CaseStudy

```
...

  |=
|   1%

| In this lesson we'll apply some of the techniques we learned in this course
to study air pollution
| data, specifically particulate matter (we'll call it pm25 sometimes), colle
cted by the U.S.
| Environmental Protection Agency. This website
| https://www.health.ny.gov/environmental/indoors/air/pmq_a.htm from New York
State offers some basic
| information on this topic if you're interested.

...

  |==
|   2%

| Particulate matter (less than 2.5 microns in diameter) is a fancy name for
dust, and breathing in
| dust might pose health hazards to the population. We'll study data from two
years, 1999 (when
| monitoring of particulate matter started) and 2012. Our goal is to see if t
here's been a noticeable
| decline in this type of air pollution between these two years.

...

  |===
|   3%

| We've read in 2 large zipped files for you using the R command read.table (
which is smart enough to
| unzip the files).  We stored the 1999 data in the array pm0 for you. Run th
e R command dim now to
| see its dimensions.

> dim(pm0)
[1] 117421      5

| Keep up the great work!

  |====
|   4%

| We see that pm0 has over 117000 lines, each containing 5 columns. In the or
iginal file, at the EPA
| website, each row had 28 columns, but since we'll be using only a few of th
ese, we've created and
| read in a somewhat smaller file. Run head on pm0 now to see what the first
few lines look like.

> head(pm0)
```

```
  V1 V2 V3       V4     V5
1  1 27  1 19990103     NA
2  1 27  1 19990106     NA
3  1 27  1 19990109     NA
4  1 27  1 19990112  8.841
5  1 27  1 19990115 14.920
6  1 27  1 19990118  3.878

| Excellent job!

  |=====
|   5%

| We see there's some missing data, but we won't worry about that now. We als
o see that the column
| names, V1, V2, etc., are not informative. However, we know that the first l
ine of the original file
| (a comment) explained what information the columns contained.

...

  |======
|   6%

| We created the variable cnames containing the 28 column names of the origin
al file. Take a look at
| the column names now.

> cnames
[1] "# RD|Action Code|State Code|County Code|Site ID|Parameter|POC|Sample Dur
ation|Unit|Method|Date|Start Time|Sample Value|Null Data Code|Sampling Freque
ncy|Monitor Protocol (MP) ID|Qualifier - 1|Qualifier - 2|Qualifier - 3|Qualif
ier - 4|Qualifier - 5|Qualifier - 6|Qualifier - 7|Qualifier - 8|Qualifier - 9
|Qualifier - 10|Alternate Method Detectable Limit|Uncertainty"

| That's the answer I was looking for.

  |=======
|   7%

| We see that the 28 column names look all jumbled together even though they'
re separated by "|"
| characters, so let's fix this. Reassign to cnames the output of a call to s
trsplit (string split)
| with 3 arguments. The first is cnames, the pipe symbol '|' is the second (u
se the quotation marks),
| and the third is the argument fixed set to TRUE. Try this now.

> cnames <- strsplit(cnames, "|", fixed = TRUE)

| That's a job well done!

  |========
|   8%

| The variable cnames now holds a list of the column headings. Take another l
ook at the column names.
```

```
> cnames
[[1]]
 [1] "# RD"                              "Action Code"
 [3] "State Code"                        "County Code"
 [5] "Site ID"                           "Parameter"
 [7] "POC"                               "Sample Duration"
 [9] "Unit"                              "Method"
[11] "Date"                              "Start Time"
[13] "Sample Value"                      "Null Data Code"
[15] "Sampling Frequency"                "Monitor Protocol (MP) ID"
[17] "Qualifier - 1"                     "Qualifier - 2"
[19] "Qualifier - 3"                     "Qualifier - 4"
[21] "Qualifier - 5"                     "Qualifier - 6"
[23] "Qualifier - 7"                     "Qualifier - 8"
[25] "Qualifier - 9"                     "Qualifier - 10"
[27] "Alternate Method Detectable Limit" "Uncertainty"


| Excellent work!

  |=========
|   9%

| Nice, but we don't need all these. Assign to names(pm0) the output of a cal
l to the function
| make.names with cnames[[1]][wcol] as the argument. The variable wcol holds
the indices of the 5
| columns we selected (from the 28) to use in this lesson, so those are the c
olumn names we'll need.
| As the name suggests, the function "makes syntactically valid names".

> names(pm0) <- make.names(cnames[[1]][wcol])

| Excellent job!

  |=========
|  10%

| Now re-run head on pm0 now to see if the column names have been put in plac
e.

> head(pm0)
  State.Code County.Code Site.ID     Date Sample.Value
1          1          27       1 19990103           NA
2          1          27       1 19990106           NA
3          1          27       1 19990109           NA
4          1          27       1 19990112        8.841
5          1          27       1 19990115       14.920
6          1          27       1 19990118        3.878

| Perseverance, that's the answer.

  |==========
|  11%
```

```
| Now it's clearer what information each column of pm0 holds. The measurement
s of particulate matter
| (pm25) are in the column named Sample.Value. Assign this component of pm0 t
o the variable x0. Use
| the m$n notation.

> x0 <- pm0$Sample.Value

| You got it!

  |===========
|  12%

| Call the R command str with x0 as its argument to see x0's structure.

> str(x0)
 num [1:117421] NA NA NA 8.84 14.92 ...

| That's correct!

  |============
|  13%

| We see that x0 is a numeric vector (of length 117000+) with at least the fi
rst 3 values missing.
| Exactly what percentage of values are missing in this vector? Use the R fun
ction mean with
| is.na(x0) as an argument to see what percentage of values are missing (NA)
in x0.

> mean(is.na(x0))
[1] 0.1125608

| You are quite good my friend!

  |=============
|  14%

| So a little over 11% of the 117000+ are missing. We'll keep that in mind. N
ow let's start
| processing the 2012 data which we stored for you in the array pm1.

...

  |==============
|  15%

| We'll repeat what we did for pm0, except a little more efficiently. First a
ssign the output of
| make.names(cnames[[1]][wcol]) to names(pm1).

> names(pm1) <- make.names(cnames[[1]][wcol])

| All that practice is paying off!

  |===============
|  16%
```

```
| Find the dimensions of pm1 with the command dim.

> dim(pm1)
[1] 1304287       5

| You nailed it! Good job!

  |================
|  18%

| Wow! Over 1.3 million entries. Particulate matter was first collected in 19
99 so perhaps there
| weren't as many sensors collecting data then as in 2012 when the program wa
s more mature. If you
| ran head on pm1 you'd see that it looks just like pm0. We'll move on though
.

...

  |=================
|  19%

| Create the variable x1 by assigning to it the Sample.Value component of pm1
.

> x1 <- pm1$Sample.Value

| Perseverance, that's the answer.

  |==================
|  20%

| Now let's see what percentage of values are missing in x1. As before, use t
he R function mean with
| is.na(x1) as an argument to find out.

> mean(is.na(x1))
[1] 0.05607125

| You are amazing!

  |===================
|  21%

| So only 5.6% of the particulate matter measurements are missing. That's abo
ut half the percentage
| as in 1999.

...

  |====================
|  22%

| Now let's look at summaries (using the summary command) for both datasets.
First, x0.
```

```
> summary(x0)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
   0.00    7.20   11.50   13.74   17.90  157.10   13217 

| Your dedication is inspiring!

  |=====================                                                    
|  23%

| The numbers in the vectors x0 and x1 represent measurements taken in microg
rams per cubic meter.
| Now look at the summary of x1.

> summary(x1)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
 -10.00    4.00    7.63    9.14   12.00  908.97   73133 

| All that hard work is paying off!

  |======================                                                   
|  24%

| We see that both the median and the mean of measured particulate matter hav
e declined from 1999 to
| 2012. In fact, all of the measurements, except for the maximum and missing
values (Max and NA's),
| have decreased. Even the Min has gone down from 0 to -10.00! We'll address
what a negative
| measurment might mean a little later. Note that the Max has increased from
157 in 1999 to 909 in
| 2012. This is quite high and might reflect an error in the table or malfunc
tions in some monitors.

...

  |=======================                                                  
|  25%

| Call the boxplot function with 2 arguments, x0 and x1.

> boxplot(x0,x1)

| Great job!

  |========================                                                 
|  26%

| Huh? Did somebody step on the boxes? It's hard to see what's going on here.
There are so many
| values outside the boxes and the range of x1 is so big that the boxes are f
lattened. It might be
| more informative to call boxplot on the logs (base 10) of x0 and x1. Do thi
s now using log10(x0)
| and log10(x1) as the 2 arguments.

> boxplot(log10(x0),log10(x1))
Warning messages:
```

```
1: In boxplot.default(log10(x0), log10(x1)) : NaNs produced
2: In bplt(at[i], wid = width[i], stats = z$stats[, i], out = z$out[z$group =
=  :
  Outlier (-Inf) in boxplot 1 is not drawn
3: In bplt(at[i], wid = width[i], stats = z$stats[, i], out = z$out[z$group =
=  :
  Outlier (-Inf) in boxplot 2 is not drawn

| That's the answer I was looking for.

  |=========================
|  27%

| A bonus! Not only do we get a better looking boxplot we also get some warni
ngs from R in Red. These
| let us know that some values in x0 and x1 were "unloggable", no doubt the 0
(Min) we saw in the
| summary of x0 and the negative values we saw in the Min of the summary of x
1.

...

  |==========================
|  28%

| From the boxplot (x0 on the left and x1 on the right), what can you say abo
ut the data?

1: The median of x1 is less than the median of x0
2: The range of x0 is greater than the range of x1
3: The boxes are too small to interpret
4: The mean of x1 is less than the mean of x0

Selection: 1

| Nice work!

  |===========================
|  29%

| Let's return to the question of the negative values in x1. Let's count how
many negative values
| there are. We'll do this in a few steps.

...

  |============================
|  30%

| First, form the vector negative by assigning to it the boolean x1<0.

> negative <- x1<0

| Your dedication is inspiring!

  |============================
|  31%
```

```
| Now run the R command sum with 2 arguments. The first is negative, and the second is na.rm set
| equal to TRUE. This tells sum to ignore the missing values in negative.

> sum(negative, na.rm = T)
[1] 26474

| Not exactly. Give it another go. Or, type info() for more options.

| Type sum(negative, na.rm = TRUE) at the command prompt.

> sum(negative, na.rm = TRUE)
[1] 26474

| You are really on a roll!

  |==============================
|  32%

| So there are over 26000 negative values. Sounds like a lot. Is it? Run the R command mean with same
| 2 arguments you just used with the call to sum. This will tell us a percentage.

> mean(negative, na.rm = TRUE)
[1] 0.0215034

| Excellent work!

  |===============================
|  33%

| We see that just 2% of the x1 values are negative. Perhaps that's a small enough percentage that we
| can ignore them. Before we ignore them, though, let's see if they occur during certain times of the
| year.

...

  |================================
|  34%

| First create the array dates by assigning to it the Date component of pm1. Remember to use the x$y
| notation.

> dates <- pm1$Date

| Keep up the great work!

  |=================================
|  35%

| To see what dates looks like run the R command str on it.
```

```
> str(dates)
 int [1:1304287] 20120101 20120104 20120107 20120110 20120113 20120116 201201
19 20120122 20120125 20120128 ...

| Perseverance, that's the answer.

  |=================================
|  36%

| We see dates is a very long vector of integers. However, the format of the
entries is hard to read.
| There's no separation between the year, month, and day. Reassign to dates t
he output of a call to
| as.Date with the 2 arguments as.character(dates) as the first argument and
the string "%Y%m%d" as
| the second.

> dates <- as.Date(as.character(dates), "%Y%m%d")

| Nice work!

  |==================================
|  37%

| Now when you run head on dates you'll see the dates in a nicer format. Try
this now.

> head(dates)
[1] "2012-01-01" "2012-01-04" "2012-01-07" "2012-01-10" "2012-01-13" "2012-01
-16"

| Your dedication is inspiring!

  |===================================
|  38%

| Let's plot a histogram of the months when the particulate matter measuremen
ts are negative. Run
| hist with 2 arguments. The first is dates[negative] and the second is the s
tring "month".

> hist(dates[negative], "month")

| Excellent job!

  |====================================
|  39%

| We see the bulk of the negative measurements were taken in the winter month
s, with a spike in May.
| Not many of these negative measurements occurred in summer months. We can t
ake a guess that because
| particulate measures tend to be low in winter and high in summer, coupled w
ith the fact that higher
| densities are easier to measure, that measurement errors occurred when the
values were low. For now
```

```
| we'll attribute these negative measurements to errors. Also, since they acc
ount for only 2% of the
| 2012 data, we'll ignore them.

...

  |=====================================
|  40%

| Now we'll change focus a bit and instead of looking at all the monitors thr
oughout the country and
| the data they recorded, we'll try to find one monitor that was taking measu
rements in both 1999 and
| 2012. This will allow us to control for different geographical and environm
ental variables that
| might have affected air quality in different areas. We'll narrow our search
and look just at
| monitors in New York State.

...

  |======================================
|  41%

| We subsetted off the New York State monitor identification data for 1999 an
d 2012 into 2 vectors,
| site0 and site1. Look at the structure of site0 now with the R command str.

> str(site0)
 chr [1:33] "1.5" "1.12" "5.73" "5.80" "5.83" "5.110" "13.11" "27.1004" "29.2
" "29.5" "29.1007" ...

| Excellent job!

  |=======================================
|  42%

| We see that site0 (the IDs of monitors in New York State in 1999) is a vect
or of 33 strings, each
| of which has the form "x.y". We've created these from the county codes (the
x portion of the
| string) and the monitor IDs (the y portion). If you ran str on site1 you'd
see 18 similar values.

...

  |========================================
|  43%

| Use the intersect command with site0 and site1 as arguments and put the res
ult in the variable
| both.

> both <- intersect(site0, site1)

| Great job!
```

```
  |===========================================
|  44%

| Take a look at both now.

> both
 [1] "1.5"     "1.12"    "5.80"    "13.11"   "29.5"    "31.3"    "63.2008" "6
7.1015" "85.55"
[10] "101.3"

| You are amazing!

  |============================================
|  45%

| We see that 10 monitors in New York State were active in both 1999 and 2012
.

...

  |=============================================
|  46%

| To save you some time and typing, we modified the data frames pm0 and pm1 s
lightly by adding to
| each of them a new component, county.site. This is just a concatenation of
two original components
| County.Code and Site.ID. We did this to facilitate the next step which is t
o find out how many
| measurements were taken by the 10 New York monitors working in both of the
years of interest. Run
| head on pm0 to see the first few entries now.

> head(pm0)
  State.Code County.Code Site.ID     Date Sample.Value county.site
1          1          27       1 19990103           NA        27.1
2          1          27       1 19990106           NA        27.1
3          1          27       1 19990109           NA        27.1
4          1          27       1 19990112        8.841        27.1
5          1          27       1 19990115       14.920        27.1
6          1          27       1 19990118        3.878        27.1

| All that practice is paying off!

  |==============================================
|  47%

| Now pm0 and pm1 have 6 columns instead of 5, and the last column is a conca
tenation of two other
| columns, County and Site.

...

  |===============================================
|  48%
```

```
| Now let's see how many measurements each of the 10 New York monitors that w
ere active in both 1999
| and 2012 took in those years. We'll create 2 subsets (one for each year), o
ne of pm0 and the other
| of pm1.

...

  |===============================================
|  49%

| The subsets will filter for 2 characteristics. The first is State.Code equa
l to 36 (the code for
| New York), and the second is that the county.site (the component we added)
is in the vector both.

...

  |===============================================
|  51%

| First create the variable cnt0 by assigning to it the output of the R comma
nd subset, called with 2
| arguments. The first is pm0, and the second is a boolean with the 2 conditi
ons we just mentioned.
| Recall that the testing for equality in a boolean requires ==, intersection
of 2 boolean conditions
| is denoted by & and membership by %in%.

> cnt0 <- subset(pm0, State.Code == 36 & county.site %in% both)

| Keep up the great work!

  |================================================
|  52%

| Recall the last command with the up arrow, and create cnt1 (instead of cnt0
). Remember to change
| pm0 to pm1. Everything else can stay the same.

> cnt1 <- subset(pm1, State.Code == 36 & county.site %in% both)

| Keep working like that and you'll get there!

  |=================================================
|  53%

| Now run the command sapply(split(cnt0, cnt0$county.site), nrow). This will
split cnt0 into several
| data frames according to county.site (that is, monitor IDs) and tell us how
many measurements each
| monitor recorded.

> sapply(split(cnt0, cnt0$county.site), nrow)
   1.12     1.5   101.3   13.11    29.5    31.3    5.80 63.2008 67.1015    85.
55
```

```
      61      122      152       61       61      183       61      122      122
7

| You got it right!

  |===============================================
|  54%

| Do the same for cnt1. (Recall your last command and change 2 occurrences of
cnt0 to cnt1.)

> sapply(split(cnt1, cnt1$county.site), nrow)
   1.12      1.5    101.3    13.11     29.5     31.3     5.80  63.2008  67.1015    85.
55
     31       64       31       31       33       15       31       30       31
31

| Perseverance, that's the answer.

  |================================================
|  55%

| From the output of the 2 calls to sapply, which monitor is the only one who
se number of
| measurements increased from 1999 to 2012?

1: 29.5
2: 63.2008
3: 85.55
4: 101.3

Selection: 3

| That's a job well done!

  |=================================================
|  56%

| We want to examine a monitor with a reasonable number of measurements so le
t's look at the monitor
| with ID 63.2008. Create a variable pm0sub which is the subset of cnt0 (this
contains just New York
| data) which has County.Code equal to 63 and Site.ID 2008.

> pm0sub <- subset(cnt0, County.Code==63 & Site.ID==2008)

| All that practice is paying off!

  |==================================================
|  57%

| Now do the same for cnt1. Name this new variable pm1sub.

> pm1sub <- subset(cnt1, County.Code==63 & Site.ID==2008)

| Keep working like that and you'll get there!
```

```
  |==========================================================
|  58%

| From the output of the 2 calls to sapply, how many rows will pm0sub have?

1: 29
2: 122
3: 30
4: 183

Selection: 2

| Keep working like that and you'll get there!

  |===========================================================
|  59%

| Now we'd like to compare the pm25 measurements of this particular monitor (
63.2008) for the 2
| years. First, create the vector x0sub by assigning to it the Sample.Value c
omponent of pm0sub.

> x0sub <- pm0sub$Sample.Value

| You got it right!

  |============================================================
|  60%

| Similarly, create x1sub from pm1sub.

> x1sub <- pm1sub$Sample.Value

| Excellent work!

  |=============================================================
|  61%

| We'd like to make our comparison visually so we'll have to create a time se
ries of these pm25
| measurements. First, create a dates0 variable by assigning to it the output
of a call to as.Date.
| This will take 2 arguments. The first is a call to as.character with pm0sub
$Date as the argument.
| The second is the format string "%Y%m%d".

> dates0 <- as.Date(as.character(pm0sub$Date), "%Y%m%d")

| Excellent job!

  |==============================================================
|  62%

| Do the same for the 2012 data. Specifically, create dates1 using pm1sub$Dat
e as your input.

> dates1 <- as.Date(as.character(pm1sub$Date), "%Y%m%d")
```

```
| Excellent work!

  |===============================================================
|  63%

| Now we'll plot these 2 time series in the same panel using the base plottin
g system. Call par with
| 2 arguments. The first is mfrow set equal to c(1,2). This will tell the sys
tem we're plotting 2
| graphs in 1 row and 2 columns. The second argument will adjust the panel's
margins. It is mar set
| to c(4,4,2,1).

> par(mfrow=c(1,2), mar=c(4,4,2,1) )

| You are quite good my friend!

  |================================================================
|  64%

| Call plot with the 3 arguments dates0, x0sub, and pch set to 20. The first
two arguments are the x
| and y coordinates. This will show the pm25 values as functions of time.

> plot(dates0, x0sub, pch = 20)

| That's a job well done!

  |=================================================================
|  65%

| Now we'll mark the median.

...

  |==================================================================
|  66%

| Use abline to add a horizontal line at the median of the pm25 values. Make
the line width 2 (lwd is
| the argument), and when you call median with x0sub, specify the argument na
.rm to be TRUE.

> abline(h = median(x0sub, na.rm = TRUE),lwd=2)

| Excellent job!

  |===================================================================
|  67%

| Now we'll do the same for the 2012 data. Call plot with the 3 arguments dat
es1, x1sub, and pch set
| to 20.

> plot(dates1, x1sub, pch = 20)
```

```
| All that practice is paying off!

  |===============================================================
|  68%

| As before, we'll mark the median of this 2012 data.

...

  |================================================================
|  69%

| Use abline to add a horizontal line at the median of the pm25 values. Make
the line width 2 (lwd is
| the argument). Remember to specify the argument na.rm to be TRUE when you c
all median on x1sub.

> abline(h = median(x1sub, na.rm = TRUE),lwd=2)

| You got it right!

  |================================================================
|  70%

| Which median is larger - the one for 1999 or the one for 2012?

1: 2012
2: 1999

Selection: 2

| Nice work!

  |=================================================================
|  71%

| The picture makes it look like the median is higher for 2012 than 1999. Clo
ser inspection shows
| that this isn't true. The median for 1999 is a little over 10 micrograms pe
r cubic meter and for
| 2012 its a little over 8. The plots appear this way because the 1999 plot .
...

1: shows different months than those in the 2012 plot
2: displays more points than the 2012 plot
3: shows a bigger range of y values than the 2012 plot

Selection: 3

| Keep working like that and you'll get there!

  |==================================================================
|  72%

| The 1999 plot shows a much bigger range of pm25 values on the y axis, from
below 10 to 40, while
```

```
| the 2012 pm25 values are much more restricted, from around 1 to 14. We shou
ld really plot the
| points of both datasets on the same range of values on the y axis. Create t
he variable rng by
| assigning to it the output of a call to the R command range with 3 argument
s, x0sub, x1sub, and the
| boolean na.rm set to TRUE.

> rng <- range(x0sub, x1sub,na.rm = TRUE)

| You are really on a roll!

  |===================================================================
|  73%

| Look at rng to see the values it spans.

> rng
[1]  3.0 40.1

| Your dedication is inspiring!

  |====================================================================
|  74%

| Here a new figure we've created showing the two plots side by side with the
same range of values on
| the y axis. We used the argument ylim set equal to rng in our 2 calls to pl
ot. The improvement in
| the medians between 1999 and 2012 is now clear. Also notice that in 2012 th
ere are no big values
| (above 15). This shows that not only is there a chronic improvement in air
quality, but also there
| are fewer days with severe pollution.

...

  |=====================================================================
|  75%

| The last avenue of this data we'll explore (and we'll do it quickly) concer
ns a comparison of all
| the states' mean pollution levels. This is important because the states are
responsible for
| implementing the regulations set at the federal level by the EPA.

...

  |======================================================================
|  76%

| Let's first gather the mean (average measurement) for each state in 1999. R
ecall that the original
| data for this year was stored in pm0.

...
```

```
  |===========================================================================
|  77%

| Create the vector mn0 with a call to the R command with using 2 arguments.
The first is pm0. This
| is the data in which the second argument, an expression, will be evaluated.
The second argument is
| a call to the function tapply. This call requires 4 arguments. Sample.Value
and State.Code are the
| first two. We want to apply the function mean to Sample.Value, so mean is t
he third argument. The
| fourth is simply the boolean na.rm set to TRUE.

> mn0 <- with(pm0, tapply(Sample.Value, State.Code, mean, na.rm=TRUE))

| You got it!

  |============================================================================
|  78%

| Call the function str with mn0 as its argument to see what it looks like.

> str(mn0)
 num [1:53(1d)] 19.96 6.67 10.8 15.68 17.66 ...
 - attr(*, "dimnames")=List of 1
  ..$ : chr [1:53] "1" "2" "4" "5" ...

| Great job!

  |=============================================================================
|  79%

| We see mn0 is a 53 long numerical vector. Why 53 if there are only 50 state
s? As it happens, pm25
| measurements for the District of Columbia (Washington D.C), the Virgin Isla
nds, and Puerto Rico are
| included in this data. They are coded as 11, 72, and 78 respectively.

...

  |==============================================================================
|  80%

| Recall your command creating mn0 and change it to create mn1 using pm1 as t
he first input to the
| call to with.

> mn1 <- with(pm1, tapply(Sample.Value, State.Code, mean, na.rm=TRUE))

| Excellent job!

  |==============================================================================
=                 |  81%

| For fun, call the function str with mn1 as its argument.

> str(mn1)
```

```
 num [1:52(1d)] 10.13 4.75 8.61 10.56 9.28 ...
 - attr(*, "dimnames")=List of 1
  ..$ : chr [1:52] "1" "2" "4" "5" ...

| Keep up the great work!

  |===========================================================================
==                |  82%

| So mn1 has only 52 entries, rather than 53. We checked. There are no entrie
s for the Virgin Islands
| in 2012. Call summary now with mn0 as its input.

> summary(mn0)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  4.862   9.519  12.315  12.406  15.640  19.956

| All that hard work is paying off!

  |===========================================================================
===               |  84%

| Now call summary with mn1 as its input so we can compare the two years.

> summary(mn1)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  4.006   7.355   8.729   8.759  10.613  11.992

| That's the answer I was looking for.

  |===========================================================================
====              |  85%

| We see that in all 6 entries, the 2012 numbers are less than those in 1999.
Now we'll create 2 new
| dataframes containing just the state names and their mean measurements for
each year. First, we'll
| do this for 1999. Create the data frame d0 by calling the function data.fra
me with 2 arguments. The
| first is state set equal to names(mn0), and the second is mean set equal to
mn0.

> d0 <- data.frame(state=names(mn0), mean=mn0)

| All that practice is paying off!

  |===========================================================================
=====             |  86%

| Recall the last command and create d1 instead of d0 using the 2012 data. (T
here'll be 3 changes of
| 0 to 1.)

> d1 <- data.frame(state=names(mn1), mean=mn1)

| You nailed it! Good job!
```

```
  |=============================================================================
======             |  87%

| Create the array mrg by calling the R command merge with 3 arguments, d0, d
1, and the argument by
| set equal to the string "state".

> mrg <- merge(d0,d1,by = "state")

| Perseverance, that's the answer.

  |=============================================================================
=======            |  88%

| Run dim with mrg as its argument to see how big it is.

> dim(mrg)
[1] 52  3

| You're the best!

  |=============================================================================
========           |  89%

| We see merge has 52 rows and 3 columns. Since the Virgin Island data was mi
ssing from d1, it is
| excluded from mrg. Look at the first few entries of mrg using the head comm
and.

> head(mrg)
  state    mean.x    mean.y
1     1 19.956391 10.126190
2    10 14.492895 11.236059
3    11 15.786507 11.991697
4    12 11.137139  8.239690
5    13 19.943240 11.321364
6    15  4.861821  8.749336

| That's correct!

  |=============================================================================
=========          |  90%

| Each row of mrg has 3 entries - a state identified by number, a state mean
for 1999 (mean.x), and a
| state mean for 2012 (mean.y).

...

  |=============================================================================
=========          |  91%

| Now we'll plot the data to see how the state means changed between the 2 ye
ars. First we'll plot
| the 1999 data in a single column at x=1. The y values for the points will b
e the state means.
```

```
| Again, we'll use the R command with so we don't have to keep typing mrg as the data environment in
| which to evaluate the second argument, the call to plot. We've already reset the graphical
| parameters for you.

...

  |==========================================================================================         |  92%

| For the first column of points, call with with 2 arguments. The first is mrg, and the second is the
| call to plot with 3 arguments. The first of these is rep(1,52). This tells the plot routine that
| the x coordinates for all 52 points are 1. The second argument is the second column of mrg or
| mrg[,2] which holds the 1999 data. The third argument is the range of x values we want, namely xlim
| set to c(.5,2.5). This works since we'll be plotting 2 columns of points, one at x=1 and the other
| at x=2.

> with(mrg, plot(rep(1, 52), mrg[, 2], xlim = c(.5, 2.5)))

| That's the answer I was looking for.

  |===========================================================================================        |  93%

| We see a column of points at x=1 which represent the 1999 state means. For the second column of
| points, again call with with 2 arguments. As before, the first is mrg. The second, however, is a
| call to the function points with 2 arguments. We need to do this since we're adding points to an
| already existing plot. The first argument to points is the set of x values, rep(2,52). The second
| argument is the set of y values, mrg[,3]. Of course, this is the third column of mrg. (We don't
| need to specify the range of x values again.)

> with(mrg, points(rep(2, 52), mrg[, 3]))

| Your dedication is inspiring!

  |============================================================================================       |  94%

| We see a shorter column of points at x=2. Now let's connect the dots. Use the R function segments
| with 4 arguments. The first 2 are the x and y coordinates of the 1999 points and the last 2 are the
| x and y coordinates of the 2012 points. As in the previous calls specify the x coordinates with
| calls to rep and the y coordinates with references to the appropriate columns of mrg.
```

```
> segments(rep(1, 52), mrg[, 2], rep(2, 52), mrg[, 3])

| Excellent job!

  |===========================================================================
=============     |  95%

| We see from the plot that the vast majority of states have indeed improved
their particulate matter
| counts so the general trend is downward. There are a few exceptions. (The t
opmost point in the 1999
| column is actually two points that had very close measurements.)

...

  |===========================================================================
==============    |  96%

| For fun, let's see which states had higher means in 2012 than in 1999. Just
use the mrg[mrg$mean.x
| < mrg$mean.y, ] notation to find the rows of mrg with this particulate prop
erty.

> mrg[mrg$mean.x < mrg$mean.y, ]
   state    mean.x    mean.y
6     15  4.861821  8.749336
23    31  9.167770  9.207489
27    35  6.511285  8.089755
33    40 10.657617 10.849870

| Great job!

  |===========================================================================
===============   |  97%

| Only 4 states had worse pollution averages, and 2 of these had means that w
ere very close. If you
| want to see which states (15, 31, 35, and 40) these are, you can check out
this website
| https://www.epa.gov/enviro/state-fips-code-listing to decode the state code
s.

...

  |===========================================================================
================  |  98%

| This concludes the lesson, comparing air pollution data from two years in d
ifferent ways. First, we
| looked at measures of the entire set of monitors, then we compared the two
measures from a
| particular monitor, and finally, we looked at the mean measures of the indi
vidual states.

...
```

```
  |==========================================================================
================= |  99%
```

| Congratulations! We hope you enjoyed this particulate lesson.

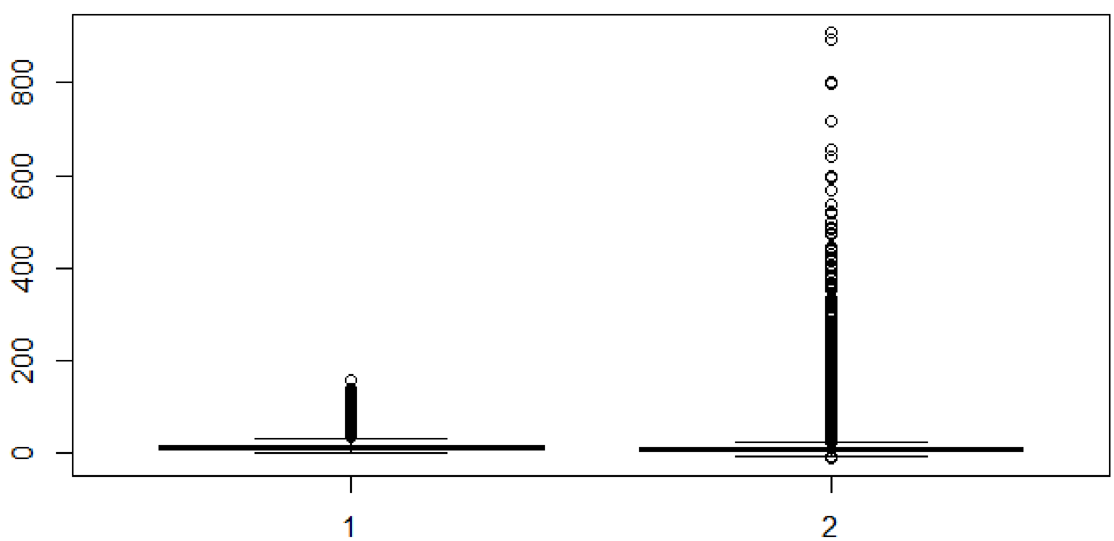
...

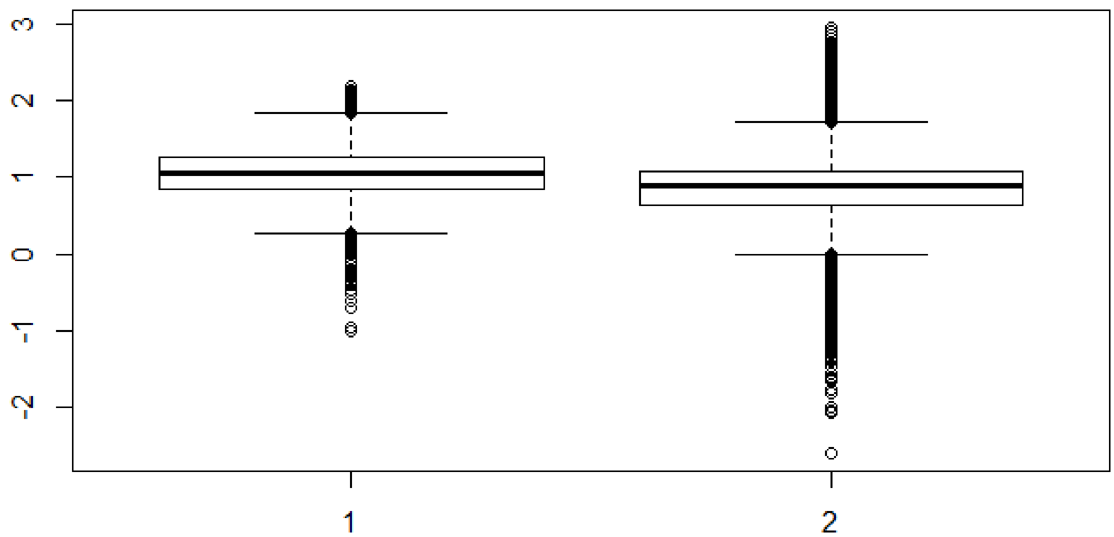
```
  |==========================================================================
==================| 100%
```

| Would you like to receive credit for completing this course on Coursera.org
?

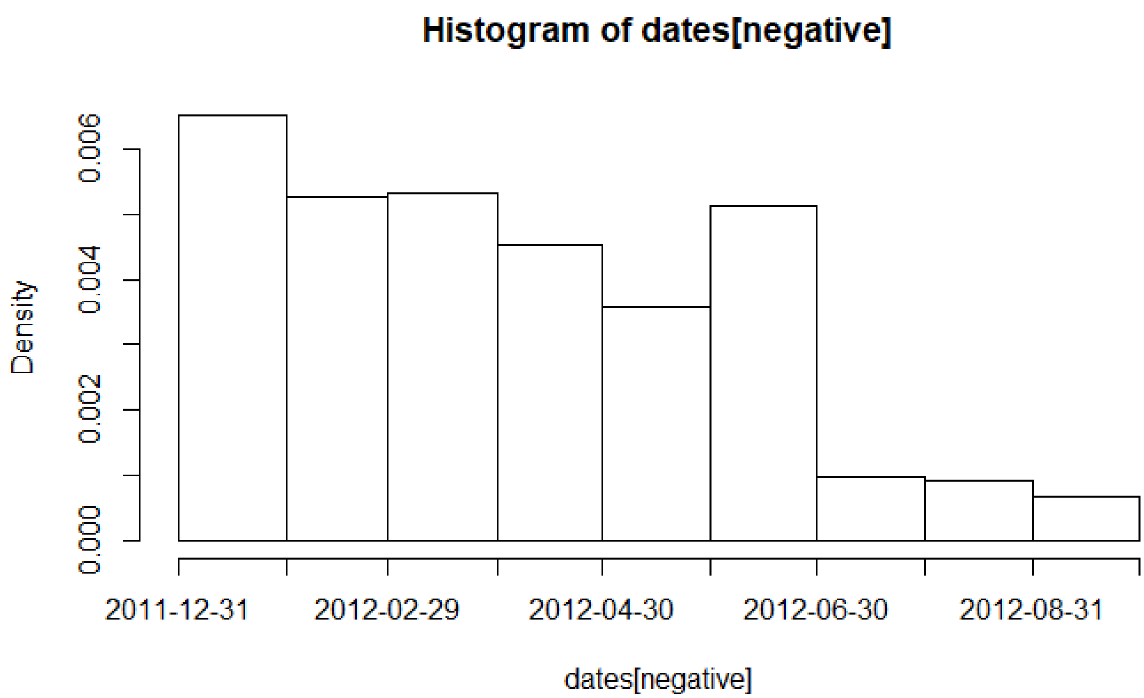
1: Yes
2: No

Plots

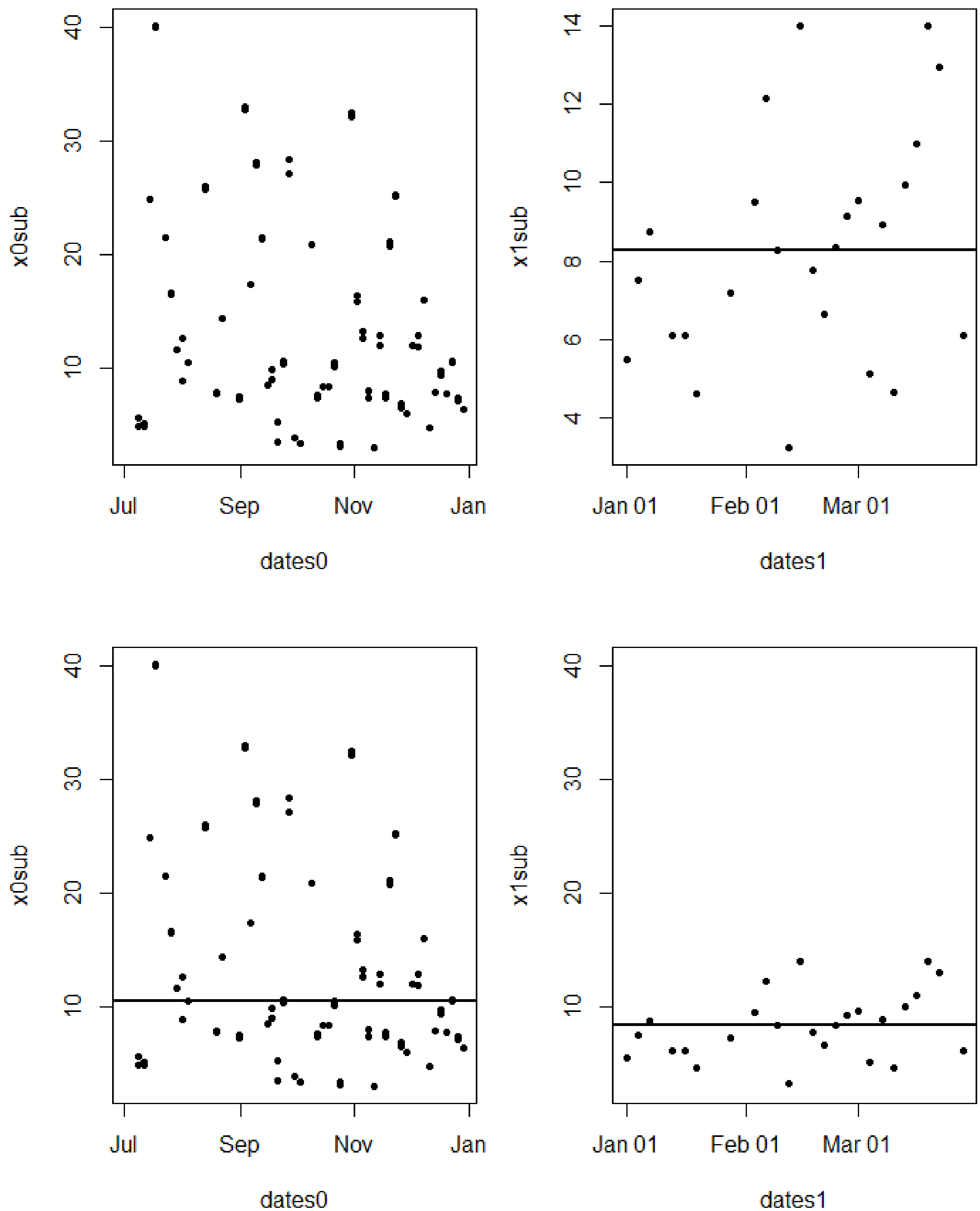


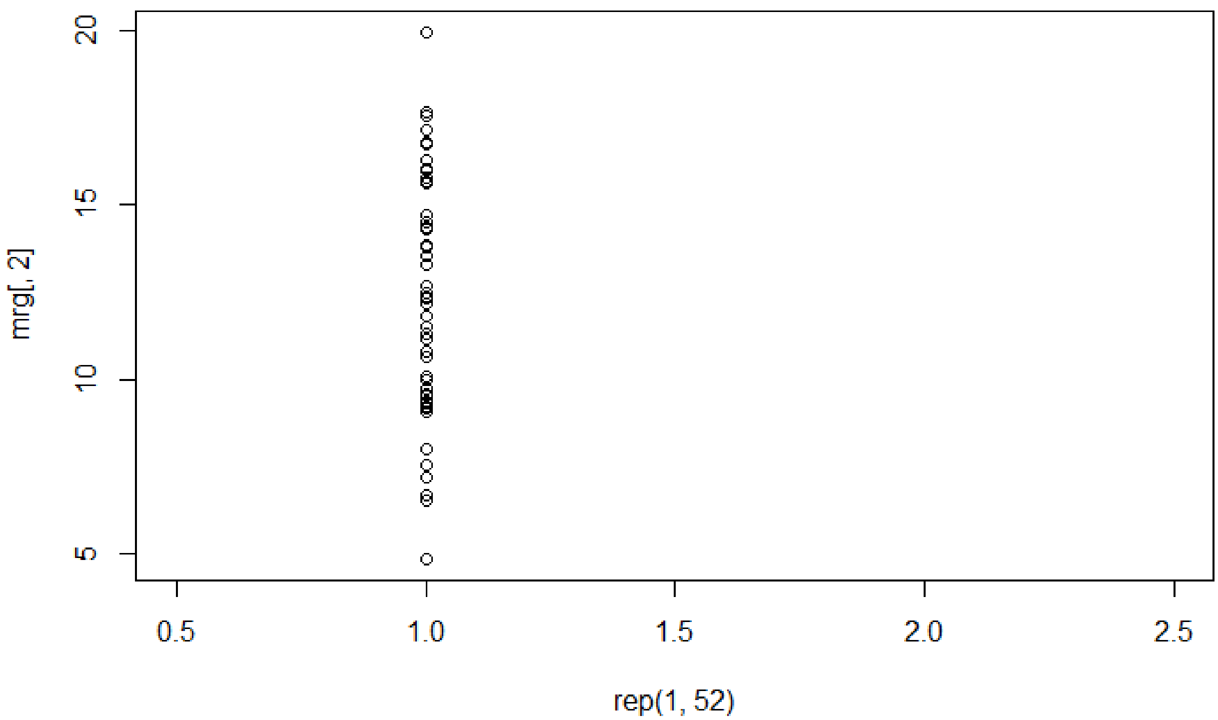


3
2
1
0
-1
-2
1
2

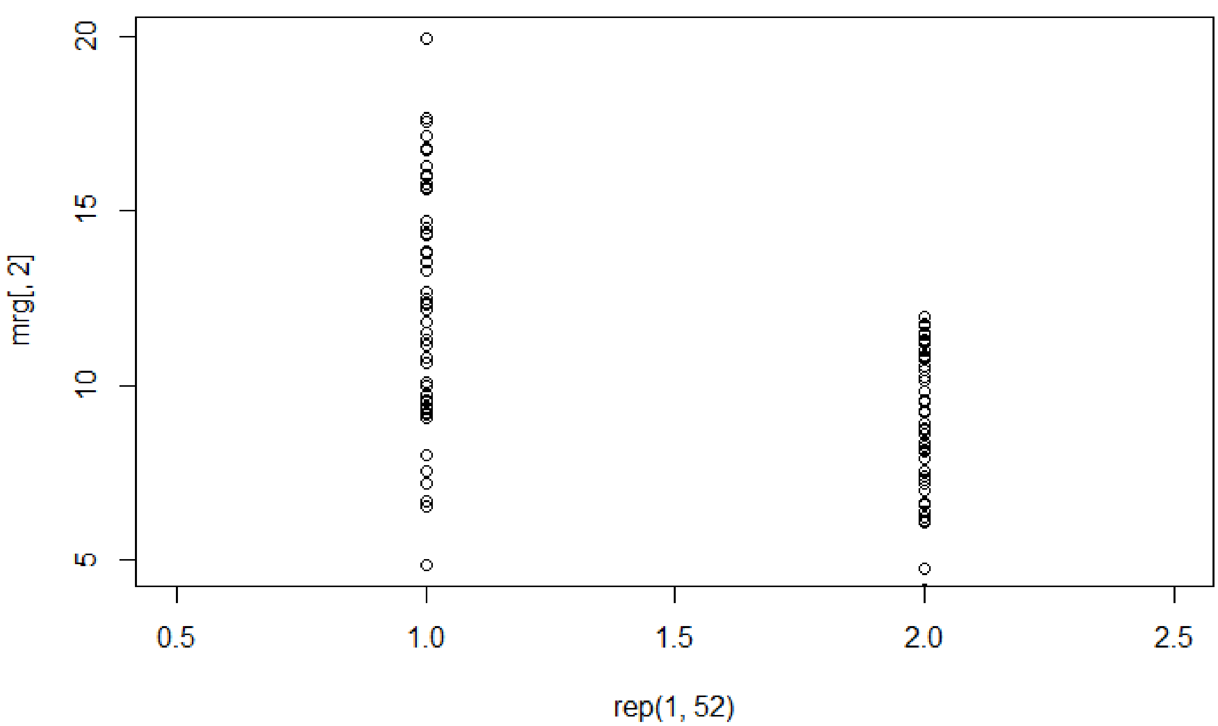


Histogram of dates[negative]
Density
0.000
0.002
0.004
0.006
2011-12-31
2012-02-29
2012-04-30
2012-06-30
2012-08-31
dates[negative]

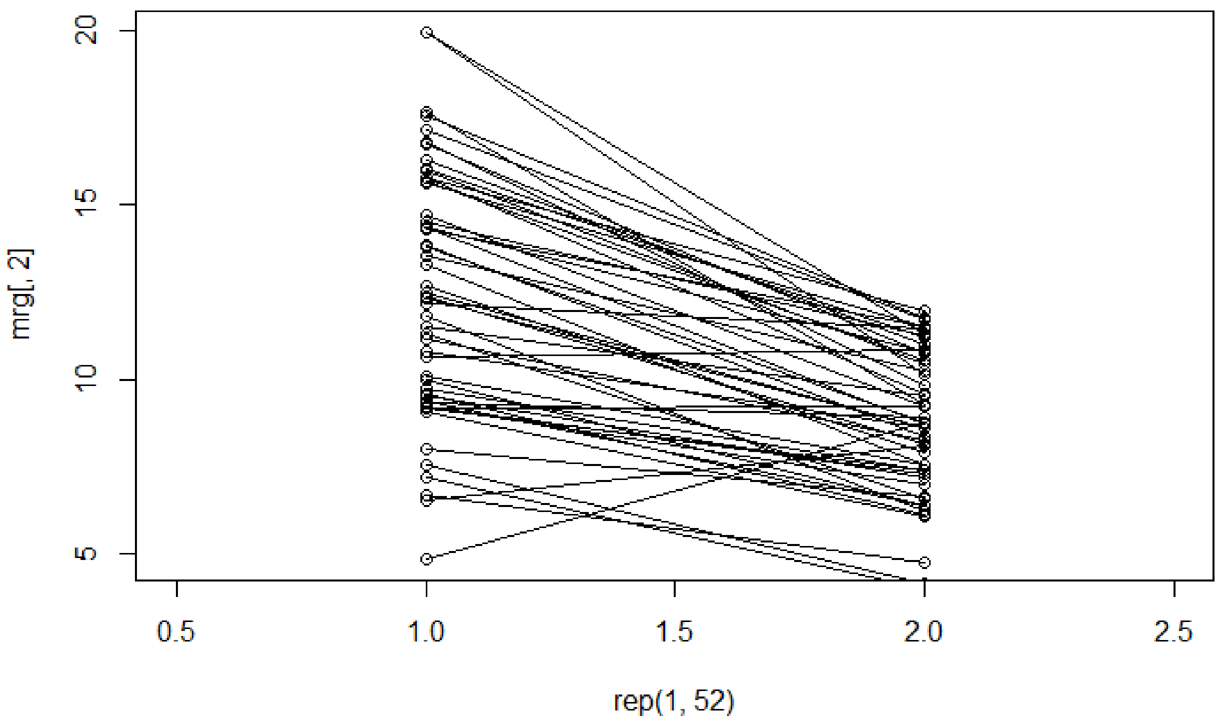

x0sub
10
20
30
40
Jul
Sep
Nov
Jan
dates0
x1sub
4
6
8
10
12
14
Jan 01
Feb 01
Mar 01
dates1
x0sub
10
20
30
40
Jul
Sep
Nov
Jan
dates0
x1sub
10
20
30
40
Jan 01
Feb 01
Mar 01
dates1



20
15
10
5
mrg[, 2]
0.5
1.0
1.5
2.0
2.5
rep(1, 52)



20
15
10
5
mrg[, 2]
0.5
1.0
1.5
2.0
2.5
rep(1, 52)



20
15
10
5
mrg[, 2]
0.5
1.0
1.5
2.0
2.5
rep(1, 52)