Statistical Data Analysis

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k Analysis of the chicago dataset:

The data set chicago, in the package gamair, contains data about air pollution and the death rate in Chicago from 1 January 1987 to 31 December 2000.

```
## Warning: package'gamair' was built under R version 4.2.0
```

Here, our response variable of interest is death, the total number of non-accidental deaths each day. The other variables in the data set are time, recorded in days before or after 31 December 1993, and five possible predictor variables:

- pm10median: the median density over the city of large pollutant particles
- pm25median: the median density of smaller pollutant particles
- o3median: the median concentration of ozone (O3) in the air
- so2median: the median concentration of sulfur dioxide (SO2) in the air
- tmpd: the mean daily temperature.

q Summary of the data:

```
##
##      death          pm10median          pm25median          o3median
##  Min.   : 69.0   Min.    :-37.3761   Min.    :-16.426   Min.    :-24.779
##  1stQu.:105.0    1st  Qu.:-13.1082   1st  Qu.: -6.588   1st  Qu.:-10.232
##  Median:114.0    Median  : -3.5391   Median  : -1.326   Median  : -3.326
##  Mean   :115.4   Mean    : -0.1464   Mean    :  0.243   Mean    : -2.179
##  3rdQu.:124.0    3rd Qu. :  8.3029   3rd Qu. :  5.344   3rd Qu. :  4.468
##  Max.   :411.0   Max.    :320.7248   Max.    : 38.150   Max.    : 43.688
##                  NA's    :251        NA's    :4387
##
##    so2median             time               tmpd
##  Min.   :-8.2061    Min.    :-2556    Min.    :-16.00
##  1stQu.:-2.6894     1st  Qu.:-1278    1st  Qu.: 35.00
##  Median:-1.2183     Median :     0    Median :  51.00
##  Mean   :-0.6361    Mean   :     0    Mean   :  50.19
##  3rd Qu.: 0.8316    3rd  Qu.: 1278    3rd  Qu.: 67.00
##  Max.   :28.9034    Max.   : 2556     Max.   :  92.00
##  NA's   :27
```

The dataset contains 5114 number of observations.

q Important points regarding the variables to be noted:

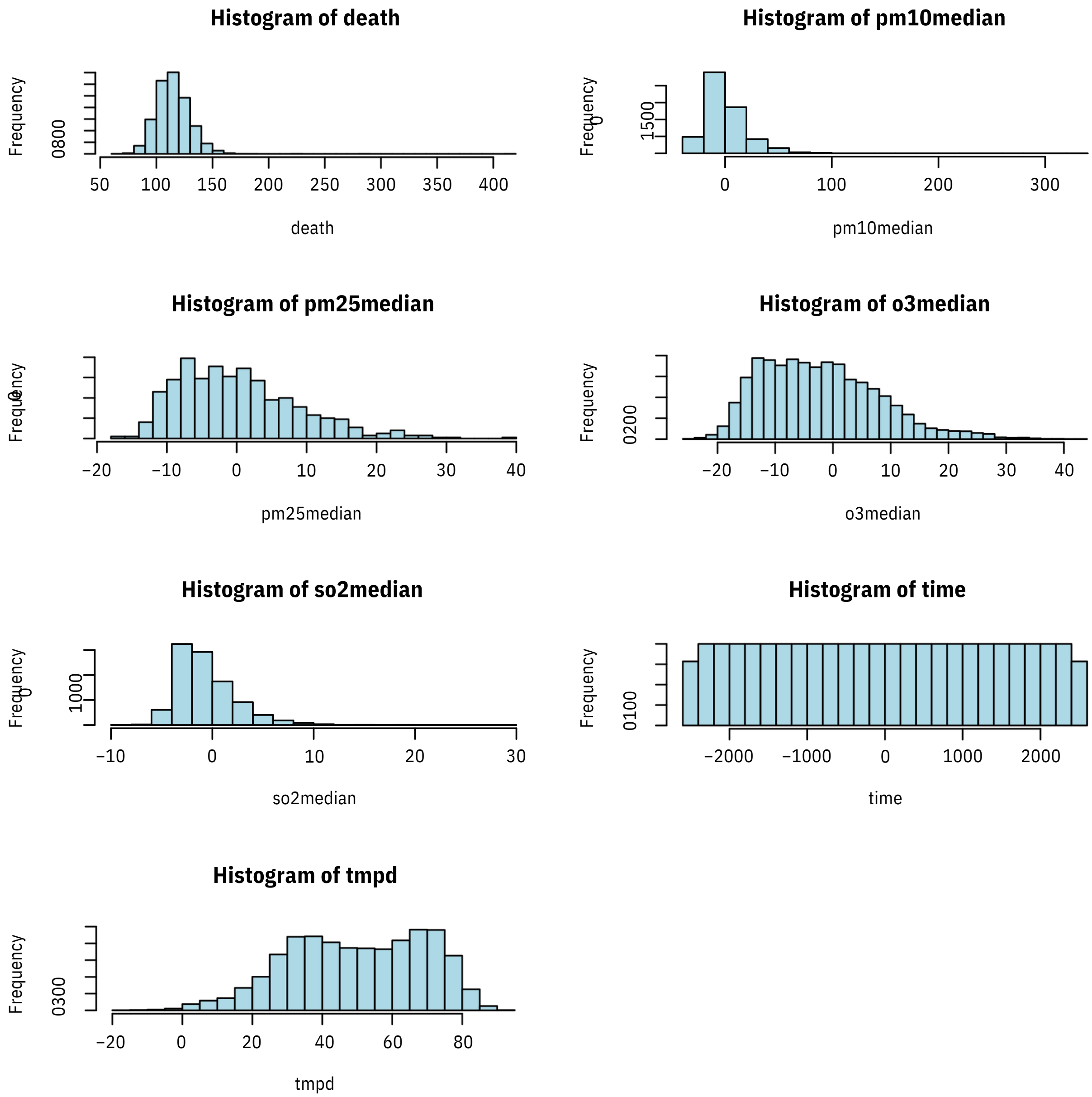
- Unit of the Temperature: The maximum temperature is 92 degree Celsius. If the temperature is measured in degrees Celsius then 92 degree Celsius is extremely high to be the temperature of a city. So, the temperature must be given in degrees Fahrenheit.

- Ignorance of the pm25median variable: We shall ignore the pm25median variable in the rest of this problem set as 4387 values of that variable are missing among the total 5114 observations. We cannot work with such a variable having so many missing values.

- Mean, variance and median of each variable:

Variable name	Mean	Variance	Median
Death	115.4189	234.0522	114
pm10median	-0.1463896	370.7924	-3.539062
pm25median	0.2430526	75.3241	-1.325843
o3median	-2.179377	104.1139	-3.325857
so2median	-0.6360707	8.562395	-1.218264
time	0	2179843	0
tmpd	50.19329	378.7697	51

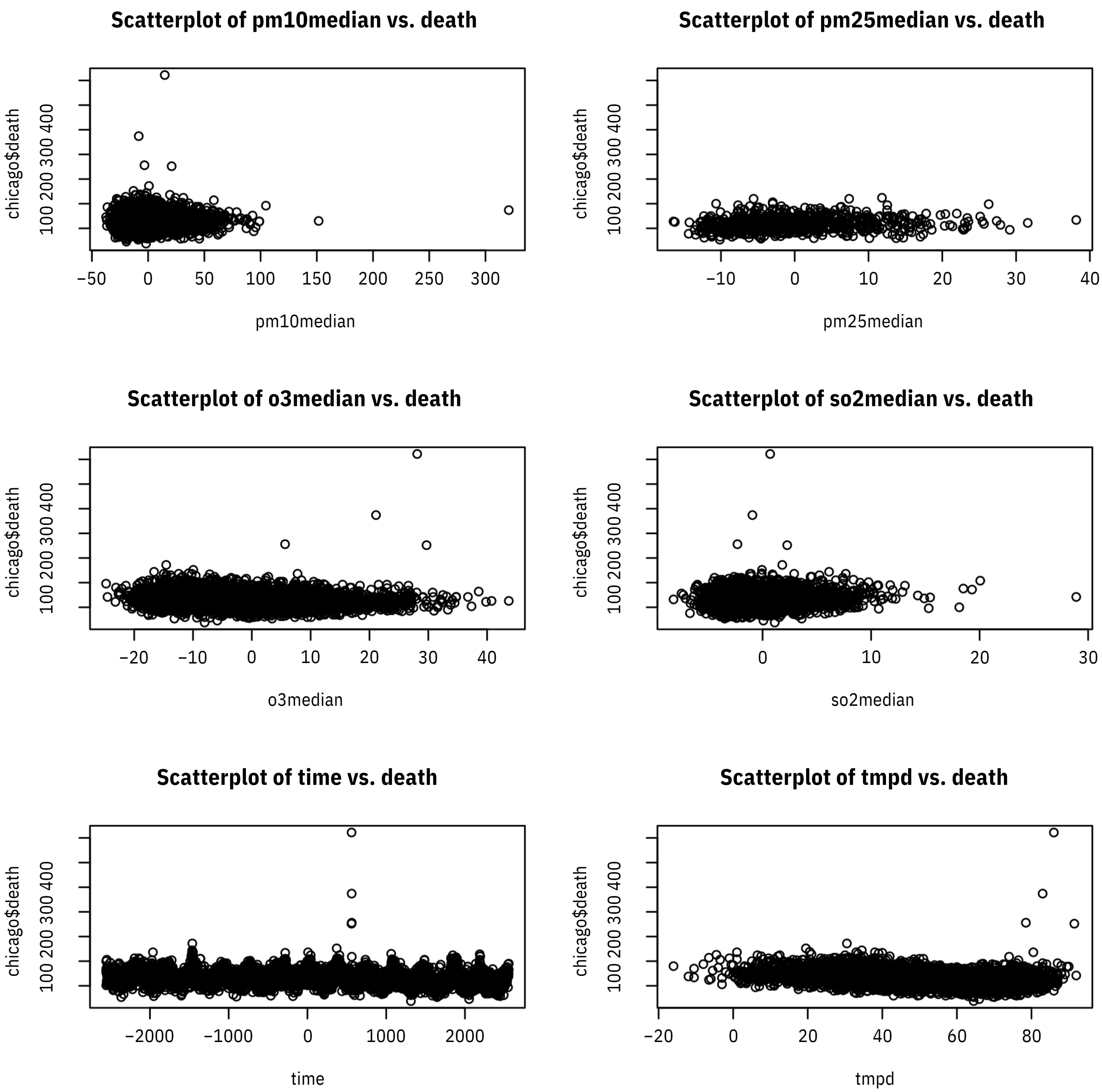
- Histogram for each variable:



Observations:

- Histogram of death: The average number of deaths is almost 115 per day, the distribution is more or less symmetric. There is some significant outliers present.
- Histogram of pm10median: The large pollutant particles over the city are very light (i.e. not so dense), the distribution is positively skewed having some potential outliers.
- Histogram of pm25median: The average median density of smaller pollutant particles is almost 0, the distribution is somewhat symmetrically distributed. There are few outliers.
- Histogram of o3median: The average median concentration of ozone (O3) in the air is near -5, the distribution is positively skewed with few potential outliers.
- Histogram of so2median: The average median concentration of sulfur dioxide (SO2) in the air is near -2, the distribution is positively skewed with some significant outliers.
- Histogram of tmpd: The average mean daily temperature is almost 50, the distribution is negatively skewed.

Scatterplot for each predictor variable against the response variable:



Observations:

- From the scatterplots it is evident that, the bivariate relationships between each predictor and the response variable may be closely linear with slope 0, except the scatterplot of death against time.
  So, the response variable death may not have any type of relation (i.e. may not be dependent on) with any of the predictor variables pm10median, pm25median, o3median, so2median and tmpd.
  There is a sinusoidal relation between time and death.

- From the scatterplots clearly we can see that there are outliers in each plot.
  - The corresponding days where we see outliers in the plot of pm10median against death:

```
#           [1]-2515.5  -2514.5  -2458.5-2449.5   -2388.5  -2354.5  -2353.5  -2184.5  -2063.5
#         [10] -2040.5  -2039.5  -2033.5  -2026.5  -2020.5  -2004.5  -2003.5  -2002.5  -2001.5
#          [19] -1955.5  -1951.5  -1787.5  -1690.5  -1689.5  -1688.5  -1668.5  -1649.5  -1639.5
#         [28] -1603.5  -1602.5  -1561.5  -1540.5  -1450.5  -1349.5  -1332.5  -1308.5  -1307.5
#         [37] -1298.5  -1252.5  -1223.5  -1222.5  -1206.5   -963.5   -961.5   -960.5   -955.5
#     [46]   -948.5   -935.5   -919.5   -918.5   -898.5   -897.5   -896.5   -882.5   -858.5
#     [55]   -823.5   -697.5   -666.5   -609.5   -603.5   -599.5   -595.5   -589.5   -588.5
#     [64]   -563.5   -562.5   -548.5   -547.5   -501.5   -471.5   -457.5   -456.5   -455.5
#     [73]   -434.5   -430.5   -429.5   -330.5   -291.5   -251.5   -218.5   -217.5   -142.5
#     [82]   -139.5   -126.5    -85.5    -84.5    -81.5    -67.5     44.5     77.5     83.5
#     [91]     93.5    112.5    114.5    115.5    140.5    155.5    165.5    166.5    167.5
#    [100]    170.5    230.5    236.5    238.5    244.5    254.5    257.5    263.5    279.5
#    [109]    293.5    300.5    515.5    530.5    531.5    532.5    557.5    558.5    576.5
#    [118]    603.5    606.5    612.5    635.5    637.5    648.5    650.5    654.5    831.5
#    [127]    869.5    902.5    909.5    910.5    947.5    976.5    977.5    978.5   1200.5
#    [136]   1214.5   1220.5   1266.5   1270.5   1301.5   1353.5   1354.5   1356.5   1370.5
#    [145]   1371.5   1374.5   1500.5   1545.5   1546.5   1595.5   1598.5   1599.5   1608.5
#    [154]   1635.5   1654.5   1655.5   1728.5   1760.5   1914.5   1949.5   1950.5   1998.5
#    [163]   2020.5   2021.5   2022.5   2069.5   2070.5   2071.5   2094.5   2110.5   2126.5
#    [172]   2127.5   2128.5   2133.5   2142.5   2147.5   2148.5   2244.5   2258.5   2287.5
#    [181]   2295.5   2308.5   2315.5   2316.5   2319.5   2349.5   2351.5   2352.5   2398.5
#    [190]   2428.5   2452.5   2453.5   2465.5   2476.5   2477.5   2482.5   2484.5   2490.5
#
#
```

- The corresponding days where we see outliers in the plot of pm25median against death:

```
##    [1]  1595.5  1882.5  1960.5  1999.5 2071.5   2231.5  2300.5  2433.5  2487.5  2490.5
##   [11]  2522.5  2540.5
```

- The corresponding days where we see outliers in the plot of o3median against death:

```
##    [1]  -2420.5  -2389.5  -2388.5             -2353.5  -2026.5    -2021.5 -2020.5  -2018.5
##  [10]  -2015.5  -2005.5  -2004.5     -1981.5 -1971.5  -1654.5    -1614.5 -1297.5  -1276.5
##  [19]  -1252.5   -925.5   -920.5   -897.5   -896.5   -895.5   -859.5   -548.5   -237.5
## [28]    149.5    168.5    533.5    538.5    539.5    558.5    559.5    560.5    908.5
## [37]    910.5    917.5    918.5   1275.5   1288.5   1638.5   1996.5   2021.5   2072.5
## [46]   2073.5   2350.5   2351.5   2401.5
```

- The corresponding days where we see outliers in the plot of so2median against death:

```
##         [1]-2553.5  -2551.5  -2543.5-2530.5   -2506.5  -2505.5  -2499.5  -2477.5  -2474.5
##      [10] -2458.5  -2457.5  -2449.5  -2436.5  -2432.5  -2431.5  -2388.5  -2310.5  -2270.5
##       [19] -2269.5  -2254.5  -2217.5  -2205.5  -2184.5  -2181.5  -2164.5  -2158.5  -2147.5
##      [28] -2142.5  -2039.5  -2004.5  -1938.5  -1864.5  -1863.5  -1862.5  -1828.5  -1826.5
##       [37] -1825.5  -1764.5  -1759.5  -1758.5  -1743.5  -1712.5  -1540.5  -1475.5  -1474.5
##      [46] -1469.5  -1468.5  -1463.5  -1395.5  -1352.5  -1253.5  -1206.5  -1158.5  -1143.5
##       [55] -1100.5  -1099.5  -1095.5  -1082.5  -1069.5  -1064.5  -1063.5  -1061.5   -882.5
##   [64]    -870.5   -868.5   -857.5   -856.5   -782.5   -771.5   -770.5   -768.5   -715.5
##   [73]    -702.5   -643.5   -633.5   -603.5   -602.5   -595.5   -588.5   -548.5   -456.5
##   [82]    -375.5   -354.5   -353.5   -352.5   -351.5   -349.5   -346.5   -345.5   -339.5
##   [91]    -331.5   -330.5   -329.5   -306.5   -305.5   -239.5   -237.5    -30.5    -18.5
##  [100]     -17.5      7.5      9.5     18.5     19.5     20.5     21.5     31.5     42.5
##  [109]      90.5    285.5    322.5    346.5    347.5    354.5    355.5    391.5    635.5
##  [118]     801.5    908.5    909.5    910.5   1074.5   1109.5   1110.5   1125.5   1126.5
##  [127]    1205.5   1213.5   1444.5   1445.5   1482.5   1491.5   1501.5   1796.5   1806.5
##  [136]    1841.5   1899.5   2031.5   2073.5   2126.5   2137.5   2191.5   2250.5   2257.5
##  [145]    2274.5   2281.5   2308.5   2311.5   2350.5   2351.5   2477.5   2495.5   2496.5
##  [154]    2548.5   2551.5
```

– The corresponding days where we see outliers in the plot of time against death:

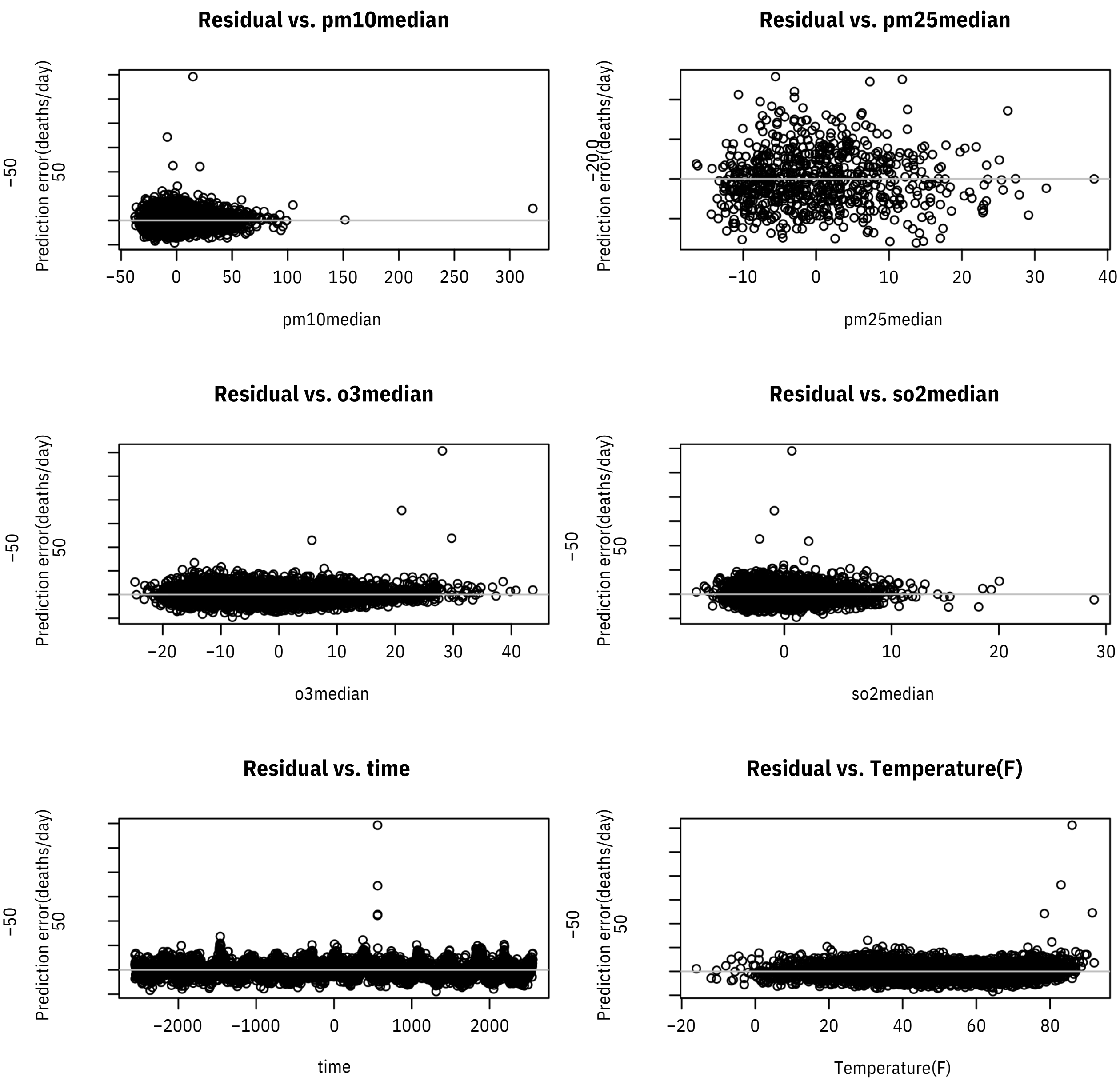
```
## numeric(0)
```

– The corresponding days where we see outliers in the plot of tmpd against death:

```
## [1]   17.5
```

Clearly, different plots share same outlier days.

· Plotting residuals against each of the predictor variables:



Clearly, only the scatterplot with the residuals on the vertical axis and the pm25median variable on the horizontal axis, looks like a constant-width blur of points around a straight flat line at height zero. For all the other plots, there are deviations from this (in substantial regions of x-axis the average residuals are positive), indicating that a simple linear regression model of the number of deaths on the predictor would be inappropriate. Therefore, the pm25median variable would be the most appropriate for fitting a linear regression model.

9 Closer observation of the relationship between death and tmpd:

We will take a closer look at the relationship between death and tmpd. Someone proposes that the relationship follows a normal error linear regression model with ε N(0, 14.22) and the true regression function E[Y|X = x] = 130-0.28x.

The theoretical regression model in context between death and tmpd is as follows:

$$Y = 130 - 0.28x + \varepsilon$$

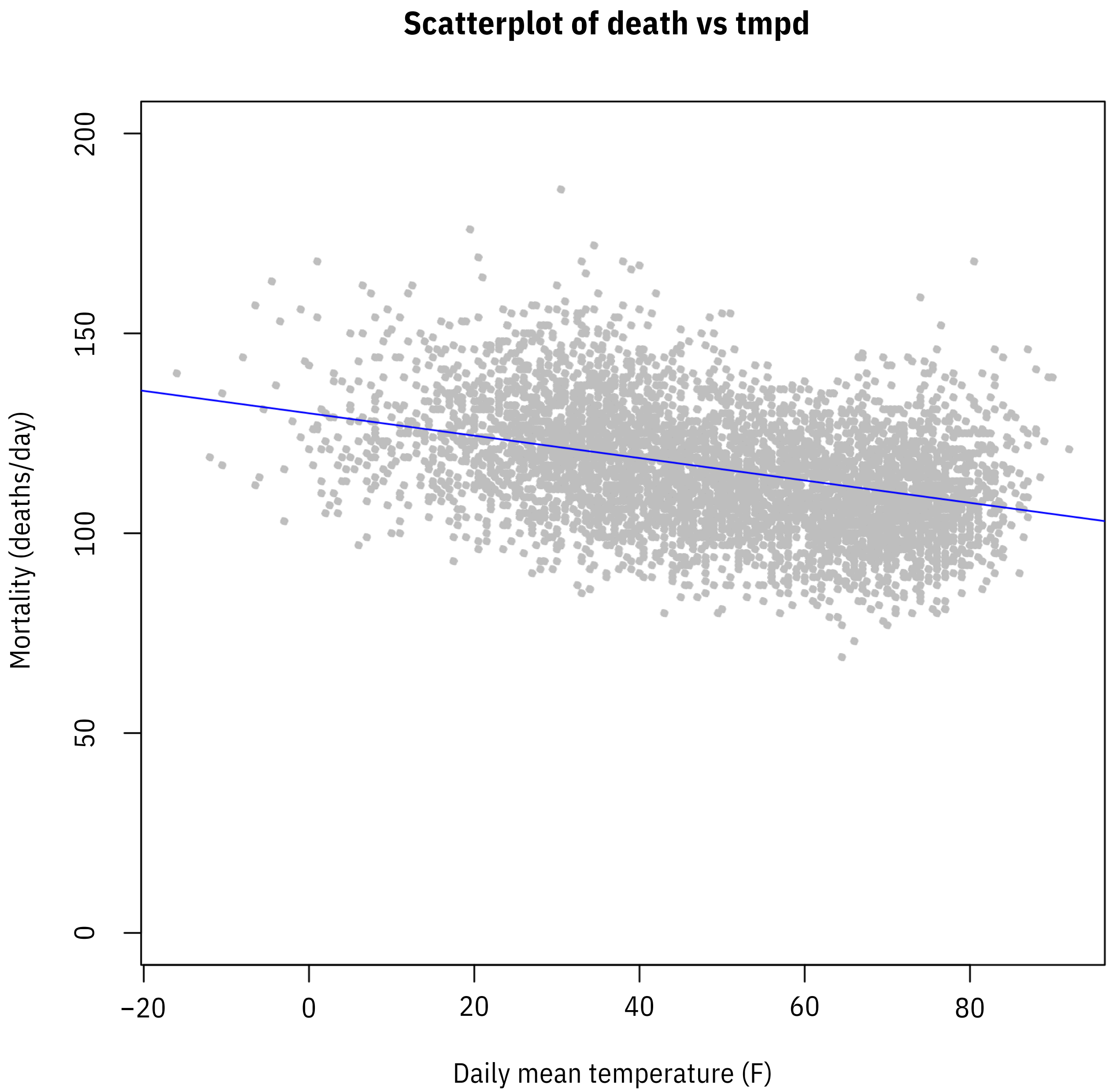
The assumptions of the model are,

- For all x, E[ε |X = x]=0, Var[ε|X = x]=σ2(= 14.22). specifically, ε N(0, 14.22)
- ε is uncorrelated across observations.

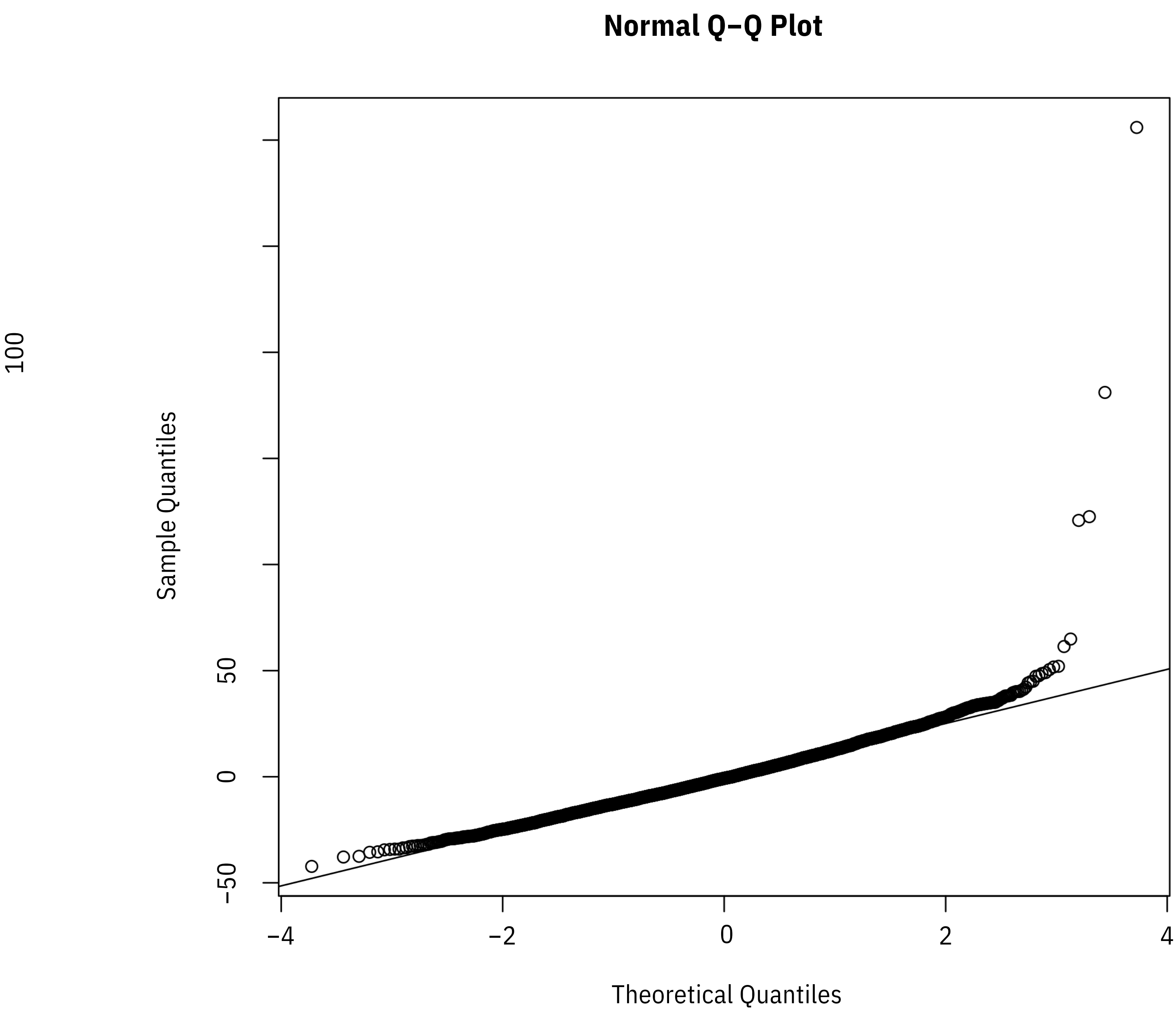
Interpretation of the proposed coefficients:

- On an average, the expected number of non-accidental deaths per day in Chicago is 130 when the mean daily temperature is 0°F.
- if we select two sets of cases from the un-manipulated distribution where the mean daily temperature differs by 1°F, we expect the number of non-accidental deaths per day in Chicago to differ by 0.28.

Scatterplot of death and tmpd along with the proposed linear function:



Checking of the normal error regression model assumption:
Q-Q Plots:



Clearly, it is evident that here the normal error regression model assumption is not appropriate.

Note:

1. The relation between the Fahrenheit scale and the Celsius scale is: $F = (\frac{9}{5} \times C) + 32$.

So, 2°C is equivalent to 35.6°F.

Now, for unit increase in temperature, we can expect the number of deaths to decrease by 0.28 per day, according to the proposed linear regression model.

So, for an increase of 35.6°F in temperature, we can expect the number of deaths to decrease by $(0.28 \times 35.6 =)\ 9.968$ per day.

Hence, the predicted change in number of deaths in a year will be, $9.968 \times 365 = 3638.32 \approx 3638$.

So, for 2°C increase in average temperature over the course of a whole year, we can expect the number of deaths to decrease by 3638 over the year.

2. The relationship between temperature and deaths is not casual.

   Since non-accidental deaths can also differ by some other reasons such as, due to pollution through different pollutants etc, i.e. there exists third variable which is the underlined factor of such relationship between temperature and deaths.

k Analysis of the “econ.csv” dataset:

The data file econ.csv contains information about the economies of the 366 “metropolitan statistical areas” (cities) of the US in 2006. In particular, it lists, for each city, the population, the total value of all goods and services produced for sale in the city that year per person (“per capita gross metropolitan product”, pcgmp), and the share of economic output coming from four selected industries.

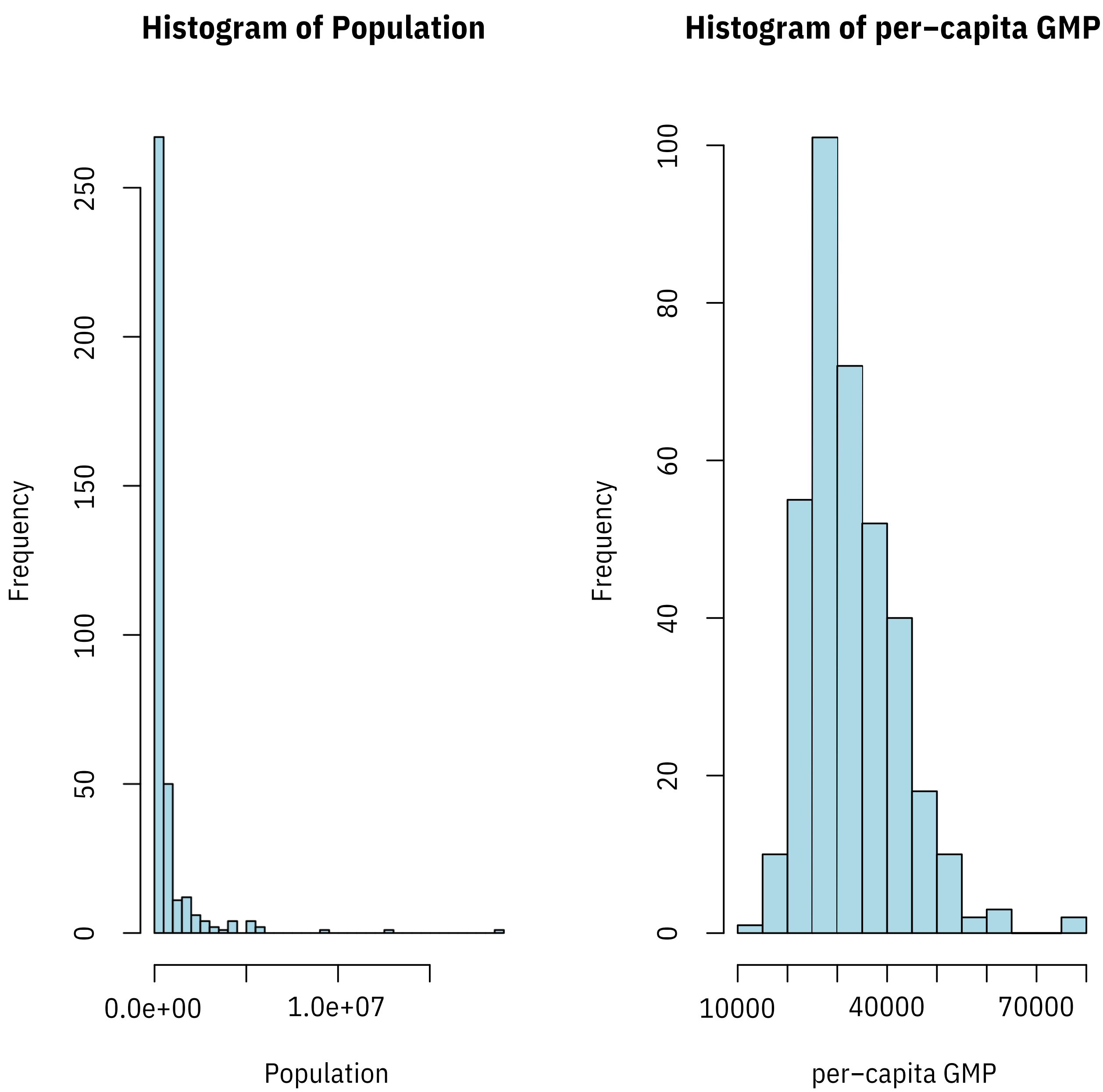
It has 366 rows and 7 columns. It contains the name of the cities (metropolitan statistical areas) in a column corresponding to each observation along with the above mentioned 6 columns.

q Summary of the data:

```
##
##      pcgmp            pop               finance            prof.tech
##  Min.    :14920   Min.    :   54980   Min.    :0.03845   Min.    :0.01474
##  1st Qu.:26533   1st Qu.:  135625   1st Qu.:0.10403   1st Qu.:0.02932
##  Median :31615   Median :  231500   Median :0.14140   Median :0.04213
##  Mean   :32923   Mean   :  680898   Mean   :0.15082   Mean   :0.04905
##  3rd Qu.:38213   3rd Qu.:  530875   3rd Qu.:0.18122   3rd Qu.:0.05932
##  Max.   :77860   Max.   :18850000   Max.   :0.38480   Max.   :0.19080
##                                      NA's   :12        NA's   :112
##
##       ict              management
##  Min.   :0.00349   Min.    :0.00042
##  1st Qu.:0.01215   1st Qu.:0.00294
##  Median :0.02218   Median :0.00651
##  Mean   :0.03910   Mean   :0.00908
##  3rd Qu.:0.04072   3rd Qu.:0.01191
##  Max.   :0.58600   Max.   :0.05431
##  NA's   :76        NA's   :157
```

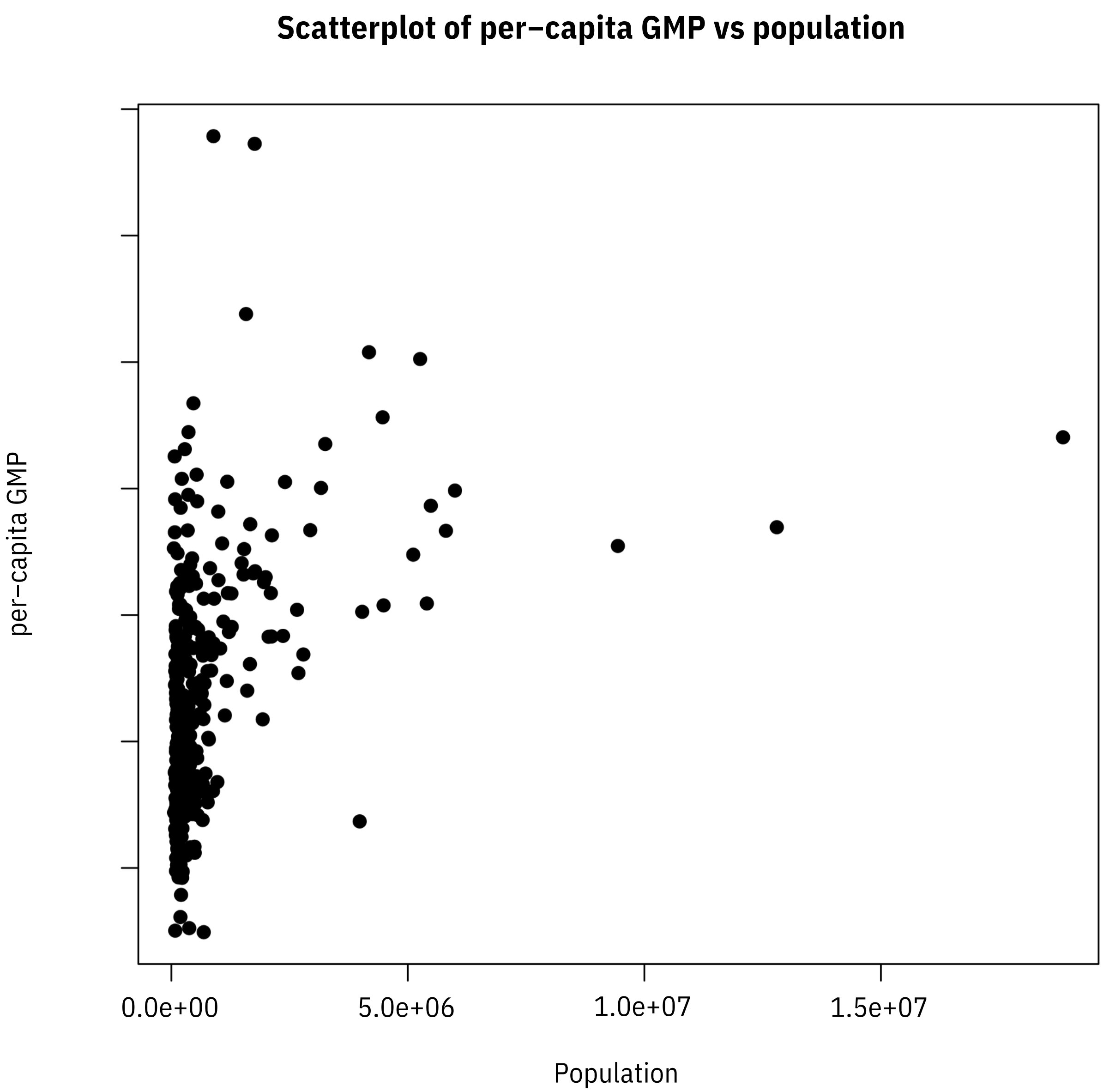
q Exploratory data Analysis:

• Histograms (univariate EDA plot) for population and for per-capita GMP:



The distribution of population is highly positively skewed i.e. a large number of cities have a little amount of population, and very few cities have huge population. There are some outliers of excessively high magnitude.
The distribution of per-capita GMP is slightly positively skewed with some potential outliers.

• Scatterplot (bivariate EDA plot) for per-capita GMP as a function of population:



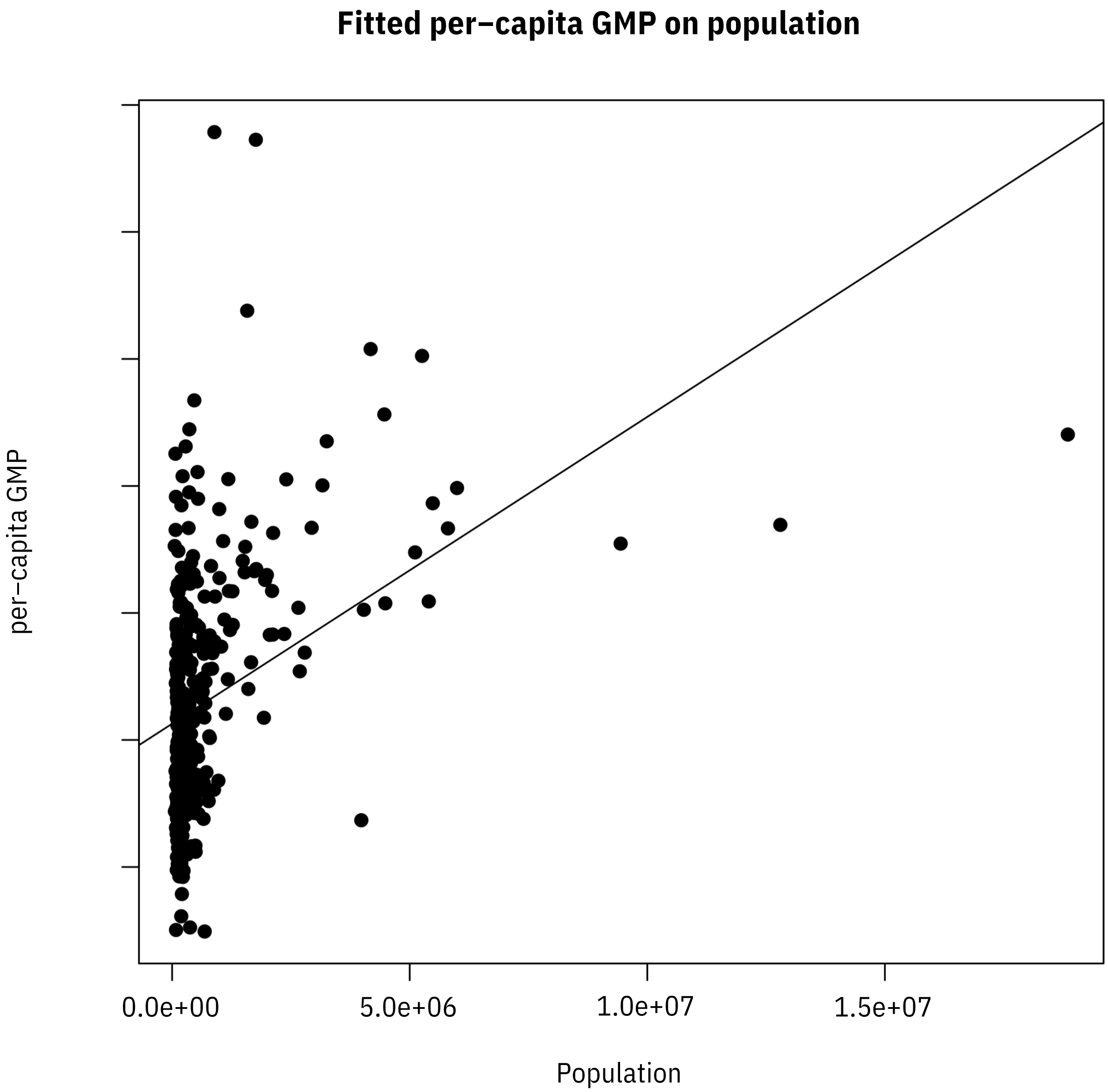
· Fitting a simple linear regression model of per-capita GMP on population:

Suppose our model is,
$Y = \alpha + \beta X + \epsilon$

where, Y denotes per-capita GMP, X denotes population and α and β are the parameters of the model and ϵ is the random error term.
The assumptions of the model are,

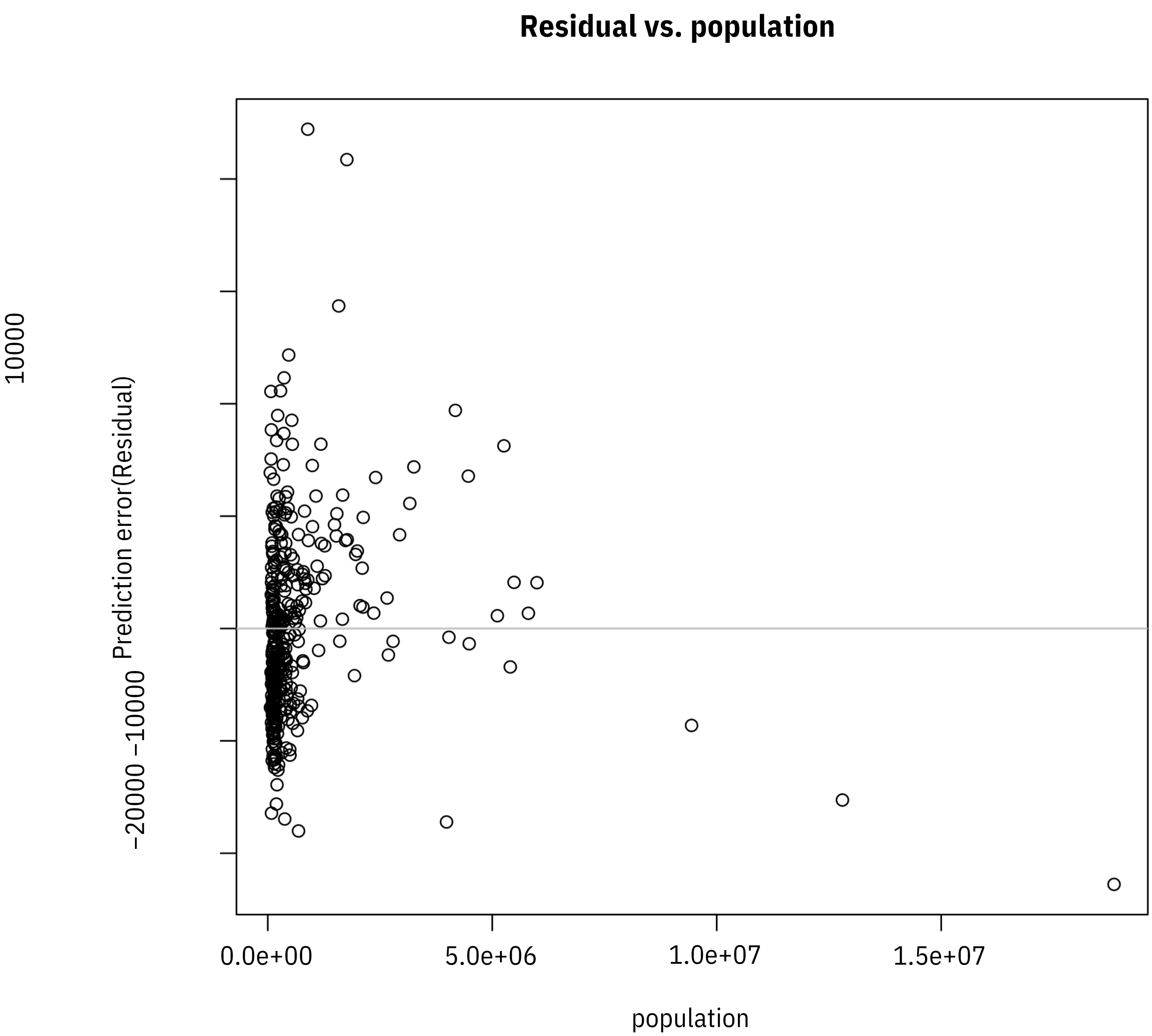
- For all x, $E[\epsilon | X = x] = 0$, $Var[\epsilon | X = x] = \sigma 2$.
- ϵ is uncorrelated across observations.

The least-square estimate of the slope is $\hat{\beta} = 0.002416201$ and least-square estimate of the intercept is $\hat{\alpha} = 31277.57$
These values are same as the coefficients obtained by the lm function.



– Comment on the fit: The line doesn't fit the data well.

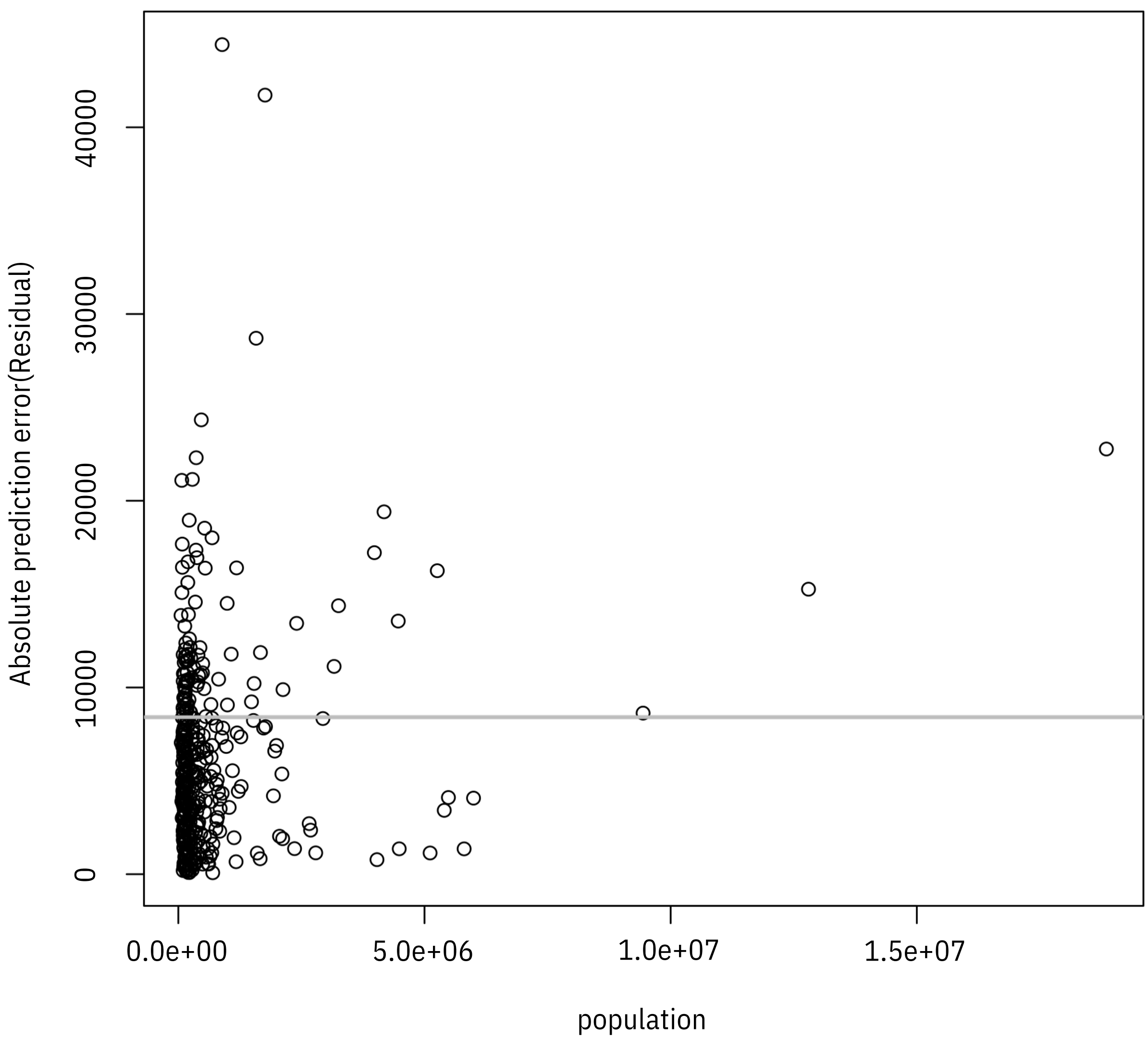
- Verification of the assumptions of the simple linear regression model:
  - Plotted residuals against the population:



Clearly, the scatterplot looks like a changing-width (shrinking) blur of points around a straight, flat line at height zero. This means that the simple-linear part of the simple linear regression model is wrong.

– Plotted absolute residuals against the population:

Absolute residual vs. population



Clearly, the points are not scattered around the flat line and after 1.0e+07 population the residuals are persistently above zero. This could be due to non-constant noise variance (technically called "heteroscedasticity"), or due to getting the functional form of the regression wrong.

Therefore, we can say that here the assumptions of the simple linear regression model don't hold.

q Observations on Pittsburgh city:

- The population of Pittsburgh is 2361000.
- The per-capita GMP of Pittsburgh is 38350.
- The per-capita GMP of Pittsburgh predicted by the model is 36982.22.
- The residual for Pittsburgh is 1367.775.
- The residual square for Pittsburgh is only 2.6% (approx.) of the MSE (The mean squared error (MSE) of the regression is 70697145). Now, as the residual for Pittsburgh is greater than 1, so we can say that the residual

for Pittsburgh is quite small compared to the mean squared error.

[Interpretation of the estimated slope:

If we select two sets of cases from the un-manipulated distribution where the population differs by 1, we expect per-capita GMP to differ by 0.002416201 unit.]

- The predicted per-capita GMP for a city with 105 more people than Pittsburgh is 37223.84.
- If 105 people were added to the population, by a policy intervention, then the predicted Pittsburgh per-capita GMP would become more closer to the observed per-capita GMP i.e. the residual would decrease.

k App endix:

(R codes)

1. Analysis of the Chicago dataset:

(a)
```
#...loading  the chicago dataset in  R
library(gamair)
data(chicago)
```

(b)
```
#...summary on each variable
summary(chicago)
dim(chicago)
```

(c) Examining the variables:

i.
```
#...maximum temperature in  Chicago
max(chicago$tmpd)
```

ii.
```
#...summary on pm25median variable
summary(chicago$pm25median)
nrow(chicago)
```

iii.
```
#...function  giving  mean,median and variance  of  each variable
mvm<-function(x)
{
    a=mean(x,na.rm=T) #mean
    b=var(x,na.rm=T)
    c=median(x,na.rm=T) #median
    return(data.frame(mean=a,variance=b,median=c))
}
mvm(chicago$death)
mvm(chicago$pm10median)
mvm(chicago$pm25median)
mvm(chicago$o3median)
mvm(chicago$so2median)
mvm(chicago$time)
mvm(chicago$tmpd)
```

iv.
```
#...histogram for each variable with appropriate number of breaks
par(mfrow=c(4,2))
for(j { in 1:(ncol(chicago)))
}
    hist(chicago[,j],xlab=colnames(chicago)[j],main=paste("Histogram of",colnames(chicago)[j])
```

(d)
```
#...plotting of each predicter variable against the response variable
par(mfrow=c(3,2))
for(j in 2:(ncol(chicago)))
{ }
    plot(x=chicago[,j],y=chicago$death,xlab=colnames(chicago)[j],main=paste("Scatterplot of", coln
```

i. written.

ii.
```
#...outlier days for the plot of pm10median against death
out=boxplot.stats(chicago$pm10median)$out
#out-the values of any data points which lie beyond the extremes of the whiskers.

out_ind=which(chicago$pm10median%in%out)
day1=chicago$time[out_ind]
day1
```

```
#...outlier days for the plot of pm25median against death
out=boxplot.stats(chicago$pm25median)$out
out_ind=which(chicago$pm25median%in%out)
day2=chicago$time[out_ind]
day2
```

```
#...outlier days for the plot of o3median against death
out=boxplot.stats(chicago$o3median)$out
out_ind=which(chicago$o3median%in%out)
day3=chicago$time[out_ind]
day3
```

```
#...outlier days for the plot of so2median against death
out=boxplot.stats(chicago$so2median)$out
out_ind=which(chicago$so2median%in%out)
day4=chicago$time[out_ind]
day4
```

```
#...outlier days for the plot of time against death
out=boxplot.stats(chicago$time)$out
out_ind=which(chicago$time%in%out)
day5=chicago$time[out_ind]
day5
```

```
#...outlier days for the plot of tmpd against death
out=boxplot.stats(chicago$tmpd)$out
out_ind=which(chicago$tmpd%in%out)
day6=chicago$time[out_ind]
day6
```

```
#...code for finding if different plots share outlier days
sum(day1%in%day2)
sum(day1%in%day3)
```

```
sum(day1%in%day4)
sum(day1%in%day5)
sum(day1%in%day6)
sum(day2%in%day3)
sum(day2%in%day4)
sum(day2%in%day5)
sum(day2%in%day6)
sum(day3%in%day4)
sum(day3%in%day5)
sum(day3%in%day6)
sum(day4%in%day5)
sum(day4%in%day6)
sum(day5%in%day6)
```

iii.

```
#...Plotting residuals against pm10median variable
death.pm10.lm<-lm(death~pm10median,data=chicago)
plot(chicago$pm10median[!is.na(chicago$pm10median)],residuals(death.pm10.lm),xlab="pm10med
abline(h=0,col="grey")

#...Plotting residuals against pm25median variable
death.pm25.lm<-lm(death~pm25median,data=chicago)
plot(chicago$pm25median[!is.na(chicago$pm25median)],residuals(death.pm25.lm),xlab="pm25me
abline(h=0,col="grey")
par(mfrow=c(3,2))

#...Plotting residuals against o3median variable
death.o3.lm<-lm(death~o3median,data=chicago)
plot(chicago$o3median[!is.na(chicago$o3median)],residuals(death.o3.lm),xlab="o3median",ylab="P
abline(h=0,col="grey")

#...Plotting residuals against so2median variable
death.so2.lm<-lm(death~so2median,data=chicago)
plot(chicago$so2median[!is.na(chicago$so2median)],residuals(death.so2.lm),xlab="so2median",yla
abline(h=0,col="grey")

#...Plotting residuals against time variable
death.time.lm<-lm(death~time,data=chicago)
plot(chicago$time[!is.na(chicago$time)],residuals(death.time.lm),xlab="time",ylab="Prediction
abline(h=0,col="grey")

#...Plotting residuals against tmpd variable
death.temp.lm<-lm(death~tmpd,data=chicago)
plot(chicago$tmpd[!is.na(chicago$tmpd)],residuals(death.temp.lm),xlab="Temperature(F)",ylab="P
abline(h=0,col="grey")
```

(e) written.

i. written.

ii. written.

iii.

```
#...scatterplot of death vs tmpd
plot(death~tmpd,data=chicago,ylim=c(0,200),xlab="Daily meantemperature(F)",ylab="Mortality (
#...proposed function
abline(a=130,b=-0.28,col="blue")
```

```
#...Q-Q  Plot  to  verify   the  distribution of    the  residuals
qqnorm(residuals(death.temp.lm)
) qqline(residuals(death.temp.lm))
```

2. Analysis of the econ.csv data file:

(a)
```
#...loading    the data  file
econ.data=read.table("D:\\AKG  Linear  Models(5th Sem)\\econ.csv",header=T,sep=",")
attach(econ.data)
#...dimension  of the   data
dim(econ.data)
```

(b)
```
#...summaryof the   six   numerical-valued columns
summary(econ.data[,-1])
```

(c)
```
#...univariate     EDAplots  for   population andfor   per-capita  GMP
par(mfrow=c(1,2))
hist(pop,xlab="Population",main="Histogram of  Population",col="lightblue",breaks=50)
hist(pcgmp,xlab="per-capita  GMP",main="Histogramof per-capita    GMP",col="lightblue",breaks=20)
```

(d)
```
#...bivariate     EDA plot for   per-capita  GMPas  a  function  of  population
plot(pop,pcgmp,xlab="Population",ylab="per-capita  GMP", main="Scatterplot of  per-capita  GMPvs  po
```

(e)
```
#...slope    of the   least-square  regression line
slope=cov(pop,pcgmp)/var(pop)
#...intercept    of the   least-square  regression line
intercept=mean(pcgmp)-(slope*mean(pop))
```

(f)
```
#...slope    returned by the  function  lm
coefficients(lm(pcgmp~pop,data=econ.data))[2]
#...intercept    returned by the  function  lm
coefficients(lm(pcgmp~pop,data=econ.data))[1]
```

(g)
```
#...bivariate     EDA plot for   per-capita  GMPas  a  function  of population
plot(pop,pcgmp,xlab="Population",ylab="per-capita  GMP", main="Scatterplot of  per-capita  GMPvs  po

#...adding   the fitted    line
abline(a=intercept,b=slope)
```

```
#...Plotting    residuals  against  the  population
model<-lm(pcgmp~pop,data=econ.data)
plot(pop,residuals(model),xlab="population",ylab="Prediction error(Residual)",main="Residual vs.
abline(h=0,col="grey")
```

```
#...Plotting    absolute residuals   against  the population
plot(pop,abs(residuals(model)),xlab="population",ylab="Absolute    prediction  error(Residual)",main="
abline(h=sqrt(mean(residuals(model)^2)),lwd=2,col="grey")
```

(h)
```
#...finding Pittsburgh in the dataset
Pitts.ind=charmatch("Pittsburgh",MSA)

#...population of Pittsburgh
pop[Pitts.ind]
#...per-capita GMP of Pittsburgh
pcgmp[Pitts.ind]

#...per-capita GMP predicted by the model
pred.pcgmp=(coefficients(model)[1])+(coefficients(model)[2])*(pop[Pitts.ind])

#...residual for Pittsburgh
Pitts.rsd=pcgmp[Pitts.ind]-pred.pcgmp
```

(i)
```
#...mean squared error of the regression
mse=mean(residuals(model)^2)
mse
```

(j)
```
#...ratio of Residual square for Pittsburgh to the Mean Residual Square or MSE
ratio=(Pitts.rsd^2)/mse
ratio
```

(k) written.

(l)
```
#...predicted per-capita GMP for a city with more people than Pittsburgh
pred.pcgmp=(coefficients(model)[1])+(coefficients(model)[2])*((10^5)+pop[Pitts.ind])
pred.pcgmp
```