BACS HW - Week 9

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Question 1) Let's make an automated recommendation system for the PicCollage mobile app.

- a. Let's explore to see if any sticker bundles seem intuitively similar:
- i. *(recommended)* Download PicCollage onto your mobile from the App Store and take a look at the style and content of various bundles in their Sticker Store: how many recommendations does each bundle have?

Ans: There are 6 recommendations for each bundle.

ii.Find a single sticker bundle that is both in our limited data set and also in the app's Sticker Store

Ans: I'll choose X'mas Sketches(col: xmassketches), and recommend these 5 bundles: xmasquotes, Xmas2012StickerPack, christmassnow, newyearsparty, snowflakeee since these 5 bundles are all related to same theme(Christmas).

- b. Let's find similar bundles using geometric models of similarity:
 - i. Let's create *cosine similarity* based recommendations for all bundles:

```
> #1
> #Import data
> #install.packages("data.table")
> library(data.table)
> ac_bundles_dt<-fread("piccollage_accounts_bundles.csv")</pre>
> ac bundles matrix<-as.matrix(ac bundles dt[,-1,with=FALSE])</pre>
> #1-b-i
> #create a matrix for top 5 recommendations for all bundles
> recom<-matrix(0,nrow=5,ncol =length(ac bundles matrix[1,]) ,dimnames =</pre>
list(c("rec1","rec2","rec3","rec4","rec5"),colnames(ac_bundles_matrix)))
> recom[,1:5]
    Maroon5V between pellington StickerLite saintvalentine
rec1
           0
                    0
                              0
                                          0
                                                         0
rec2
                    0
                              0
                                          0
                                                         0
           0
           0
                   0
                                          0
rec3
           0
rec4
                   0
                                          0
                                          0
rec5
           0
                    0
                              0
                                                         0
> #Write a function to calculate cosine similarity
> cossim<-function(matrix){</pre>
```

```
return<-matrix(0,nrow=6,ncol =length(ac_bundles_matrix[1,]) ,dimnames =</pre>
list(c("rec1","rec2","rec3","rec4","rec5","rec6"),colnames(ac_bundles_matri
x)))
  for (i in 1:length(ac_bundles_matrix[1,])){
     a<-matrix[,i]
     cos<-c()#create cosine similarity matrix</pre>
     for(j in 1:length(ac_bundles_matrix[1,])){
       b<-matrix[,j]</pre>
       cos<-c(cos, sum(a*b)/(sqrt(sum(a^2))*sqrt(sum(b^2))))#compute cosine
similarity
    }
return[,i]=colnames(ac_bundles_matrix)[order(cos,decreasing=TRUE)[1:6]]
#put the top 1-6 bundles into recommendation matrix
  return[] #return recommendation matrix
+ }
> top6<-cossim(ac_bundles_matrix)</pre>
> top6[,'xmassketches']
             rec1
                                rec2
                                                   rec3
                         "vintagexmas"
   "pacmanholiday"
                                              "yummyfood"
                                rec5
             rec4
                                                   rec6
"watercolorywinter" "wordstoliveby"
                                             "helloautumn"
> recom<-top6[1:5,] #"xmassketches" itself doesn't appear in top 6</pre>
> recom[,"xmassketches"]
             rec1
                                rec2
                                                   rec3
                         "vintagexmas"
   "pacmanholiday"
                                              "yummyfood"
             rec4
                                rec5
"watercolorywinter" "wordstoliveby"
```

Ans: According to cosine similarity, the top 5 recommendations for 'xmassketches' is:"pacmanholiday", "vintagexmas", "yummyfood", "watercolorywinter", "wordstoliveby".

ii. Let's create *correlation* based recommendations.

```
> #1-b-ii
> #create a matrix for top 5 recommendations for all bundles
> recom<-matrix(0,nrow=5,ncol =length(ac_bundles_matrix[1,]) ,dimnames =
list(c("rec1","rec2","rec3","rec4","rec5"),colnames(ac_bundles_matrix)))</pre>
```

```
> #Some adujstment on correlation
> col_means <- apply(ac_bundles_matrix, 2, mean)</pre>
> col means matrix <- t(replicate(nrow(ac bundles matrix),col means))</pre>
> ac_bundles_matrix_cor <- ac_bundles_matrix - col_means_matrix</pre>
> top6 <- cossim(ac bundles matrix cor)</pre>
> top6[,'xmassketches']
              rec1
                                  rec2
                                                      rec3
                        "vintagexmas"
    "pacmanholiday"
                                                 "yummyfood"
              rec4
                                  rec5
                                                      rec6
"watercolorywinter"
                        "wordstoliveby"
                                               "helloautumn"
> recom<-top6[1:5,]#"xmassketches" itself doesn't appear in top 6</pre>
> recom[,"xmassketches"]
              rec1
                                  rec2
                                                      rec3
   "pacmanholiday"
                          "vintagexmas"
                                                 "yummyfood"
                                  rec5
              rec4
"watercolorywinter"
                         "wordstoliveby"
```

Ans: According to correlation similarity, the top 5 recommendations for 'xmassketches'is:"pacmanholiday", "vintagexmas", "yummyfood", "watercolorywinte r", "wordstoliveby". And the result is same as cosine similarity.

iii. Let's create adjusted-cosine based recommendations.

```
#1-b-iii
> #create a matrix for top 5 recommendations for all bundles
> recom<-matrix(0,nrow=5,ncol =length(ac_bundles_matrix[1,]) ,dimnames =</pre>
list(c("rec1","rec2","rec3","rec4","rec5"),colnames(ac_bundles_matrix)))
> #Some adujstment for adjusted-cosine similarity
> account_means <- apply(ac_bundles_matrix, 1, mean)</pre>
> account_means_matrix <- replicate(ncol(ac_bundles_matrix),account_means)</pre>
> ac_bundles_matrix_adjcos <- ac_bundles_matrix - account_means_matrix</pre>
> top6 <- cossim(ac bundles matrix adjcos)</pre>
> top6[,'xmassketches']
              rec1
                                  rec2
                                                     rec3
        "dayofdead"
                         "xmassketches"
                                             "summergetaway"
              rec4
                                  rec5
                                                     rec6
"watercolorywinter"
                         "pacmanholiday"
                                              "helloautumn"
> recom[1,]<-top6[1,]#"xmassketches" itself appears in top 6</pre>
> recom[2:5,]<-top6[3:6,] #remove itself</pre>
> recom[,"xmassketches"]
```

```
rec1 rec2 rec3
"dayofdead" "summergetaway" "watercolorywinter"
rec4 rec5
"pacmanholiday" "helloautumn"
```

Ans: According to adjusted-cosine similarity, the top 5 recommendations for 'xmassketches' is: "dayofdead", "summergetaway", "watercolorywinter", "pacmanholiday", "helloautumn", which is different from the above two results.

c. (not graded) Are the three sets of geometric recommendations similar in nature (theme/keywords) to the recommendations you picked earlier using your intuition alone? What reasons might explain why your computational geometric recommendation models produce different results from your intuition?

Ans: No, they are totally different from the five bundles I pick by intuition, while looking at the results produced by computer, I'll still consider it reasonable, since bundles like "summergetaway", "watercolorywinter", "vintagexmas", "yummyfood" still relate to the events that happen in Christmas or the feature of Christmas itself. And I think the difference between computation model and my intuition may probably be the aspect of my consideration.

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

Ans: Cosine similarity doesn't take center(mean) into consideration, while correlation and adjusted-cosine do and the centers they take are different.

Question 2) Correlation is at the heart of many data analytic methods so let's explore it further.

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: We'll expect the slope nearly close to 0, since it is horizontal.

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

Ans: Similarly, we'll also expect the correlation is nearly close to 0, since horizonal set indicates that the movement of x is totally unrelated to y.

- 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 the x and y would you generally expect?

Ans: I'll expect the slope to be nearly 0, since the set of points fill the entire plotting area, we can't observe any trend in it.

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

Ans: Also, the correlation of x and y will be expected to be 0. For a fixed x-axis (ex.look at x=5), there will appear many points with different y and we can see that the relationship between x and y must not be 1-1 related.

c. Create a diagonal set of random points trending upwards at 45 degrees i.What *raw slope* of the x and y would you *generally* expect? (note that x, y have the same scale)

Ans: We'll expect the slope of the regression line to be around 1 since the set of points is diagonal(slope=1) but they don't completely lie on the same line and upward(positive). ii.What is the correlation of x and y that you would *generally* expect?

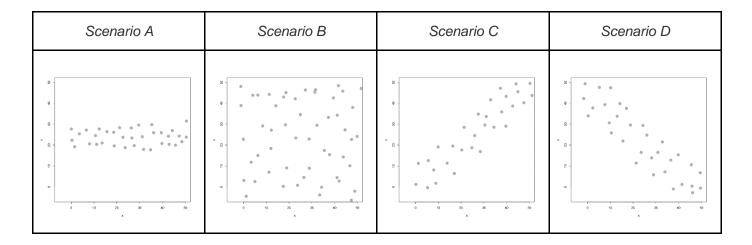
Ans: I'll expect the correlation of x and y to be >0 and <1. The set of points exhibits a positive diagonal trend, which indicates certain positive relationship between x and y, while these points don't completely lie on the same line, so correlation will be smaller than 1 and bigger than 0.

d. Create a diagonal set of random trending downwards at 45 degrees i.What *raw slope* of the x and y would you *generally* expect? (note that x, y have the same scale)

Ans: I'll expect the slope of the regression line to be around -1 since the set of points is diagonal(slope=-1) but they don't completely lie on the same line.

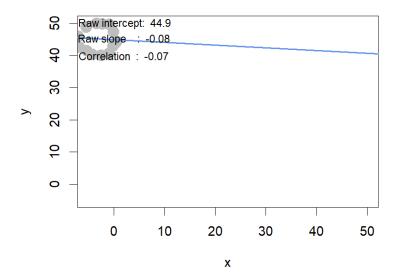
ii.What is the correlation of x and y that you would *generally* expect?

Ans: I'll expect the correlation of x and y to be >-1 and <0. The set of points exhibits a negative diagonal trend, which indicates certain negative relationship between x and y, while these points don't completely lie on the same line, so correlation will be smaller than 0 and bigger than -1.



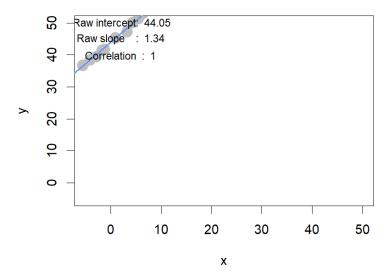
Apart from any of the above scenarios, find another pattern of data points with no correlation (r ≈ 0).
 (can create a pattern that visually suggests a strong relationship but produces r ≈ 0?)

Ans: Create a pattern of points with distribution visually similar to a circle, and we can observe this relationship by eyes while its correlation of x and y is nearly 0.



f. Apart from any of the above scenarios, find another pattern of data points with perfect correlation (r ≈ 1).
 (can you find a scenario where the pattern visually suggests a different relationship?)

Ans: As long as we create a set of data points that lies on the same line and the slope of line isn't 0, the correlation between x and y must be 1.



- g. Let's see how correlation relates to simple regression, by simulating any *linear* relationship you wish:
- i.Run the simulation and record the points you create: pts <interactive_regression()

 (simulate either a positive or negative relationship)</pre>

```
> pts<-interactive_regression()
```

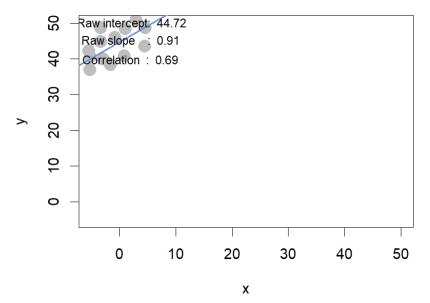
ii. Use the lm() function to estimate the *regression intercept and slope* of pts to ensure they are the same as the values reported in the simulation plot: $summary(lm(pts\$y \sim pts\$x))$

```
> #original regression line
> summary( lm( pts$y ~ pts$x ))
Call:
lm(formula = pts$y ~ pts$x)
Residuals:
   Min
            1Q Median
                           3Q
                                 Max
-5.0264 -3.9951 0.4059 2.9360 7.2758
Coefficients:
          Estimate Std. Error t value Pr(>|t|)
                        1.1862 37.701 7.8e-14 ***
(Intercept) 44.7211
pts$x
                                3.308 0.00625 **
             0.9103
                       0.2752
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 4.054 on 12 degrees of freedom

Multiple R-squared: 0.4769, Adjusted R-squared: 0.4333

F-statistic: 10.94 on 1 and 12 DF, p-value: 0.006251
```



Ans: The regression intercept and slope of pts are same as the values reported in the simulation plot.

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

Ans: Yes, the correlation of x and y is the same as reported in the plot

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

What is the relationship between *correlation* and the *standardized simple-regression* estimates?

```
#standardized
> pts$x<-scale(pts$x)
> pts$y<-scale(pts$y)
> #standardized regression line
> summary( lm( pts$y ~ pts$x ))

Call:
lm(formula = pts$y ~ pts$x)
```

```
Residuals:
    Min
             1Q Median
                             3Q
                                    Max
-0.93335 -0.74186 0.07537 0.54519 1.35103
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.672e-17 2.012e-01 0.000 1.00000
pts$x
          6.906e-01 2.088e-01 3.308 0.00625 **
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.7528 on 12 degrees of freedom
Multiple R-squared: 0.4769, Adjusted R-squared: 0.4333
F-statistic: 10.94 on 1 and 12 DF, p-value: 0.006251
> cor(pts)
               у
x 1.000000 0.690592
y 0.690592 1.000000
```

Ans: Even the values have been standardized, the correlation of x and y still doesn't change, and the standardized regression coefficient is the correlation and the intercept is 0.