HW10_106022103

106022103

2021/5/2

Assist

- Disscussed with `106000199`, and she helped me for
  - how to get a row/col in a matrix
  - how to rename a matrix

Set up

import libary

```
library(data.table)
library(lsa)
```

Useful function

```
# function provided by teacher
interactive_regression <- function() {
  cat("Click on the plot to create data points; hit [esc] to stop")
  plot(NA, xlim=c(-5,50), ylim=c(-5,50))
  points = data.frame()
  repeat {
    click_loc <- locator(1)
    if (is.null(click_loc)) break
    if(nrow(points) == 0 ) {
      points <- data.frame(x=click_loc$x, y=click_loc$y)
    } else {
      points <- rbind(points, c(click_loc$x, click_loc$y))
    }
    plot(points, xlim=c(-5,50), ylim=c(-5,50), pch=19, cex=2, col="gray")
    if (nrow(points) < 2) next

    model <- lm(points$y ~ points$x)
    abline(model, lwd=2, col="cornflowerblue")
    text(1, 50, paste(c("Raw intercept: ", round(model$coefficients[1], 2)), collapse=" "))
    text(1, 45, paste(c("Raw slope    : ", round(model$coefficients[2], 2)), collapse=" "))
    text(1, 40, paste(c("Correlation  : ", round(cor(points$x, points$y), 2)), collapse=" "))
  }

  return(points)
}
```

Read File

```
ac_bundles_dt <- fread("data/piccollage_accounts_bundles.csv")
ac_bundles_matrix <- as.matrix(ac_bundles_dt[, -1, with=FALSE])
```

Q1

(a) explore sticker bundles

i. How many recommendations does each bundle have **ANSWER:** There are 6 recommendations.

ii. Find a single sticker bundle, and recommend five other bundles in our dataset that might have similar usage patterns as this bundle. **ANSWER:**

- I Choose the bundle **doodleholiday**
- I guess the similar bundles: **washiholiday**, **hipsterholiday**, **jollyholiday**, **holidaycheers**, **pacmanholiday**

(b) geometric models of similarity

i. cosine similarity

Create a matrix or data.frame of the top 5 recommendations for all bundles
Create a new function that automates the above functionality: it should take an accounts-bundles matrix as a parameter, and return a data object with the top 5 recommendations for each bundle in our data set, using cosine similarity.
What are the top 5 recommendations for the bundle you chose to explore earlier?

```
# Create a new function
# return a top-k similar items
topK_similar <- function(M, k = 5){
  M_consine <- cosine(M)
  N <- NCOL(M) # how many items
  topK_martix <- t(sapply(1:N,
                  function(x) {
                      names(sort(M_consine[x,], decreasing = TRUE)[2:(k+1)])
                    })) # the first will be itself
  rownames(topK_martix) <- colnames(M)
  colnames(topK_martix) <- sapply(1:k, function(x) {sprintf("Top%d",x)})
  topK_martix
}
```

```
ac_bundles_top5 <- topK_similar(ac_bundles_matrix)
ac_bundles_top5["doodleholiday",]
```

```
##          Top1          Top2          Top3          Top4          Top5
##      "bemine"   "cutoutluv" "ladolcevita"  "stationery"  "watercolor"
```

```
ac_bundles_matrix_mc_col <- apply(ac_bundles_matrix, 2,
                                  function(x) {x-mean(x)}) # 1:row op, 2:col op
ac_bundles_mc_col_top5 <- topK_similar(ac_bundles_matrix_mc_col)
ac_bundles_mc_col_top5["doodleholiday",]
```

ii. correlation based recommendations

```
##          Top1          Top2          Top3          Top4          Top5
##      "bemine"   "cutoutluv" "ladolcevita"  "stationery"  "watercolor"
```

```r
ac_bundles_matrix_mc_row <- t(apply(ac_bundles_matrix, 1,
                                    function(x) {x-mean(x)})) # 1:row op, 2:col op
ac_bundles_mc_row_top5 <- topK_similar(ac_bundles_matrix_mc_row)
ac_bundles_mc_row_top5["doodleholiday",]
```

iii. adjusted-cosine based recommendations

```
##             Top1             Top2             Top3             Top4
##      "cutoutluv"         "bemine"    "ladolcevita"  "cutevalentine"
##             Top5
## "eastersurprise"
```

(c) (not graded) Why and what differenct in these three sets of geometric recommendations and the recommendations you picked earlier using your intuition alone?

ANSWER: These three sets of geometric recommendations are totally same but different with my guess. The possible reason is the recommendations I picked are just a guess without any data.

(d) (not graded) What do you think is the conceptual difference in cosine similarity, correlation, and adjusted-cosine?

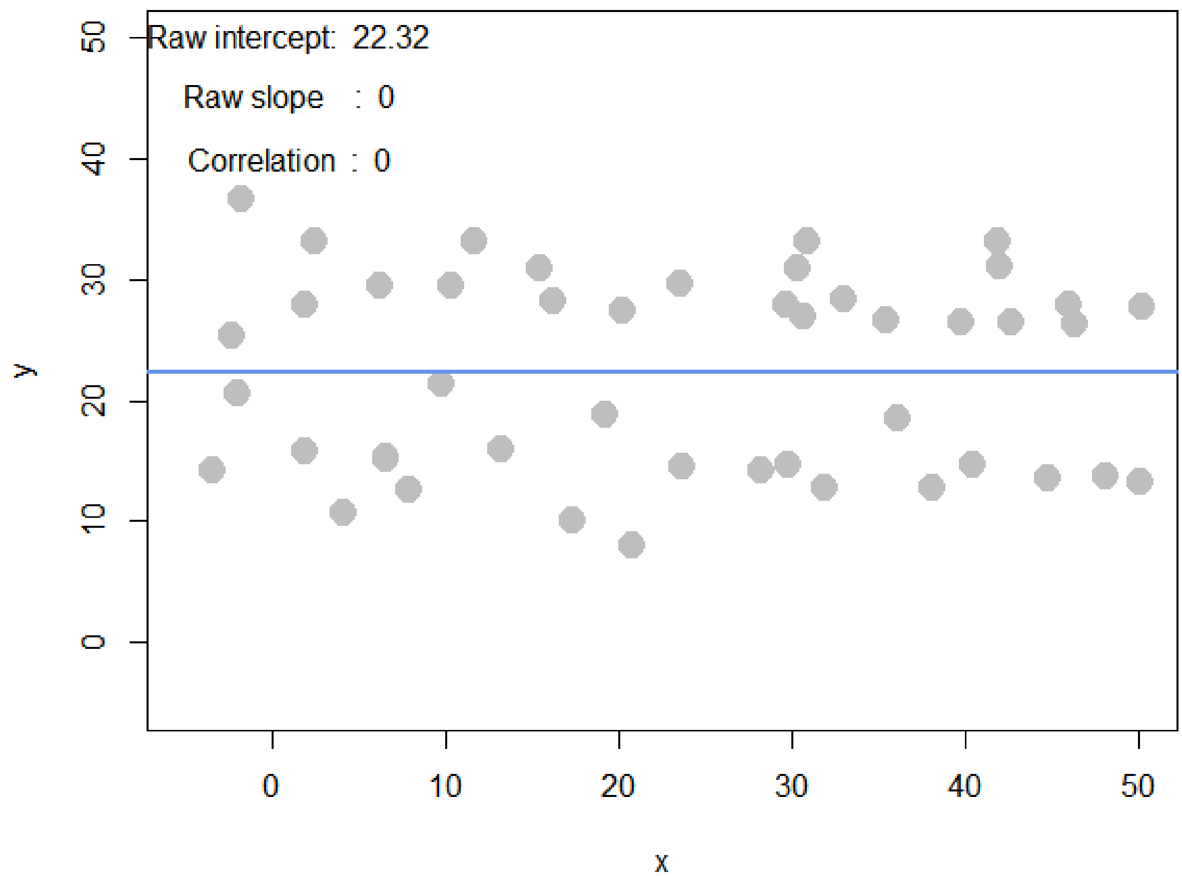
ANSWER:

- cosine similarity: Take the items as **vector**s, and defines the similarity between them as **the angle between these vectors** .
- correlation: The **difference in rating scale between different users are not taken into account.** To adjusted cosine similarity offsets this drawback, correlation is based on how much the ratings by common users for a pair of items deviate from average ratings for those items.
- adjusted-cosine: **Different users have different ratings schemes.** To adjusted cosine similarity offsets this drawback,

Q2

(a) Create a horizontal set of random points, with a relatively narrow but flat distribution.

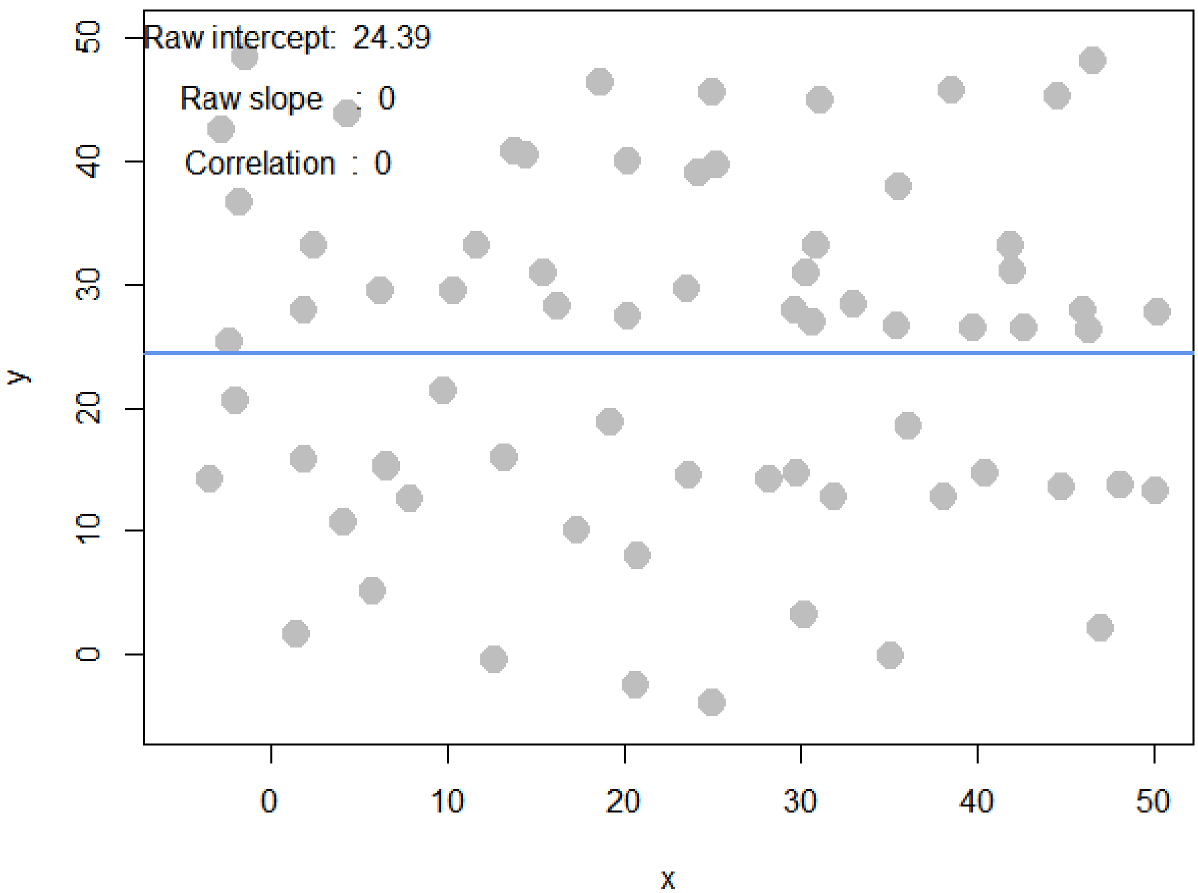
ANSWER:



- I expect the slope will be around 0.
- I expect the correlation will be around 0.
- The result is similar to what I expected.

(b)

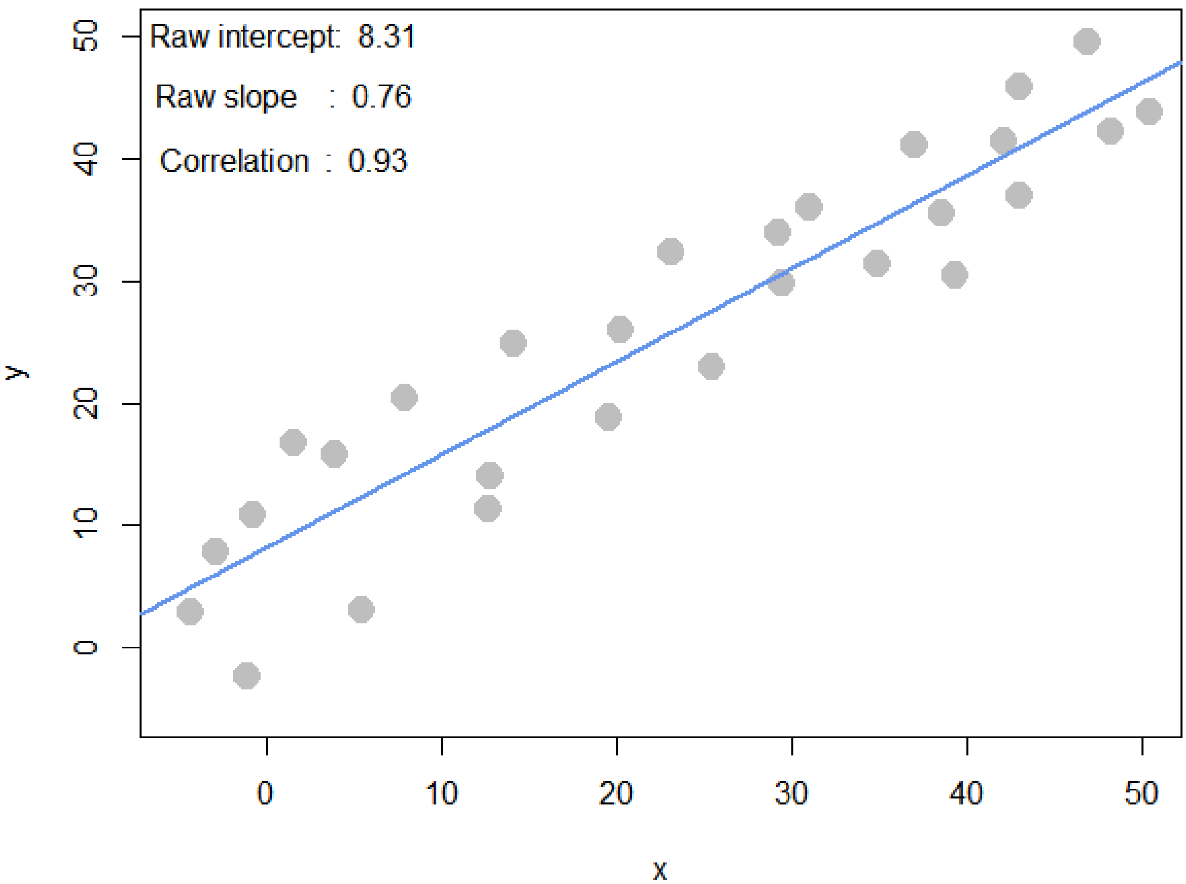
ANSWER:



- I expect the slope will be around 0.
- I expect the correlation will be around 0.
- The result is similar to what I expected.

(c)

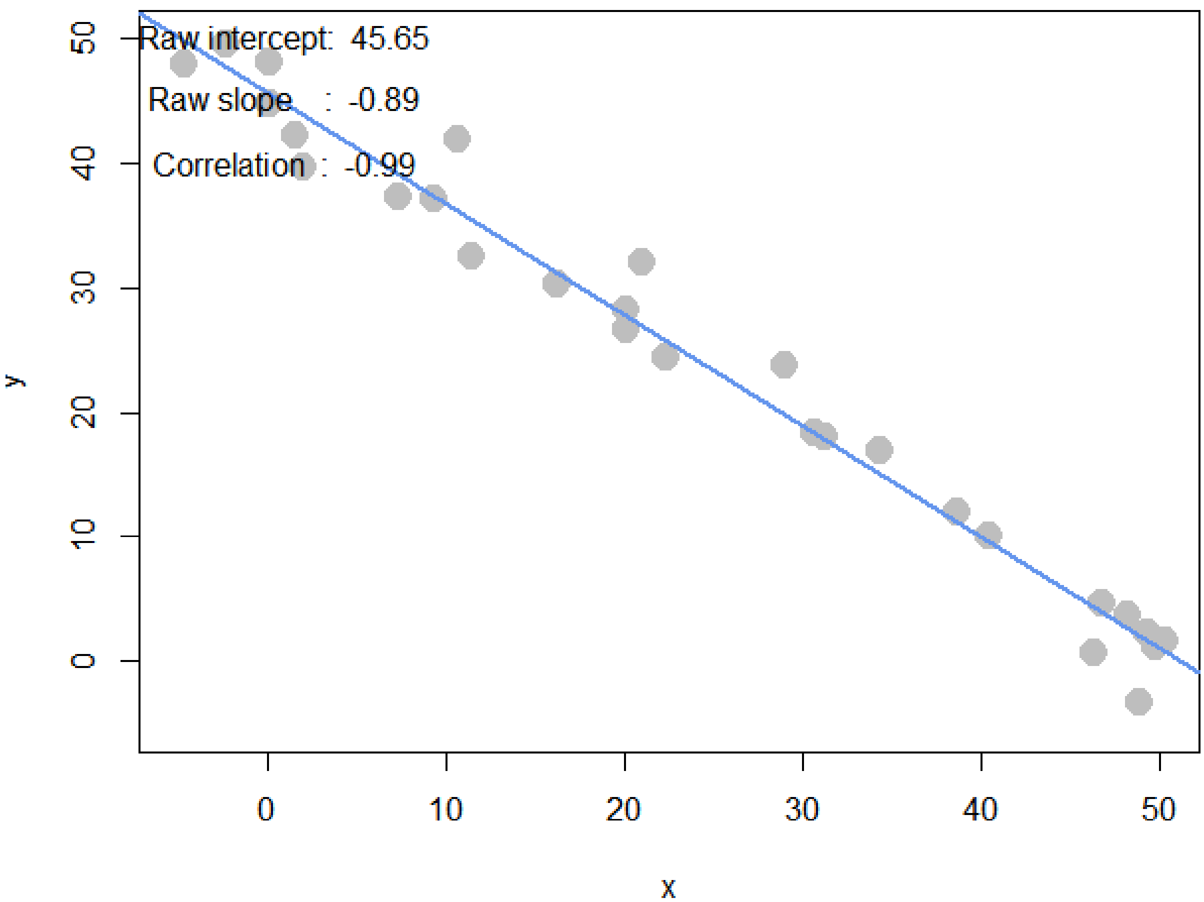
ANSWER:



- I expect the slope will be around 1.
- I expect the correlation will be around 1.
- The result of correlation is similar to what I expected, and there is a little difference between 1 and 0.76. I think it just because the diagonal set I drew is not a perfect 45-degree trend.

(d)

ANSWER:

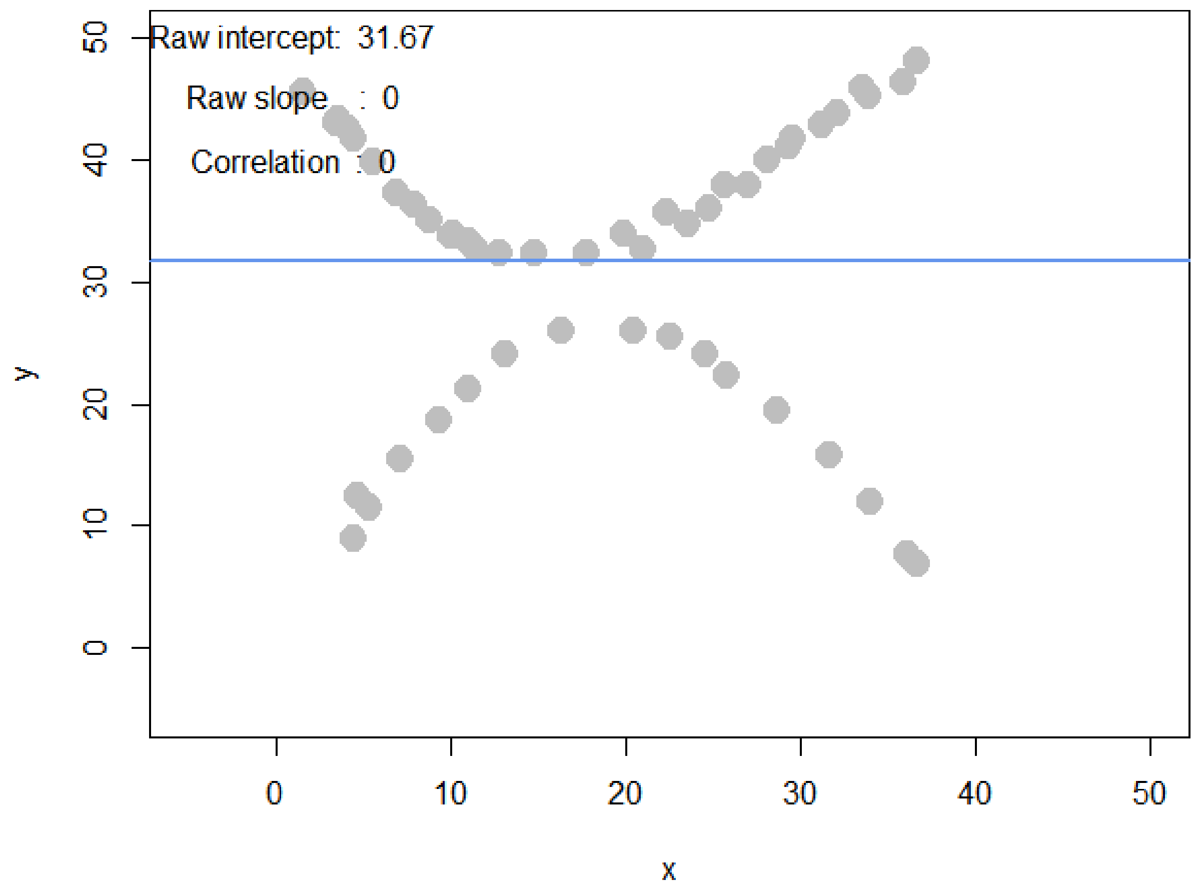


- I expect the slope will be around -1.
- I expect the correlation will be around -1.
- The result is similar to what I expected. Notice the correlation should be -1 instaed of 1 because they are **nagtive correlation**

(e) Apart from any of the above scenarios, find another pattern of data points with no correlation ($r \approx 0$).

(optionally: can create a pattern that visually suggests a strong relationship but produces $r \approx 0$?)

ANSWER:

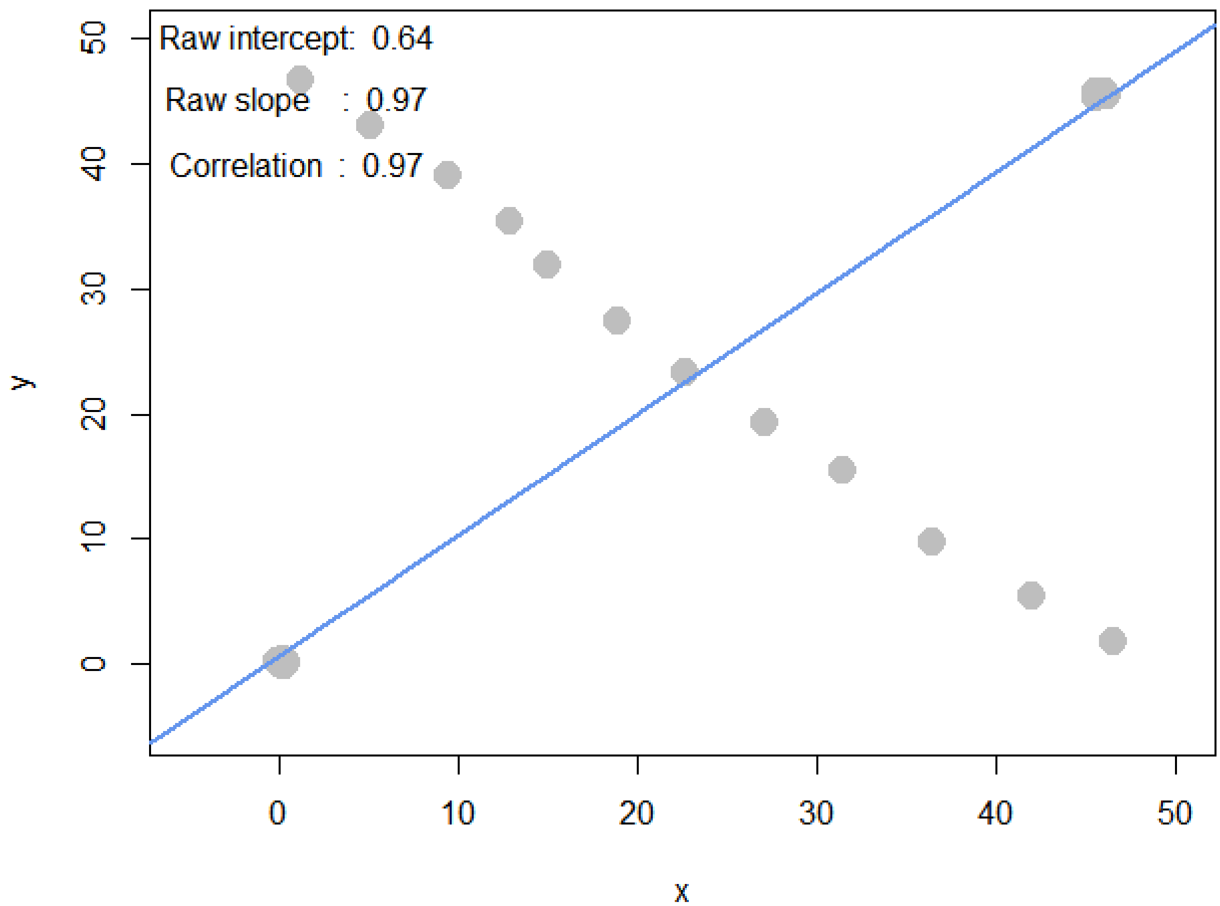


- As the diagonal showed, we can see there are two curve relation.
- However, the correlation is 0.

(f) Apart from any of the above scenarios, find another pattern of data points with perfect correlation ($r \approx 1$).

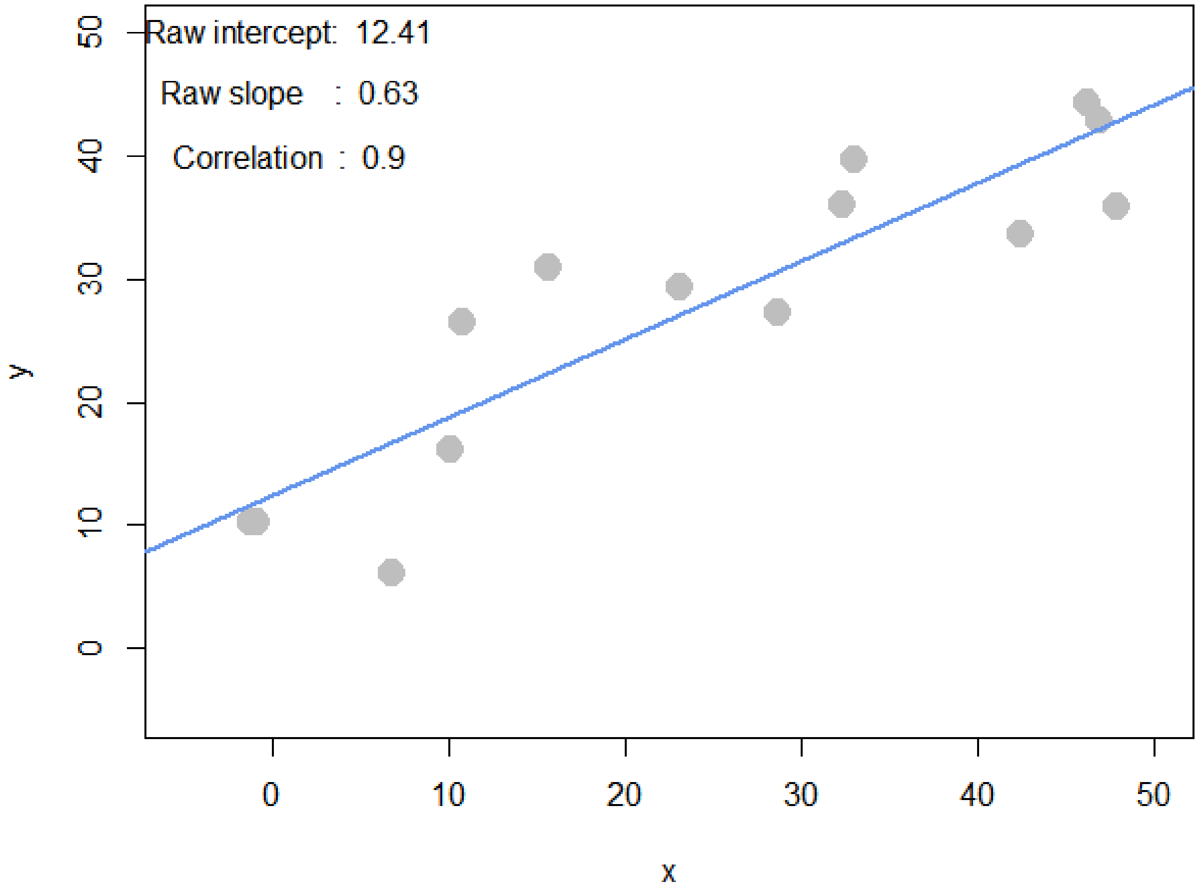
(optionally: can you find a scenario where the pattern visually suggests a different relationship?)

ANSWER:



(g)

Because `interactive_regression` can't run in Rmarkdown knit, we have to run these commands in console and save the variables `pts`.




```
pts <- interactive_regression()
saveRDS(pts, file = "W:/Rtmp/pts.rds")
```

```
pts <- readRDS(file = "W:/Rtmp/pts.rds")
summary( lm( pts$y ~ pts$x ))
```

```
##
## Call:
## lm(formula = pts$y ~ pts$x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.4920  -3.0704  -0.2273   3.0828   8.6915
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 12.41134    2.69741   4.601  0.00061 ***
## pts$x        0.63442    0.09072   6.993 1.45e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.792 on 12 degrees of freedom
```

```
## Multiple R-squared:  0.803,  Adjusted R-squared:  0.7866
## F-statistic: 48.91 on 1 and 12 DF,  p-value: 1.448e-05
```

```
pts["Normilized_x"] <- as.data.frame(scale(pts$x))
pts["Normilized_y"] <- as.data.frame(scale(pts$y))
cor(pts)
```

```
##                      x         y Normilized_x Normilized_y
## x            1.0000000 0.8960905    1.0000000    0.8960905
## y            0.8960905 1.0000000    0.8960905    1.0000000
## Normilized_x 1.0000000 0.8960905    1.0000000    0.8960905
## Normilized_y 0.8960905 1.0000000    0.8960905    1.0000000
```

ANSWER: The relationship between correlation and the standardized simple-regression estimates are totally same.

Reference Link

- The Number of Rows/Columns of an Array
- Matrix Function in R – Master the apply() and sapply() functions in R
- Named Vectors
- R - order(),sort(),rank()
- Extract matrix column values by matrix column name
- Working with data in a matrix
- Correlation Coefficient
- Item-based collaborative filtering
- Adjusted Cosine Similarity
- R saveRDS Function