HW10

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Question 1

a.

i. How many recommendations does each bundle have?

ANSWER : 6 recommendation per bundle(IOS).

ii. Use intuition to recommend 5 bundles!

ANSWER : I chose Maroon5v first, then my recommendation are as follows: 1.beatsmusic 2. MonsterHigh 3. RetroSummer 4. New Years Party 5. xoxo

b.

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

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

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

i. Create cosine similarities for all bundles

1. Create top 5 recommend matrix or df

```
similiar_matrix <- cosine(ac_bundles_matrix)
diag(similiar_matrix) <- 0 # won't be considered
recommend <- data.frame()
for(bundle in row.names(similiar_matrix)){
  recommend <- rbind(recommend,names(similiar_matrix[bundle, order(similiar_matrix[bundle,],dec
reasing = TRUE)]))
}
row.names(recommend) <- row.names(similiar_matrix)
colnames(recommend) <- c(1:ncol(similiar_matrix))
top5_recom <- recommend[,1:5]
head(top5_recom,3)
```

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

2. Create a function to create top 5 recommend matrix

```r
mk_recom5 <- function(ac_bundles_matrix){
  similiar_matrix <- cosine(ac_bundles_matrix)
  diag(similiar_matrix) <- 0 # won't be considered
  recommend <- data.frame()
  for(bundle in row.names(similiar_matrix)){
    recommend <- rbind(recommend,names(similiar_matrix[bundle, order(similiar_matrix[bundle,],d
ecreasing = TRUE)]))
  }
  row.names(recommend) <- row.names(similiar_matrix)
  colnames(recommend) <- c(1:ncol(similiar_matrix))
  top5_recom <- recommend[,1:5]
  return (top5_recom)
}
head(mk_recom5(ac_bundles_matrix),3)
```

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

3.Top 5 of your chosen bundles

```r
top5_recom["Maroon5V",]
```

```
##                   1           2    3     4    5
## Maroon5V OddAnatomy beatsmusic xoxo alien word
```

Not really surprised to see that Maroon5 is similiar to aliens, only aliens can make that kind of cool beatsmusic huh? Since aliens are here, it's quite normal that anatomy is here too. I heard that aliens are notorious for disecting homo sapiens, kinda gross lol.

ii. Create correlation based recommendations

```r
center_apply <- function(x) {
    apply(x, 2, function(y) y - mean(y))
}
centered_ac_bundles <- center_apply(ac_bundles_matrix)
head(mk_recom5(centered_ac_bundles),3)
```

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

The recommended items are still the same for Maroon5.

iii. Create adjusted cosine based recommendations

```
transpose_ac <- t(ac_bundles_matrix)
center_apply <- function(x) {
    apply(x, 2, function(y) y - mean(y))
}
t_centered_ac_bundles <- center_apply(transpose_ac)
t1_centered_ac_bundles <- t(t_centered_ac_bundles)
head(mk_recom5(t1_centered_ac_bundles),3)
```

```
##                            1     2          3                4           5
## Maroon5V          OddAnatomy  word       xoxo       beatsmusic   supercute
## between     BlingStickerPack  xoxo       gwen      Monsterhigh OddAnatomy
## pellington        springrose 8bit2 backtocool tropicalparadise julyfourth
```

The recommended items changes slightly here, Maroon 5 is not similiar to aliens, and beatsmusic differs to this bundle more. However, anatomy is still in first place, which is quite odd indeed.

c. Are the three sets of geometric recommendations similar in nature ? What reasons might explain why your computational geometric recommendation models produce different results from your intuition?

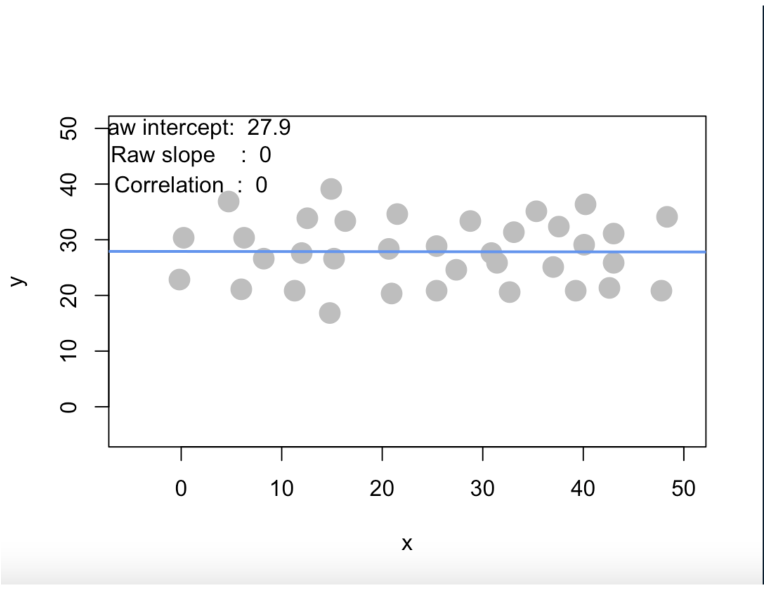
ANSWER : I guessed some right! However my guessing is just randomly picking the topics that I like, and the computational methods are based on distance, so obviously there will be difference.

d. Conceptual difference in cosine similarity, correlation, and adjusted-cosine?

1. Cosine similarity can only calculate on vectors, hence the items are embedded into vectors first to calculate cosine distance.
2. Correlation is a statistical measure which doesn't use distance as heuristic but the expectation of the inputted features.
3. In our case, the adjusted cosine method can maintain balance due to the randomness of different users that will give different ratings.

Question 2

a. Create horizontal random points



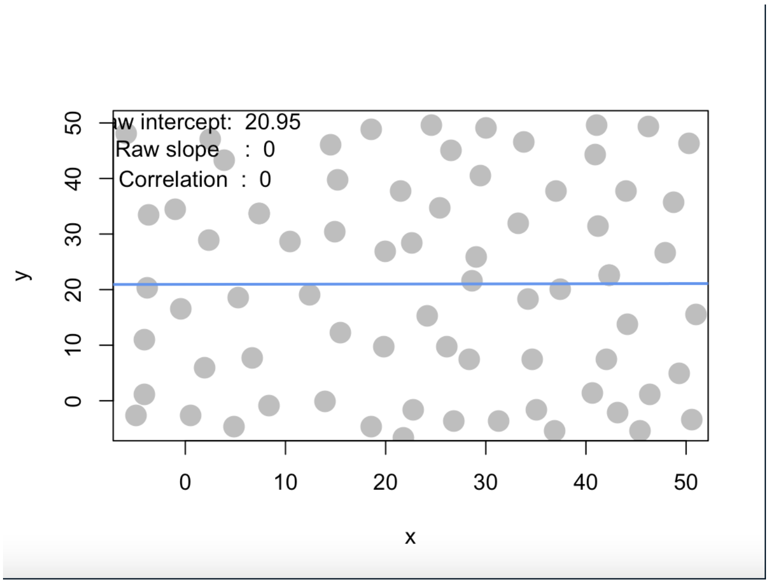
i. Raw Slope

ANSWER: Since the points are horizontal, the slope would be expected to be around zero $(0/x = 0)$, and thus the simulation proves it.

ii. Correlation

ANSWER: Since the points are horizontal, the y points only hover up and down in a little amount. Hence, we can expect the correlation to be zero, since y can be seen as not altered by increasing x.

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



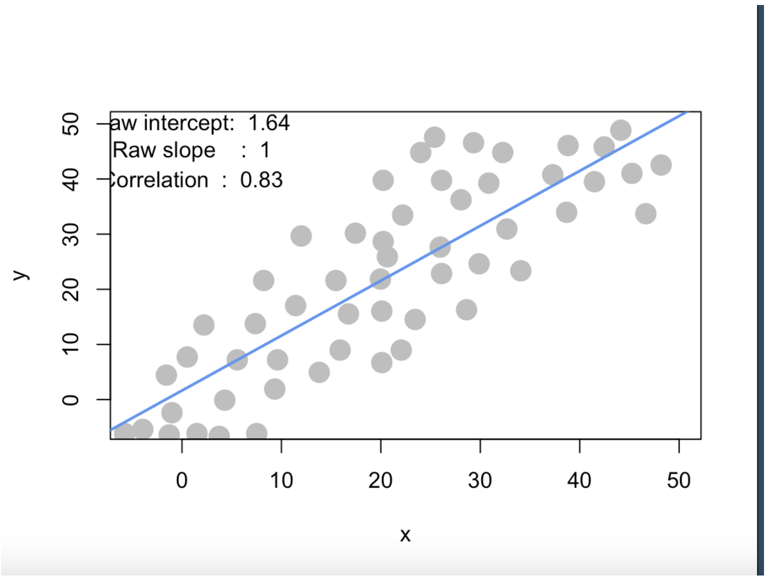
i. Raw Slope

ANSWER: Since the points are distributed entirely and randomly in the plot, it can be expected that the raw slope will be near zero if the y axis and x axis are distributed evenly.

ii. Correlation

ANSWER: Since the points are randomly distributed and filling the entire plot, it can be expected that the correlation will be about zero. Because the points are randomly distributed along the plot without any geometric meaning.

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



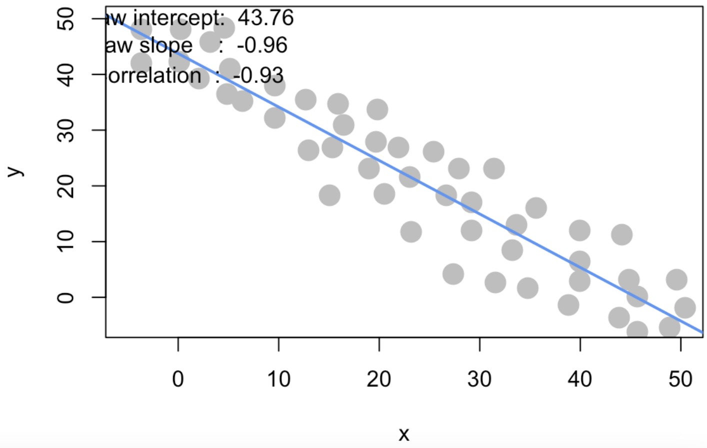
i. Raw Slope

ANSWER: Since the points are distributed around a 45 degree angle line, the slope can be expected to be 1 $(y/x) = 1$.

ii. Correlation

ANSWER: Since the x points trend the same as the y points, the expected correlation should be 1.

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



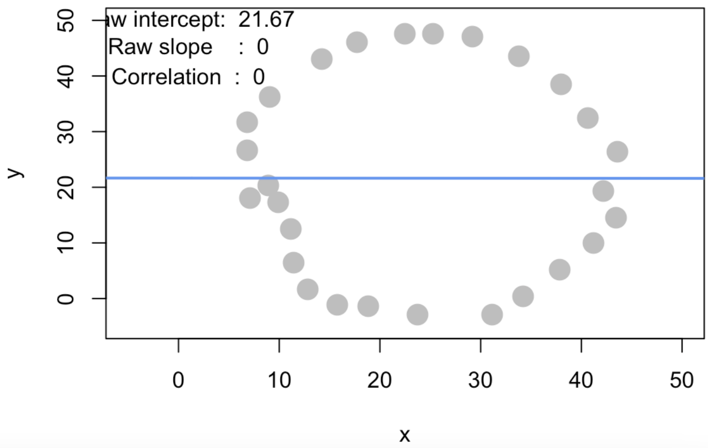
i. Raw Slope

ANSWER: Since the points are distributed around a 45 degree angle line but sloping downward, the slope can be expected to be -1 $(-y/x) = -1$.

i. Correlation

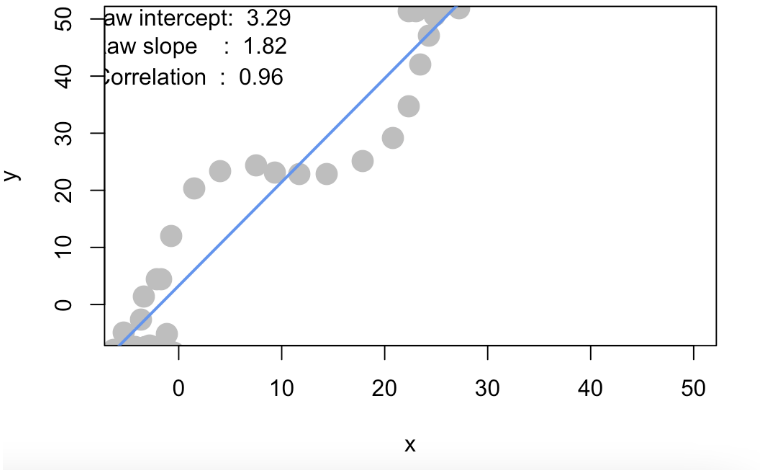
ANSWER: Since the x points trend the exact opposite way as the y points, the expected correlation should be -1.

e. Find another pattern of data points with no correlation



We can easily see that this resembles an ugly circle, which can be described by $(x - 25)^2 + (y - 25)^2 = r^2$ However, the x and y points do not have correlation.

f. find another pattern of data points with perfect correlation

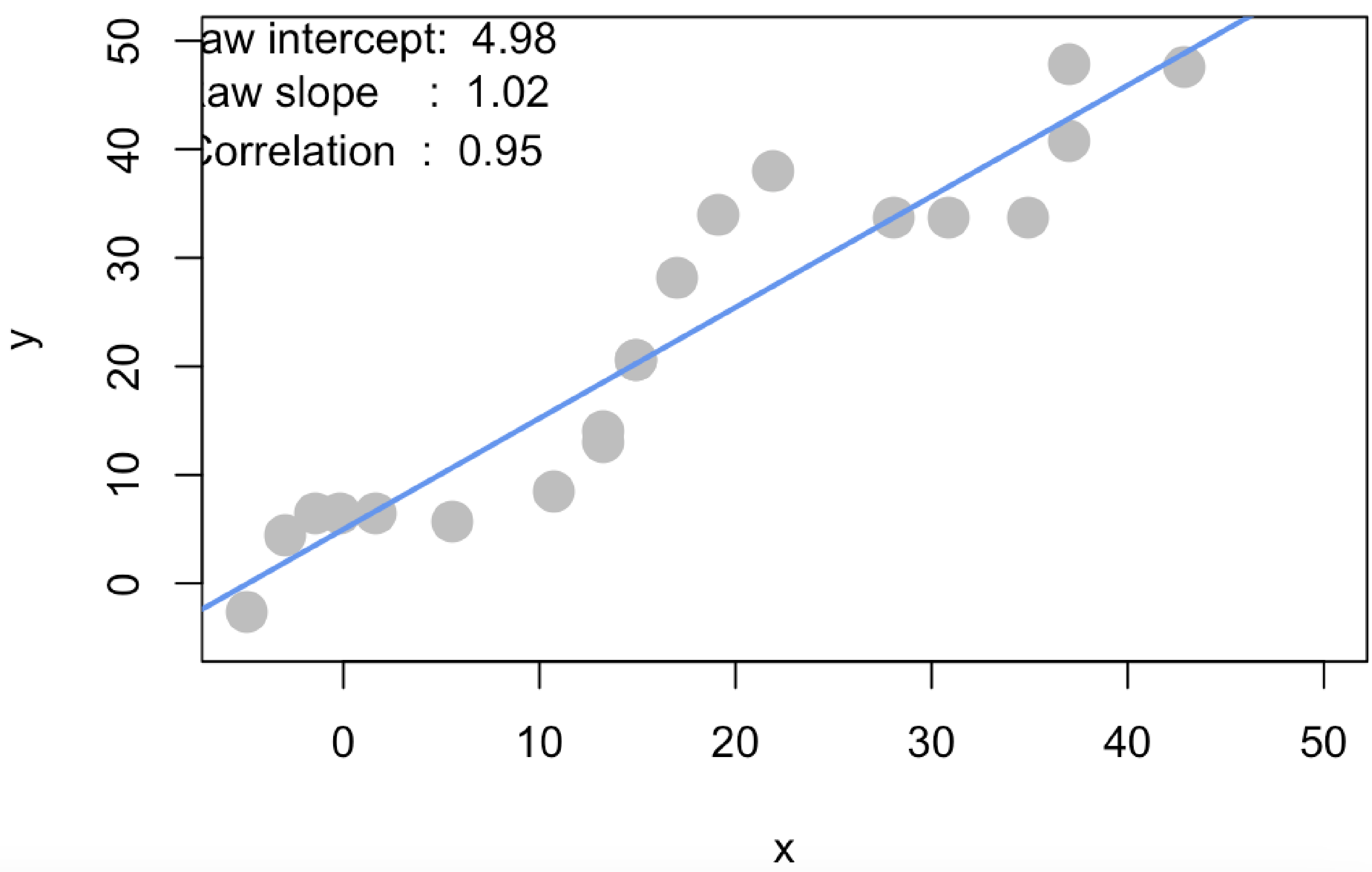


This plot is highly correlated x and y, also able to find an odd degree polynomial equation to describe this plot too.

g. How correlation relates to simple regression

i. Simulate points with interactive regression

```
#pts <- interactive_regression()
pts <- data.frame(x =c(-4.9244164,-2.9675264,-1.4299699,-0.1719691,1.6451431,5.5589232
 ,10.7307041, 13.2467056, 13.2467056,14.9240399, 14.9240399, 17.0207078,19.1173758,21.9129330,2
8.063158,30.8587161,34.9122741,37.0089420,37.0089420,42.8796122), y = c(-2.636982, 4.429640,6.4
48674,  6.448674,  6.448674,  5.691536
,8.467709, 13.010537, 14.020054, 20.581917, 20.581917, 28.153297
,33.958022 ,37.996091 ,33.705642, 33.705642 ,33.705642 ,40.772264
,47.838885 ,47.586506))
```



ii. Use the lm() function to estimate the regression intercept

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

```
##
## Call:
## lm(formula = pts$y ~ pts$x)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.4909 -3.2683 -0.1017  2.6020 10.5929
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4.9761     1.7707    2.81   0.0116 *
## pts$x         1.0235     0.0806   12.70 2.02e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.154 on 18 degrees of freedom
## Multiple R-squared:  0.8996, Adjusted R-squared:  0.894
## F-statistic: 161.2 on 1 and 18 DF,  p-value: 2.02e-10
```

The slope and intercept is same in plot.

iii. Estimate the correlation of x and y

```
cor(pts)
```

```
##           x         y
## x 1.0000000 0.9484594
## y 0.9484594 1.0000000
```

Same as indicated in plot, however it is quite obvious since the demo_simple_regression.R also uses *cor* function to calculate correlation.

iv. Re-estimate the regression using standardized values of both x and y from pts

```
std_pts <- data.frame(x = scale(pts$x), y = scale(pts$y))
summary( lm( std_pts$y ~ std_pts$x ))
```

```
##
## Call:
## lm(formula = std_pts$y ~ std_pts$x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.47320 -0.20646 -0.00642  0.16437  0.66916
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 3.941e-17  7.280e-02     0.0        1
## std_pts$x   9.485e-01  7.469e-02    12.7 2.02e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3256 on 18 degrees of freedom
## Multiple R-squared:  0.8996, Adjusted R-squared:  0.894
## F-statistic: 161.2 on 1 and 18 DF,  p-value: 2.02e-10
```

After standardization, the intercept is close to 0.

```
cor(std_pts)
```

```
##           x         y
## x 1.0000000 0.9484594
## y 0.9484594 1.0000000
```

The correlation doesn't change after standarization.

v.Relationship between correlation and the standardized simple-regression estimates

The coefficients of the linear model(x) is the correlation of x and y points!