HW9

108048110

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BACS HW - Week 9

Prerequisite

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

```
## Warning: package 'data.table' was built under R version 4.1.2
```

```
bundle_dt <- fread('piccollage_accounts_bundles.csv')
bundle_m <- as.matrix(bundle_dt[,-1])
```

Question 1) Making an automated recommendation system for the PicCollage mobile app.

a. Explore to see if any sticker bundles seem intuitively similar.

i. Download `PicCollage` and take look at the style and content of bundles in their Sticker Store.

- How many recommendations does each bundle have?
  Ans. 6

```r
head(colnames(bundle_dt))
```

ii. Find a sticker bundle that is both in our limited data set and also in the app's Sticker Store. Use your intuition to guess 5 other bundles in our dataset that might have similar usage patterns as this bundle.

```
## [1] "account_id"     "Maroon5V"       "between"        "pellington"
## [5] "StickerLite"    "saintvalentine"
```

```r
set.seed(125)
sticker_num <- round(runif(1, 0, 166), 0)
cat(sticker_num)
```

```
## 137
```

```r
names(bundle_dt[,137])
```

```
## [1] "cutevalentine"
```

- **Intuition:** I'm guessing `Valentine stickers`, `happy`, `Saint Valentine`, `Heart Sticker Pack`, `Valentine 2013 Sticker Pack`
  - **Note.** I randomly choose the $137th$ sticker lies in the given bundles, which is **`cute valentine`**. However, there is no `cute valentine` in the app store, but `cute valentines`.

```r
names(bundle_dt[,c(6, 18, 44, 66, 119)])
```

```
## [1] "saintvalentine"          "HeartStickerPack"
## [3] "happy"                   "Valentine2013StickerPack"
## [5] "valentineStickers"
```

b. Find similar bundles using geometric models of similarity.

i. Cosine Similarity

1. Create a matrix or data.frame of the top 5 recommendations for all bundles.
2. Create a new function that automates the functionality: 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.
3. What are the top 5 recommendations for the bundle you chose to explore earlier?

```r
 library(lsa)
```

```
## Loading required package: SnowballC
```

```r
cosine_m <- cosine(bundle_m)

# After passing a matrix into sort_names,
# the function will sort each row values in a decreasing order,
# and then returns a recommendation list.
sort_name <- function(m){

  # 1 is for checking on the values
  total_m <- list()

  for(i in 1:length(colnames(m))){
    temp = as.matrix(t(sort(m[i,], decreasing = TRUE)))
    if(i==1){
      total_m$new_m <- colnames(temp)
      total_m$new_v <- temp
    }else{
    total_m$new_m <- rbind(total_m$new_m, colnames(temp))
    total_m$new_v <- rbind(total_m$new_v, temp)
    }
  }
  return(total_m)
}

# this function caluculates the cosine similarity,
# and then pass the matric to the above sort_names function;
# eventually returns a recommendation list.

recommend <- function(m, FUN='cos'){

  M <- list()

  if(FUN=='cos'){
    c_m <- cosine(m)
  }else if(FUN=='cor'){
    c_m <- cor(m)
  }
  M$new_m <- sort_name(c_m)$new_m
  M$corr_v <- c_m
  row.names(M$new_m) <- colnames(cosine_m)
  colnames(M$new_m) <- 1:length(colnames(cosine_m))
  row.names(M$corr_v) <- colnames(cosine_m)
  colnames(M$corr_v) <- colnames(cosine_m)
  return(M)
}


new_m <- sort_name(cosine_m)$new_m

new_v <- sort_name(cosine_m)$new_v
row.names(new_m) <- colnames(cosine_m)
colnames(new_m) <- 1:length(colnames(cosine_m))

knitr::kable(new_m[1:3, 1:6])
```

	1	2	3	4	5	6
Maroon5V	Maroon5V	OddAnatomy	beatsmusic	xoxo	alien	word
between	between	BlingStickerPack	xoxo	gwen	OddAnatomy	AccessoriesStickerPack
pellington	pellington	springrose	8bit2	mmlm	julyfourth	tropicalparadise

ii. Correlation

1. Reuse the function you created above (don't change it.)
2. Give the function an accounts-bundles matrix where each bundle has already been mean-centered in advance.
3. Now what are the top **5** recommendations for the bundle you chose to explore earlier?

```
cosine_similarity_m <- recommend(bundle_m)$new_m
knitr::kable(head(cosine_similarity_m['cutevalentine',]))
```

x
cutevalentine
happy
starrytribe
ladolcevita
cutoutluv
watercolor

```
cal_corr <- function(m){
  MAX <- max(ncol(m), nrow(m))
  bundle_means <- apply(m, 2, mean)
  bundle_means_m <- t(replicate(nrow(m), bundle_means))
  bundle_corr_m <- m-bundle_means_m
  if (ncol(bundle_corr_m)==MAX) {new_m <- cosine(t(bundle_corr_m))}
  else {new_m <- cosine(bundle_corr_m)}
  return(new_m)
}

bundle_cor_m <- cal_corr(bundle_m)
knitr::kable(bundle_cor_m[1:6,1:6])
```

	Maroon5V	between	pellington	StickerLite	saintvalentine	HipsterChicSara
Maroon5V	1.0000000	0.3404237	0.0833948	0.1819977	0.1264803	0.1738999
between	0.3404237	1.0000000	0.0448948	0.2510295	0.0451938	0.1315935
pellington	0.0833948	0.0448948	1.0000000	0.0580603	0.0388991	0.0351444
StickerLite	0.1819977	0.2510295	0.0580603	1.0000000	0.0982191	0.2443120
saintvalentine	0.1264803	0.0451938	0.0388991	0.0982191	1.0000000	0.0422198
HipsterChicSara	0.1738999	0.1315935	0.0351444	0.2443120	0.0422198	1.0000000

```
correlation_m <- recommend(bundle_cor_m)$new_m
correlation_v <- recommend(bundle_cor_m)$corr_v
# Just to make sure.
# correlation_m <- recommend(bundle_m, FUN='cor')
```

```
knitr::kable(head(correlation_m['cutevalentine',]))
```

x
cutevalentine
starrytribe
happy
ladolcevita
cutoutluv
supersassy

iii. Adjusted-Cosine

1. Reuse the function you created above (don't change it.)
2. Give the function an accounts-bundles matrix where each bundle has already been mean-centered in advance.
3. Now what are the top **5** recommendations for the bundle you chose to explore earlier?

```
temp <- as.data.frame(bundle_dt[,-1])
temp <- transpose(temp, keep.names = 'rn')
row.names(temp) <- temp$rn
temp = as.matrix(temp[,-1])
adjust_cosine_m <- cal_corr(temp)
knitr::kable(adjust_cosine_m[1:6,1:6])
```

	Maroon5V	between	pellington	StickerLite	saintvalentine	HipsterChicSara
Maroon5V	1.0000000	0.1935507	-0.1122475	0.0071392	-0.0264064	0.0464890
between	0.1935507	1.0000000	-0.3509766	0.1422776	-0.2625570	0.0263532
pellington	-0.1122475	-0.3509766	1.0000000	-0.5207707	0.4303719	-0.3106207
StickerLite	0.0071392	0.1422776	-0.5207707	1.0000000	-0.3580384	0.2275033
saintvalentine	-0.0264064	-0.2625570	0.4303719	-0.3580384	1.0000000	-0.2268427
HipsterChicSara	0.0464890	0.0263532	-0.3106207	0.2275033	-0.2268427	1.0000000

```
ad_cosine_m <- recommend(adjust_cosine_m)$new_m
ad_cosine_v <- recommend(adjust_cosine_m)$new_v
knitr::kable(head(ad_cosine_m['cutevalentine',]))
```

x
cutevalentine
ladolcevita
cutoutluv
supersassy
hipsteroverlays
eastersurprise

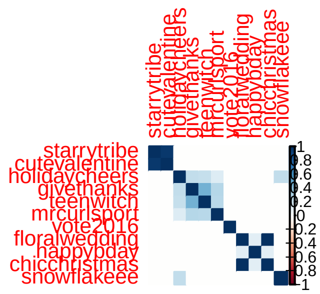
Visualization

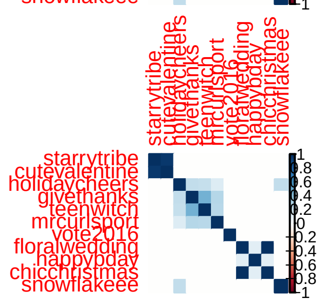
```
library(corrplot)
```

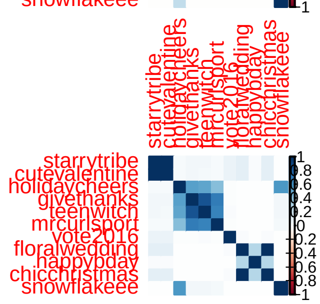
```
## Warning: package 'corrplot' was built under R version 4.1.3

## corrplot 0.92 loaded
```

```
par(mfrow=c(3,1))
corr_m <- cor(bundle_m)
corrplot(corr_m[135:145, 135:145], method='color')
corrplot(bundle_cor_m[135:145,135:145], method='color')
corrplot(correlation_v[135:145, 135:145], method='color')
```







c. Are the 3 sets of recommendations similar in nature to the recommendations you picked earlier using your intuition alone? What reasons might explain why your recommendation models produce different results from your intuition?

- **Ans.** No, it's not similar at all! I choose the following 5 recommendation based on the names of the sticker bundles, while my recommendation model calculates the sets based on the cosine similarity of an actual usage data.

d. What do you think is the conceptual difference in cosine similarity, correlation, and adjusted-cosine?

- **Ans.**

- **Cosine Similarity**

  Cosine similarity is a measure of similarity between two non-zero vectors of an inner product space that measures the cosine of the angle between them.

  For example, in text mining, each term is notionally assigned a different dimension and a document is characterized by a vector where the value of each dimension corresponds to the number of times that term appears in the document. Cosine similarity then gives a useful measure of how similar two documents are likely to be in terms of their subject matter.

- **Correlation**

  Correlation is calculated based on how much the ratings by common users for a pair of items deviate from average ratings for those items.

- **Adjusted-Cosine similarity**

  Adjusted cosine similarity measure is a modified form of cosine similarity where we take into account that different users have different ratings schemes; in other words, some users might rate items highly in general, and others might give items lower ratings as a preference.

- One fundamental difference between cosine and adjusted-cosine similarity is that the former method is computed along the rows of the matrix but in case of the item-based CF the similarity is computed along the columns.

  Computing bundles similarity using basic `cosine measure` has one important drawback, the difference in rating scale between different accounts are not taken into account. The `adjusted cosine similarity` offsets this drawback by subtracting the corresponding user average from each co-rated pair.

Prerequisite

```
if(!exists('foo',mode='function')) source("demo_simple_regression.R")
#interactive_regression()
```

Question 2) Correlation

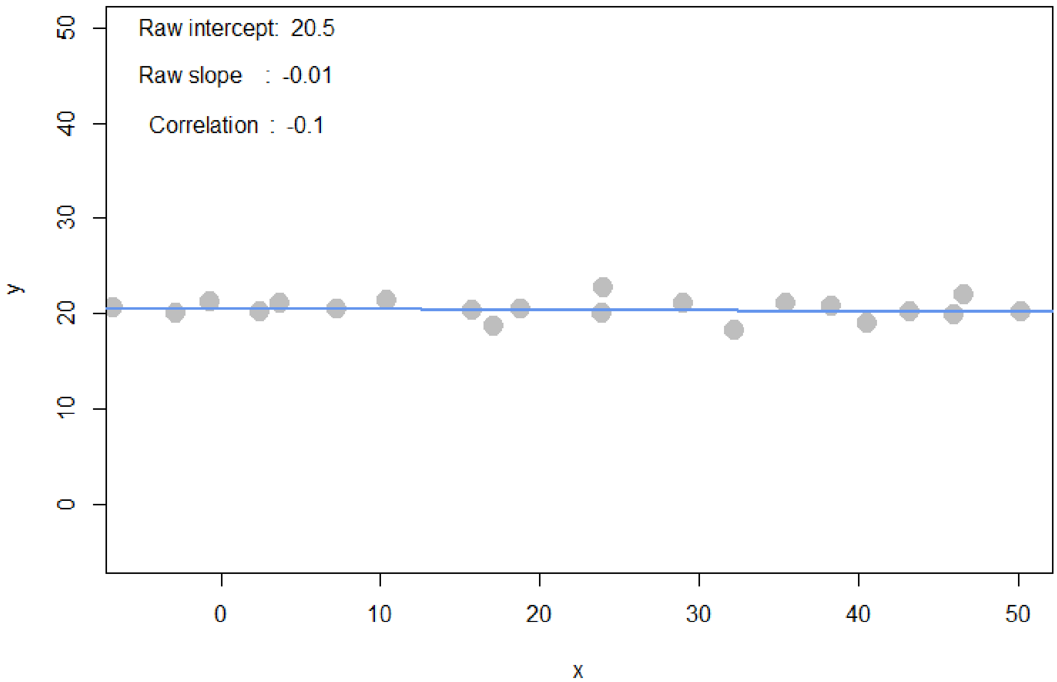
a. Create a horizontal set of random points, with a relatively narrow but flat distribution.

i. What raw slope of x and y would you generally expect?

- **Ans.** Raw slope of x and y is expected to be 0.

ii. What is the correlation of x and y that you would generally expect?

- **Ans.** Correlation is expected to be 0. (ie. No relationship is between them at all)



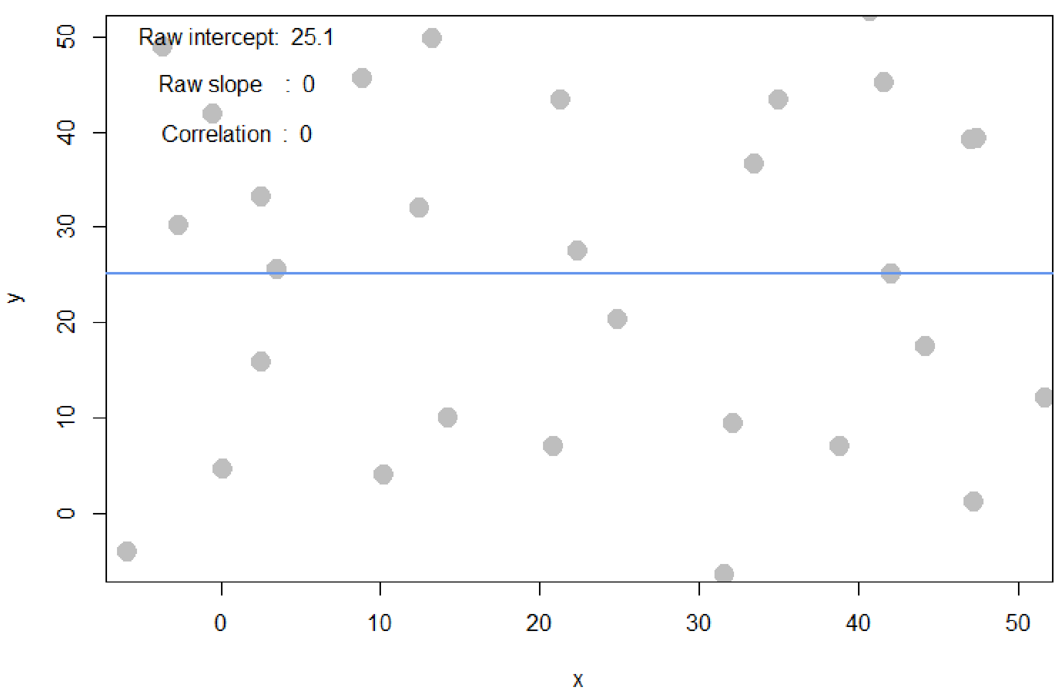
b. Create a completely random set of points to fill the entire plotting area, along both x-axis and y-axis.

i. What raw slope of x and y would you generally expect?

- **Ans.** Raw slope of x and y is expected to be 0.

ii. What is the correlation of x and y that you would generally expect?

- **Ans.** Correlation is expected to be 0. (ie. No relationship is between them at all)



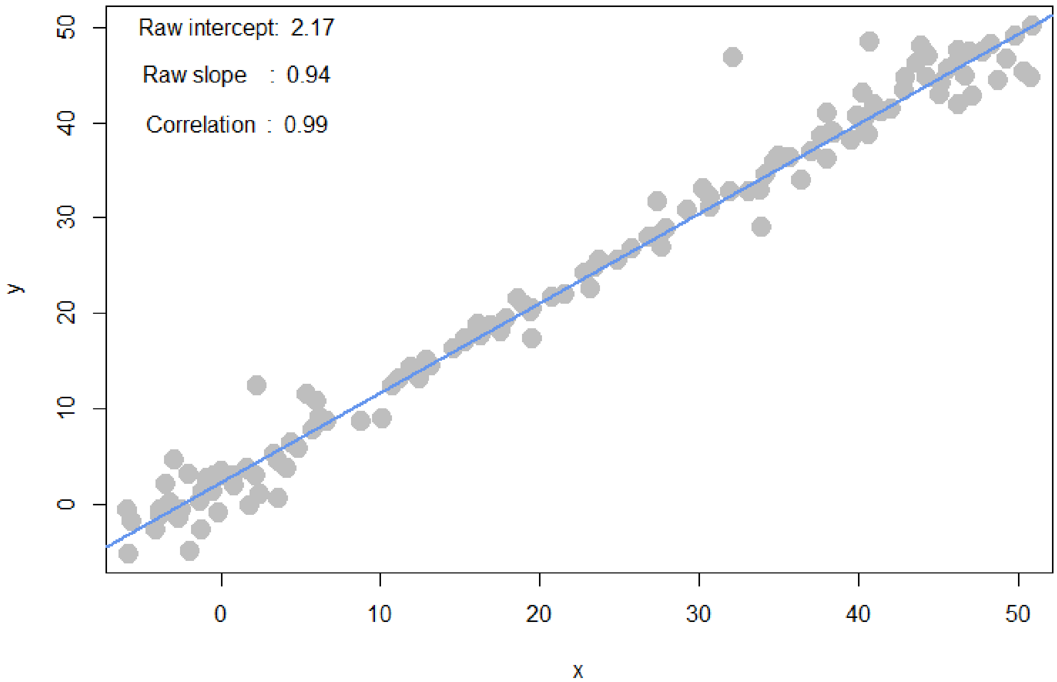
c. Create a diagonal set of random points trending upwards at 45 degrees.

i. What raw slope of x and y would you generally expect?

- **Ans.** Raw slope of x and y is expected to be 1.

ii. What is the correlation of x and y that you would generally expect?

- **Ans.** Correlation is expected to be 1.



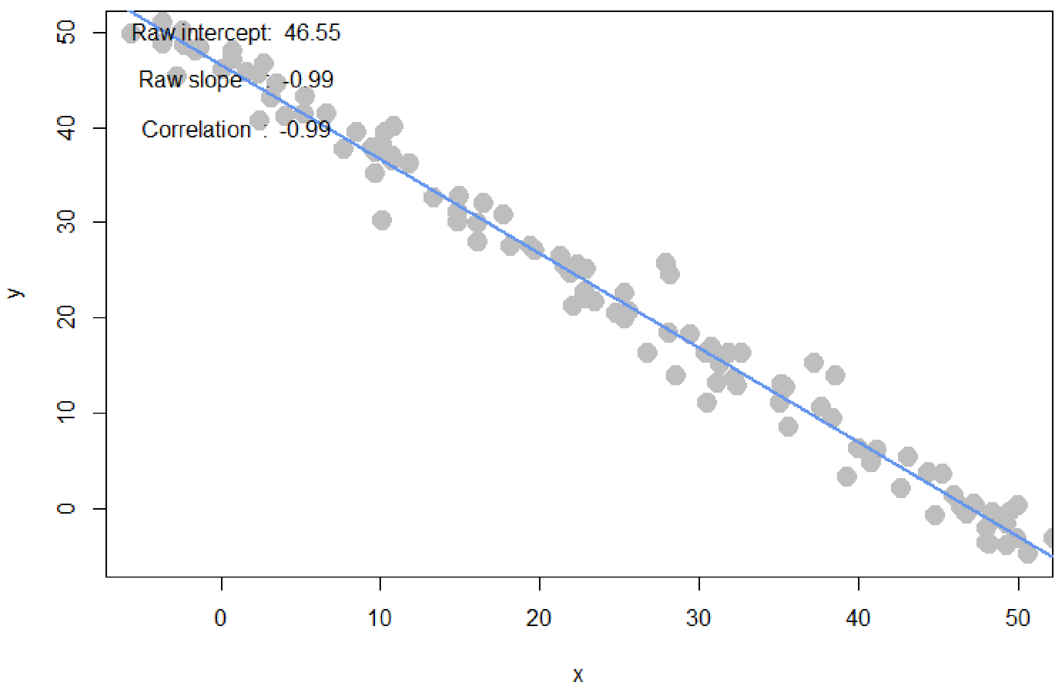
d. Create a diagonal set of random trending downwards at 45 degrees.

i. What raw slope of x and y would you generally expect?

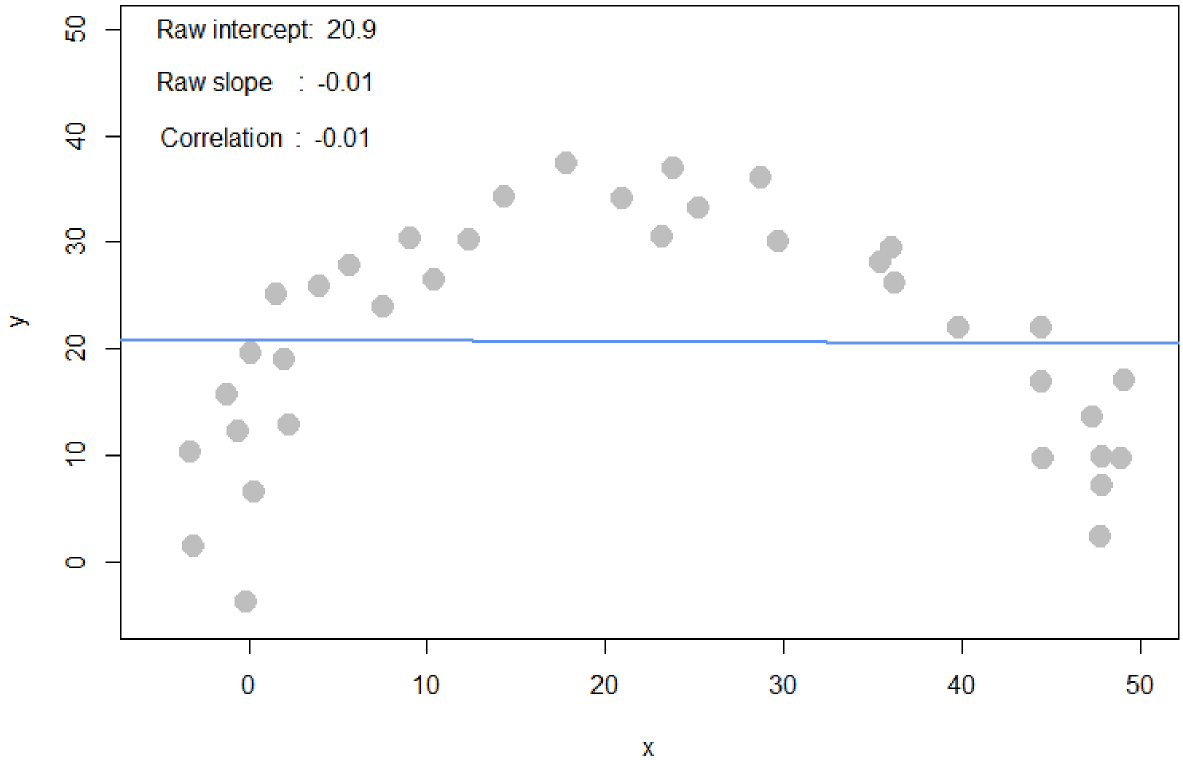
- **Ans.** Raw slope of x and y is expected to be -1.

ii. What is the correlation of x and y that you would generally expect?

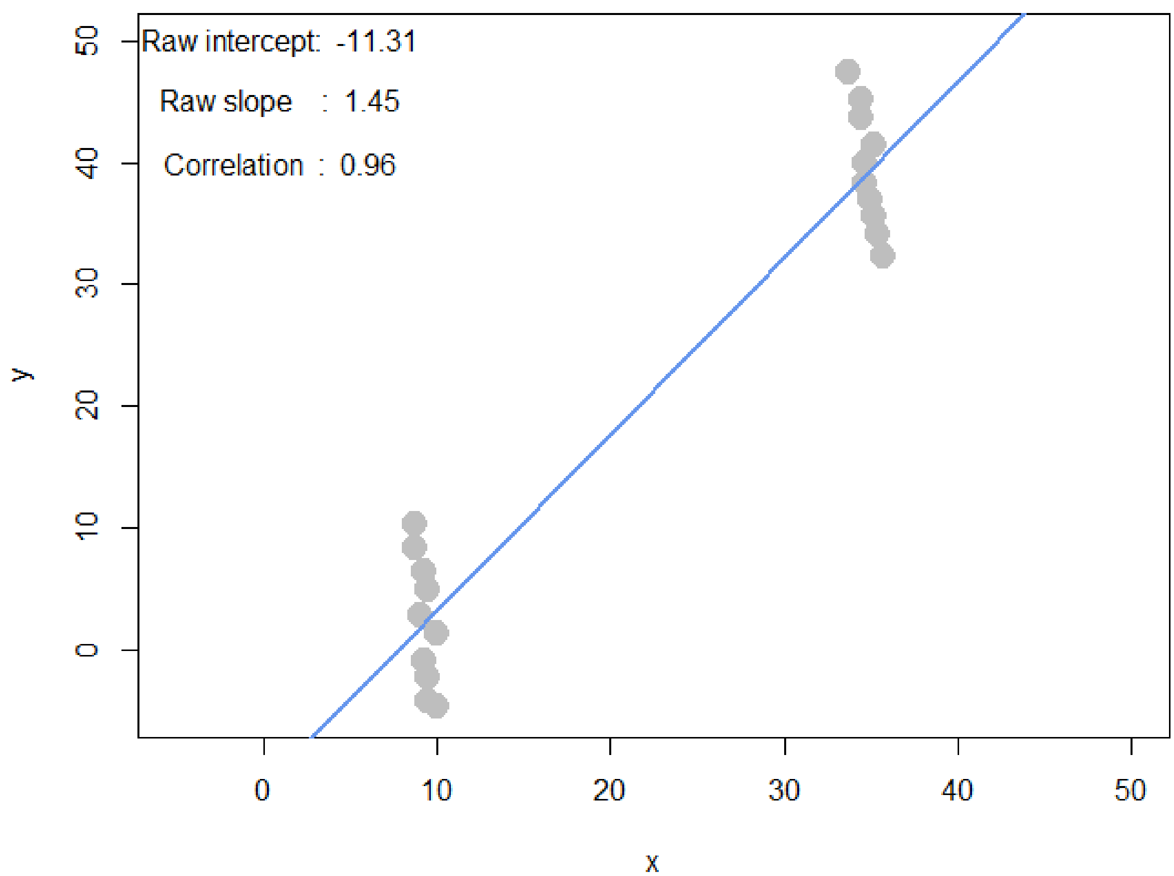
- **Ans.** Correlation is expected to be -1.


Raw intercept: 46.55
Raw slope : -0.99
Correlation : -0.99
y
x
0
10
20
30
40
50

e. Find another pattern of data points with no correlation (r 0). (Create a pattern that visually suggests a strong relationship but produces r 0?)



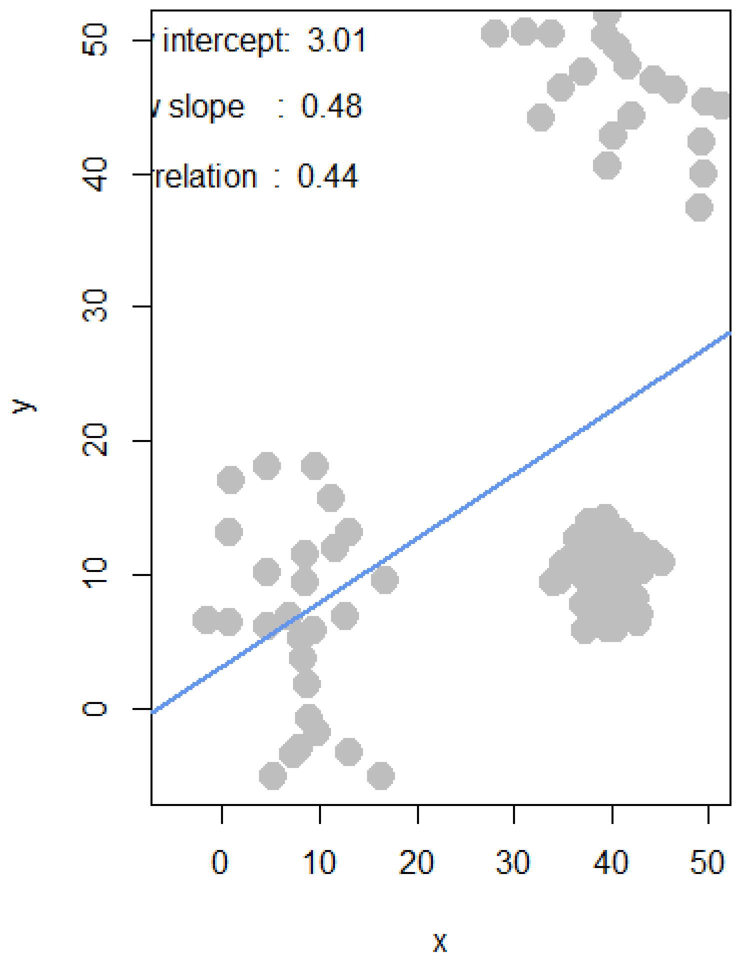
f. Find another pattern of data points with perfect correlation (r   1). (Find a scenario where the pattern visually suggests a different relationship?)



g. Let's see how correlation relates to simple regression, by simulating any linear relationship you wish:

```
#pts <- interactive_regression()
```

i. Run the simulation and record the points you create: `pts <- interactive_regression()`**:**




```
#summary(lm(pts$y ~ pts$x))
```

ii. Use the `lm()` **function to estimate the regression intercept and slope of** `pts` **to ensure they are the same as the values reported in the simulation plot:** `summary( lm( pts$y ~ pts$x ))`

Table 7: Residuals

Min	1Q	Median	3Q	Max
-17.235	-12.249	-7.866	11.708	330821

Table 8: Coefficients

	Estimate	**Std Err**	t value	prob($> \|t\|$)
Intercept	3.015	3.619	0.833	0.407
pts$x	0.479	0.108	4.442	0

Residual Standard Error	15.34
Multiple R-squared	0.196
Adjusted R-squared	0.186
F-statistic	19.73
Degree of Freedom	81
p-value	0

```
#cor(pts)
```

iii. Estimate the correlation of x and y to see it is the same as reported in the plot: `cor(pts)`

Table 10: Correlation of `x` and `y`

	x	**y**
x	1	0.443
y	0.443	1

```
#standardize <- function(v){
  #diff <- v - mean(v)
  #std <- sd(v)
  #return(diff/std)
#}

#standardized_df <- data.frame(x=standardize(pts$x),
 #                              y=standardize(pts$y))

#knitr::kable(standardized_df)
```

iv. Now, standardize the values of both `x` and `y` from `pts` and re-estimate the regression slope.

- **Thoughts:** I'm guessing that the regression slope wouldn't change.

Table 11: Residuals

Min	1Q	Median	3Q	Max
-1.014	-0.72	-0.462	0.689	1.9891

Table 12: Coefficients

	Estimate	Std Err	t value	Prob($> \|t\|$)
Interception	0	0	0	1
Standardized_df$x	0	0	4.442	0

Residual Standard Error	0.902
Multiple R-squared	0.196
Adjusted R-squared	0.186
F-statistic	19.73
Degree of Freedom	81
p-value	0

Table 14: Correlation of `x` and `y`

	x	y
x	1	0.443
y	0.443	1

```r
#summary(lm(standardized_df$y ~ standardized_df$x))
#cor(standardized_df)
```

v. What is the relationship between correlation and the standardized simple-regression estimates? Ans. The correlation values do not change.