UN Nutrition Analysis

Sathvik Maridasana Nagaraj

2024-07-21

```
# Import the CSV file
Nutrition_Physical_Activity_and_Obesity <- read.csv("D:/BioInformatics/US Nut
rition Analysis/Nutrition__Physical_Activity__and_Obesity.csv")

# View the first few rows of the dataset
head(Nutrition_Physical_Activity_and_Obesity)

##   YearStart YearEnd LocationAbbr LocationDesc
## 1      2020    2020           US     National
## 2      2014    2014           GU         Guam
## 3      2013    2013           US     National
## 4      2013    2013           US     National
## 5      2015    2015           US     National
## 6      2015    2015           GU         Guam
##                                 Datasource                  Class
## 1 Behavioral Risk Factor Surveillance System       Physical Activity
## 2 Behavioral Risk Factor Surveillance System Obesity / Weight Status
## 3 Behavioral Risk Factor Surveillance System Obesity / Weight Status
## 4 Behavioral Risk Factor Surveillance System Obesity / Weight Status
## 5 Behavioral Risk Factor Surveillance System       Physical Activity
## 6 Behavioral Risk Factor Surveillance System       Physical Activity
##                          Topic
## 1 Physical Activity - Behavior
## 2      Obesity / Weight Status
## 3      Obesity / Weight Status
## 4      Obesity / Weight Status
## 5 Physical Activity - Behavior
## 6 Physical Activity - Behavior
##
Question
## 1
Percent of adults who engage in no leisure-time physical activity
## 2
Percent of adults aged 18 years and older who have obesity
## 3
Percent of adults aged 18 years and older who have obesity
## 4
Percent of adults aged 18 years and older who have an overweight classificati
on
## 5                                                    Percent of adults who ac
hieve at least 300 minutes a week of moderate-intensity aerobic physical acti
vity or 150 minutes a week of vigorous-intensity aerobic activity (or an equi
```

```
valent combination)
## 6 Percent of adults who achieve at least 150 minutes a week of moderate-in
tensity aerobic physical activity or 75 minutes a week of vigorous-intensity
aerobic physical activity and engage in muscle-strengthening activities on 2
or more days a week
##   Data_Value_Unit Data_Value_Type Data_Value Data_Value_Alt
## 1              NA           Value       30.6           30.6
## 2              NA           Value       29.3           29.3
## 3              NA           Value       28.8           28.8
## 4              NA           Value       32.7           32.7
## 5              NA           Value       26.6           26.6
## 6              NA           Value       27.4           27.4
##   Data_Value_Footnote_Symbol Data_Value_Footnote Low_Confidence_Limit
## 1                                                                29.4
## 2                                                                25.7
## 3                                                                28.1
## 4                                                                31.9
## 5                                                                25.6
## 6                                                                18.6
##   High_Confidence_Limit Sample_Size Total Age.years.            Education
## 1                  31.8       31255
## 2                  33.3         842                 High school graduate
## 3                  29.5       62562
## 4                  33.5       60069
## 5                  27.6       30904
## 6                  38.5         125
##   Gender            Income Race.Ethnicity             GeoLocation ClassID
## 1                               Hispanic                              PA
## 2                                       (13.444304, 144.793731)     OWS
## 3        $50,000 - $74,999                                          OWS
## 4        Data not reported                                          OWS
## 5        Less than $15,000                                           PA
## 6                              Hispanic (13.444304, 144.793731)      PA
##   TopicID QuestionID DataValueTypeID LocationID StratificationCategory1
## 1     PA1       Q047           VALUE         59          Race/Ethnicity
## 2    OWS1       Q036           VALUE         66               Education
## 3    OWS1       Q036           VALUE         59                  Income
## 4    OWS1       Q037           VALUE         59                  Income
## 5     PA1       Q045           VALUE         59                  Income
## 6     PA1       Q044           VALUE         66          Race/Ethnicity
##       Stratification1 StratificationCategoryId1 StratificationID1
## 1            Hispanic                      RACE           RACEHIS
## 2 High school graduate                       EDU         EDUHSGRAD
## 3    $50,000 - $74,999                       INC           INC5075
## 4    Data not reported                       INC             INCNR
## 5    Less than $15,000                       INC         INCLESS15
## 6            Hispanic                      RACE           RACEHIS

library(readr)
```

```
## Warning: package 'readr' was built under R version 4.4.1
```

```
library(gridExtra)
```

```
## Warning: package 'gridExtra' was built under R version 4.4.1
```

```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 4.4.1
```

```
library(huxtable)
```

```
## Warning: package 'huxtable' was built under R version 4.4.1
```

```
##
## Attaching package: 'huxtable'
```

```
## The following object is masked from 'package:ggplot2':
##
##     theme_grey
```

```
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 4.4.1
```

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

```
## The following object is masked from 'package:huxtable':
##
##     add_rownames
```

```
## The following object is masked from 'package:gridExtra':
##
##     combine
```

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

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

```
library(broom)
```

```
## Warning: package 'broom' was built under R version 4.4.1
```

```
library(huxtable)
library(flextable)
```

```
## Warning: package 'flextable' was built under R version 4.4.1
```

```
##
## Attaching package: 'flextable'

## The following objects are masked from 'package:huxtable':
##
##     align, as_flextable, bold, font, height, italic, set_caption,
##     valign, width
```

###Introduction In this simple analysis we will reorganize the data to create three time series of the united states concerning obesity, physical activity, and fruit and vegetable consumption scores. After analyzing the trends on a national basis we will then go on to compare California and Texas, the two most populous states.

###1. Construct the time series First we simplify the dataset deleting

1. The duplicate variables.
2. The variables not usefull for our analyisis or with too many not available data.

At the end we will remain with this data:

```
data<-Nutrition_Physical_Activity_and_Obesity[,-c(2,4,5,6,8,9,10,12,13,14,18,
24:33)]

colnames(data)<-c("year","location","topic","value", "low_conf_lim","high_con
f_lim","sample_size","age","education","gender","income","race")
```

Now we can check if it s worth keeping the variables with NA. For doing so we build a simple function that counts the percentage of na data for a variable

```
na_perc<-function(x){
  a<-round(sum(is.na(x))/length(x)*100)
  paste(a,"%")}



a<-na_perc(data$age)
b<-na_perc(data$education)
c<-na_perc(data$gender)
d<-na_perc(data$income)
e<-na_perc(data$race)

tabella <- data.frame( nrow= c("age","education","gender","income","race"),c(
a,b,c,d,e))
colnames(tabella)<-c("percentage of not available data")
rownames(tabella) <- c("age","education","gender","income","race")
tabella
```

percentage of not available data	
age	0 %

education	0 %
gender	0 %
income	0 %
race	0 %

These variables are for the most part composed of nonavailable data. However, we do not eliminate them right away because since we will be creating subdatasets there may be an adequate number of observations to use them in the future.

In order to create the time series we arrange the data by year

```
data<-arrange(data,data$year)
```

We filter for the "US" location

```
data_us<- data[data$location== "US", ]
```

And finally we can filter by topic, creating tree national dataset about:

1. Obesity
2. Physical activity
3. Fruit and vegetables consumption

```
#national obesity dataset over time
data_us_ob<-data_us[data_us$topic == "Obesity / Weight Status", ]

#national Physical Activity - Behavior dataset over time
data_us_pa<-data_us[data_us$topic == "Physical Activity - Behavior", ]

#national Fruits and Vegetables - Behavior dataset over time
data_us_fv<-data_us[data_us$topic == "Fruits and Vegetables - Behavior", ]
```

###2. National Obesity score over years

```
ggplot(data = data_us_ob, aes(x = year, y= value))+
  geom_point()+
  stat_summary(
    geom = "point",
    fun = "mean",
    col = "black",
    size = 3,
    shape = 24,
    fill = "red")+
  geom_smooth(method = "lm")+
  ggtitle("National obesity score over years")
```

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

We can see that the obesity score has rised over the years, lets check this with a regression line

```
model<-lm(data= data_us_ob , value ~ year)
huxreg("National obesity score"= model,
       statistics = FALSE,
       error_format = "")

## Warning in huxreg(`National obesity score` = model, statistics = FALSE, :
Unrecognized statistics: FALSE
## Try setting `statistics` explicitly in the call to `huxreg()`
```

	National obesity score
(Intercept)	-470.836 ***
year	0.250 ***
*** p < 0.001; ** p < 0.01; * p < 0.05.	

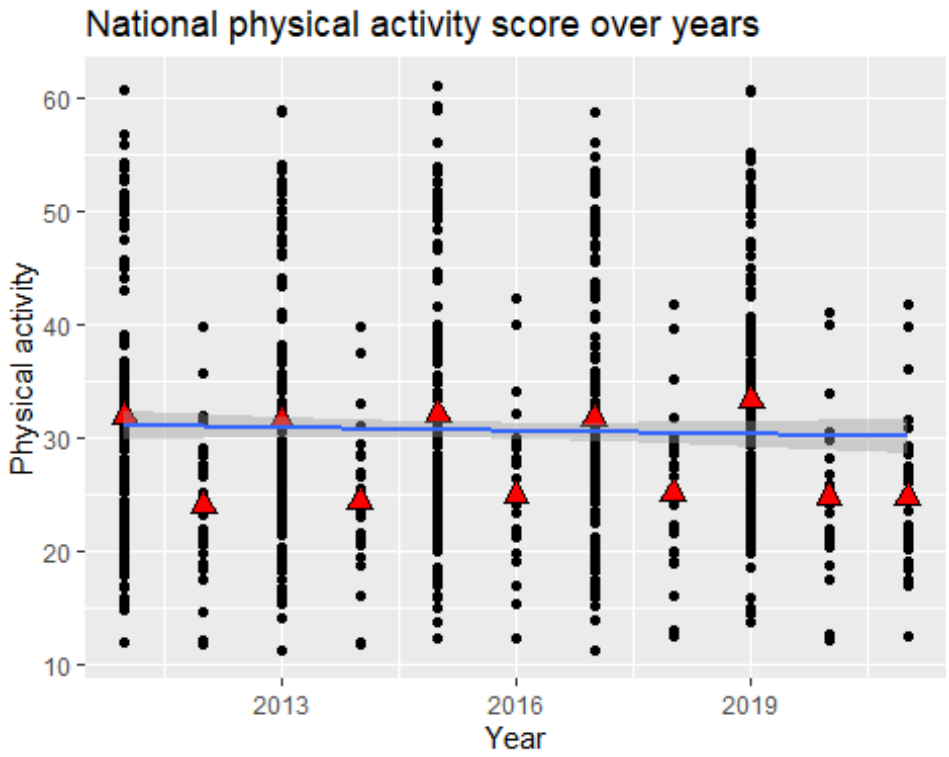
On average adding a year u have an increase of 0.250 on the obesity score that s statistically significant.

It s important to note that we are not going to investigate statistical significance and R squared because these regressions will only serve to give us an idea of the slope of the trend that is more analytical than the visual idea of scatterplots. During the whole analysis we are going to consider a significance level of 90%.

###3. National physical activity score over years

```
ggplot(data = data_us_pa, aes(x = year, y= value))+
  geom_point()+
  stat_summary(
    geom = "point",
    fun = "mean",
    col = "black",
    size = 3,
    shape = 24,
    fill = "red")+
  geom_smooth(method = "lm")+
  ggtitle("National physical activity score over years")+
  ylab("Physical activity")+
  xlab("Year")
```

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



Before coming to conclusions about trends in physical activity over the years we note how ratings drop from one year to the next so we need to study what is happening in the data.

```r
a<-sum(data_us_pa$year == "2011")
b<-sum(data_us_pa$year == "2012")
c<-sum(data_us_pa$year == "2013")
d<-sum(data_us_pa$year == "2014")
e<-sum(data_us_pa$year == "2015")
f<-sum(data_us_pa$year == "2016")
g<-sum(data_us_pa$year == "2017")
h<-sum(data_us_pa$year == "2018")
i<-sum(data_us_pa$year == "2019")
j<-sum(data_us_pa$year == "2020")
k<-sum(data_us_pa$year == "2021")

tabella <- matrix( c(a,b,c,d,e,f,g,h,i,j,k),nrow = 1)
colnames(tabella)<-c(2011:2021)
rownames(tabella) <- c("observations")
tabella
```

```
##              2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021
## observations  140   28  140   28  140   28  140   28  140   28   28
```

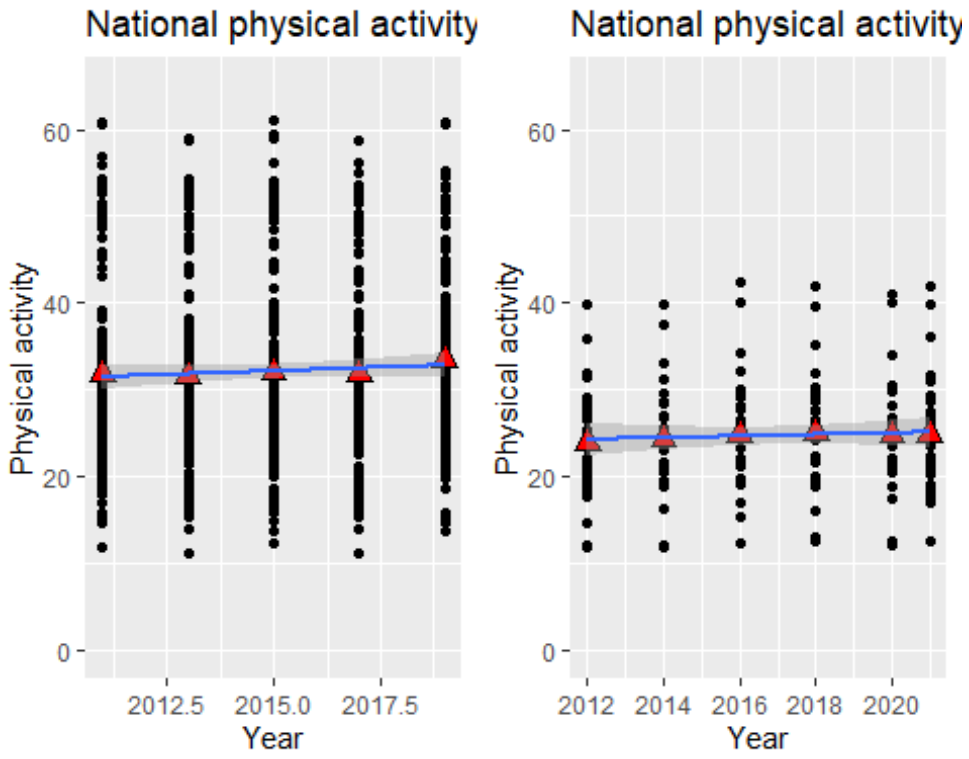
Year-to-year observations alternate from 28 to 140 with the last two years being 28.

We then split the data with 28 and 140 observations so that we can see if their trends change.

```r
#create the data subset for samples of 28 and 140 observations

datasub140 <- data_us_pa[data_us_pa$year %in% c(2011, 2013,2015,2017,2019), ]
datasub28 <- data_us_pa[data_us_pa$year %in% c(2012, 2014,2016,2018,2020,2021
), ]


plot140<-
  ggplot(data = datasub140, aes(x = year, y= value))+
  geom_point()+
  ylim(0,65)+
  stat_summary(
    geom = "point",
    fun = "mean",
    col = "black",
    size = 3,
    shape = 24,
    fill = "red")+
  geom_smooth(method = "lm")+
  ggtitle("National physical activity score over years")+
  ylab("Physical activity")+
  xlab("Year")

plot28<-
  ggplot(data = datasub28, aes(x = year, y= value))+
```

```
  geom_point()+
  ylim(0,65)+
  stat_summary(
    geom = "point",
    fun = "mean",
    col = "black",
    size = 3,
    shape = 24,
    fill = "red")+
  geom_smooth(method = "lm")+
  ggtitle("National physical activity score over years")+
  ylab("Physical activity")+
  xlab("Year")

grid.arrange(plot140,plot28,ncol=2)
```

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



When we have 140 observations your physical activity level is higher on average than when we have 28. The most important thing however is that physical activity has remained stationary in both cases as we can see from the regression (both slope coefficients are low and not significant).

```
model28<-lm(data= datasub28 , value ~ year)
model140<-lm(data= datasub140 , value ~ year)
```

```
huxreg("model 28 obs" = model28,
       "model 140 obs" = model140,
       statistics ="r.squared" ,
       error_format = "")
```

	model 28 obs	model 140 obs
(Intercept)	-158.963	-306.373
year	0.091	0.168
r.squared	0.002	0.002

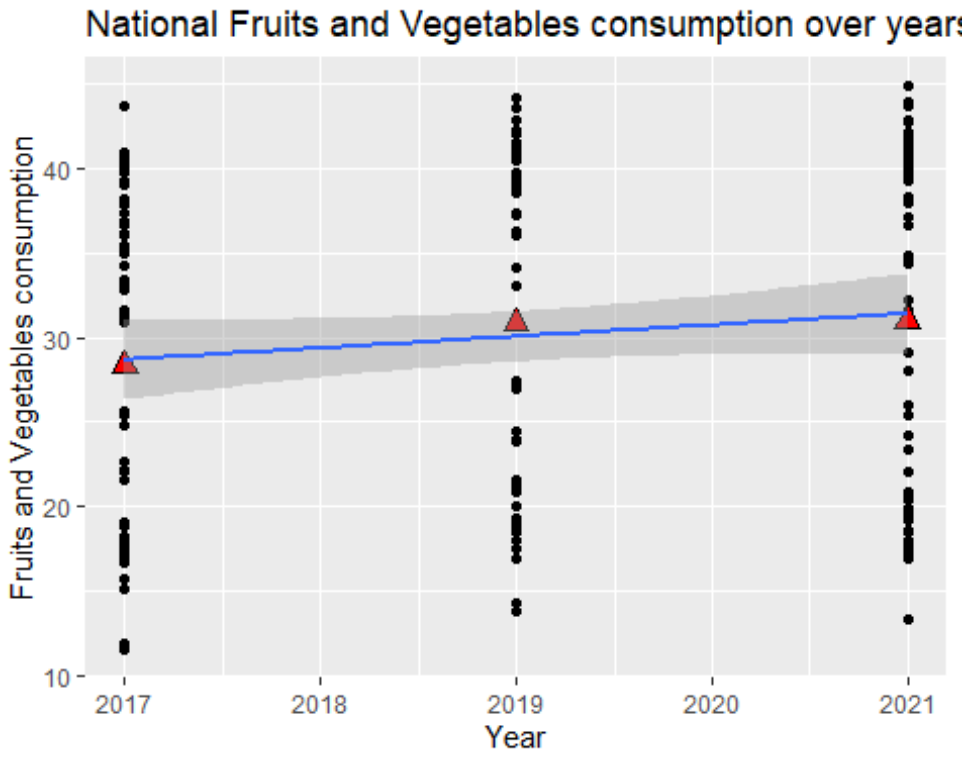
*** p < 0.001; ** p < 0.01; * p < 0.05.

###4. National Fruits and Vegetables consumption over years

For fruit and vegetable consumption we note an increasing trend but the available data only cover 2017, 2019 and 2021.

```
ggplot(data = data_us_fv, aes(x = year, y= value))+
  geom_point()+
  stat_summary(
    geom = "point",
    fun = "mean",
    col = "black",
    size = 3,
    shape = 24,
    fill = "red")+
  geom_smooth(method = "lm")+
  ggtitle("National Fruits and Vegetables consumption over years")+
  ylab("Fruits and Vegetables consumption")+
  xlab("Year")
```

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



However, despite the lack of data, we can state that there has not been a conspicuous growth in fruit and vegetable consumption. The slope coefficient indeed is infact not statistically significant.

```
model_fv<-lm(data= data_us_fv , value ~ year)

huxreg("model fv" = model_fv,
      statistics ="r.squared" ,
       error_format = "")
```

	model fv
(Intercept)	-1343.605
year	0.680
r.squared	0.013

*** p < 0.001; ** p < 0.01; * p < 0.05.

###5. California and Texas comparison The previous method at the national level can be used to partition data and compare various states. In this example we are going to consider only the data from the 2 most important states by population (California and Texas) so we construct two datasets for the two states.

```
#california data
data_ca<- data[data$location== "CA", ]

#texas data
data_tx<- data[data$location== "TX", ]
```

Then we further partition the dataset for each state by dividing it by obesity, physical activity, and fruit and vegetable consumption. Now we have the time series of the three topics of the analysis and we can investigate them.

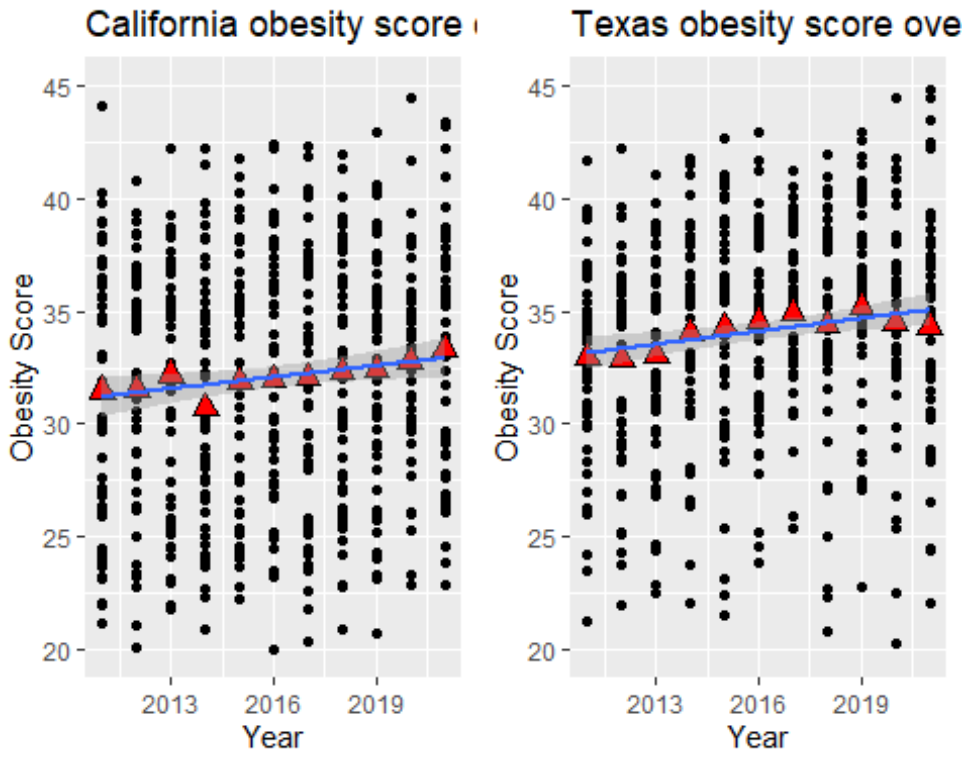
```
#national obesity dataset over time
data_ca_ob<-data_ca[data_ca$topic == "Obesity / Weight Status", ]
#national Physical Activity - Behavior dataset over time
data_ca_pa<-data_ca[data_ca$topic == "Physical Activity - Behavior", ]
#national Fruits and Vegetables - Behavior dataset over time
data_ca_fv<-data_ca[data_ca$topic == "Fruits and Vegetables - Behavior", ]

#national obesity dataset over time
data_tx_ob<-data_tx[data_tx$topic == "Obesity / Weight Status", ]
#national Physical Activity - Behavior dataset over time
data_tx_pa<-data_tx[data_tx$topic == "Physical Activity - Behavior", ]
#national Fruits and Vegetables - Behavior dataset over time
data_tx_fv<-data_tx[data_tx$topic == "Fruits and Vegetables - Behavior", ]
```

##5.1 Obesity score comparison

```
california_obesity<-ggplot(data = data_ca_ob, aes(x = year, y= value))+
  geom_point()+
  stat_summary(
    geom = "point",
    fun = "mean",
    col = "black",
    size = 3,
    shape = 24,
    fill = "red")+
  ylim(20,45)+
  geom_smooth(method = "lm")+
  ggtitle("California obesity score over years")+
  ylab("Obesity Score")+
  xlab("Year")

texas_obesity<-ggplot(data = data_tx_ob, aes(x = year, y= value))+
  geom_point()+
  stat_summary(
    geom = "point",
```

```
    fun = "mean",
    col = "black",
    size = 3,
    shape = 24,
    fill = "red")+
  ylim(20,45)+
  geom_smooth(method = "lm")+
  ggtitle("Texas obesity score over years")+
  ylab("Obesity Score")+
  xlab("Year")

grid.arrange(california_obesity,texas_obesity,ncol=2)
```

```
## Warning: Removed 73 rows containing non-finite outside the scale range
## (`stat_summary()`).

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

## Warning: Removed 73 rows containing non-finite outside the scale range
## (`stat_smooth()`).

## Warning: Removed 73 rows containing missing values or values outside the s
cale range
## (`geom_point()`).

## Warning: Removed 66 rows containing non-finite outside the scale range
## (`stat_summary()`).

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

## Warning: Removed 66 rows containing non-finite outside the scale range
## (`stat_smooth()`).

## Warning: Removed 66 rows containing missing values or values outside the s
cale range
## (`geom_point()`).
```



Texas has higher levels of obesity, and in both states it has risen. Through the regression table we can identify the linear coefficient to see in which state it grew the fastest.

```
reg_ca<-lm(data=data_ca_ob, value ~ year )
reg_tx<-lm(data=data_tx_ob, value ~ year )


huxreg("California obesity" = reg_ca,
       "Texas obesity" = reg_tx,
       statistics = "",
       error_format = "")
```

```
## Warning in huxreg(`California obesity` = reg_ca, `Texas obesity` = reg_tx,
: Unrecognized statistics:
## Try setting `statistics` explicitly in the call to `huxreg()`
```

	California obesity	Texas obesity
(Intercept)	-493.494 **	-450.212 **
year	0.260 **	0.240 **

*** p < 0.001; ** p < 0.01; * p < 0.05.

Thanks to the regression we can see that California started from a lower level of obesity but it experienced a more pronounced growth.

##5.2 Physical activity score comparison

```
california_pa<- ggplot(data = data_ca_pa, aes(x = year, y= value))+
                  geom_point()+
                  stat_summary(
                    geom = "point",
                    fun = "mean",
                    col = "black",
                    size = 3,
                    shape = 24,
                    fill = "red")+
                  geom_smooth(method = "lm")+
                  ggtitle("California physical activity score over years")+
                  ylab("Physical activity")+
                  xlab("Year")

texas_pa<- ggplot(data = data_tx_pa, aes(x = year, y= value))+
                  geom_point()+
                  stat_summary(
                    geom = "point",
                    fun = "mean",
                    col = "black",
                    size = 3,
                    shape = 24,
                    fill = "red")+
                  geom_smooth(method = "lm")+
                  ggtitle("Texas physical activity score over years")+
                  ylab("Physical activity")+
                  xlab("Year")

grid.arrange(california_pa,texas_pa)
```

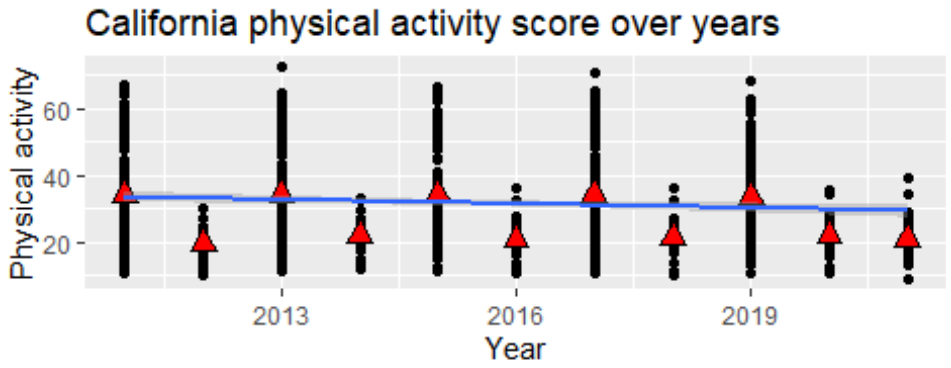
```
## Warning: Removed 38 rows containing non-finite outside the scale range
## (`stat_summary()`).
```

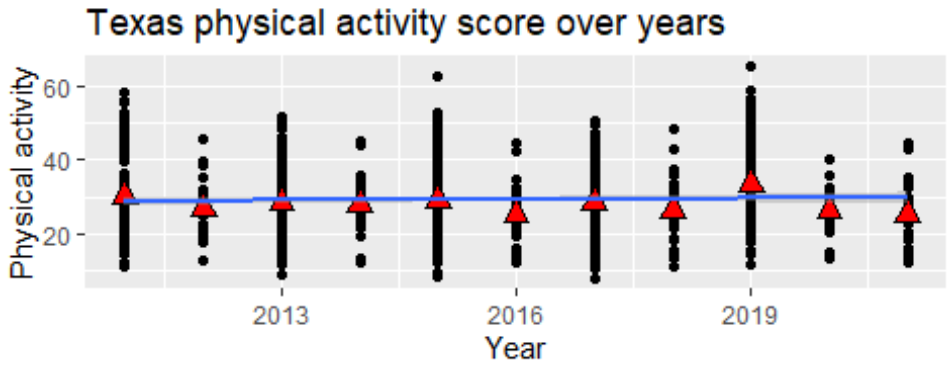
```
## `geom_smooth()` using formula = 'y ~ x'
```

```
## Warning: Removed 38 rows containing non-finite outside the scale range
## (`stat_smooth()`).
```

```
## Warning: Removed 38 rows containing missing values or values outside the s
cale range
## (`geom_point()`).
```

```
## Warning: Removed 54 rows containing non-finite outside the scale range
## (`stat_summary()`).

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

## Warning: Removed 54 rows containing non-finite outside the scale range
## (`stat_smooth()`).

## Warning: Removed 54 rows containing missing values or values outside the s
cale range
## (`geom_point()`).
```






```
california <- lm(data= data_ca_pa, value ~ year)
texas <- lm(data= data_tx_pa , value ~ year)

huxreg("California pa" = california,
       "Texas pa" = texas,
       statistics ="r.squared" ,
       error_format = "")
```

	California pa	Texas pa
(Intercept)	845.434 **	-148.377
year	-0.404 *	0.088

r.squared	0.008	0.001

*** p < 0.001; ** p < 0.01; * p < 0.05.

We can say that in texas the physical activity score remained unchanged while in California it worsened as evidenced by the statistically significant negative slope coefficient.

##5.3 Fruit and vegetable consumption score comparison

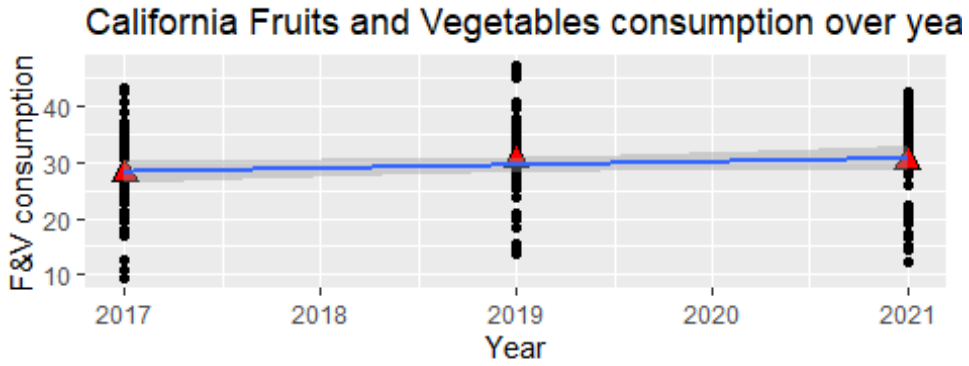
```
california<-ggplot(data = data_ca_fv, aes(x = year, y= value))+
            geom_point()+
            stat_summary(
              geom = "point",
              fun = "mean",
              col = "black",
              size = 3,
              shape = 24,
              fill = "red")+
            geom_smooth(method = "lm")+
            ggtitle("California Fruits and Vegetables consumption over years"
)+
            ylab("F&V consumption")+
            xlab("Year")

texas<-ggplot(data = data_tx_fv, aes(x = year, y= value))+
        geom_point()+
        stat_summary(
          geom = "point",
          fun = "mean",
          col = "black",
          size = 3,
          shape = 24,
          fill = "red")+
        geom_smooth(method = "lm")+
        ggtitle("Texas Fruits and Vegetables consumption over years")+
        ylab("F&V consumption")+
        xlab("Year")

grid.arrange(california,texas)
```

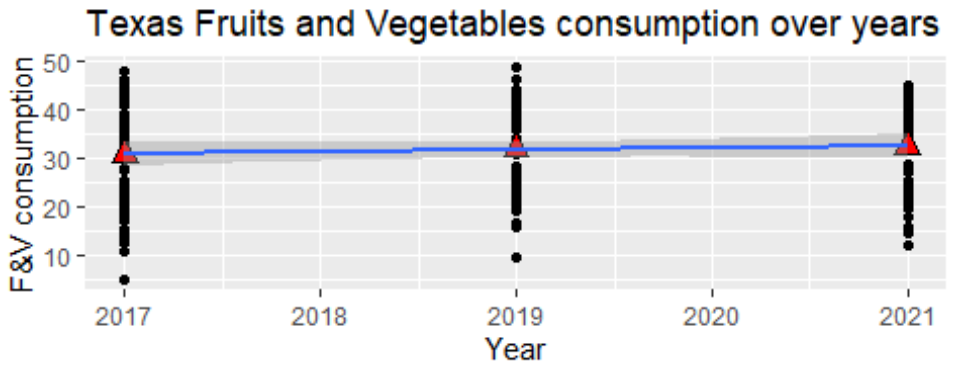
```
## Warning: Removed 8 rows containing non-finite outside the scale range
## (`stat_summary()`).
```

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

```
## Warning: Removed 8 rows containing non-finite outside the scale range
## (`stat_smooth()`).
```

```
## Warning: Removed 8 rows containing missing values or values outside the sc
ale range
## (`geom_point()`).

## Warning: Removed 8 rows containing non-finite outside the scale range
## (`stat_summary()`).

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

## Warning: Removed 8 rows containing non-finite outside the scale range
## (`stat_smooth()`).

## Warning: Removed 8 rows containing missing values or values outside the sc
ale range
## (`geom_point()`).
```






```
model_fv_ca<-lm(data= data_ca_fv , value ~ year)
model_fv_tx<-lm(data= data_tx_fv , value ~ year)

huxreg("California fv" = model_fv_ca,
       "Texas fv"= model_fv_tx,
        statistics ="r.squared" ,
        error_format = "")
```

	California fv	Texas fv
(Intercept)	-1152.003	-750.205

year	0.585	0.387
r.squared	0.012	0.004

*** p < 0.001; ** p < 0.01; * p < 0.05.

Finally we note how there was no significant increase in fruit and vegetable consumption in either state.

###Conclusion We can conclude saying that:

1. On a national base: The obesity score has increased over the years while The physical activity and fruit-vegetables consumption remained stationary
2. Comparing California and Texas: The obesity score has increased over the years, especially in California The physical activity score has decreased in California, remaining constant in Texas The fruit-vegetable consumption has not increased in both countries