W271 Lab3

Issac Law, Mayukh Dutta, Mike King

Question 1

```
# load data
load(file = "driving.RData")
sum(is.na(data))
```

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

```
table(data$state)
```

```
##
##  1  3  4  5  6  7  8 10 11 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29
## 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25
## 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51
## 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25
```

```
table(data$year)
```

```
##
## 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995
##   48   48   48   48   48   48   48   48   48   48   48   48   48   48   48   48
## 1996 1997 1998 1999 2000 2001 2002 2003 2004
##   48   48   48   48   48   48   48   48   48
```

There are no missing data and this is a **balanced panel**. For each state there are 25 observations, correponding to 25 years. For each year, there are 48 observations, corresponding to 48 states.

```
dwtest(totfatrte ~ seatbelt+minage+zerotol+sl70plus+gdl+bac08+bac10+
          perse+vehicmilespc+unem+perc14_24, data=data)
```

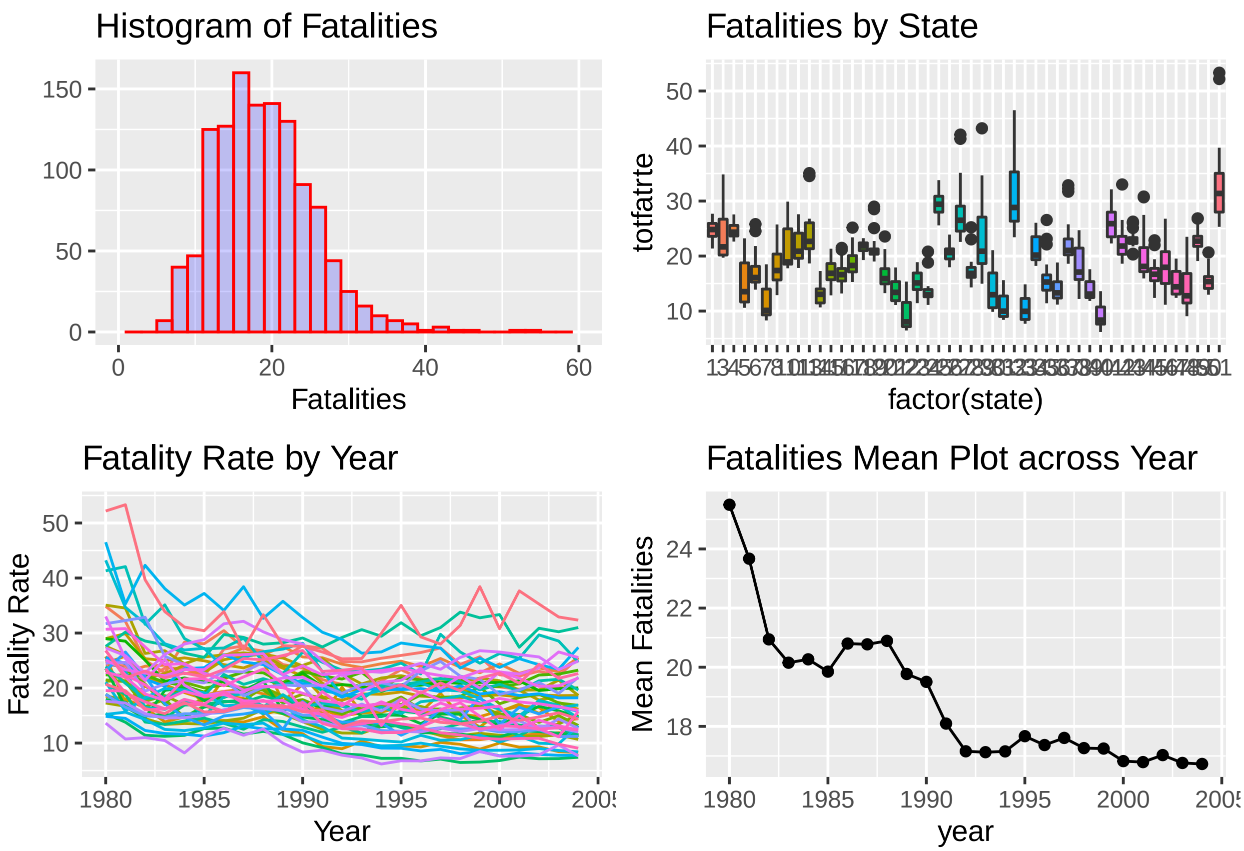
```
##
##  Durbin-Watson test
##
## data:  totfatrte ~ seatbelt + minage + zerotol + sl70plus + gdl + bac08 +     bac10 + perse
## DW = 0.42474, p-value < 2.2e-16
## alternative hypothesis: true autocorrelation is greater than 0
```

Null hypothesis is rejected, this confirms the violation of independence assumption. Therefore we will have to use panel methods for analysis.

```
# dependent variable, totfatrte
p1<-qplot(data$totfatrte,geom="histogram",binwidth =2,main = "Histogram of Fatalities", xlab =
```

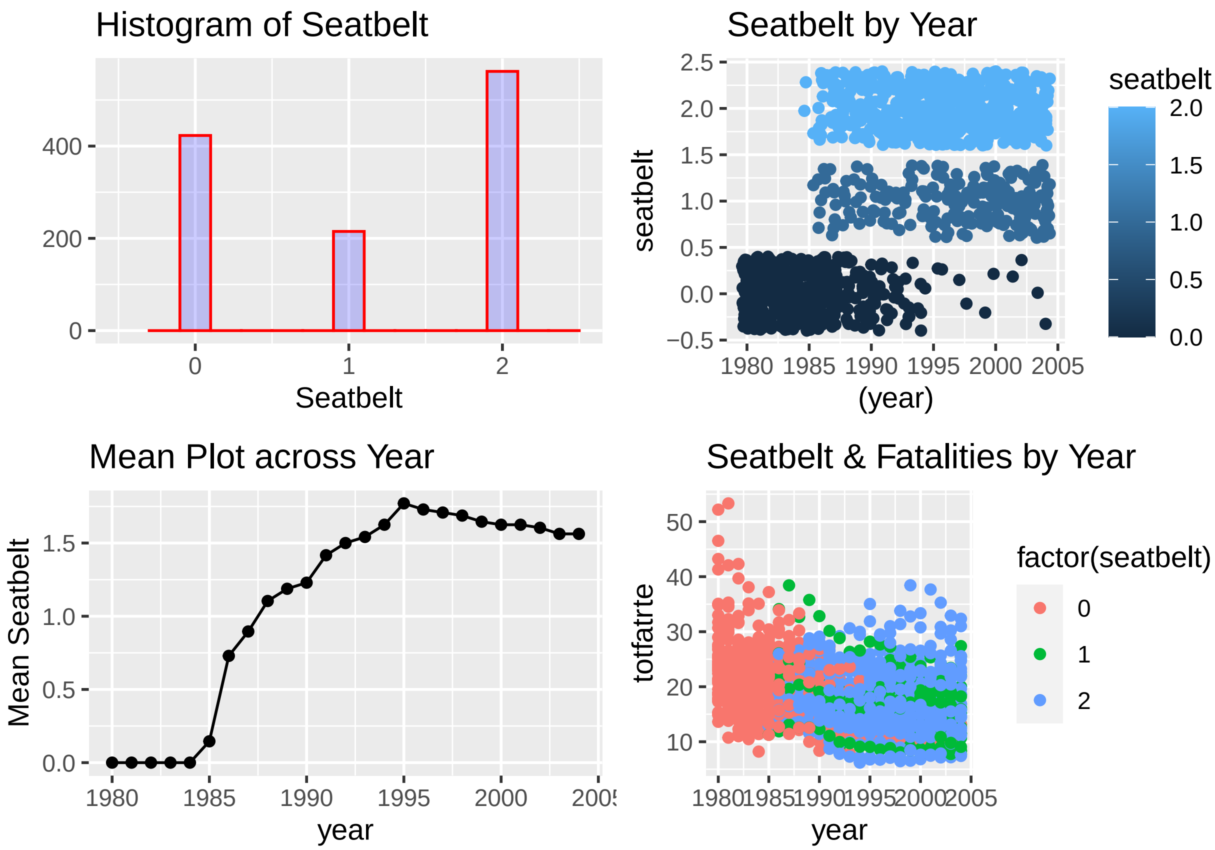
```r
p2 <- ggplot(data, aes(factor(state), totfatrte))+geom_boxplot(aes(fill = factor(state)), show
p3 <-ggplot(data, aes(year, totfatrte)) + geom_line(aes(col = as.factor(state))) + ggtitle("Fat
p4<-data %>% group_by(year)%>%summarise(mean_group=mean(totfatrte))%>%ggplot(aes(x=year, y=mean
grid.arrange(p1,p2,p3,p4,nrow=2)
```

```
## Warning: Removed 2 rows containing missing values (geom_bar).
```



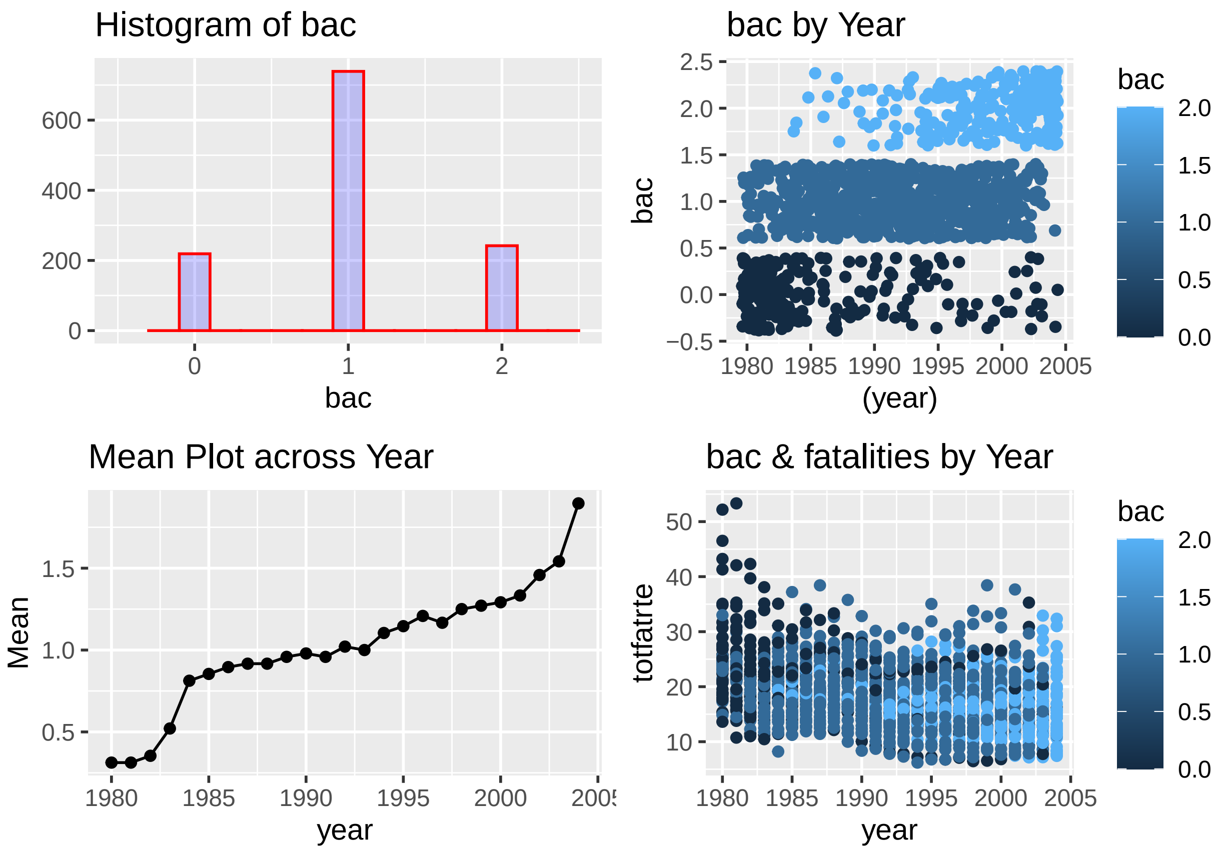
Most of values of fatalities are betwee 10 to 30 per 100,000 population. We observed that state 32 and state 51 have higher fatalities rate. Over the year, we observed that there are 2 periods which fatality rate changed more than any other time period. The first is 1980 through 1983 and the second is 1988 through 1992. The other timespans (1983-1988 and 1992-2004) show nearly stationary fatality rates.

```r
# seatbelt
p1<-qplot(data$seatbelt,geom="histogram",binwidth =0.2,main = "Histogram of Seatbelt", xlab = "
p2<-ggplot(data, aes((year), seatbelt))+geom_jitter(aes(color=seatbelt)) +ggtitle("Seatbelt by
p3<-data %>% group_by(year)%>%summarise(mean_group=mean(seatbelt))%>%ggplot(aes(x=year, y=mean_
p4<-ggplot(data,aes(year, totfatrte)) + geom_point(aes(color=factor(seatbelt)))+ggtitle("Seatbe
grid.arrange(p1,p2,p3,p4,nrow=2)
```



Over the years, states started with mostly no seatbelt laws until 1985. Since 1985 states changed to have primary seatbelt law and secondary seatbelt law. From 1995, some more states change from secondary seatbelt law to primary seatbelt law. Primary seatbelt law is stricter than secondary seatbelt law, we observe stricter seatbelt law implemented by states over years.

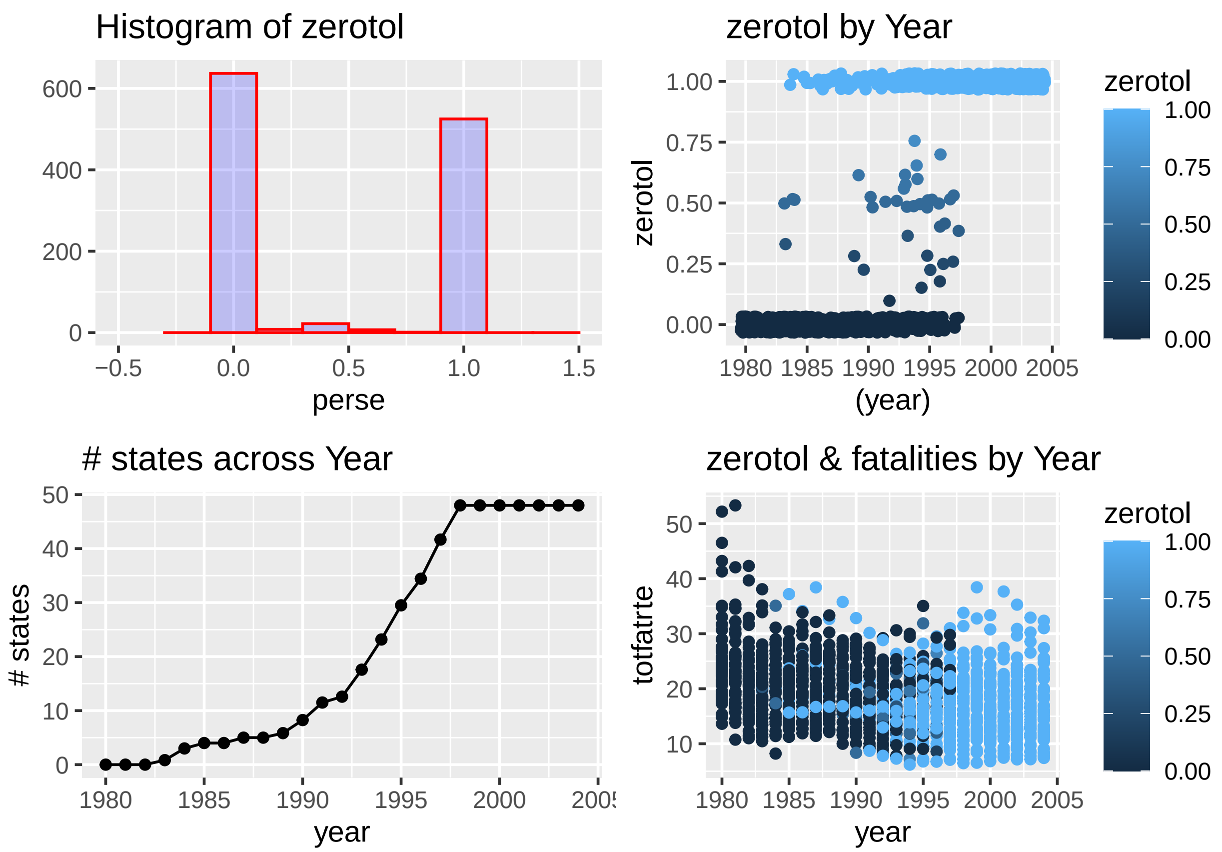
```
# bac08 & bac10
data$bac <- ifelse(round(data$bac08)==1, 2, ifelse(round(data$bac10)==1,1,0))
p1<-qplot(data$bac,geom="histogram",binwidth =0.2,main = "Histogram of bac", xlab = "bac",fill=
p2<-ggplot(data, aes((year), bac))+geom_jitter(aes(color=bac)) +ggtitle("bac by Year") + theme
p3<-data %>% group_by(year)%>%summarise(mean_group=mean(bac))%>%ggplot(aes(x=year, y=mean_group
p4<-ggplot(data,aes(year, totfatrte)) + geom_point(aes(color=bac))+ ggtitle("bac & fatalities b
grid.arrange(p1,p2,p3,p4,nrow=2)
```



In these plot, value 2 corresponds to blood alcohol level 0.08% and value 1 correspond to blood alcohol level 0.10%. Majority of data points in dataset have value of 1. Over year we observe that majority of states had no law on blood alcohol level, and then states started to implement law on blood alcohol level with 0.10%, and then more states implemented law on blood alcohol level 0.08%. And the end of the time period, majority of states had law on blood alcohol level with 0.08%. There is pattern of stricter law over years, and this is correlated with lower fatality rates over years.

```
# zerotol
p1<-qplot(data$zerotol,geom="histogram",binwidth =0.2,main = "Histogram of zerotol", xlab = "pe
p2<-ggplot(data, aes((year), zerotol))+geom_jitter(aes(color=zerotol)) +ggtitle("zerotol by Yea
p3<-data %>% group_by(year)%>%summarise(sum_group=sum(zerotol))%>%ggplot(aes(x=year, y=sum_grou
p4<-ggplot(data,aes(year, totfatrte)) + geom_point(aes(color=zerotol))+ggtitle("zerotol & fatal
grid.arrange(p1,p2,p3,p4,nrow=2)
```

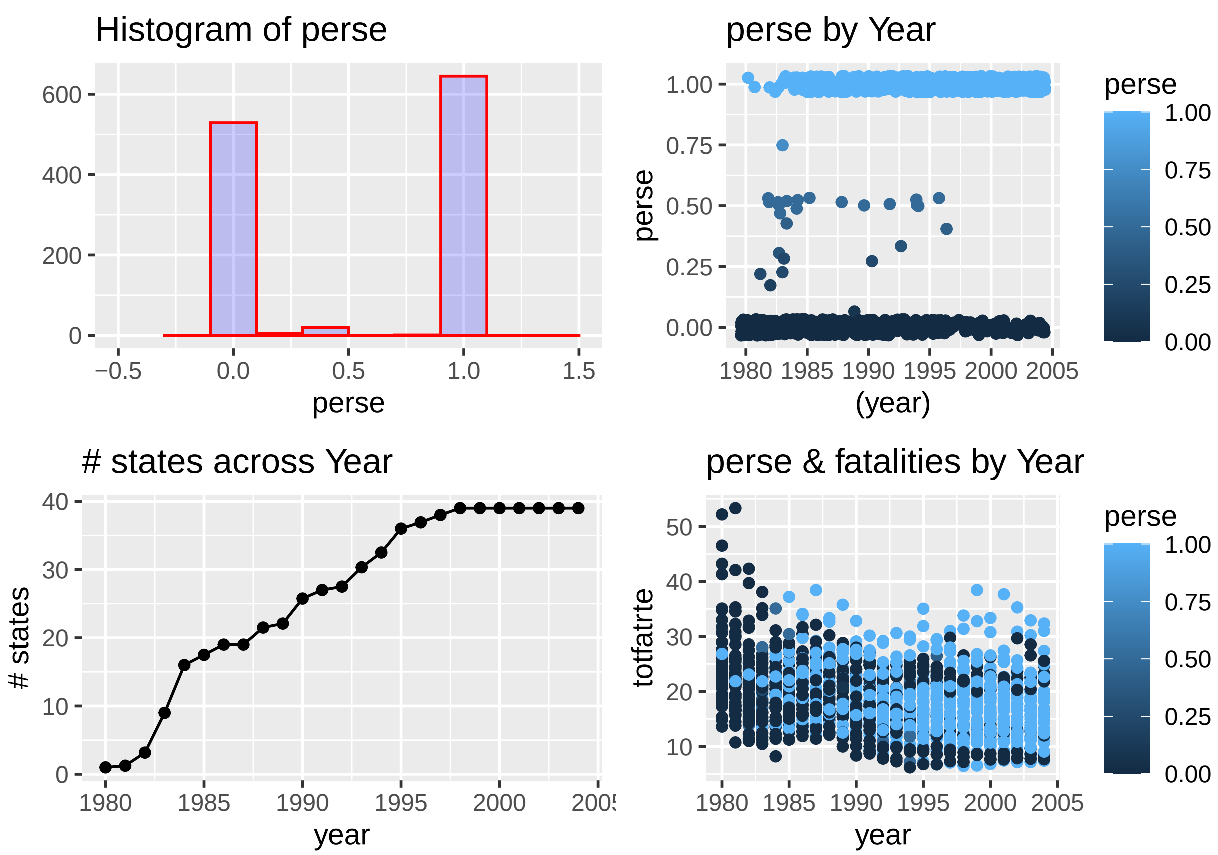
```
## Warning: Removed 1 rows containing missing values (geom_bar).
```



At the start of time period, no states have zero tolerance law. Starting from year 1983, some states started to have zero tolerance law and more states followed in subsequent years. Since year 1996, all states have zero tolerance law. The implementation of this stricter law looks correlated with the decreasing fatality rates over years.

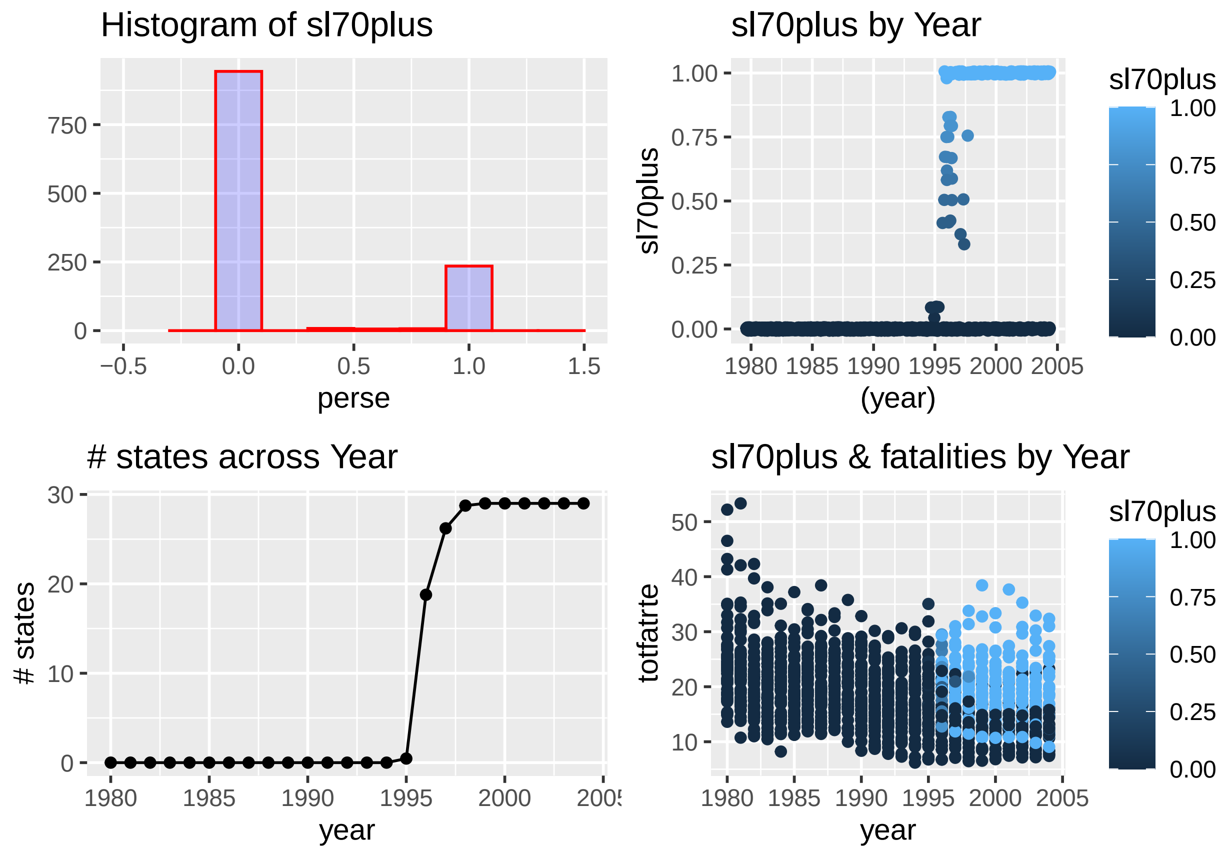
```
# perse
p1<-qplot(data$perse,geom="histogram",binwidth =0.2,main = "Histogram of perse", xlab = "perse"
p2<-ggplot(data, aes((year), perse))+geom_jitter(aes(color=perse)) +ggtitle("perse by Year") +
p3<-data %>% group_by(year)%>%summarise(sum_group=sum(perse))%>%ggplot(aes(x=year, y=sum_group)
p4<-ggplot(data,aes(year, totfatrte)) + geom_point(aes(color=perse)) + ggtitle("perse & fatali
grid.arrange(p1,p2,p3,p4,nrow=2)
```

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



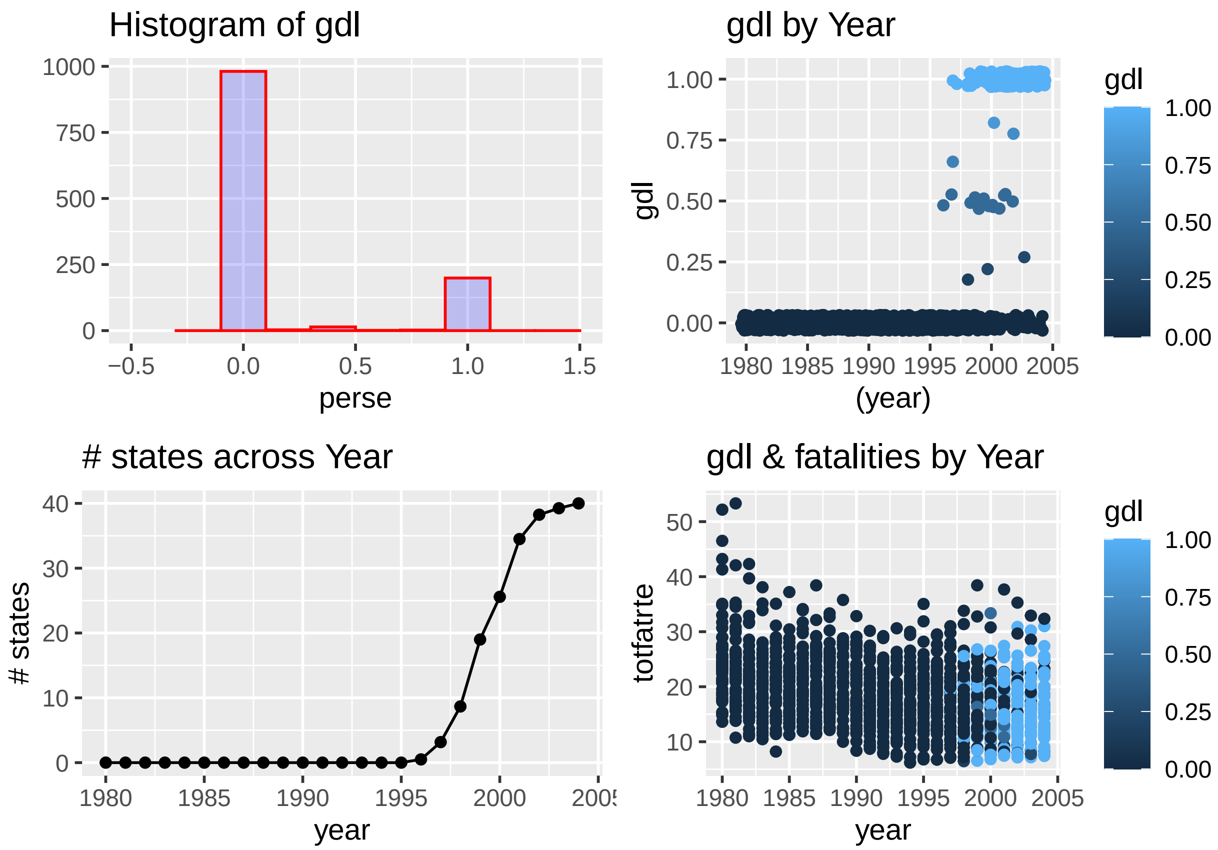
Around half of data points have value of 0 and the other half have values of 1. Over time, we observe that more states implemented the per se law. This increasing trend show some correlation with fatality rates.

```
# sl70plus
p1<-qplot(data$sl70plus,geom="histogram",binwidth =0.2,main = "Histogram of sl70plus", xlab = "
p2<-ggplot(data, aes((year), sl70plus))+geom_jitter(aes(color=sl70plus)) +ggtitle("sl70plus by
p3<-data %>% group_by(year)%>%summarise(sum_group=sum(sl70plus))%>%ggplot(aes(x=year, y=sum_gro
p4<-ggplot(data,aes(year, totfatrte)) + geom_point(aes(color=sl70plus)) + ggtitle("sl70plus & f
grid.arrange(p1,p2,p3,p4,nrow=2)
```



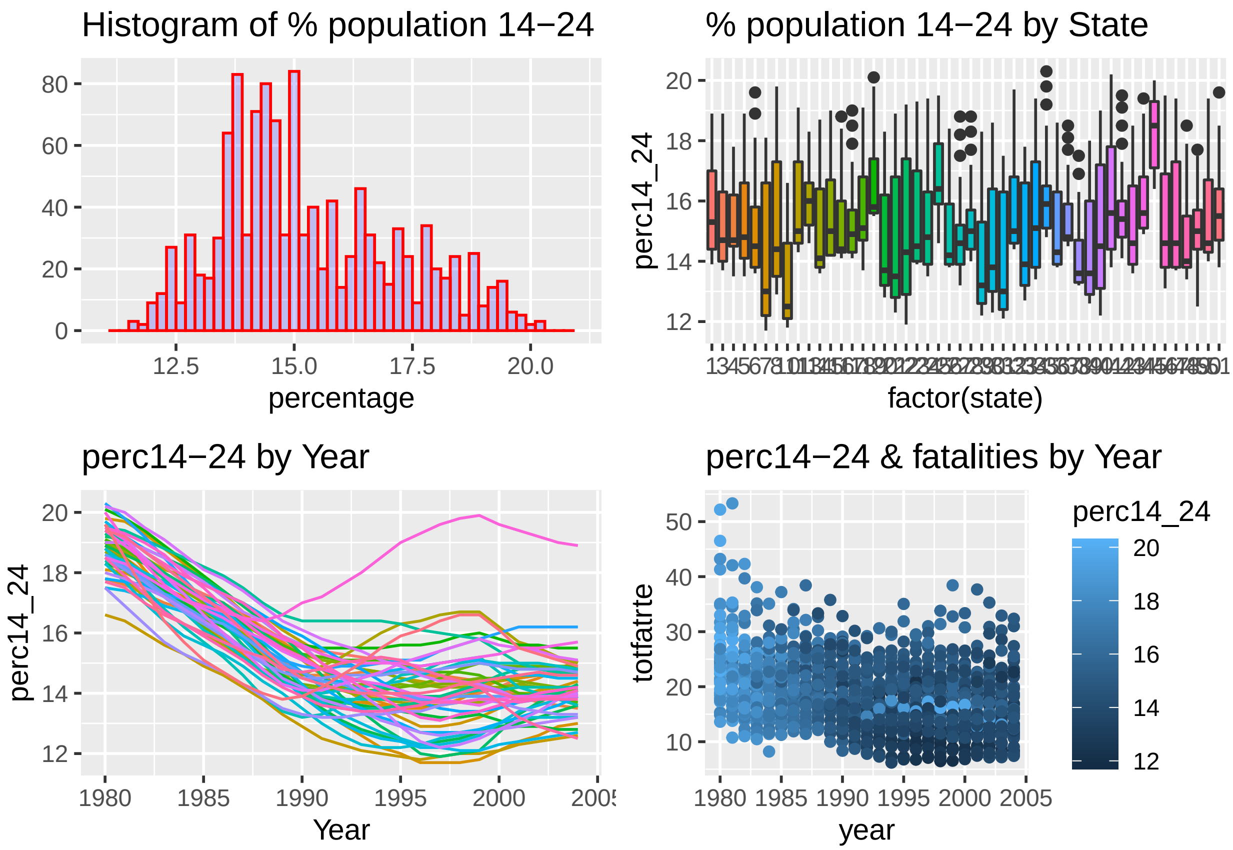
Most data points are with value 0. All states have stricter speed limit at before year 1995. Since 1995, some states started to relax the limit on speed and after year 1999, around 30 states have speed limit of 70, 75 or no limit.

```
# gdl
p1<-qplot(data$gdl,geom="histogram",binwidth =0.2,main = "Histogram of gdl", xlab = "perse",fil
p2<-ggplot(data, aes((year), gdl))+geom_jitter(aes(color=gdl)) +ggtitle("gdl by Year") + theme
p3<-data %>% group_by(year)%>%summarise(sum_group=sum(gdl))%>%ggplot(aes(x=year, y=sum_group))
p4<-ggplot(data,aes(year, totfatrte)) + geom_point(aes(color=gdl))+ggtitle("gdl & fatalities by
grid.arrange(p1,p2,p3,p4,nrow=2)
```



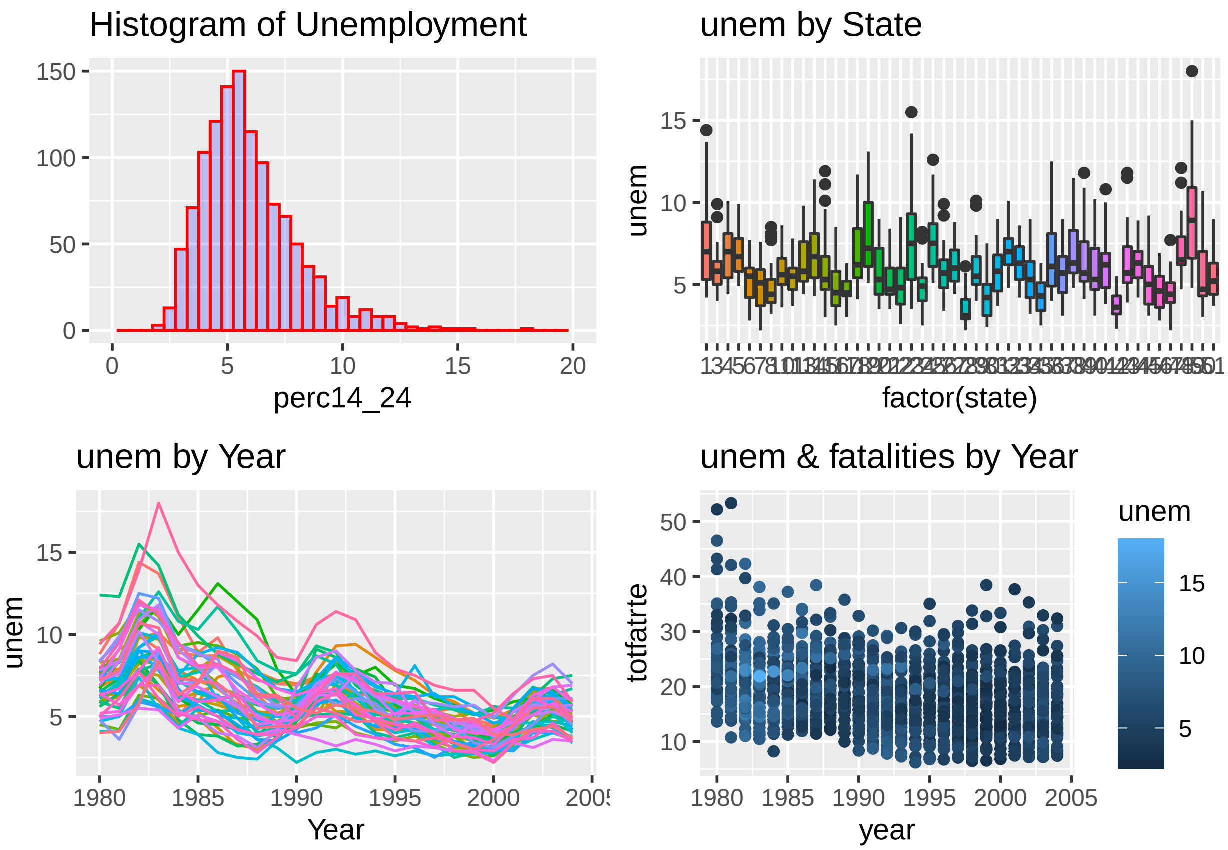
Most data points in dataset are with value 0. From plots across years, we observed that states started to have graduated drivers license law since 1996, and more states follow this trend. At then end of time period, most of states implemented this law. During this period of increasing states implementing GDL, fatality rates does not seem to show decreasing trend.

```
# perc14_24
p1<-qplot(data$perc14_24,geom="histogram",binwidth = 0.2,main = "Histogram of % population 14-2
p2<-ggplot(data, aes(factor(state), perc14_24))+geom_boxplot(aes(fill = factor(state)),show.leg
p3 <-ggplot(data, aes(year, perc14_24)) + geom_line(aes(col = as.factor(state))) + ggtitle("pe
p4<-ggplot(data,aes(year, totfatrte)) + geom_point(aes(color=perc14_24))+ggtitle("perc14-24 & 
grid.arrange(p1,p2,p3,p4,nrow=2)
```



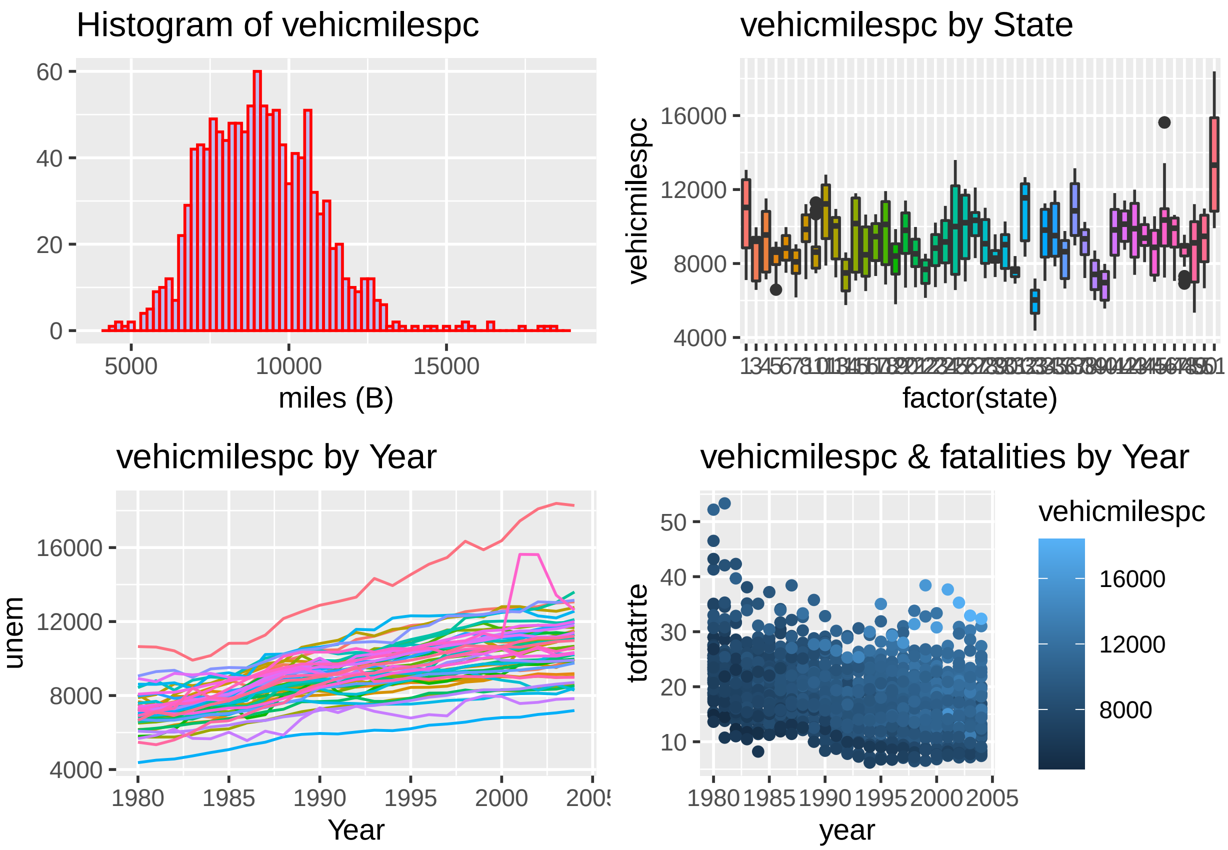
Majority of values are in range of 13% to 18%. We observed that state 45 has higher percentage of 14-24 years old population, especially after year 1988. The decreasing trend of % population of 14-24 show some degree of correlation to the decreasing trend of fatality rate.

```
# unem
p1<-qplot(data$unem,geom="histogram",binwidth = 0.5,main="Histogram of Unemployment",xlab = "pe
p2<-ggplot(data, aes(factor(state), unem))+geom_boxplot(aes(fill = factor(state)),show.legend=F
p3 <-ggplot(data, aes(year, unem)) + geom_line(aes(col = as.factor(state))) + ggtitle("unem by
p4<-ggplot(data,aes(year, totfatrte)) + geom_point(aes(color=unem))+ggtitle("unem & fatalities
grid.arrange(p1,p2,p3,p4,nrow=2)
```



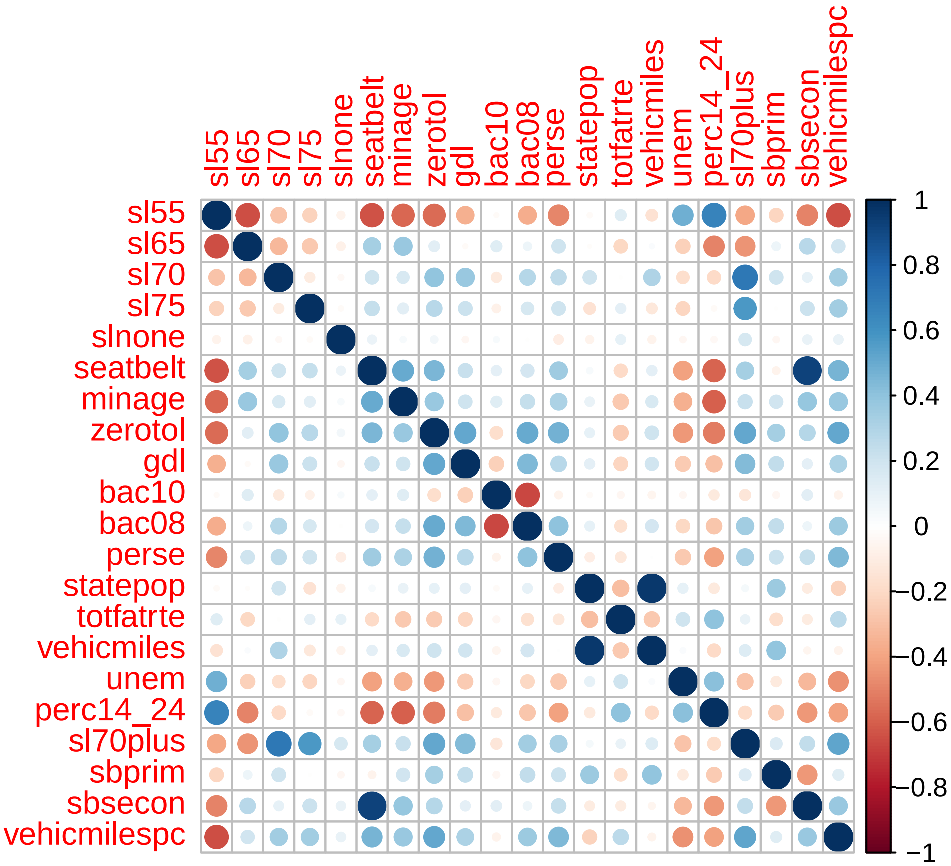
Most of values are between 3% to 10%, with some outliers above 14%. We observe that state 41 has higher unemployment rate across years. The decreasing trend of unemployment rate show correlation with the decreasing trend of fatality rates.

```
# vehicmilespc
p1<-qplot(data$vehicmilespc,geom="histogram",binwidth = 200,main = "Histogram of vehicmilespc"
p2<-ggplot(data, aes(factor(state), vehicmilespc))+geom_boxplot(aes(fill = factor(state)),show
p3 <-ggplot(data, aes(year, vehicmilespc)) + geom_line(aes(col = as.factor(state))) + ggtitle(
p4<-ggplot(data,aes(year, totfatrte)) + geom_point(aes(color=vehicmilespc))+ggtitle("vehicmiles
grid.arrange(p1,p2,p3,p4,nrow=2)
```



Most values are between 5000 to 14000, with some outliers above 15000. State 45 has higher vehicle miles traveled across years consistently. There is a general upward trend across years and this shows some degree of negative correlation with fatality rates.

```
# Correlation plot
driving.panel <- pdata.frame(data, c("state","year"), drop.index = TRUE)
M <- cor(driving.panel[,c(1:12,19:20,23:28,54)])
corrplot(M, method='circle')
```



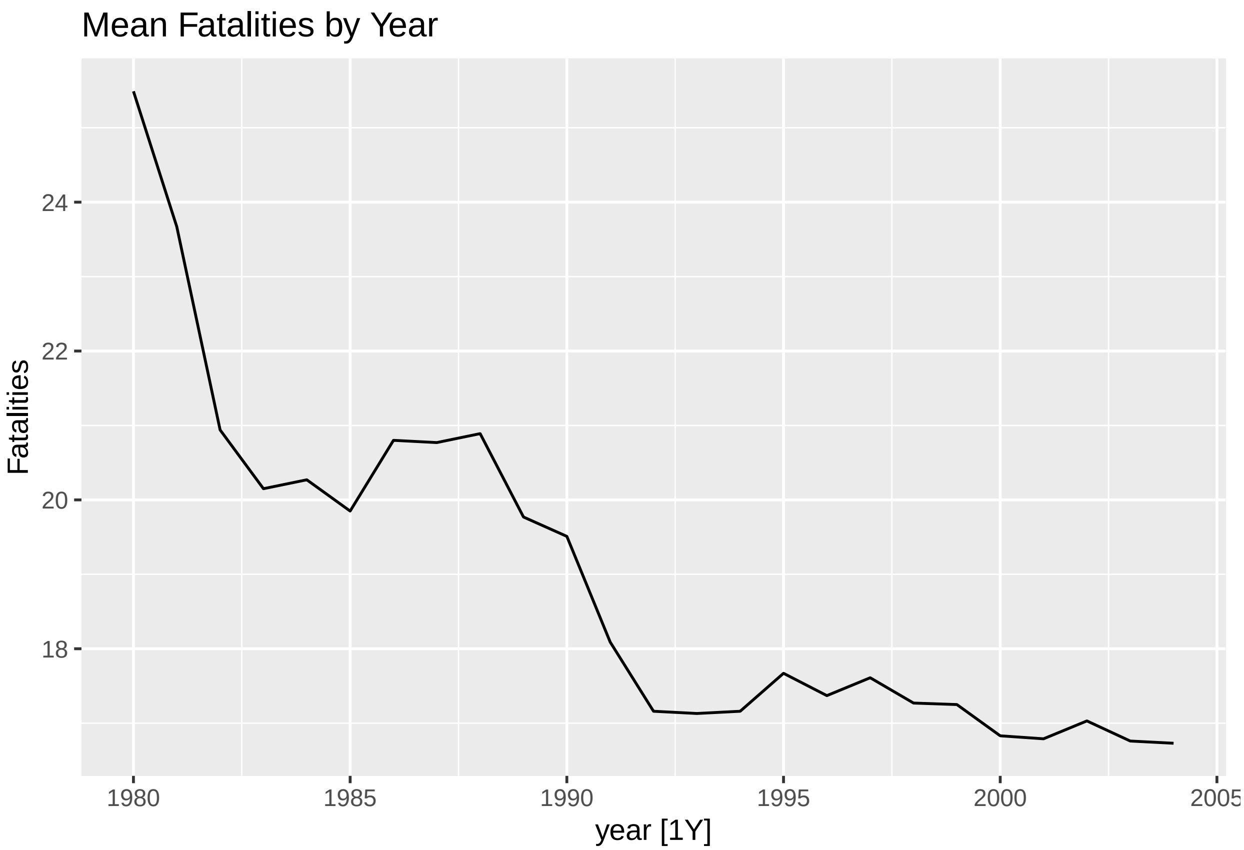
Question 2

Variable *totfatrte* is defined as total number of fatalities in 100,000 population.

```
byYear.mean <- aggregate(data, by=list(data$year), FUN=mean)
mean.totfatrte.df = round(data.frame(year=1980:2004, mean.totfatrte=byYear.mean$totfatrte), 2)
t(mean.totfatrte.df)
```

```
##                   [,1]    [,2]    [,3]    [,4]    [,5]    [,6]   [,7]    [,8]
## year           1980.00 1981.00 1982.00 1983.00 1984.00 1985.00 1986.0 1987.00
## mean.totfatrte   25.49   23.67   20.94   20.15   20.27   19.85   20.8   20.77
##                   [,9]   [,10]   [,11]   [,12]   [,13]   [,14]   [,15]   [,16]
## year           1988.00 1989.00 1990.00 1991.00 1992.00 1993.00 1994.00 1995.00
## mean.totfatrte   20.89   19.77   19.51   18.09   17.16   17.13   17.16   17.67
##                  [,17]   [,18]   [,19]   [,20]   [,21]   [,22]   [,23]   [,24]
## year           1996.00 1997.00 1998.00 1999.00 2000.00 2001.00 2002.00 2003.00
## mean.totfatrte   17.37   17.61   17.27   17.25   16.83   16.79   17.03   16.76
##                  [,25]
## year           2004.00
## mean.totfatrte   16.73
```

```r
as_tsibble(mean.totfatrte.df,index=year)%>%autoplot(mean.totfatrte)+ggtitle("Mean Fatalities by
```



Mean of total fatalities show decreasing trend over years. After year 1992, when mean fatalities drop below 18, this number show a stable trend.

```r
# Linear Regression
fit.lm <- lm(totfatrte ~ factor(year), data=data)
summary(fit.lm)
```

```
##
## Call:
## lm(formula = totfatrte ~ factor(year), data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.9302  -4.3468  -0.7305   3.7488  29.6498
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       25.4946     0.8671  29.401  < 2e-16 ***
## factor(year)1981  -1.8244     1.2263  -1.488 0.137094
## factor(year)1982  -4.5521     1.2263  -3.712 0.000215 ***
## factor(year)1983  -5.3417     1.2263  -4.356 1.44e-05 ***
## factor(year)1984  -5.2271     1.2263  -4.263 2.18e-05 ***
```

```
## factor(year)1985  -5.6431     1.2263  -4.602 4.64e-06 ***
## factor(year)1986  -4.6942     1.2263  -3.828 0.000136 ***
## factor(year)1987  -4.7198     1.2263  -3.849 0.000125 ***
## factor(year)1988  -4.6029     1.2263  -3.754 0.000183 ***
## factor(year)1989  -5.7223     1.2263  -4.666 3.42e-06 ***
## factor(year)1990  -5.9894     1.2263  -4.884 1.18e-06 ***
## factor(year)1991  -7.3998     1.2263  -6.034 2.14e-09 ***
## factor(year)1992  -8.3367     1.2263  -6.798 1.68e-11 ***
## factor(year)1993  -8.3669     1.2263  -6.823 1.43e-11 ***
## factor(year)1994  -8.3394     1.2263  -6.800 1.66e-11 ***
## factor(year)1995  -7.8260     1.2263  -6.382 2.51e-10 ***
## factor(year)1996  -8.1252     1.2263  -6.626 5.25e-11 ***
## factor(year)1997  -7.8840     1.2263  -6.429 1.86e-10 ***
## factor(year)1998  -8.2292     1.2263  -6.711 3.01e-11 ***
## factor(year)1999  -8.2442     1.2263  -6.723 2.77e-11 ***
## factor(year)2000  -8.6690     1.2263  -7.069 2.67e-12 ***
## factor(year)2001  -8.7019     1.2263  -7.096 2.21e-12 ***
## factor(year)2002  -8.4650     1.2263  -6.903 8.32e-12 ***
## factor(year)2003  -8.7310     1.2263  -7.120 1.88e-12 ***
## factor(year)2004  -8.7656     1.2263  -7.148 1.54e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.008 on 1175 degrees of freedom
## Multiple R-squared:  0.1276, Adjusted R-squared:  0.1098
## F-statistic: 7.164 on 24 and 1175 DF,  p-value: < 2.2e-16
```

F-statistic is 7.164 with p-value significantly below threshold level. Using year as explanatory is significant at 95% level. This show that total fatalities is decreasing over time and it is statistically significant. Driving became safer over time.

Question 3

Variables bac08, bac10, perse, sbprim, sbsecon, sl70plus, gdl are supposed to be binary variables. But due to the fact that some states implemented the law in middle of year, some of the these variables have values between 0 and 1. For correct modeling of binary variables, we need all values to be 0 or 1, for approximation, we will round the values to be 0 or 1.

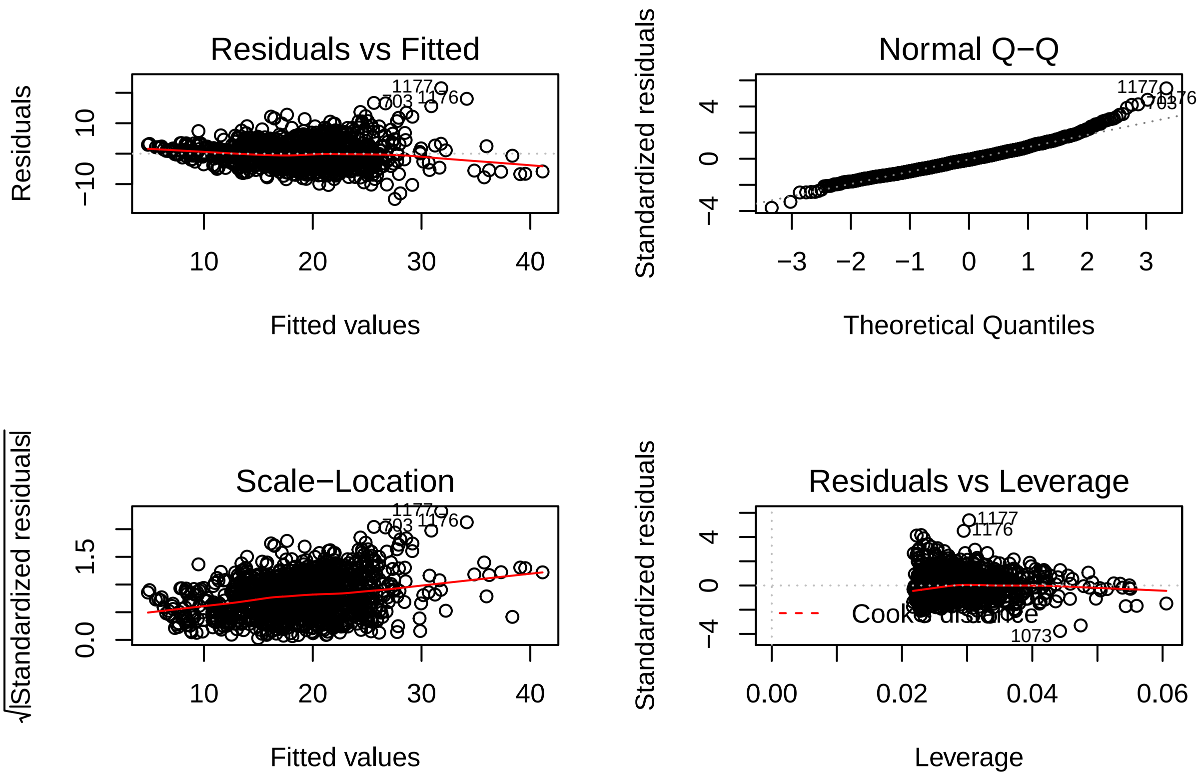
```
data.round <- data;data.round$bac08<-factor(round(data$bac08), levels=c(0,1));
data.round$bac10<-factor(round(data$bac10), levels=c(0,1));data.round$perse<-factor(round(data$
data.round$sbprim<-factor(round(data$sbprim),levels=c(0,1));data.round$sbsecon<-factor(round(da
data.round$sl70plus<-factor(round(data$sl70plus), levels=c(0,1));data.round$gdl<-factor(round(d
fit.lm2 <- lm(totfatrte ~ factor(year)+bac08+bac10+perse+sbprim+sbsecon+sl70plus+gdl+perc14_24+
summary(fit.lm2)
```

```
##
## Call:
## lm(formula = totfatrte ~ factor(year) + bac08 + bac10 + perse +
##     sbprim + sbsecon + sl70plus + gdl + perc14_24 + unem + vehicmilespc,
```

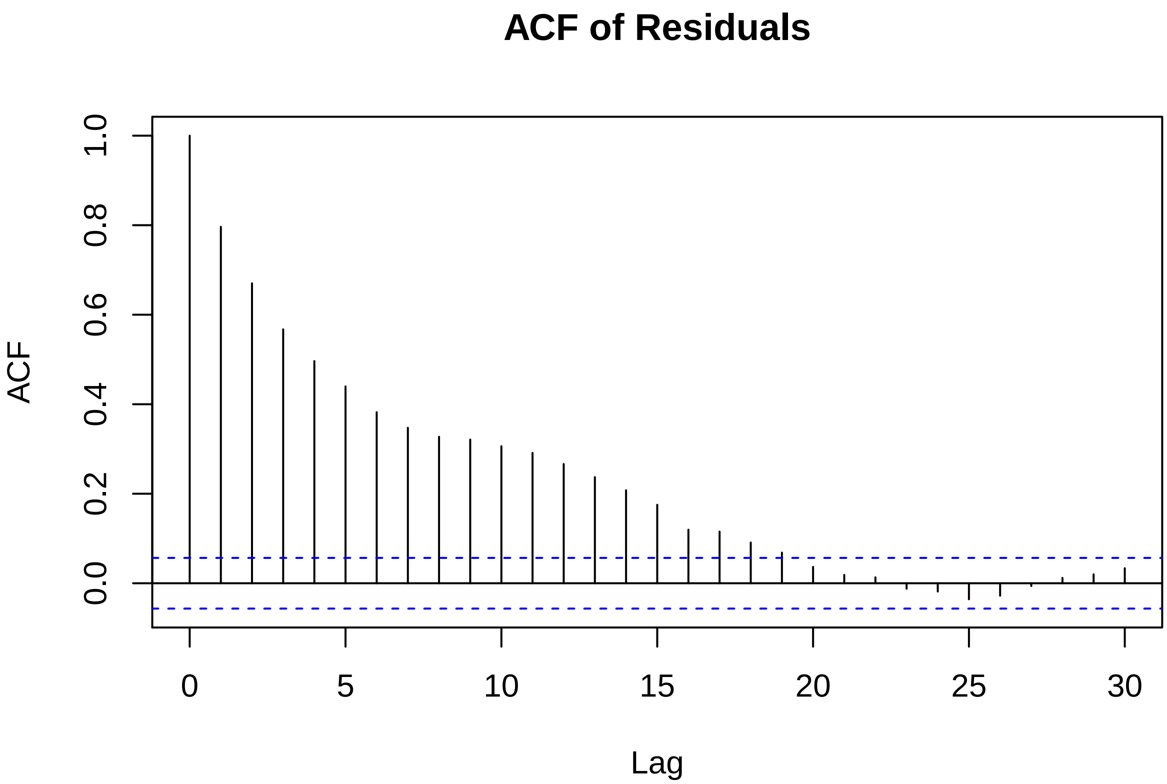
```
##     data = data.round)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -14.8962  -2.7265  -0.3033   2.3323  21.5064
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -2.826e+00  2.478e+00  -1.141 0.254236
## factor(year)1981 -2.184e+00  8.290e-01  -2.634 0.008539 **
## factor(year)1982 -6.657e+00  8.547e-01  -7.789 1.49e-14 ***
## factor(year)1983 -7.589e+00  8.671e-01  -8.752  < 2e-16 ***
## factor(year)1984 -5.974e+00  8.730e-01  -6.843 1.25e-11 ***
## factor(year)1985 -6.603e+00  8.915e-01  -7.407 2.47e-13 ***
## factor(year)1986 -5.947e+00  9.290e-01  -6.401 2.23e-10 ***
## factor(year)1987 -6.459e+00  9.656e-01  -6.689 3.48e-11 ***
## factor(year)1988 -6.691e+00  1.013e+00  -6.607 5.97e-11 ***
## factor(year)1989 -8.159e+00  1.052e+00  -7.757 1.89e-14 ***
## factor(year)1990 -9.060e+00  1.076e+00  -8.421  < 2e-16 ***
## factor(year)1991 -1.121e+01  1.099e+00 -10.194  < 2e-16 ***
## factor(year)1992 -1.300e+01  1.121e+00 -11.591  < 2e-16 ***
## factor(year)1993 -1.288e+01  1.134e+00 -11.358  < 2e-16 ***
## factor(year)1994 -1.253e+01  1.154e+00 -10.855  < 2e-16 ***
## factor(year)1995 -1.203e+01  1.183e+00 -10.176  < 2e-16 ***
## factor(year)1996 -1.403e+01  1.224e+00 -11.459  < 2e-16 ***
## factor(year)1997 -1.430e+01  1.242e+00 -11.517  < 2e-16 ***
## factor(year)1998 -1.512e+01  1.262e+00 -11.978  < 2e-16 ***
## factor(year)1999 -1.518e+01  1.276e+00 -11.900  < 2e-16 ***
## factor(year)2000 -1.554e+01  1.296e+00 -11.996  < 2e-16 ***
## factor(year)2001 -1.645e+01  1.316e+00 -12.500  < 2e-16 ***
## factor(year)2002 -1.703e+01  1.331e+00 -12.798  < 2e-16 ***
## factor(year)2003 -1.742e+01  1.336e+00 -13.033  < 2e-16 ***
## factor(year)2004 -1.698e+01  1.369e+00 -12.399  < 2e-16 ***
## bac081           -2.194e+00  4.891e-01  -4.487 7.94e-06 ***
## bac101           -1.238e+00  3.616e-01  -3.423 0.000641 ***
## perse1           -6.499e-01  2.943e-01  -2.208 0.027433 *
## sbprim1          -9.420e-02  4.910e-01  -0.192 0.847868
## sbsecon1          6.430e-02  4.299e-01   0.150 0.881124
## sl70plus1         3.239e+00  4.352e-01   7.443 1.91e-13 ***
## gdl1             -3.476e-01  5.101e-01  -0.682 0.495682
## perc14_24         1.401e-01  1.229e-01   1.140 0.254611
## unem              7.675e-01  7.796e-02   9.844  < 2e-16 ***
## vehicmilespc      2.927e-03  9.485e-05  30.860  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.052 on 1165 degrees of freedom
## Multiple R-squared:  0.6064, Adjusted R-squared:  0.595
```

```
## F-statistic:  52.8 on 34 and 1165 DF,  p-value: < 2.2e-16
```

```r
par(mfrow=c(2,2));plot(fit.lm2);
```




```r
par(mfrow=c(1,1));acf(fit.lm2$residuals, main="ACF of Residuals");
```



Variables *bac08* and *bac10* are binary indicator variables, indicating if a state had law of blood alcohol content of level 0.08% and 0.10% repectively. From mean plot of variables *bac08* and *bac10* in EDA, we see that majority of state start with no law on blood alcohol content, and then implementing a 0.10% limit, and then a more strict limit of 0.08%. Coefficient of *bac10* can be interpreted as, states with blood alcohol content limit 0.10% law have 1.238 less fatalities per 100,000 population.Coefficient of *bac08* can be interpreted as, states with blood alcohol content limit 0.08% law have 2.194 less fatalities per 100,000 population.

Variable *perse* (per se law) has p-value of 0.027433 in pooled OLS result. This variable is statistically significant at 95% level. It shows that there is empirical evidence that per se law has impact on fatalities.

Variable *sbprim* (primary seat belt law) has p-value of 0.847868 in pooled OLS result. This variable is not statistically significant at 95% level. It shows that there is not empirical evidence that primary seat belt law has impact on fatalities.

One thing to note is that, from regression diagnostic, we observed heteroskedasticity on residuals from scale-location plot and serial correlations on residuals from ACF graph. Serial correlations on residuals suggest there is unobserved fixed effects. Serial correlations and heteroskedasticity on residuals suggest the test statistics in pooled OLS result are not valid.

Question 4

```
data.panel = pdata.frame(data.round, index=c("state", "year"))
fit.plm.fe <-plm(totfatrte~bac08+bac10+perse+sbprim+sbsecon+sl70plus+gdl+perc14_24+unem+vehicm
                 data=data.panel, model='within')
summary(fit.plm.fe)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = totfatrte ~ bac08 + bac10 + perse + sbprim + sbsecon +
##     sl70plus + gdl + perc14_24 + unem + vehicmilespc, data = data.panel,
##     model = "within")
##
## Balanced Panel: n = 48, T = 25, N = 1200
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -7.196355 -1.199164 -0.068262  1.137700 14.554645
##
## Coefficients:
##                 Estimate  Std. Error  t-value  Pr(>|t|)
## bac081       -1.54934878  0.33484339  -4.6271 4.132e-06 ***
## bac101       -1.15290142  0.23139549  -4.9824 7.250e-07 ***
## perse1       -1.40105536  0.23799390  -5.8869 5.166e-09 ***
## sbprim1      -1.86938834  0.34668462  -5.3922 8.454e-08 ***
## sbsecon1     -0.88032830  0.24914282  -3.5334 0.0004266 ***
## sl70plus1    -1.13047368  0.23850465  -4.7398 2.408e-06 ***
## gdl1         -0.58719959  0.22493208  -2.6106 0.0091577 **
## perc14_24     0.97632522  0.07069974  13.8095 < 2.2e-16 ***
## unem         -0.59813653  0.05100886 -11.7261 < 2.2e-16 ***
## vehicmilespc  0.00024665  0.00010162   2.4271 0.0153745 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    12134
## Residual Sum of Squares: 5571.9
## R-Squared:      0.54081
## Adj. R-Squared: 0.51789
## F-statistic: 134.498 on 10 and 1142 DF, p-value: < 2.22e-16
```

In fixed effect model, the coefficient of *bac10* is similar to pooled OLS and and the coefficient of *bac08* is smaller in absolute value. *perse* is highly statistically significant in fixed effects model but it was marginally statistically significant in pooled OLS. *sbprim* is highly statistically significant in fixed effects model but it was not statistically significant in pooled OLS.

Result from fixed effect model is more reliable. In pooled OLS, we have to assume no unobserved fixed effects, otherwise test statistics are not valid. While in fixed effects model, we are allowed to have unobserved fixed effects present in population model and this fixed effect is allowed to be correlated with explanatory variables. In ACF graph of pooled OLS residuals, we see that serial correlations and this suggests the present of unobserved effect. Therefore assumptions of OLS are not met and pooled OLS result is not reliable. Fixed effect model is the preferred choice.

Question 5

```
fit.plm.re <- plm(totfatrte~bac08+bac10+perse+sbprim+sbsecon+sl70plus+gdl+perc14_24+unem+vehicm
                  data=data.panel, model='random')
phtest(fit.plm.fe, fit.plm.re)
```

```
##
##  Hausman Test
##
## data:  totfatrte ~ bac08 + bac10 + perse + sbprim + sbsecon + sl70plus +  ...
## chisq = 72875, df = 10, p-value < 2.2e-16
## alternative hypothesis: one model is inconsistent
```

P-value is smaller than 0.05, we can reject null hypothesis that random effect model is preferred. Fixed Effect model should be chosen for our analysis.

Question 6

Increase miles driven per capita by 1000, the expect total fatalities per 100,000 population increase by 0.00024665 * 1000 = 0.24665, holding all other variables constant.

Question 7

Estimators are not efficient. All statistical inference are not valid. If unobserved effect is uncorrelated with all explanatory variables, estimators are consistent, otherwise estimators are not consistent.