## hw5

## Qianhui Yang

## 10/28/2020

#### Q1

The accuracy is 0.918, is much better than the last homework GBM result which is only about 0.5

```
## # A tibble: 6 x 3
## # Groups:
                Gender [2]
##
     Gender exp_group
                            n
##
     <fct>
             <chr>
                        <int>
## 1 Female test
                         1666
## 2 Female train
                         1667
## 3 Female validate
                         1667
## 4 Male
             test
                         1666
## 5 Male
                         1667
             train
## 6 Male
             validate
                         1667
## [1] 0.9211158
```

## $\mathbf{Q2}$

- 1. there are some missing data represented by power=0 and total=5, which are omitted, the omitted data has 434 rows of observations.
- 2. we need two components to get 85% of variation in the data set
- 3. Yes. Because the Durability has a range between 0-120, while the rest of the variables have 0-100. The normalization will make sure that each variable weight the same
- 4. Yes, the "total" column really is the total as the values in the other columns
- 5. If we include the total column in the PCA, the largest principle components PC1 has Total column correspond the largest proportion (0.52) 6.PCA can't classify the alignment of superhero, PCA function on the linear correlation, indicate that in each group of alignment, there are little linear correlation between each other. May be because the fact that the alignment of superhero does not relate to their ability, it is randomly assigned by the writer.

```
## Importance of components:
##
                             PC1
                                     PC2
                                             PC3
                                                       PC4
                                                                PC5
                                                                         PC6
                          46.664 23.6134 22.8884 18.88294 17.74412 17.02230
## Standard deviation
## Proportion of Variance
                          0.516
                                 0.1321
                                          0.1241
                                                  0.08449
                                                            0.07461
  Cumulative Proportion
                           0.516
                                 0.6481
                                          0.7722
                                                  0.85673
                                                           0.93134
   Importance of components:
                                    PC2
                                           PC3
                                                  PC4
                                                           PC5
                             PC1
                                                                   PC6
## Standard deviation
                          1.6412 1.0353 0.8695 0.7831 0.74653 0.55485
## Proportion of Variance 0.4489 0.1787 0.1260 0.1022 0.09289 0.05131
## Cumulative Proportion 0.4489 0.6276 0.7536 0.8558 0.94869 1.00000
## Warning: In prcomp.default(total_super, scale. = T, graph = FALSE) :
   extra argument 'graph' will be disregarded
```

```
## Importance of components:
##
                              PC1
                                     PC2
                                            PC3
                                                     PC4
                                                             PC5
                                                                     PC6
                                                                                PC7
## Standard deviation
                           1.9211 1.0366 0.8695 0.78316 0.74661 0.55491 2.856e-16
  Proportion of Variance 0.5272 0.1535 0.1080 0.08762 0.07963 0.04399 0.000e+00
   Cumulative Proportion
                           0.5272 0.6807 0.7888 0.87638 0.95601 1.00000 1.000e+00
##
                       PC1
                                   PC2
                                                PC3
                                                            PC4
                                                                         PC5
   Intelligence 0.2496939 -0.60774304
                                        0.60332047 -0.01526458
                                                                 0.41765874
##
##
  Strength
                0.4213660
                            0.16406255 -0.28736310
                                                     0.26366604
                                                                 0.36562901
## Speed
                0.3469851
                            0.28532893
                                        0.03652766 -0.87143286
                                                                 0.04583000
## Durability
                0.4280366
                            0.20751276 -0.20342168
                                                     0.31444116
                                                                 0.18853211
## Power
                            0.20627640
                                        0.48732635
                                                     0.23723409 -0.68592601
                0.3578820
## Combat
                0.2407513 -0.65969518 -0.52266011 -0.12482382 -0.42847391
  Total
                0.5200471 -0.03885949 -0.00718631
                                                    0.01085131 -0.01214364
##
##
                          PC6
                                     PC7
   Intelligence
                 0.036805516 -0.1681645
##
##
   Strength
                -0.665084678 -0.2596432
##
   Speed
                 0.026818310 -0.1861172
## Durability
                 0.733783483 -0.2438995
## Power
                -0.130336944 -0.2193658
## Combat
                 0.003081813 -0.1857071
## Total
                -0.012372817
                              0.8529778
     Principal Component Analysis
   2 -
                                                                                Col.
PC2
                                                                                    bad
                                                                                    good
                                                                                    neutral
  -2
```

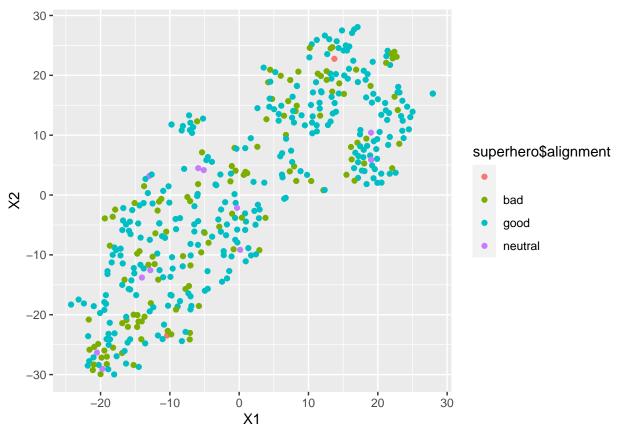
#### Q3

-2.5

Similar to PCA, TSNE did not do show a classification of superhero alignment. t-SNE (t-Distributed Stochastic Neighbor Embedding) is nonlinear dimensionality reduction technique in which interrelated high dimensional data (usually hundreds or thousands of variables) is mapped into low-dimensional data (like

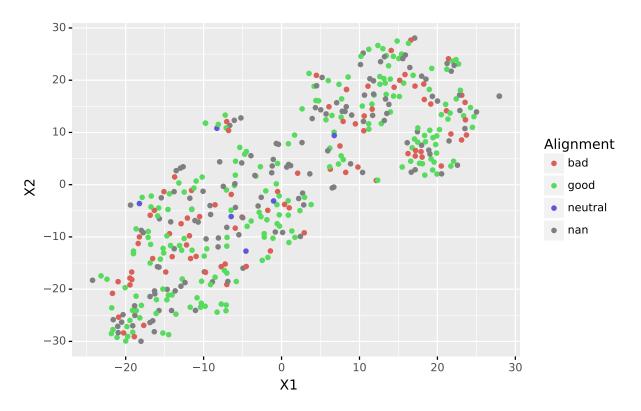
0.0 PC1 2.5

2 or 3 variables) while preserving the significant structure (relationship among the data points in different variables) of original high dimensional data. The result shows no nonlinear correlation in the superhero alignment group.



```
## List of 1
## $ legend.position: chr "right"
## - attr(*, "class")= chr [1:2] "theme" "gg"
## - attr(*, "complete")= logi FALSE
## - attr(*, "validate")= logi TRUE
```

# $\mathbf{Q4}$



The python codes are hided in the report but can be found in the Rmarkdown code. #Q5 The best accuracy is 0.71.

```
## # A tibble: 6 x 3
## # Groups:
               alignment [2]
##
     alignment exp_group
##
     <chr>
               <chr>
                          <int>
## 1 bad
               test
                             40
## 2 bad
               train
                             41
## 3 bad
               validate
                             40
## 4 good
               test
                             99
## 5 good
                            100
               train
## 6 good
               validate
## Stochastic Gradient Boosting
##
## 141 samples
     6 predictor
##
     2 classes: 'bad', 'good'
##
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 10 times)
## Summary of sample sizes: 126, 127, 127, 127, 127, 127, ...
## Resampling results across tuning parameters:
##
##
     interaction.depth n.trees
                                 Accuracy
                                             Kappa
                                  0.7021905 0.099797248
##
                          50
```

```
##
     1
                        100
                                  0.6838095 0.090196111
##
                        150
                                 0.6653333 0.063186900
     1
                                  0.6732857 0.063298446
##
     2
                         50
     2
##
                        100
                                  0.6433333 0.021550071
##
     2
                        150
                                  0.6263333
                                            0.003287784
     3
                                  0.6687619 0.068863089
##
                         50
##
     3
                        100
                                  0.6305714 0.015934602
     3
                                  0.6403333 0.059661551
##
                        150
##
## Tuning parameter 'shrinkage' was held constant at a value of 0.1
## Tuning parameter 'n.minobsinnode' was held constant at a value of 10
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were n.trees = 50, interaction.depth =
   1, shrinkage = 0.1 and n.minobsinnode = 10.
## [1] 0.705036
```

#### Q6

A conceptual question: why do we need to characterize our models using strategies like k-fold cross validation? Why can't we just report a single number for the accuracy of our model?

No. Because it is possible that we have selected data that can't represent our data set. It can not predict the data which is known as overfiting. To prevent this happens and make sure we can repeat the result, we use cross validation to lower the bias.

#### $\mathbf{Q7}$

Describe in words the process of recursive feature elimination.

First, after the initial set of feature training, the importance of each feature which is calculated by the coefficient and feature importance attribute. Then, the least important feature will be eliminated and from the current model and result as a less featured model. The process in repeated until the feature is eliminated to the numbers we want.