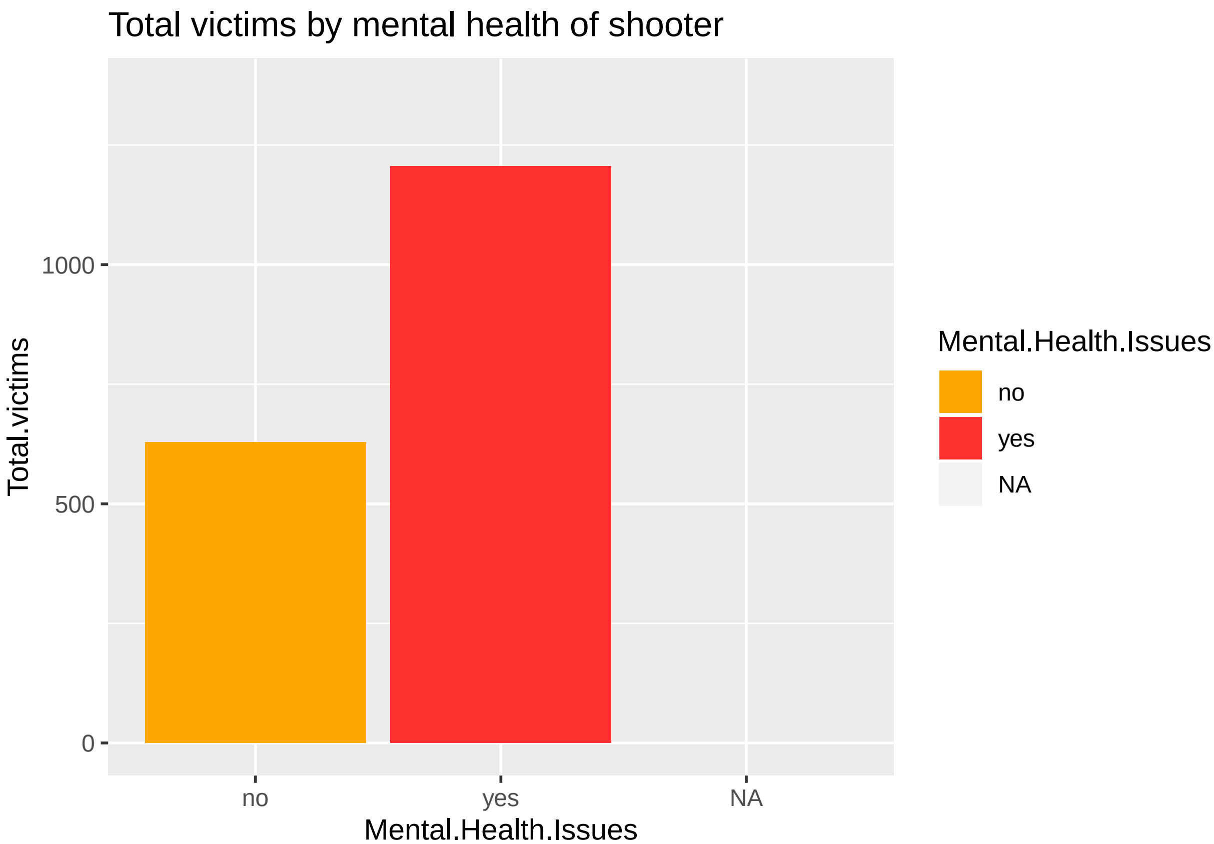


3.2)

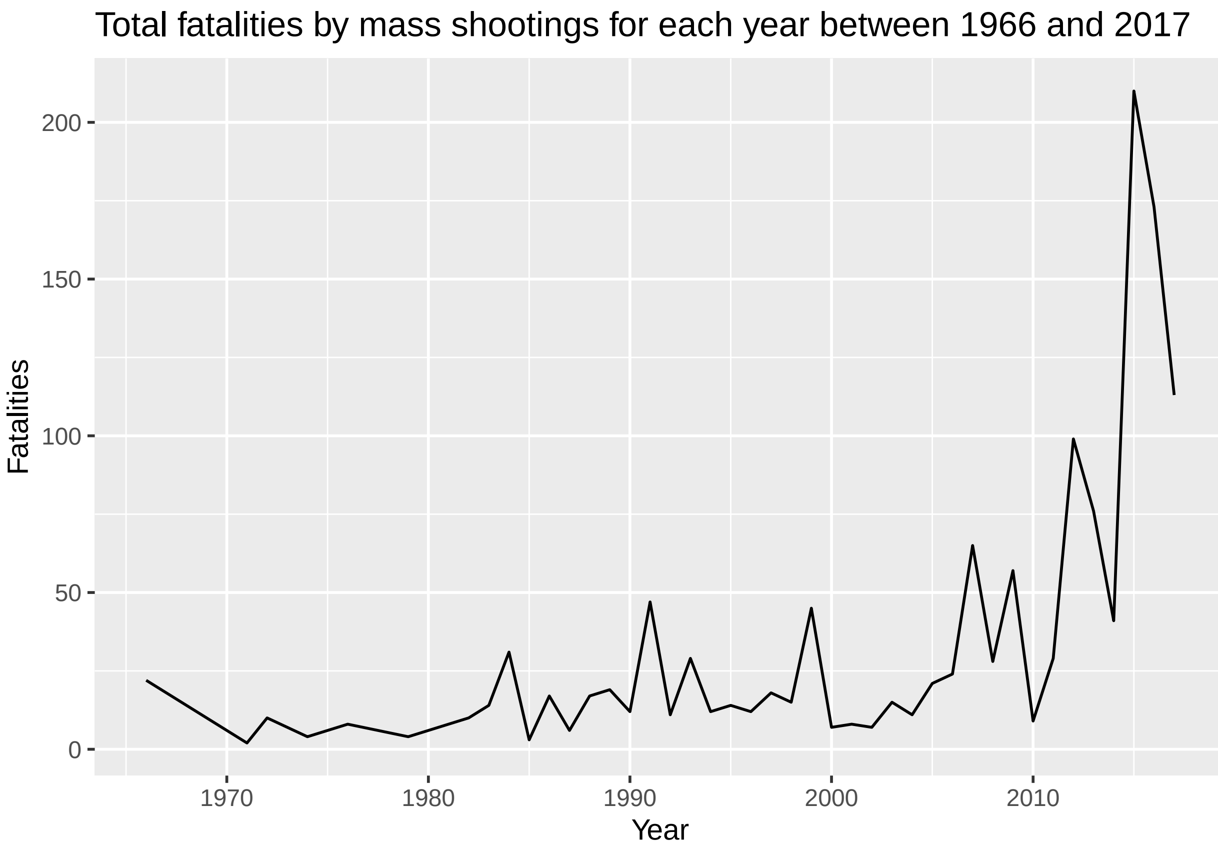
```r
ggplot(data=shootings, aes(x=Mental.Health.Issues, y=Fatalities, fill=Mental.Health.Issues)) +
  scale_fill_manual(values=c("orange1", "firebrick1")) +
  geom_bar(stat="identity") +
  ggtitle("Fatalities by mental health of shooter")
```



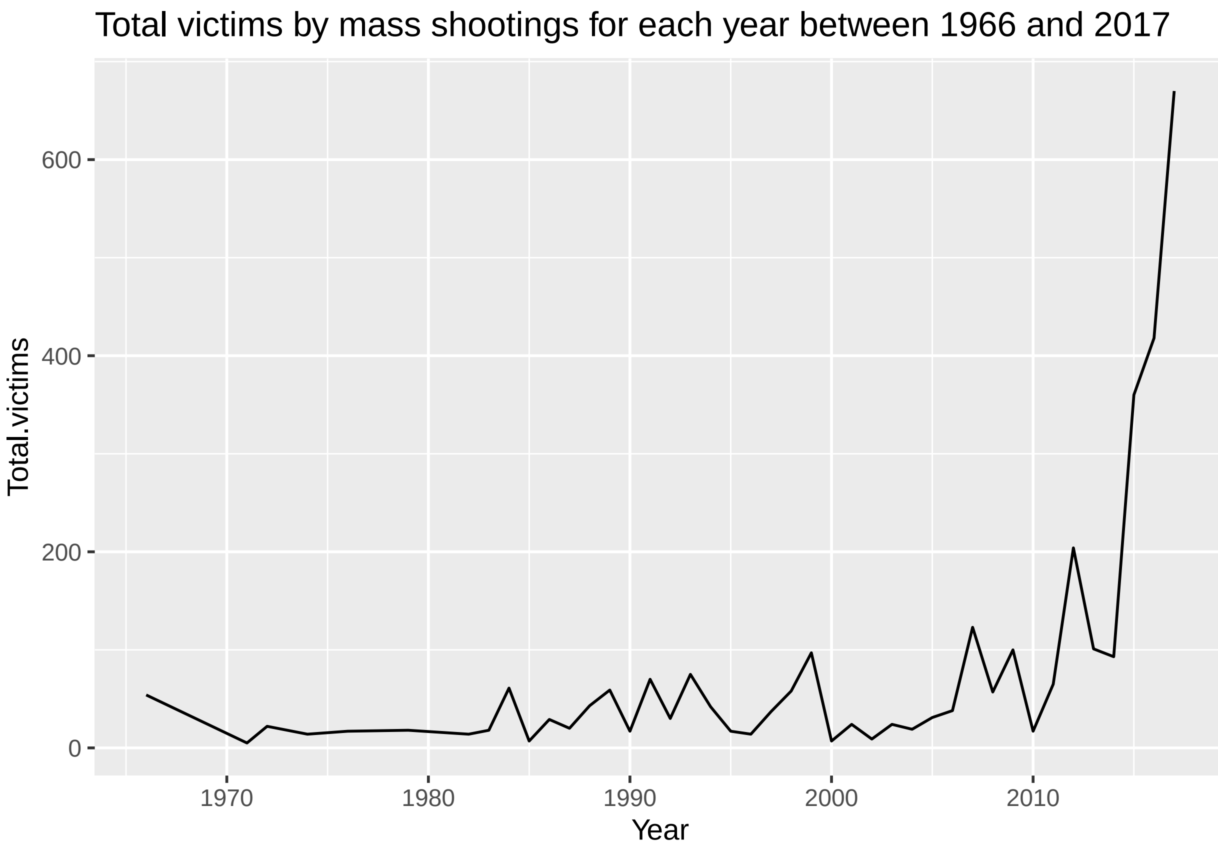

```r
ggplot(data=shootings, aes(x=Mental.Health.Issues, y=Total.victims, fill=Mental.Health.Issues)) +
  scale_fill_manual(values=c("orange1", "firebrick1")) +
  geom_bar(stat="identity") +
  ggtitle("Total victims by mental health of shooter")
```



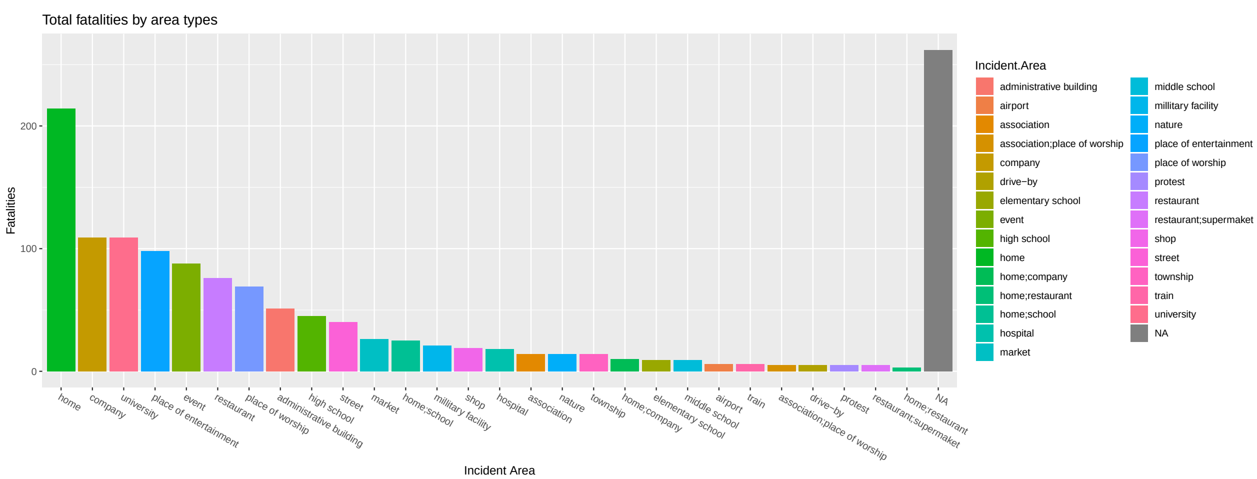

```
ggplot(shootings, aes(x=Year, y=Fatalities)) +
  stat_summary(fun.y = sum, geom="line") +
  ggtitle("Total fatalities by mass shootings for each year between 1966 and 2017")
```



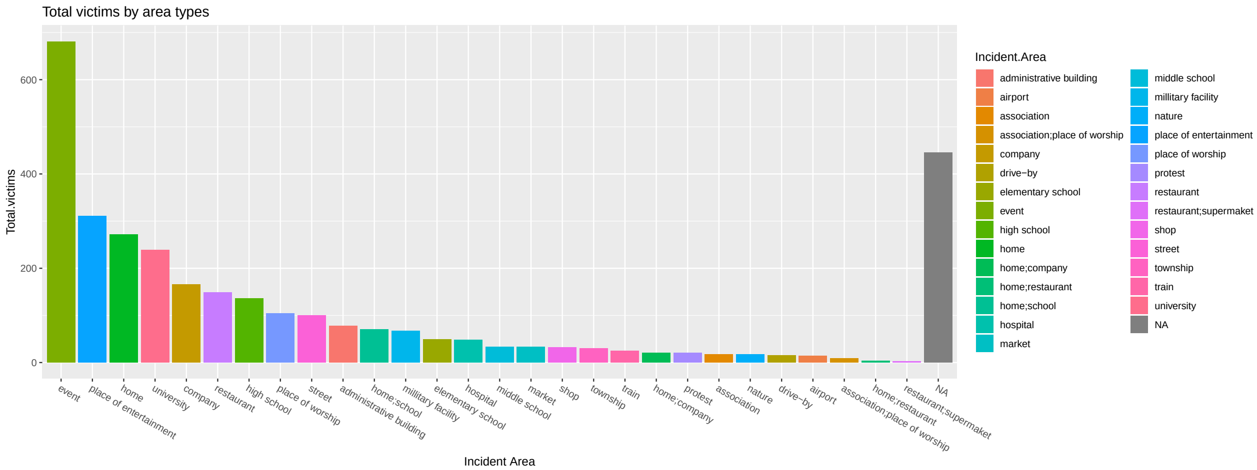

```r
ggplot(shootings, aes(x=Year, y=Total.victims)) +
  stat_summary(fun.y = sum, geom="line") +
  ggtitle("Total victims by mass shootings for each year between 1966 and 2017")
```




```
ggplot(data=shootings, aes(x=reorder(Incident.Area, -Fatalities, function(x){ sum(x) }), y=Fatalities,
  theme(axis.text.x=element_text(angle=-30,hjust=0)) +
  xlab("Incident Area") +
  geom_bar(stat="identity") +
  ggtitle("Total fatalities by area types")
```

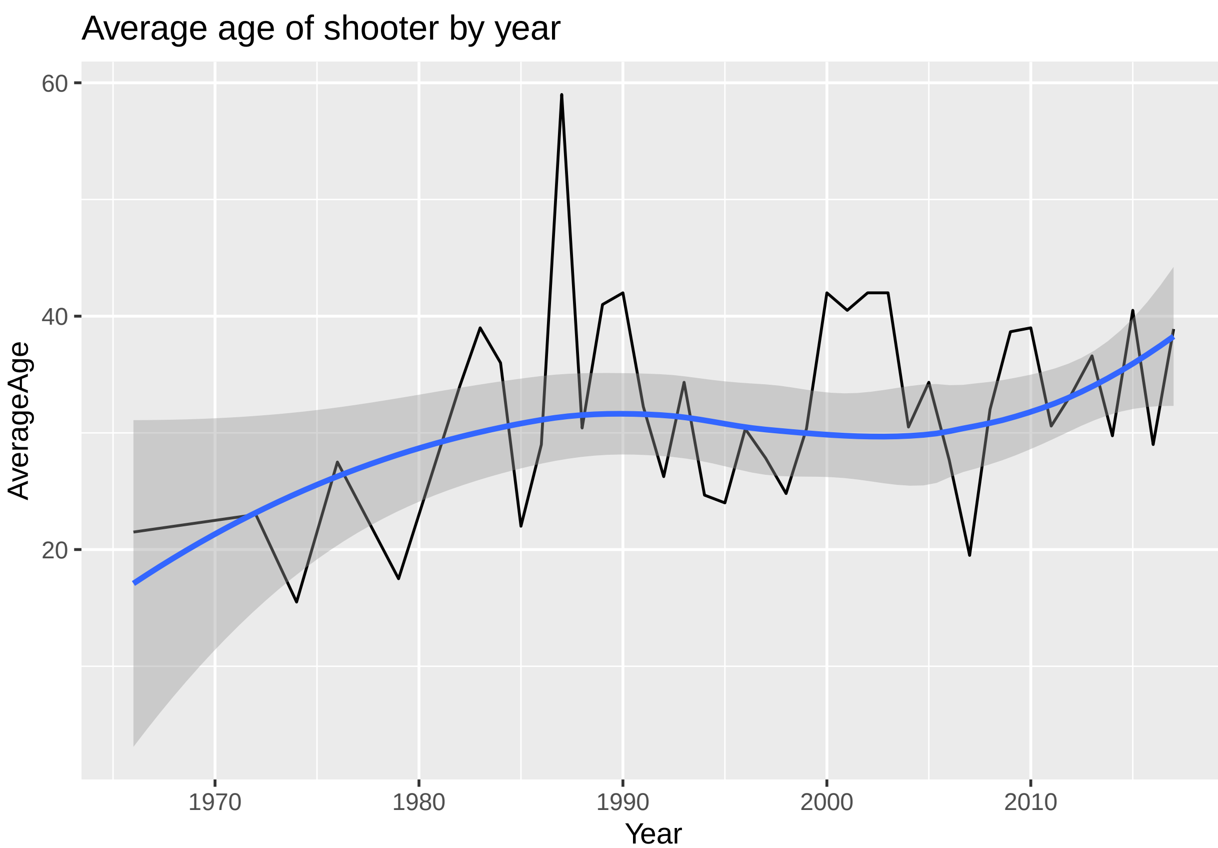



```
ggplot(data=shootings, aes(x=reorder(Incident.Area, -Total.victims, function(x){ sum(x) }), y=Total.vic
  theme(axis.text.x=element_text(angle=-30,hjust=0)) +
  xlab("Incident Area") +
  geom_bar(stat="identity", na.rm = TRUE) +
  ggtitle("Total victims by area types")
```

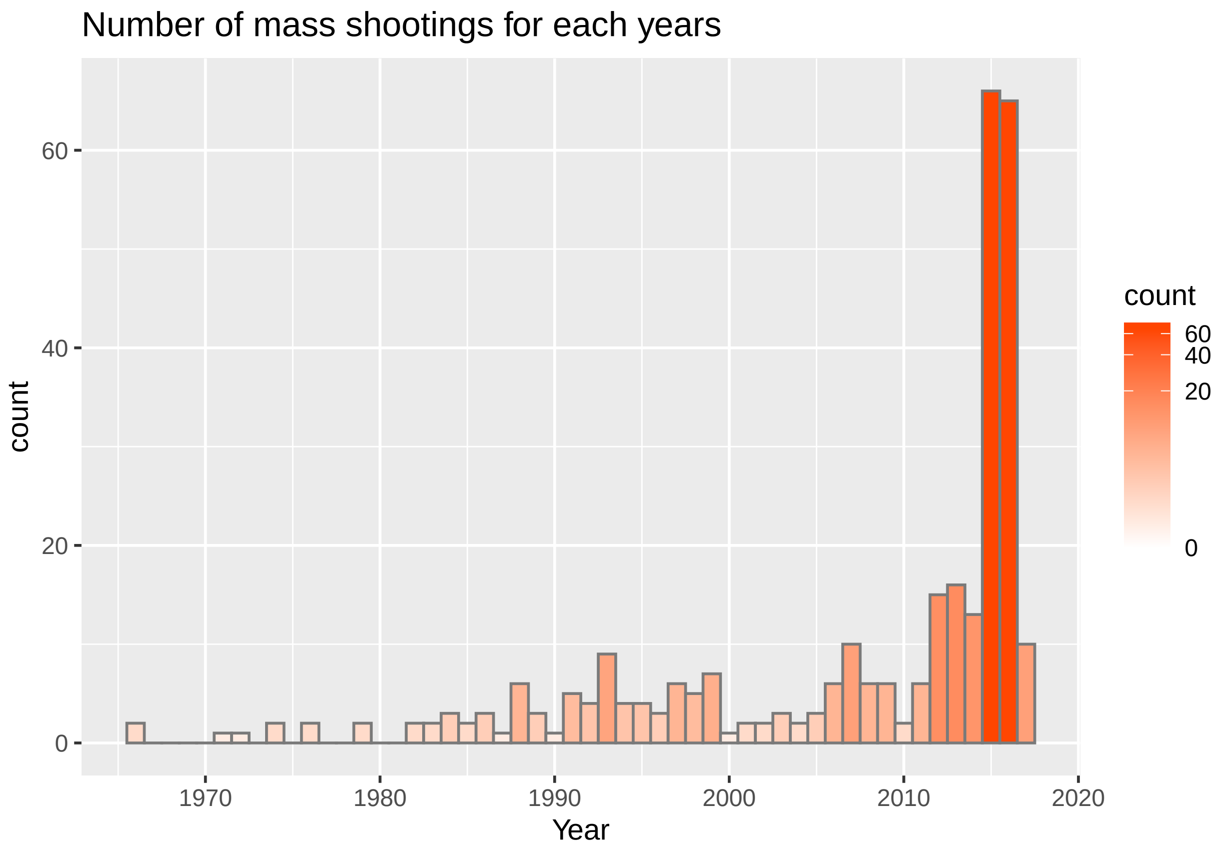



```r
ggplot(shootings, aes(x=Year, y=AverageAge)) +
  stat_summary(fun.y = mean, geom="line", na.rm = TRUE) +
  geom_smooth(na.rm = TRUE) +
  ggtitle("Average age of shooter by year")
```

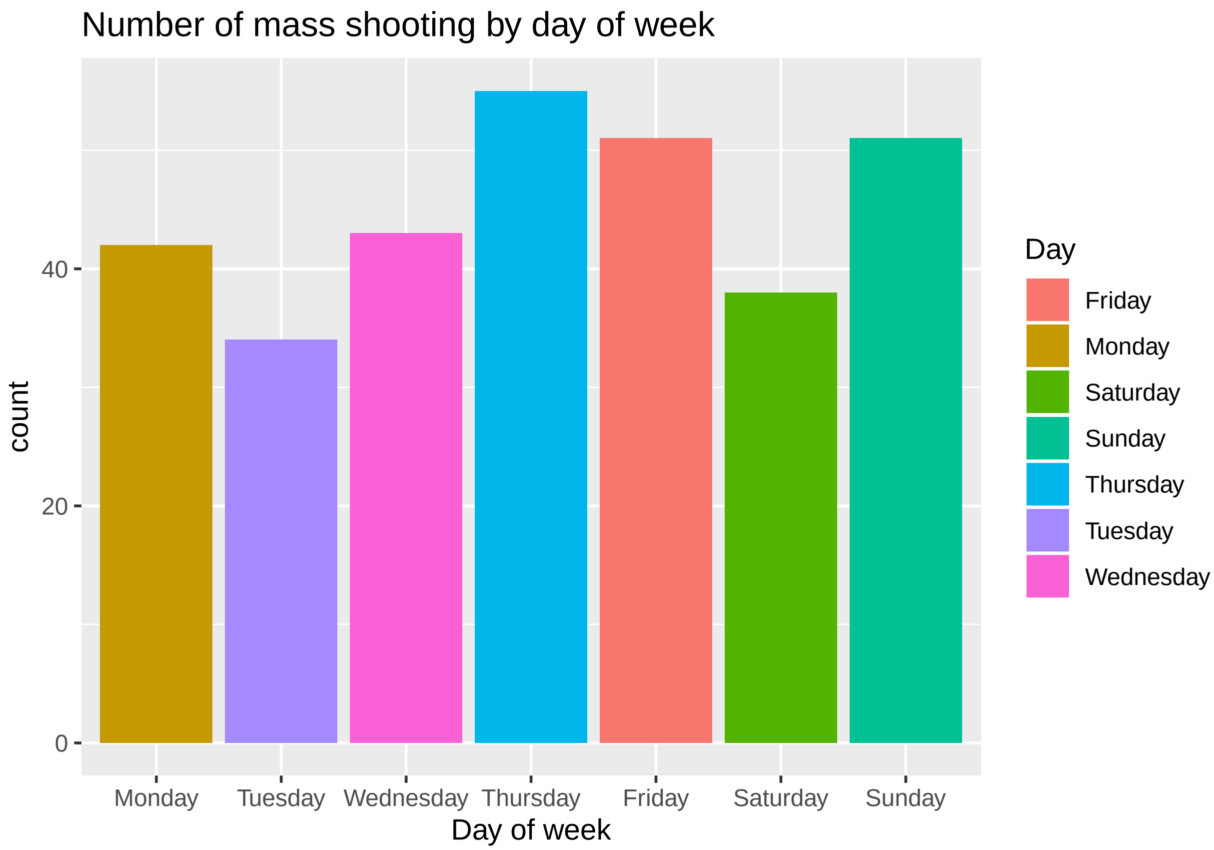
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



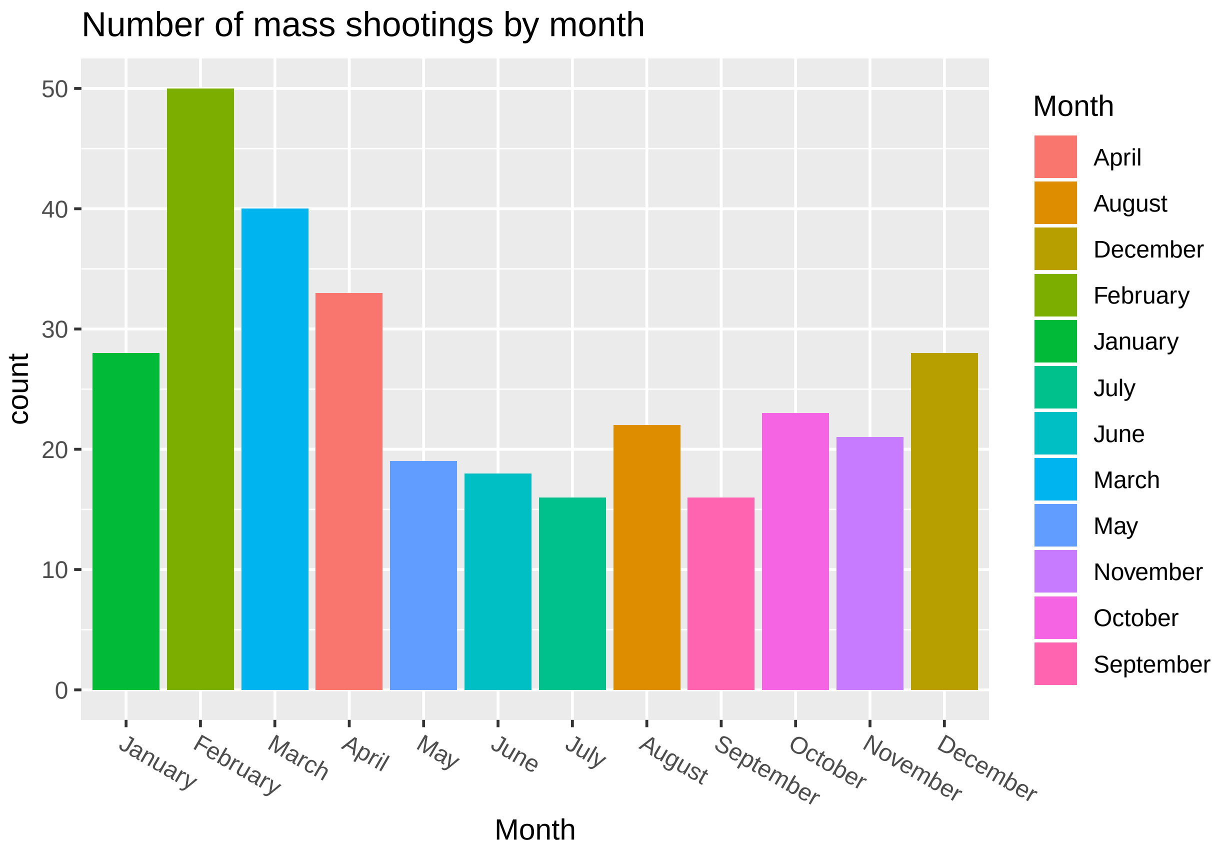

```r
ggplot(shootings, aes(x=Year, fill=..count..)) +
  geom_histogram(aes(y = stat(count)), colour="grey48", binwidth = 1) +
  scale_fill_gradient(low='white', high='orangered', trans = "pseudo_log") +
  ggtitle("Number of mass shootings for each years")
```




```r
day_order <- c('Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday')
ggplot(data=shootings, aes(x=factor(Day, level = day_order), fill=Day)) +
  xlab("Day of week") +
  geom_bar() +
  ggtitle("Number of mass shooting by day of week")
```




```
month_order <- c('January', 'February', 'March', 'April', 'May', 'June', 'July', 'August', 'September',
ggplot(data=shootings, aes(x=factor(Month, level = month_order), fill=Month)) +
  theme(axis.text.x=element_text(angle=-30,hjust=0)) +
  xlab("Month") +
  geom_bar() +
  ggtitle("Number of mass shootings by month")
```



3.4)

Malgrés la distribution non normale de notre échantillon, nous avons effectué des test de Student pour comparer la moyenne d'une variable quantitative à une variable qualitative à deux niveaux (deux valeurs possible). Ces tests nous permettes de dire si une valeur a une influence sur une autre.

```
t.test(shootings$Total.victims ~ shootings$Mental.Health.Issues)
```

```
##
##  Welch Two Sample t-test
##
## data:  shootings$Total.victims by shootings$Mental.Health.Issues
## t = -3.4376, df = 142.57, p-value = 0.0007696
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -7.554907 -2.038393
## sample estimates:
##  mean in group no mean in group yes
##          6.912088         11.708738
```

```
t.test(shootings$Total.victims ~ shootings$Open.Close.Location)
```

```
##
##  Welch Two Sample t-test
##
## data:  shootings$Total.victims by shootings$Open.Close.Location
## t = -0.58158, df = 79.897, p-value = 0.5625
## alternative hypothesis: true difference in means is not equal to 0
```

```
## 95 percent confidence interval:
##  -19.02473  10.41989
## sample estimates:
## mean in group close  mean in group open
##            9.127962           13.430380
```

La p-value étant supérieur à 0.05, le nombre de victime est bel est bien influencé par l'accessibilité du lieu (si le lieu était ouvert au public ou non).

```r
t.test(shootings$Total.victims ~ shootings$Gender)
```

```
##
##  Welch Two Sample t-test
##
## data:  shootings$Total.victims by shootings$Gender
## t = -1.2999, df = 112.34, p-value = 0.1963
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -7.604488  1.579135
## sample estimates:
## mean in group female   mean in group male
##              7.60000             10.61268
```

La p-value étant supérieur à 0.05, le nombre de victime est bel est bien influencé par le genre du tireur dans notre échantillons.

```r
t.test(shootings$AverageAge ~ shootings$Mental.Health.Issues)
```

```
##
##  Welch Two Sample t-test
##
## data:  shootings$AverageAge by shootings$Mental.Health.Issues
## t = 1.4516, df = 110.65, p-value = 0.1495
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.164305  7.540808
## sample estimates:
##  mean in group no mean in group yes
##          33.31034          30.12209
```

La p-value étant supérieur à 0.05, l'age du tireur influe bien sur ses troubles mentaux.

```r
t.test(shootings$AverageAge ~ shootings$Open.Close.Location)
```

```
##
##  Welch Two Sample t-test
##
## data:  shootings$AverageAge by shootings$Open.Close.Location
## t = -0.77815, df = 27.136, p-value = 0.4432
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -9.958124  4.480866
## sample estimates:
## mean in group close  mean in group open
##            31.19615            33.93478
```

La p-value étant supérieur à 0.05, l'age du tireur influe bien sur ses troubles mentaux.

```r
t.test(shootings$Age ~ shootings$Gender)
```

```
##
##  Welch Two Sample t-test
##
## data:  shootings$Age by shootings$Gender
## t = 0.69416, df = 4.2694, p-value = 0.5235
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -11.46681  19.36919
## sample estimates:
## mean in group female   mean in group male
##             35.60000             31.64881
```

3.4) correlations

Pour créer une matrice de correlations, on va utiliser la fonction `cor`

```r
cor(shootings.quantitative, use = "complete.obs")
```

```
##                  Fatalities   Injured Total.Victims Policeman.Killed AverageAge
## Fatalities       1.00000000 0.6396994     0.7268558       0.04602368 0.18576485
## Injured          0.63969942 1.0000000     0.9927638       0.10668619 0.15278967
## Total.Victims    0.72685584 0.9927638     1.0000000       0.10217468 0.16321469
## Policeman.Killed 0.04602368 0.1066862     0.1021747       1.00000000 0.03288462
## AverageAge       0.18576485 0.1527897     0.1632147       0.03288462 1.00000000
```

On remarque des correlations importantes au niveau des Fatalities, Injured et Total.Victims

On peut aussi tester la correlation de deux colonnes en utilisant un text ANOVA, cette fois-ci avec des données qualitatives

```r
summary(aov(Fatalities ~ Race, data = shootings))
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## Race          6    572   95.39   2.631 0.0171 *
## Residuals   264   9572   36.26
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 43 observations deleted due to missingness
```

```r
summary(aov(Total.victims ~ Race, data = shootings))
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## Race          6   3103   517.2    0.38  0.891
## Residuals   264 359283  1360.9
## 43 observations deleted due to missingness
```

Le nombre de mort n'est pas lié à la race du tireur. Cependant le nombre de victime l'est.

```r
summary(aov(Fatalities ~ Weapon.Type, data = shootings))
```

```
##             Df Sum Sq Mean Sq F value Pr(>F)
## Weapon.Type 23   1239   53.86   0.773  0.755
## Residuals   91   6344   69.71
## 199 observations deleted due to missingness
```

```r
summary(aov(Total.victims ~ Weapon.Type, data = shootings))
```

```
##             Df Sum Sq Mean Sq F value Pr(>F)
## Weapon.Type 23  33838    1471   0.424  0.989
## Residuals   91 315405    3466
## 199 observations deleted due to missingness
```

On remarque que le nombre de mort et de victime est fortement lié au type de l'arme utilisé.

```r
summary(aov(Fatalities ~ Cause, data = shootings))
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## Cause        13    465   35.78   1.961 0.0252 *
## Residuals   219   3995   18.24
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 81 observations deleted due to missingness
```

```r
summary(aov(Total.victims ~ Cause, data = shootings))
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## Cause        13   2167  166.67   1.946 0.0265 *
## Residuals   219  18752   85.62
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 81 observations deleted due to missingness
```

Les causes de la fusillade de masses ne sont pas liés au nombre de mort et/ou victimes.

```r
summary(aov(AverageAge ~ Cause, data = shootings))
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## Cause        12   2930   244.1   1.519  0.124
## Residuals   137  22025   160.8
## 164 observations deleted due to missingness
```

La p-value étant supérieure à 0.05, on peux estimer que la cause d'une fusillade est lié à l'age du tireur.

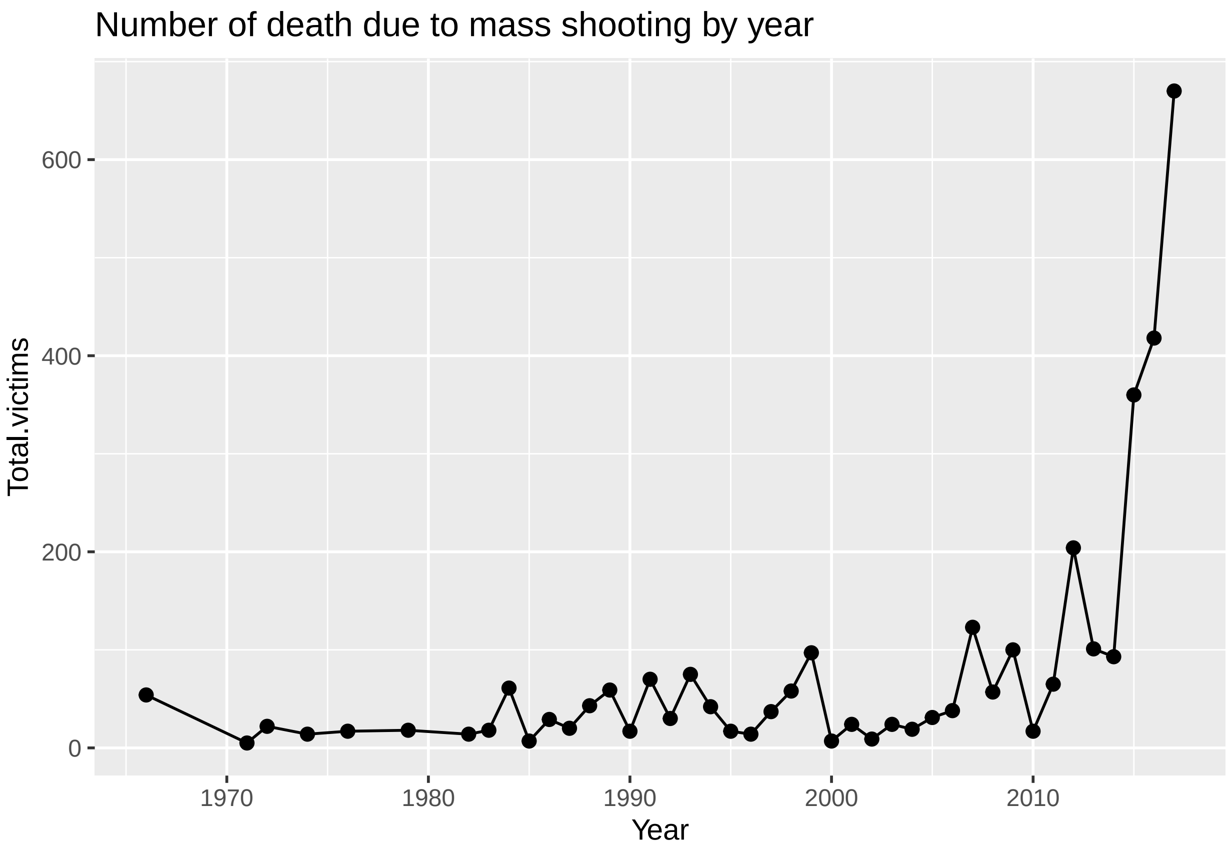
3.5)

Pour analyser les sommes des victimes, blessés et morts par années, on va d'abord créer un nouveau data frame les contenants :

```
##    Year Fatalities Total.victims Injured
## 1  1966         22            54      33
## 2  1971          2             5       4
## 3  1972         10            22      13
## 4  1974          4            14      10
## 5  1976          8            17       9
## 6  1979          4            18      14
## 7  1982         10            14       5
## 8  1983         14            18       4
## 9  1984         31            61      32
## 10 1985          3             7       4
## 11 1986         17            29      13
## 12 1987          6            20      14
## 13 1988         17            43      28
## 14 1989         19            59      43
## 15 1990         12            17       6
## 16 1991         47            70      26
```

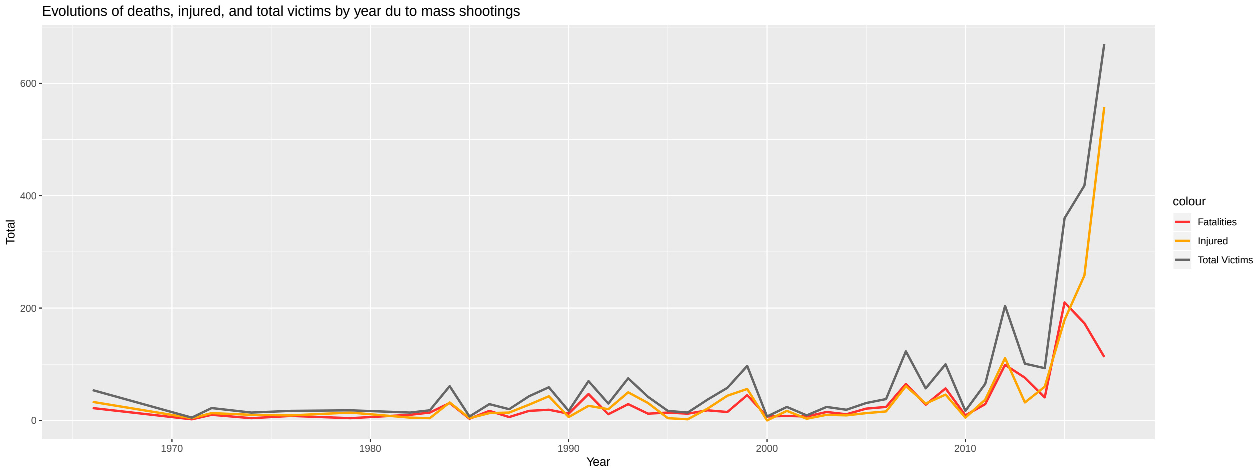
```
## 17 1992          11              30       20
## 18 1993          29              75       50
## 19 1994          12              42       31
## 20 1995          14              17        4
## 21 1996          12              14        2
## 22 1997          18              37       21
## 23 1998          15              58       44
## 24 1999          45              97       56
## 25 2000           7               7        0
## 26 2001           8              24       17
## 27 2002           7               9        3
## 28 2003          15              24       10
## 29 2004          11              19        9
## 30 2005          21              31       13
## 31 2006          24              38       16
## 32 2007          65             123       61
## 33 2008          28              57       30
## 34 2009          57             100       46
## 35 2010           9              17        5
## 36 2011          29              65       37
## 37 2012          99             204      111
## 38 2013          76             101       32
## 39 2014          41              93       60
## 40 2015         210             360      179
## 41 2016         173             418      258
## 42 2017         113             670      558
```

```
ggplot(shootings.by.year, aes(x=Year, y=Total.victims)) +
  geom_point(size=2, aes(size=20)) +
  stat_summary(fun.y = sum, geom="line") +
  ggtitle("Number of death due to mass shooting by year")
```



On remarque que le nombre de victimes est en forte hausse depuis 2010.

```
ggplot(shootings.by.year, aes(x=Year)) +
  geom_line(aes(Year, Fatalities, color="Fatalities"), size=1) +
  geom_line(aes(Year, Injured, color="Injured"), size=1) +
  geom_line(aes(Year, Total.victims, color="Total Victims"), size=1) +
  scale_colour_manual(values = c("Fatalities" = "firebrick1", "Injured" = "orange", "Total Victims" = "g
  ylab("Total") +
  ggtitle("Evolutions of deaths, injured, and total victims by year du to mass shootings")
```



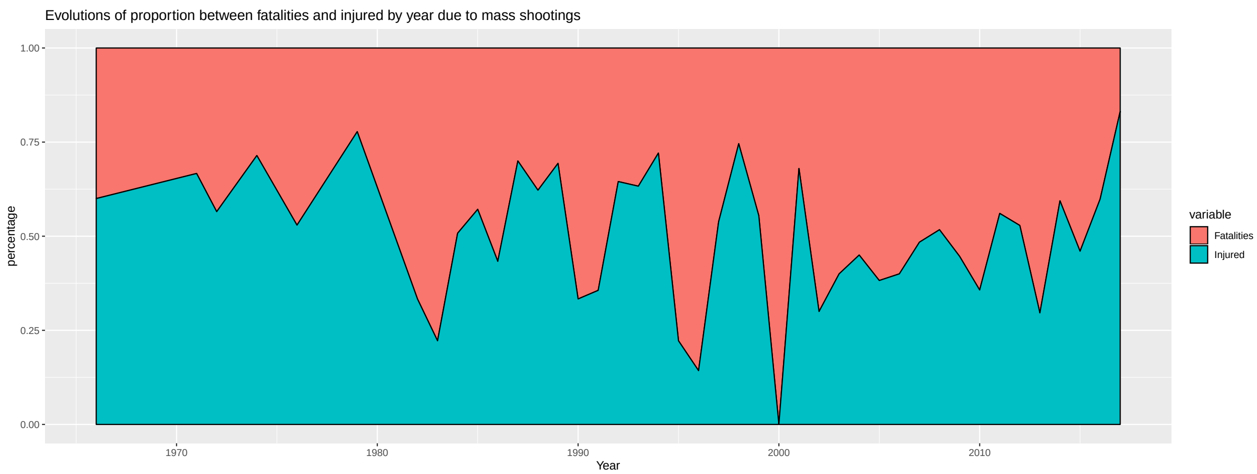
On peut remarquer une chute du nombre de morts par rapport au nombre de blessés dans les dernières année malgrés la forte hausse des victimes dès les année 2010.

```r
shootings$Total.victims <- as.numeric(shootings$Total.victims)
shootings$Injured <- as.numeric(shootings$Injured)
shootings$Fatalities <- as.numeric(shootings$Fatalities)

data <- shootings %>%
  gather(key = "variable", value = "value", Injured, Fatalities)
data <- data[,c("variable", "value", "Year")]

data <- data  %>%
  dplyr::group_by(Year, variable) %>%
  dplyr::summarise(n = sum(value)) %>%
  dplyr::mutate(percentage = n / sum(n))

ggplot(data, aes(x=Year, y = percentage, fill = variable)) +
  geom_area(color = "black") +
  ggtitle("Evolutions of proportion between fatalities and injured by year due to mass shootings")
```



La proportion est assez ératique et ne semble pas avoir de tendance générale malgrés certains extremes.

3.6)

Pour faire des prédictions sur le nombre total de victimes on va d'abord créer nos modèles et vérifier leurs importance et répresentation

```r
victims.regression.linear <- lm(Total.victims ~ Year, data=shootings.by.year)

summary(victims.regression.linear)
```

```
##
## Call:
## lm(formula = Total.victims ~ Year, data = shootings.by.year)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -127.64  -68.99  -16.07   20.61  491.80
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -9492.560   2497.079  -3.801 0.000481 ***
## Year            4.795      1.251   3.832 0.000439 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 109.1 on 40 degrees of freedom
## Multiple R-squared:  0.2685, Adjusted R-squared:  0.2502
## F-statistic: 14.68 on 1 and 40 DF,  p-value: 0.0004394
```

```
victims.regression.exp <- lm(log(Total.victims) ~ Year, data=shootings.by.year)

summary(victims.regression.exp)
```

```
##
## Call:
## lm(formula = log(Total.victims) ~ Year, data = shootings.by.year)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.8991 -0.6204  0.0247  0.6197  1.8578
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -90.79047   20.55466  -4.417 7.42e-05 ***
## Year          0.04732    0.01030   4.594 4.27e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8977 on 40 degrees of freedom
## Multiple R-squared:  0.3454, Adjusted R-squared:  0.3291
## F-statistic: 21.11 on 1 and 40 DF,  p-value: 4.27e-05
```

```
shootings.by.year.2010 <- filter(shootings.by.year, Year >= 2010)

victims.regression.linear.2010 <- lm(Total.victims ~ Year, data=shootings.by.year.2010)

summary(victims.regression.linear.2010)
```

```
##
## Call:
## lm(formula = Total.victims ~ Year, data = shootings.by.year.2010)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -188.45  -43.83   11.95   65.46  145.83
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -162660.74   35569.51  -4.573  0.00380 **
## Year             80.90      17.67   4.580  0.00377 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 114.5 on 6 degrees of freedom
## Multiple R-squared:  0.7776, Adjusted R-squared:  0.7405
## F-statistic: 20.97 on 1 and 6 DF,  p-value: 0.003771
```

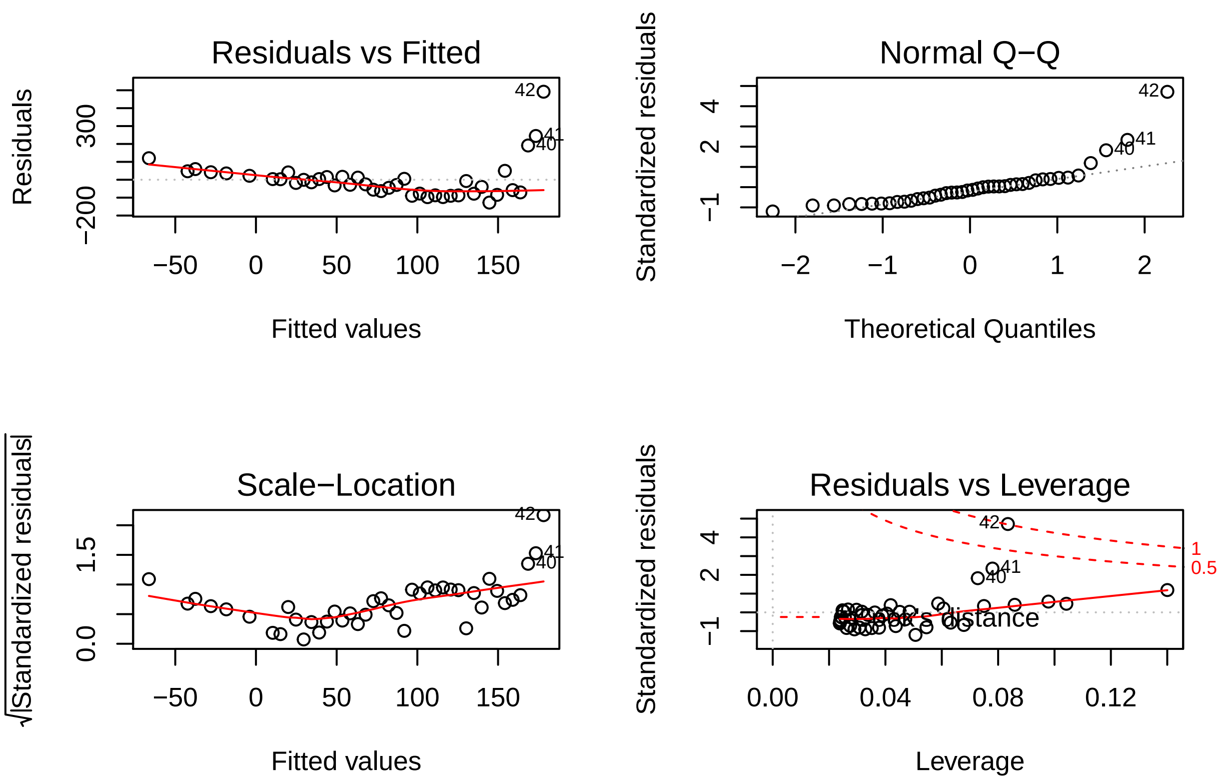
```r
victims.regression.exp.2010 <- lm(log(Total.victims) ~ Year, data=shootings.by.year.2010)

summary(victims.regression.exp.2010)
```

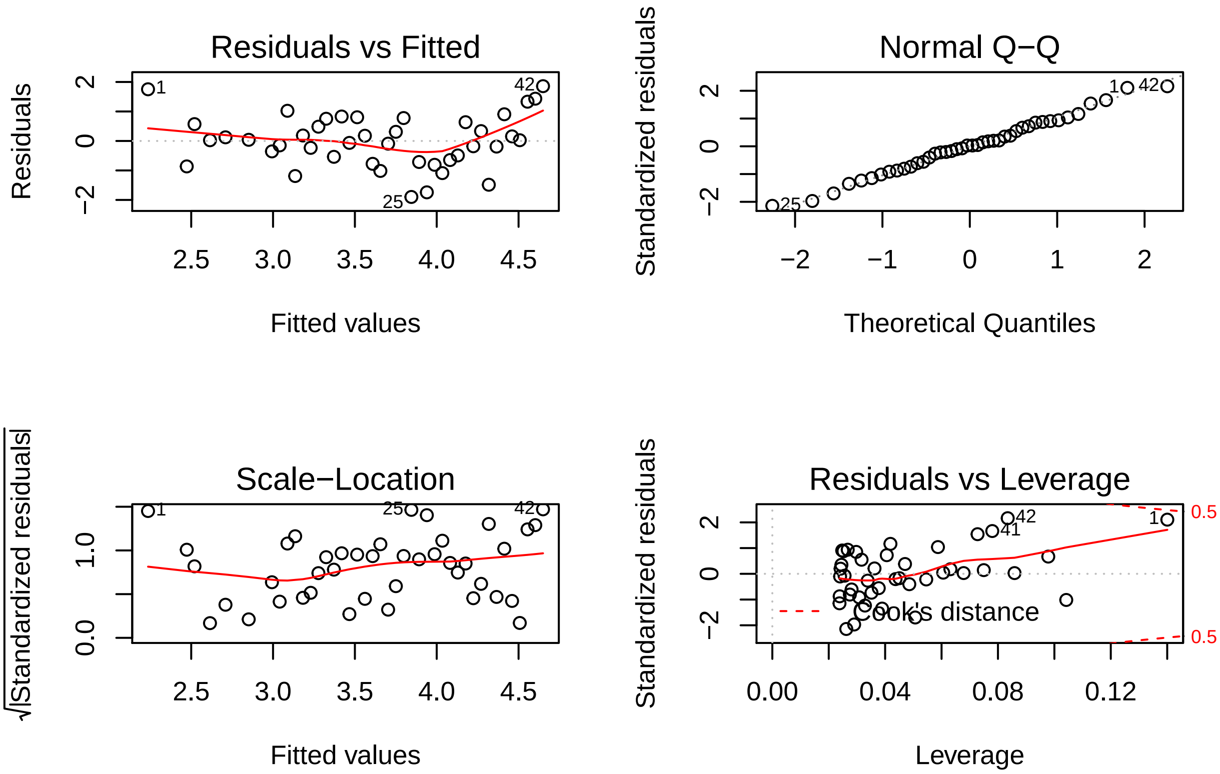
```
##
## Call:
## lm(formula = log(Total.victims) ~ Year, data = shootings.by.year.2010)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.67332 -0.27283 -0.02517  0.25226  0.98471
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -873.41004  178.43938  -4.895  0.00273 **
## Year           0.43625    0.08862   4.923  0.00265 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5743 on 6 degrees of freedom
## Multiple R-squared:  0.8015, Adjusted R-squared:  0.7685
## F-statistic: 24.23 on 1 and 6 DF,  p-value: 0.00265
```

On va maintenant tester les importances de nos 4 modèles

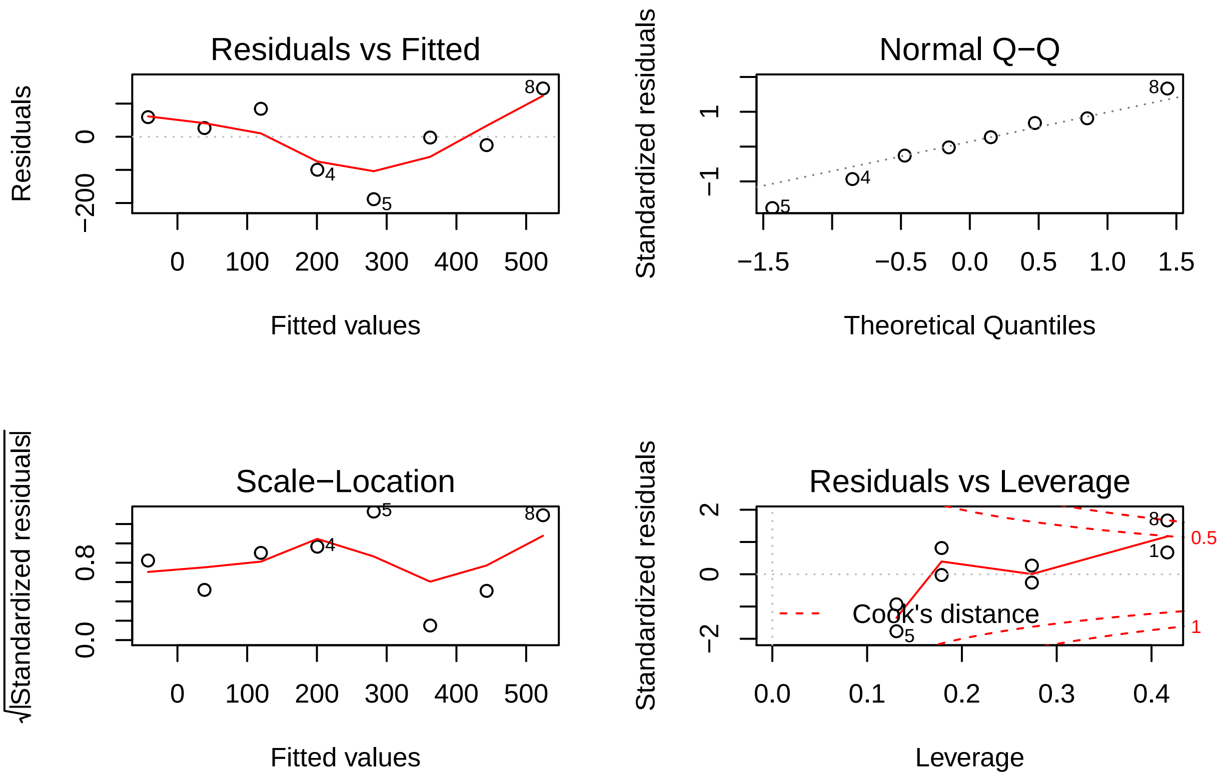
```r
par(mfrow = c(2, 2))
plot(victims.regression.linear)
```



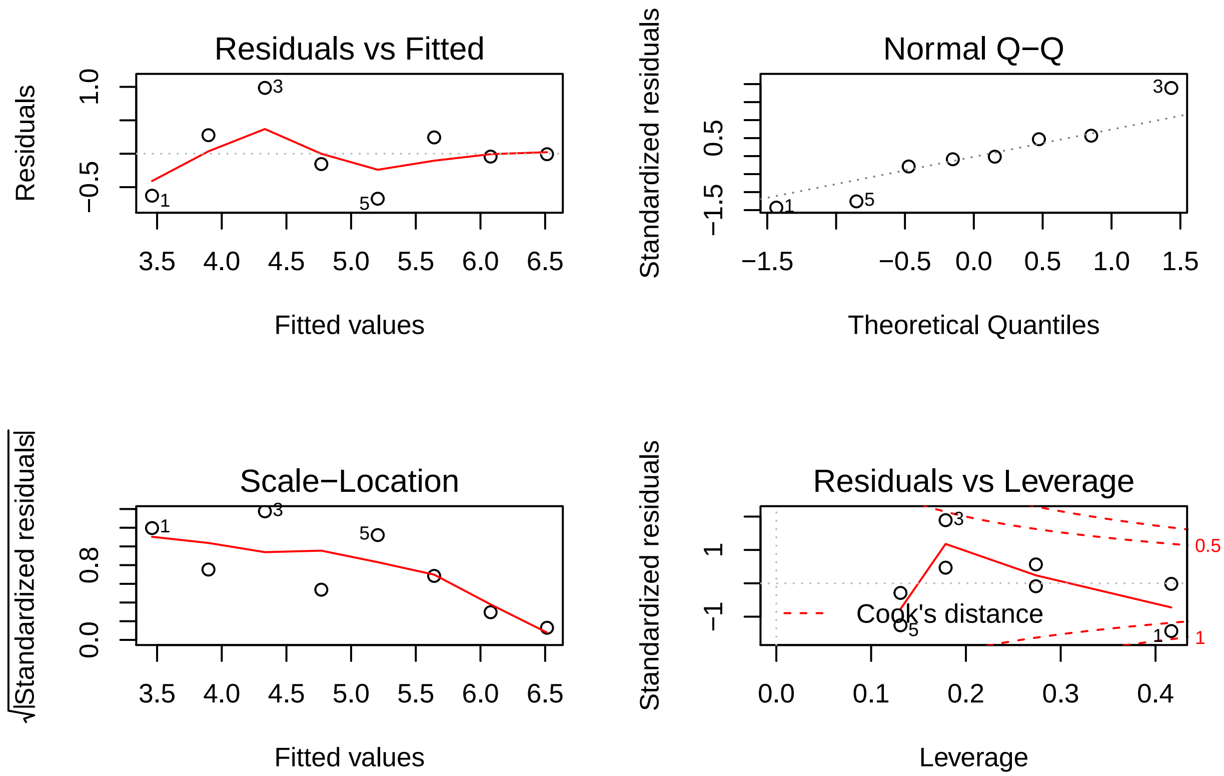

```r
par(mfrow = c(2, 2))
plot(victims.regression.exp)
```




```r
par(mfrow = c(2, 2))
plot(victims.regression.linear.2010)
```




```r
par(mfrow = c(2, 2))
plot(victims.regression.exp.2010)
```



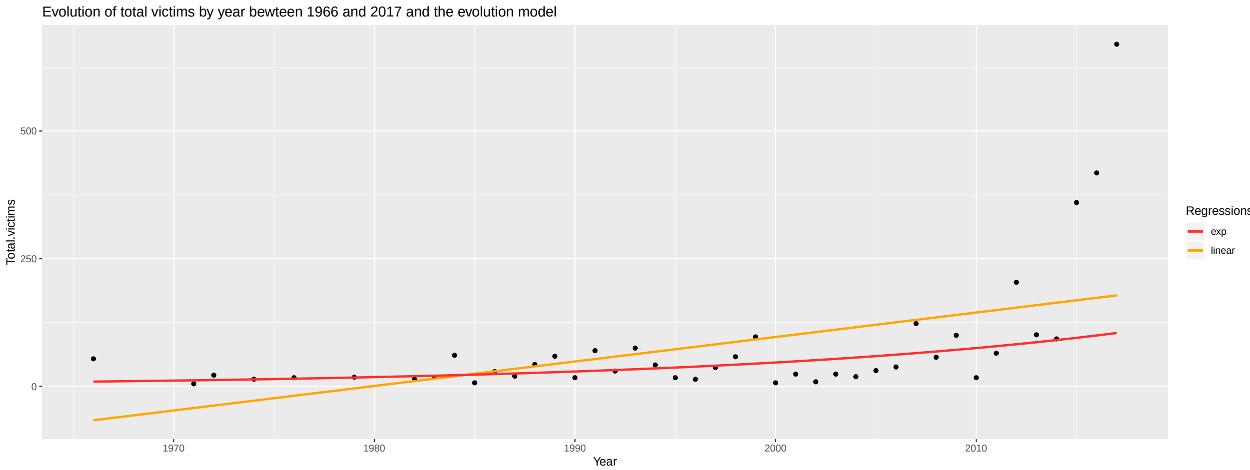
Sur nos quatres modèles, aucuns ne sont assez satisfaisants, il faudrait retirer des outliers pour que nos modèles soit représentatifs mais cela serait un cas de cherry-picking.

Les deux modèles entre 1966 et 2017 sembles les plus réprésentatifs pour la période mais ne prennent pas correctement en compte les évolutions du nombre de victime sur les dernières année de l'échantillon.

Par manque de donnée, les modèles entre 2010 et 2017 sont aussi très peu représentatifs à en juger par leurs graphiques précedents.

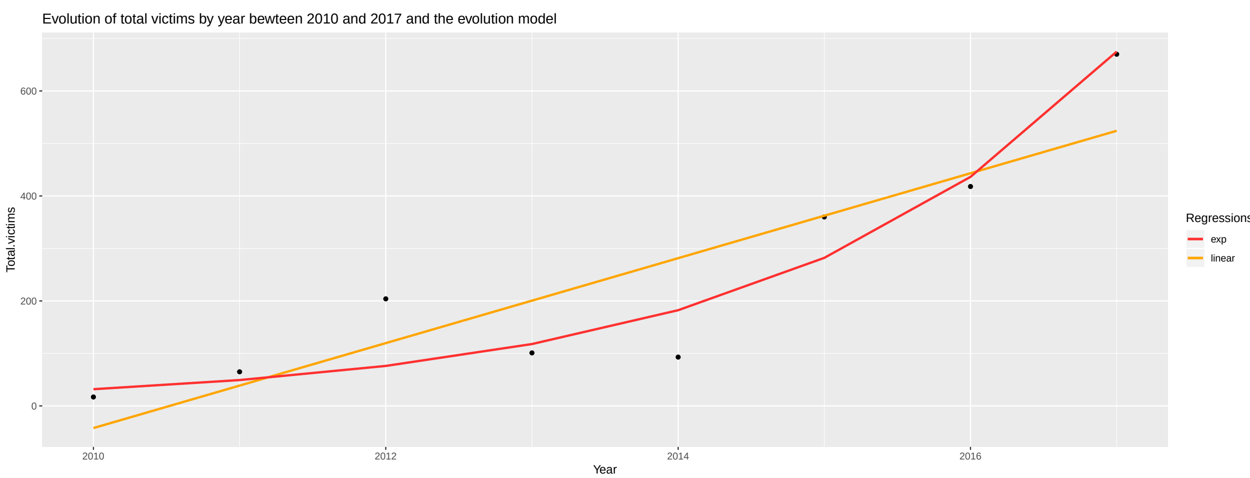
Les deux modèles entre 1966 et 2017 se traduisent sur graphique comme ceci :

```
shootings.by.year %>%
  mutate( model = predict(victims.regression.linear)) %>%
  mutate( model.exp = exp(predict(victims.regression.exp))) %>%
  ggplot(x = Year) +
  geom_point( aes(Year, Total.victims)) +
  geom_line( aes(Year, model, colour="linear"), size=1) +
  geom_line( aes(Year, model.exp, colour="exp"), size=1) +
  scale_colour_manual(name = 'Regressions', values =c('linear'='orange','exp'='firebrick1')) +
  ggtitle("Evolution of total victims by year bewteen 1966 and 2017 and the evolution model")
```



Les deux modèles entre 2010 et 2017 se traduisent sur graphique comme ceci :

```
shootings.by.year.2010 %>%
  mutate( model = predict(victims.regression.linear.2010)) %>%
  mutate( model.exp = exp(predict(victims.regression.exp.2010))) %>%
  ggplot(x = Year) +
  geom_point( aes(Year, Total.victims) ) +
  geom_line( aes(Year, model, colour="linear"), size=1) +
  geom_line( aes(Year, model.exp, colour="exp"), size=1) +
  scale_colour_manual(name = 'Regressions', values =c('linear'='orange','exp'='firebrick1')) +
  ggtitle("Evolution of total victims by year bewteen 2010 and 2017 and the evolution model")
```



Pour effectuer les predictions à differents moments dans le futur on va utiliser la fonction `predict` :

```
dates <- data.frame(Year=c(2018, 2020, 2025, 2030, 2050, 2075, 2100))
predict(victims.regression.linear, dates)
```

```
##        1        2        3        4        5        6        7
## 182.9945 192.5838 216.5569 240.5300 336.4225 456.2882 576.1538
```

```
exp(predict(victims.regression.exp, dates))
```

```
##         1         2         3         4         5         6         7
##  109.5914  120.4692  152.6249  193.3635  498.1629 1625.9883 5307.1755
```

```r
dates <- data.frame(Year=c(2018, 2020, 2025, 2030, 2050, 2075, 2100))
predict(victims.regression.linear.2010, dates)
```

```
##         1         2         3         4         5         6         7
##  605.0714  766.8810 1171.4048 1575.9286 3194.0238 5216.6429 7239.2619
```

```r
dates <- data.frame(Year=c(2018, 2020, 2025, 2030, 2035))
exp(predict(victims.regression.exp.2010, dates))
```

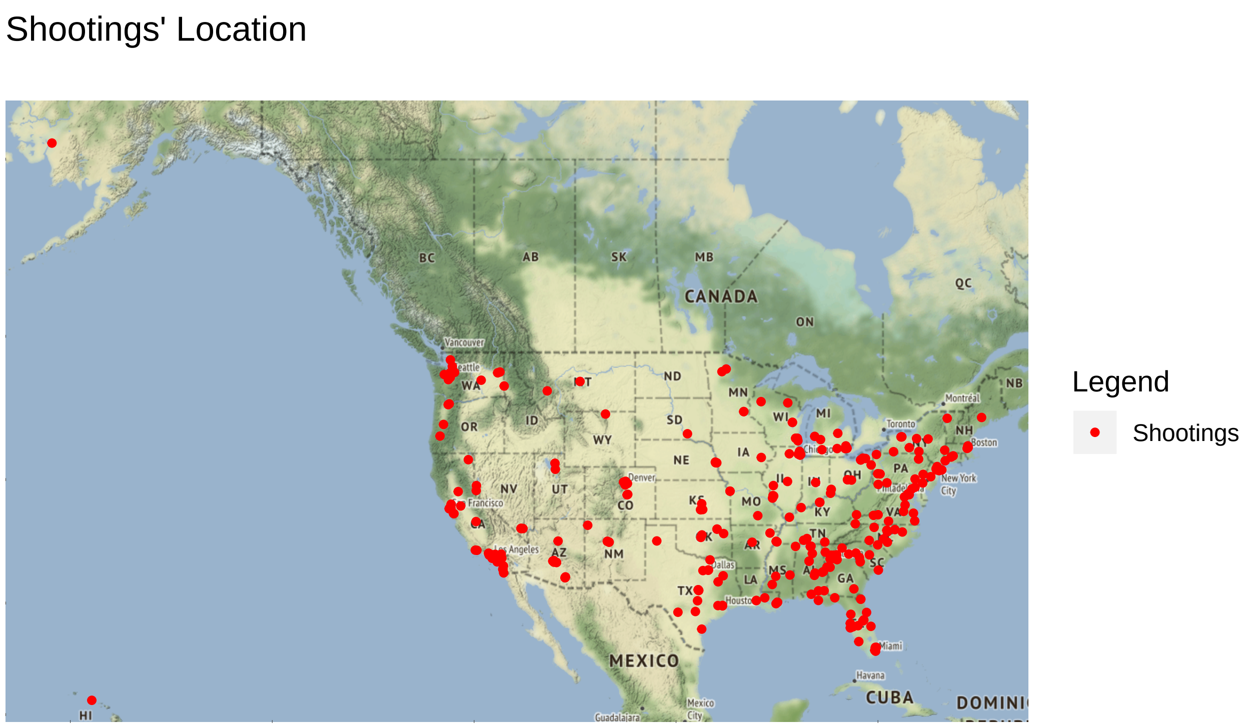
```
##           1           2           3           4           5
##    1044.122    2498.486   22130.482  196022.007 1736276.078
```

On remarque que certaines prédictions semble réaliste et d'autrs comme l'exponentielle entre 2010 et 2017 deviennent très vite irréalistes.

Le modèles exponentiel semble mieux convenir pour la partie [1966;2017] alors que le modèle linéaire convient mieux à la partie [2010; 2017]

4) Scatterplot des fusillades

```r
qmplot(Longitude, Latitude, data = shootings, maptype = "toner-lite", color = "red", size = I(1)) +
  labs(title = "Shootings' Location\n", x = "", y = "", color = "Legend") +
  scale_color_manual(labels = c("Shootings"), values = c("red"))
```



5) Carte des fusillades regroupés en KMeans cluster

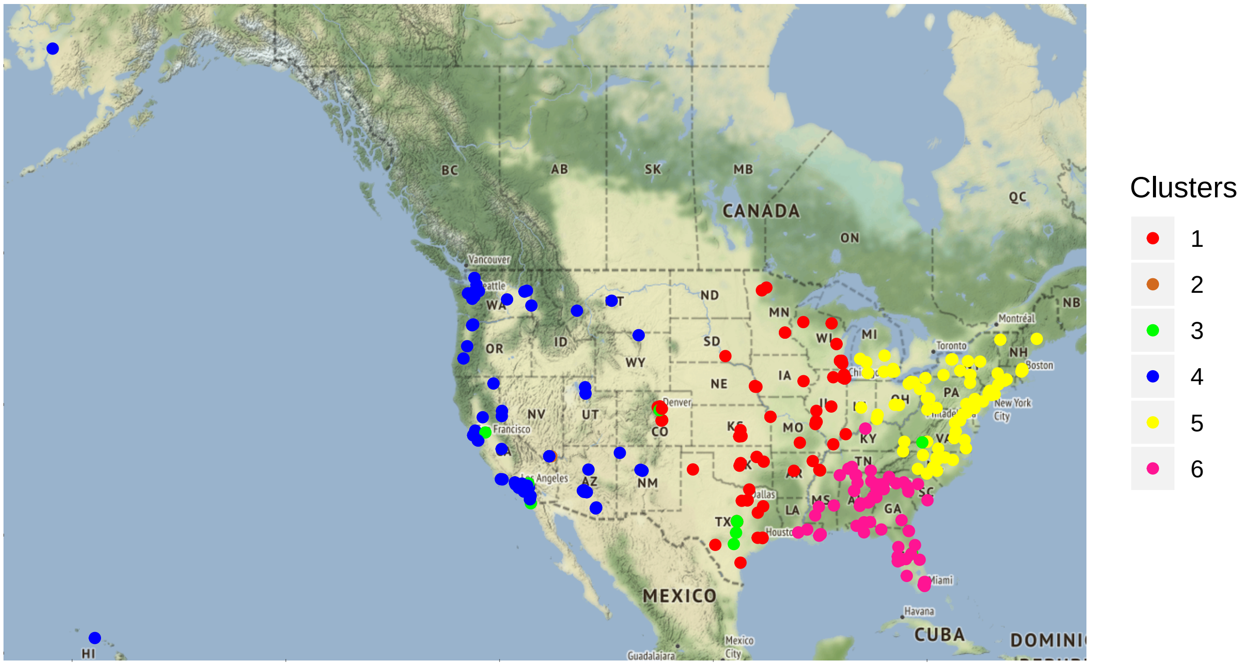
```r
shootings_bis <- shootings

clusters <- kmeans(shootings_bis[c('Latitude', 'Longitude', 'Total.victims')], 6)

# Save the cluster number in the dataset as column
shootings_bis$Clusters <- as.factor(clusters$cluster)
```

```r
qmplot(Longitude, Latitude, data = shootings_bis, maptype = "terrain-background", color = Clusters) +
  labs(title = "K Means clustering Visualition of mass shootings in the US\n", x = "", y = "", color =
  scale_color_manual(labels = c("1", "2", "3", "4", "5", "6"),
                     values =  c("red", "chocolate", "green", "blue", "yellow", "deeppink"))
```

K Means clustering Visualition of mass shootings in the US



Le nombre de cluster “optimal” pour cette méthode a été obtenu de manière empirique

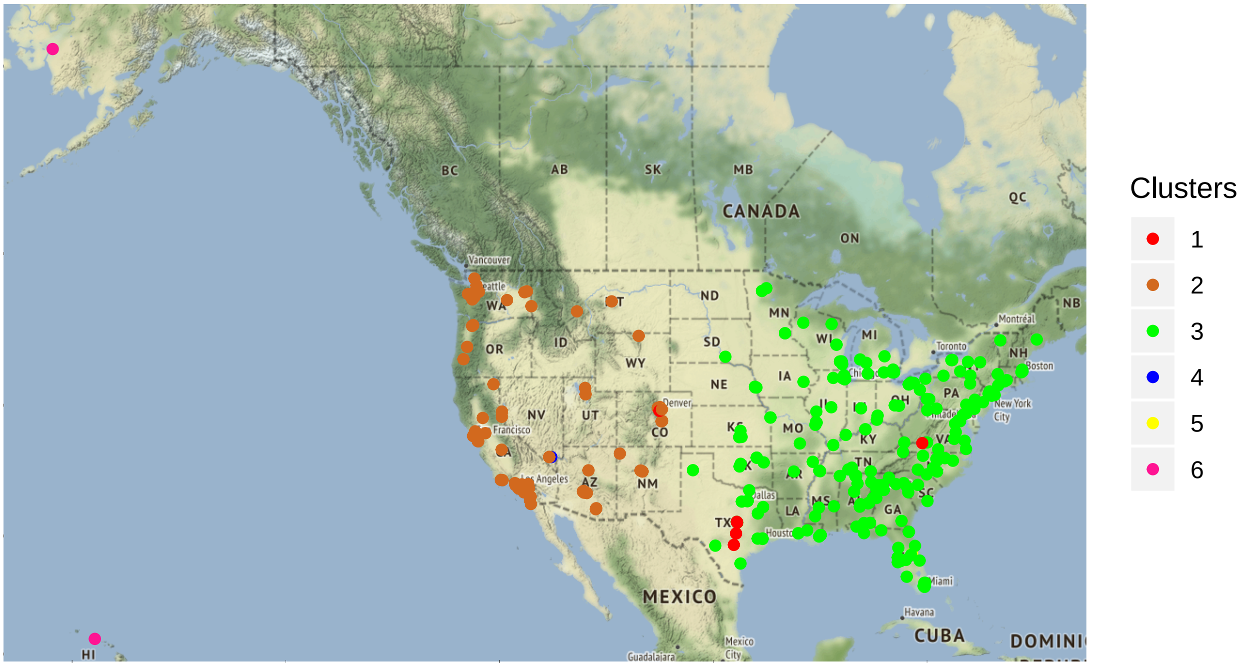
6) Carte des fusillades regroupés hiérarchiquement

```r
hierachical.cluster <- hclust(dist(shootings[c('Latitude', 'Longitude', 'Total.victims')]))
cut_cluster <- cutree(hierachical.cluster, k = 6)

shootings_bis$HierarchicalClusters <- as.factor(cut_cluster)

qmplot(Longitude, Latitude, data = shootings_bis, maptype = "terrain-background", color = HierarchicalCl
  labs(title = "Hierarchical clustering Visualition of mass shootings in the US\n", x = "", y = "", colo
  scale_color_manual(labels = c("1", "2", "3", "4", "5", "6"),
                     values =  c("red", "chocolate", "green", "blue", "yellow", "deeppink"))
```

Hierarchical clustering Visualition of mass shootings in the US



Le nombre de cluster “optimal” pour cette méthode a été obtenu en visualisant le dendrogramme des regroupements hiérarchiques et en essayant de prendre des groupes ayant des données suffisament proches.

7) Comparaison avec d’autres jeu de données

Pour cette partie, nous avons décidé de recouper les données des fusillades de masses avec des données gouvernementales permettant de savoir où ont été décerné les licences pour vendre les armes en janvier 2017 (donc où se trouvent les points de ventes d’armes aux USA).

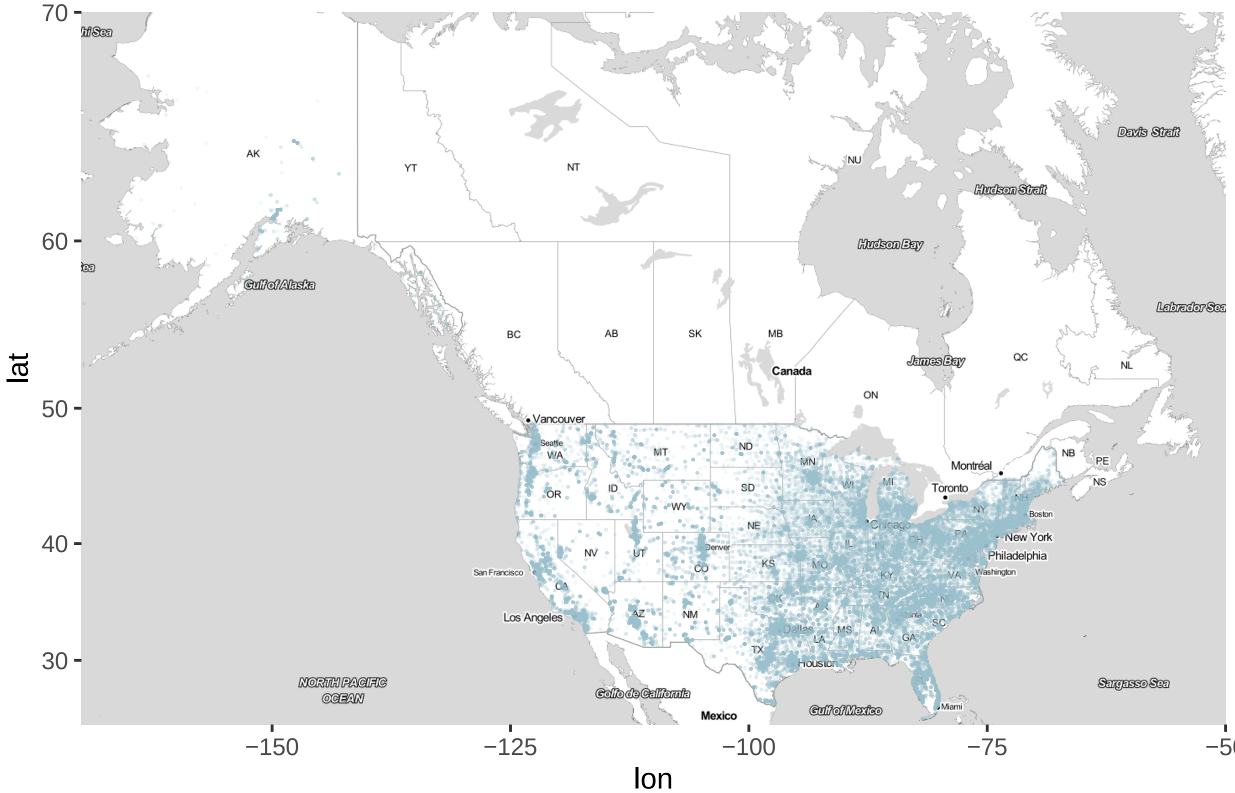
Source des données: (Gouvernement Fédéral des Etats Unis)[https://www.atf.gov/firearms/listing-federal-firearms-licensees-ffls-2017]

Ce choix se justifie par le raisonnement suivant, plus il y a d’armuriers, plus l’offre d’armes est élevé et donc surement la demande. Donc Les populations locales ont probablement plus d’armes que dans les endroits où il y a moins d’armuriers. Plus il y a d’armes en circulation, plus les chances de fusillades sont, potentiellement élevé.

Donc ce que nous souhaiterions mettre en évidence est un lien, une corrélation entre le nombre de fusillades dans un état et le nombre de license pour vendre des armes situé dans cet état.

```
ggmap(get_stamenmap(bbox = c(left = -170, bottom = 24, right = -50, top = 70), zoom = 4,
        color = "color",
        maptype = "toner-lite", force = FALSE
)) + geom_point(aes(x = Longitude, y = Latitude), color = "lightblue3", data = gun_license, size = 0.01
  theme(legend.position="bottom")
```

```
## Warning: Removed 1806 rows containing missing values (geom_point).
```




```r
cor(Data$ShootingsPct, Data$ShopsPct)
```

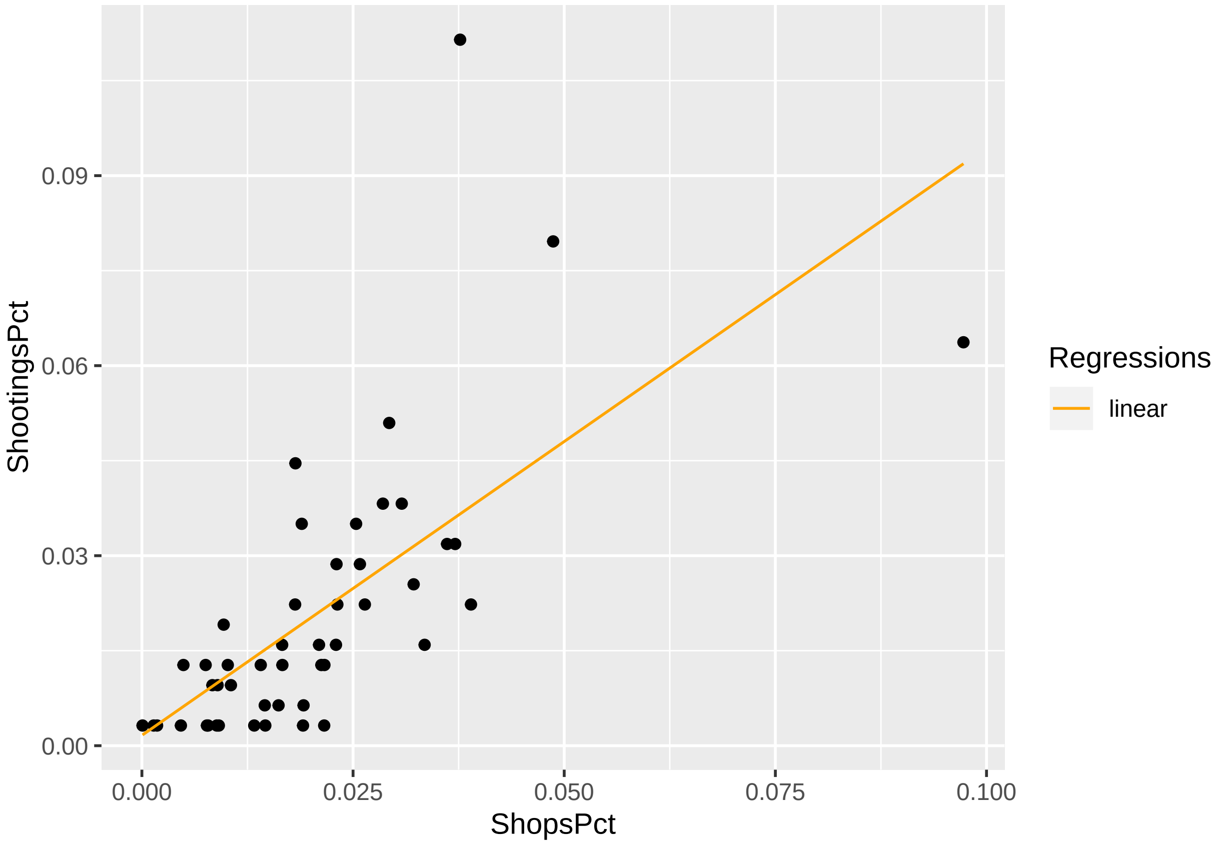
```
## [1] 0.6821753
```

Le résultat précédent permet de voir que le pourcentage de fusillade par état et de magasins d'armes semble corrélé. Pour modéliser cette corrélation nous utilisons une regression linéaire.

```r
rel <- lm(ShootingsPct ~ ShopsPct, data = Data)
summary(rel)
```

```
##
## Call:
## lm(formula = ShootingsPct ~ ShopsPct, data = Data)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.028186 -0.007422 -0.002339  0.003900  0.074878
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.001631   0.003778   0.432    0.668
## ShopsPct    0.927807   0.146626   6.328 9.33e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01588 on 46 degrees of freedom
## Multiple R-squared:  0.4654, Adjusted R-squared:  0.4537
## F-statistic: 40.04 on 1 and 46 DF,  p-value: 9.328e-08
```

```r
Data %>%
  mutate( model = predict(rel)) %>%
  ggplot(x = ShopsPct) +
  geom_point( aes(ShopsPct, ShootingsPct) ) +
  geom_line( aes(ShopsPct, model, colour="linear")) +
  scale_colour_manual(name = 'Regressions', values =c('linear'='orange'))
```



Comme le montre le graphique et le résumé de la régression linéaire, le modèle de données correspond de manière satisfaisante aux données réelles.

8) Carte des incidents par état (BONUS)

```r
shootings.State$state <- shootings.State$State

plot_usmap(data = shootings.State, values = "n", color = "black") +
  scale_fill_continuous(low = "lightgoldenrodyellow", high = "red", name = "Shootings", label = scales:
  theme(legend.position = "right") +
  ggtitle("US Shootings By State")
```

US Shootings By State