

# NEWFINAL

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```
#set working directory
setwd("/cloud/project")
###Importing my original data set to RStudio and calling it MCE
MCE<-read.csv("Mall_Customers_extended.csv", header=TRUE)

#to view variable names
names(MCE)

## [1] "Unnamed..0"           "CustomerID"          "Genre"
## [4] "Age"                  "Annual.Income..k.."   "Spending.Score..1.100."
## [7] "IncomePerAge"         "SpendingEfficiency" "AgeCategory"
## [10] "HighSpender"          "IncomeTier"           "OnlineShopFreq"
## [13] "LoyaltyScore"          "Satisfaction"        "CreditUtilization"

##### Step 1: Perform a K-Means Cluster analysis #####
# I created MCEcluster1 data frame with the only 3 variables needed
# for my cluster: annual income, spending score, age

MCEcluster<-data.frame(MCE)

MCEcluster1<-MCEcluster[,c("Annual.Income..k..", "Spending.Score..1.100.", "Age")]

MCEcluster1

##      Annual.Income..k.. Spending.Score..1.100. Age
## 1             15            39    19
## 2             15            81    21
## 3             16             6    20
## 4             16            77    23
## 5             17            40    31
## 6             17            76    22
## 7             18             6    35
## 8             18            94    23
## 9             19             3    64
## 10            19            72    30
## 11            19            14    67
## 12            19            99    35
## 13            20            15    58
## 14            20            77    24
## 15            20            13    37
## 16            20            79    22
## 17            21            35    35
## 18            21            66    20
## 19            23            29    52
```

## 20	23	98	35
## 21	24	35	35
## 22	24	73	25
## 23	25	5	46
## 24	25	73	31
## 25	28	14	54
## 26	28	82	29
## 27	28	32	45
## 28	28	61	35
## 29	29	31	40
## 30	29	87	23
## 31	30	4	60
## 32	30	73	21
## 33	33	4	53
## 34	33	92	18
## 35	33	14	49
## 36	33	81	21
## 37	34	17	42
## 38	34	73	30
## 39	37	26	36
## 40	37	75	20
## 41	38	35	65
## 42	38	92	24
## 43	39	36	48
## 44	39	61	31
## 45	39	28	49
## 46	39	65	24
## 47	40	55	50
## 48	40	47	27
## 49	40	42	29
## 50	40	42	31
## 51	42	52	49
## 52	42	60	33
## 53	43	54	31
## 54	43	60	59
## 55	43	45	50
## 56	43	41	47
## 57	44	50	51
## 58	44	46	69
## 59	46	51	27
## 60	46	46	53
## 61	46	56	70
## 62	46	55	19
## 63	47	52	67
## 64	47	59	54
## 65	48	51	63
## 66	48	59	18
## 67	48	50	43
## 68	48	48	68
## 69	48	59	19
## 70	48	47	32
## 71	49	55	70
## 72	49	42	47
## 73	50	49	60

## 74	50	56	60
## 75	54	47	59
## 76	54	54	26
## 77	54	53	45
## 78	54	48	40
## 79	54	52	23
## 80	54	42	49
## 81	54	51	57
## 82	54	55	38
## 83	54	41	67
## 84	54	44	46
## 85	54	57	21
## 86	54	46	48
## 87	57	58	55
## 88	57	55	22
## 89	58	60	34
## 90	58	46	50
## 91	59	55	68
## 92	59	41	18
## 93	60	49	48
## 94	60	40	40
## 95	60	42	32
## 96	60	52	24
## 97	60	47	47
## 98	60	50	27
## 99	61	42	48
## 100	61	49	20
## 101	62	41	23
## 102	62	48	49
## 103	62	59	67
## 104	62	55	26
## 105	62	56	49
## 106	62	42	21
## 107	63	50	66
## 108	63	46	54
## 109	63	43	68
## 110	63	48	66
## 111	63	52	65
## 112	63	54	19
## 113	64	42	38
## 114	64	46	19
## 115	65	48	18
## 116	65	50	19
## 117	65	43	63
## 118	65	59	49
## 119	67	43	51
## 120	67	57	50
## 121	67	56	27
## 122	67	40	38
## 123	69	58	40
## 124	69	91	39
## 125	70	29	23
## 126	70	77	31
## 127	71	35	43

## 128	71	95	40
## 129	71	11	59
## 130	71	75	38
## 131	71	9	47
## 132	71	75	39
## 133	72	34	25
## 134	72	71	31
## 135	73	5	20
## 136	73	88	29
## 137	73	7	44
## 138	73	73	32
## 139	74	10	19
## 140	74	72	35
## 141	75	5	57
## 142	75	93	32
## 143	76	40	28
## 144	76	87	32
## 145	77	12	25
## 146	77	97	28
## 147	77	36	48
## 148	77	74	32
## 149	78	22	34
## 150	78	90	34
## 151	78	17	43
## 152	78	88	39
## 153	78	20	44
## 154	78	76	38
## 155	78	16	47
## 156	78	89	27
## 157	78	1	37
## 158	78	78	30
## 159	78	1	34
## 160	78	73	30
## 161	79	35	56
## 162	79	83	29
## 163	81	5	19
## 164	81	93	31
## 165	85	26	50
## 166	85	75	36
## 167	86	20	42
## 168	86	95	33
## 169	87	27	36
## 170	87	63	32
## 171	87	13	40
## 172	87	75	28
## 173	87	10	36
## 174	87	92	36
## 175	88	13	52
## 176	88	86	30
## 177	88	15	58
## 178	88	69	27
## 179	93	14	59
## 180	93	90	35
## 181	97	32	37

```

## 182          97          86  32
## 183          98          15  46
## 184          98          88  29
## 185          99          39  41
## 186          99          97  30
## 187         101          24  54
## 188         101          68  28
## 189         103          17  41
## 190         103          85  36
## 191         103          23  34
## 192         103          69  32
## 193         113           8  33
## 194         113          91  38
## 195         120          16  47
## 196         120          79  35
## 197         126          28  45
## 198         126          74  32
## 199         137          18  32
## 200         137          83  30

#Now, I'm going to create a new file called MCEsv with my 3 values standardized so that I can begin running my clusters
MCEcluster2<-data.frame(MCEcluster1)

MCEsv <- scale(MCEcluster2)

#View first 5 observations
head(MCEsv,n=5)

##      Annual.Income...k.. Spending.Score..1.100.      Age
## [1,] -1.734646 -0.4337131 -1.4210029
## [2,] -1.734646  1.1927111 -1.2778288
## [3,] -1.696572 -1.7116178 -1.3494159
## [4,] -1.696572  1.0378135 -1.1346547
## [5,] -1.658498 -0.3949887 -0.5619583

##### K-Means Algorithm #####
#The factoextra package creates clusters in R studio

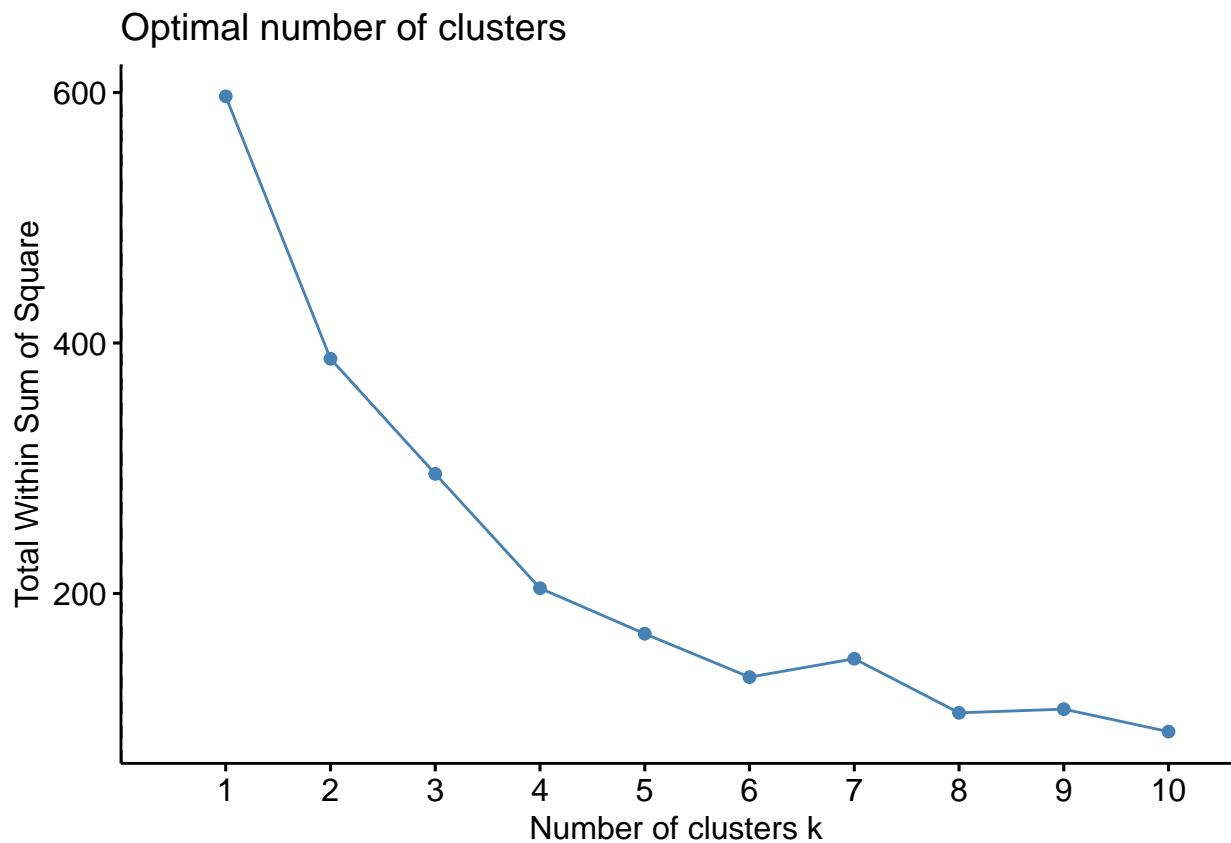
install.packages("factoextra")
library(factoextra)

install.packages("rstatix")
library(rstatix)

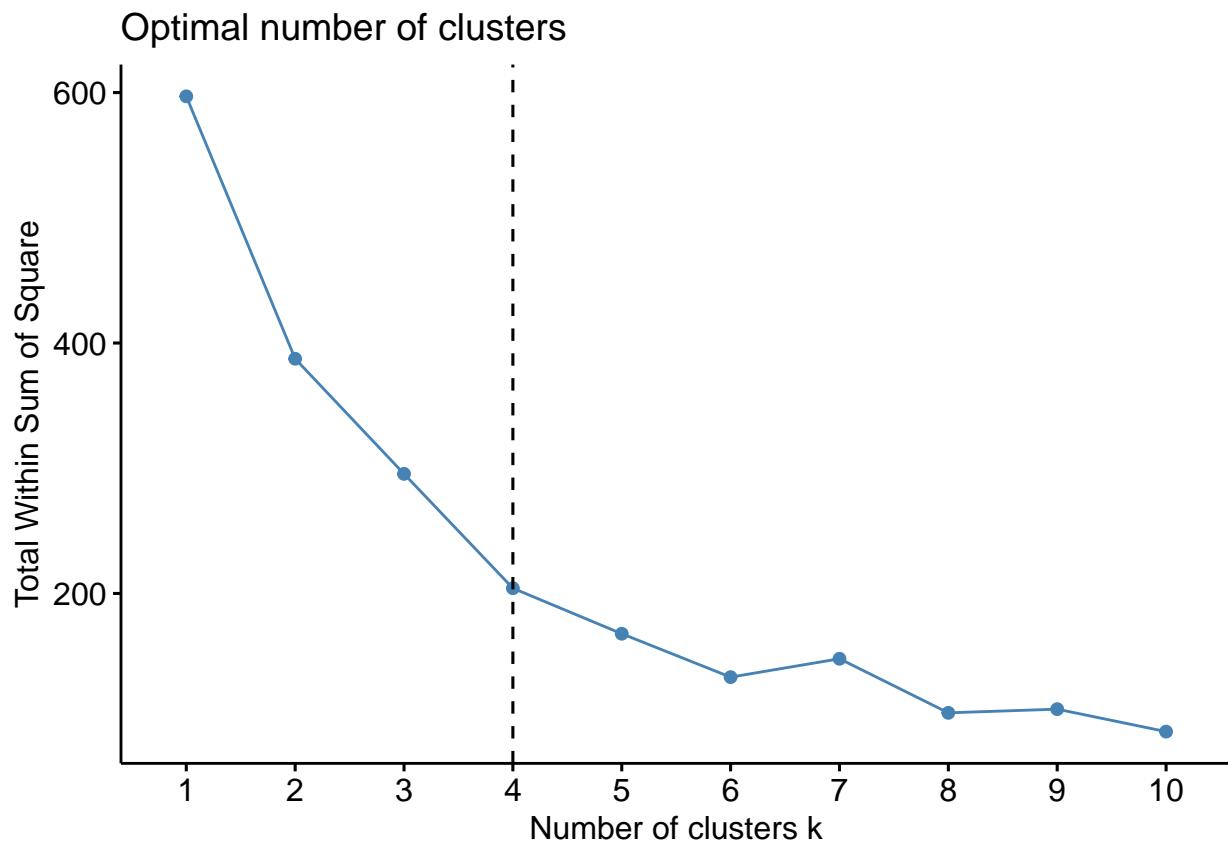
#To find the number of clusters needed we use the fviz_nbclust function

fviz_nbclust(MCEsv, kmeans, method="wss") + geom_vline(xintercept = 0, linetype = 2)

```



```
## I'm using 4 clusters based on the graph in my plots box
fviz_nbclust(MCEsv, kmeans, method="wss") + geom_vline(xintercept = 4, linetype = 2)
```



```

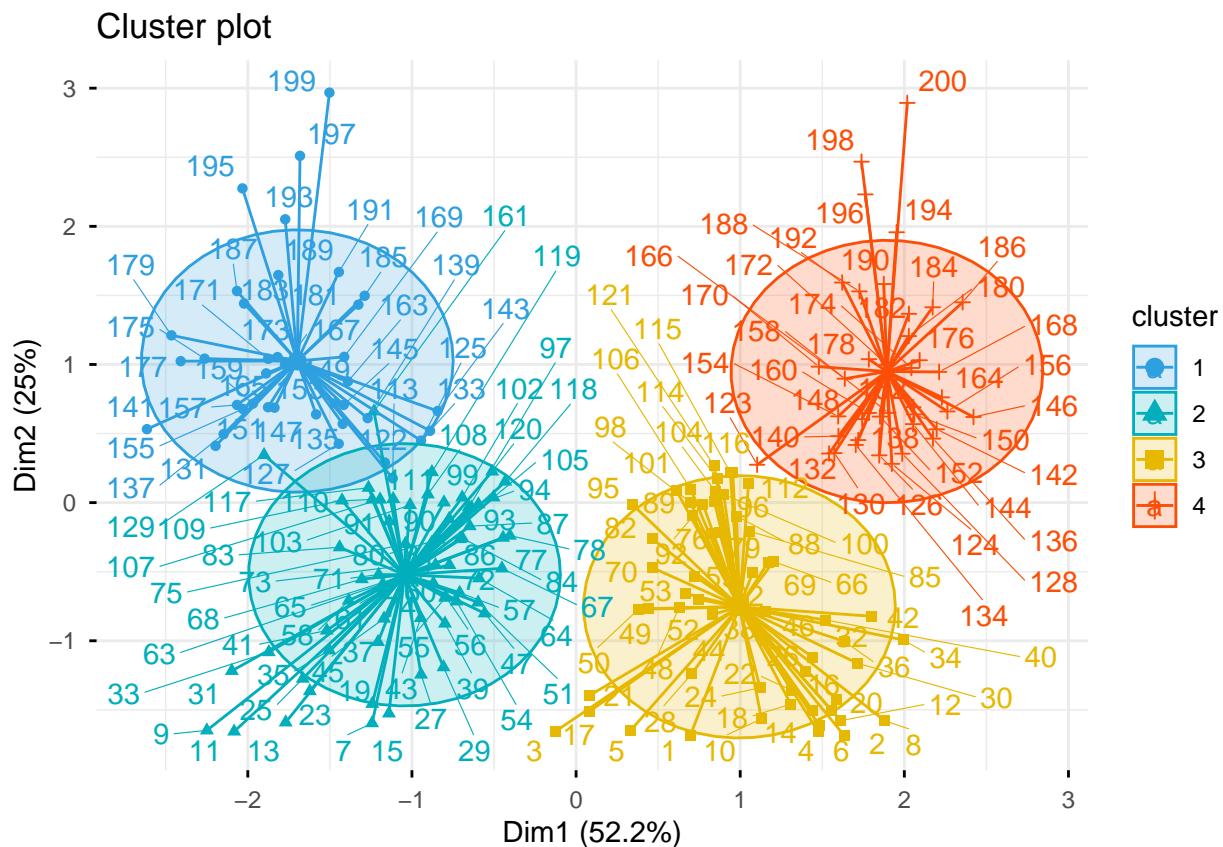
## Available components:
##
## [1] "cluster"         "centers"        "totss"          "withinss"       "tot.withinss"
## [6] "betweenss"       "size"           "iter"           "ifault"

##### Step 2: Create the Clustering Visual #####
#reating a new dataset using the cbind() function to merge the subset data
#created in step 1, and the km.res$clsuter

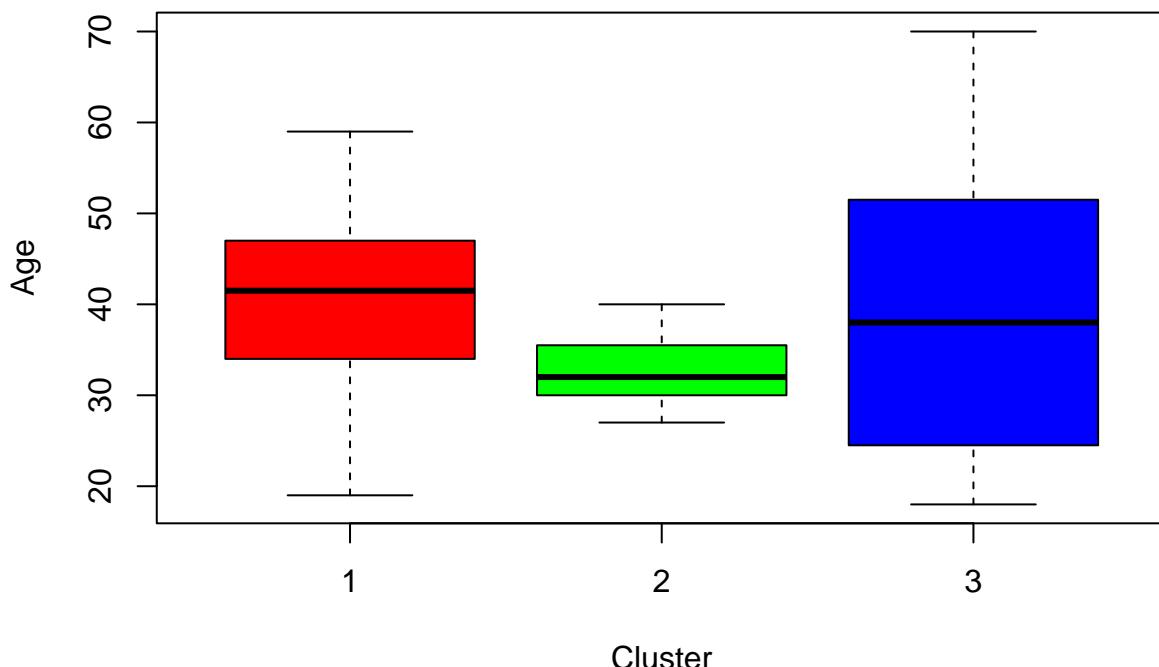
dd <- cbind(MCESv, cluster=km.res$cluster)

fviz_cluster(km.res, data=dd,
             palette = c("#2E9FDF", "#00AFBB", "#E7B800", "#FC4E07"),
             ellipse.type = "euclid", #Concentration ellipse
             star.plot = TRUE, #Add segments from centroids to items
             repel = TRUE, #Avoid label overplotting
             ggtheme = theme_minimal())

```

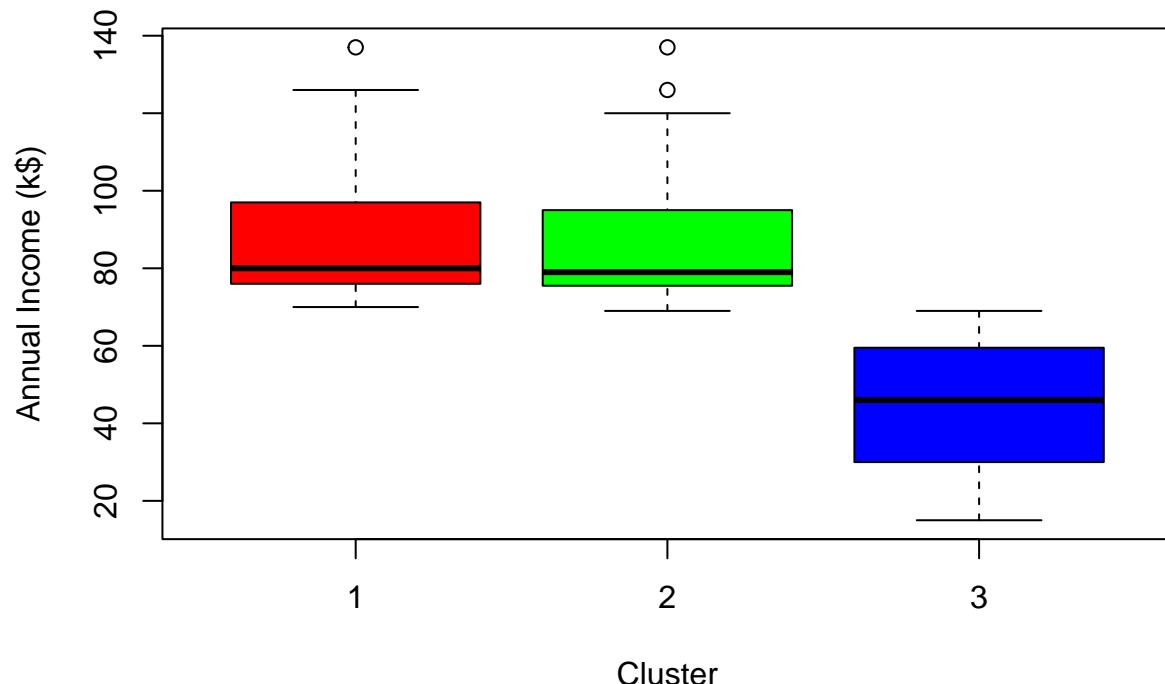


```
#boxplot  
# Step 1: Select columns for clustering  
data_for_clustering <- MCE[, c("Age", "Annual.Income..k..", "Spending.Score..1.100.")]  
  
# Step 2: Run k-means clustering  
  
set.seed(123) # for reproducibility  
km.res <- kmeans(data_for_clustering, centers = 3, nstart = 25)
```



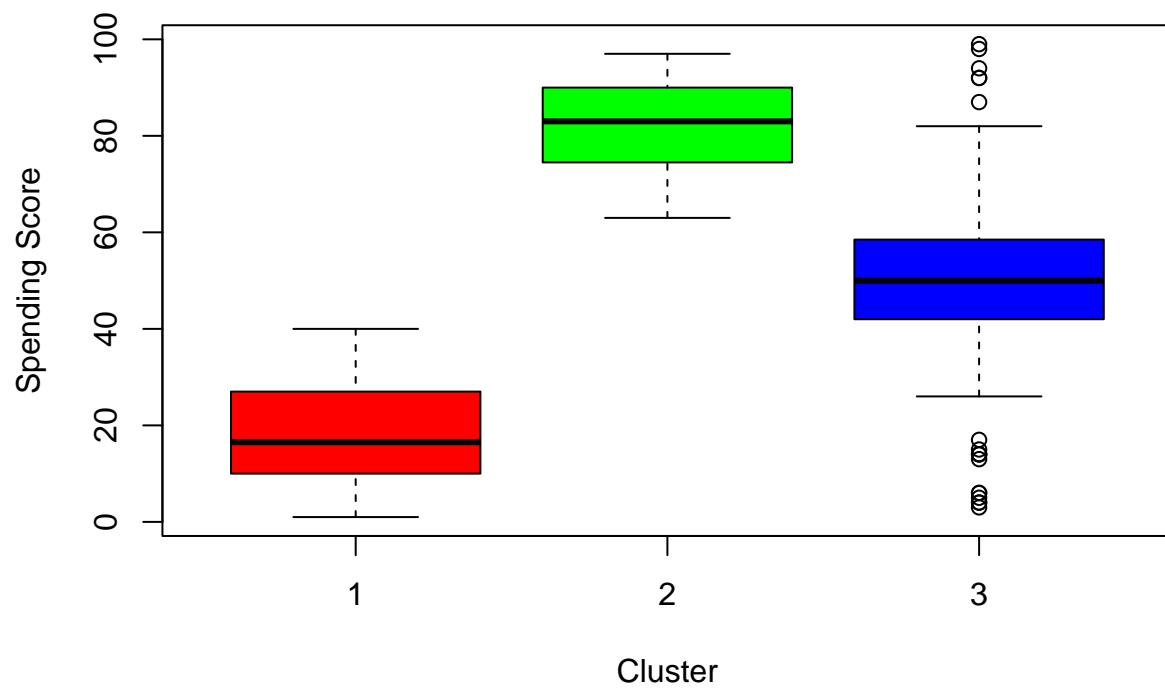
```
# Boxplot for Annual Income across clusters
boxplot(Annual.Income..k.. ~ Cluster, data = MCE_clustered,
        main = "Distribution of Annual Income Across Clusters",
        xlab = "Cluster", ylab = "Annual Income (k$)",
        col = c("red", "green", "blue"))
```

## Distribution of Annual Income Across Clusters



```
# Boxplot for Spending Score across clusters
boxplot(Spending.Score..1.100. ~ Cluster, data = MCE_clustered,
        main = "Distribution of Spending Score Across Clusters",
        xlab = "Cluster", ylab = "Spending Score",
        col = c("red", "green", "blue"))
```

## Distribution of Spending Score Across Clusters



```

#####
# descriptive tables #
#####

install.packages("stargazer")
library(stargazer)

cluster1 <- subset(MCE_clustered, Cluster == 1)
cluster2 <- subset(MCE_clustered, Cluster == 2)
cluster3 <- subset(MCE_clustered, Cluster == 3)

variables <- c("Age", "Annual.Income..k..", "Spending.Score..1.100.")

stargazer(cluster1[, variables], type = "text", title = "Cluster 1 Descriptive Stats")

##
## Cluster 1 Descriptive Stats
## =====
## Statistic      N   Mean   St. Dev. Min Max
## -----
## Age           38 40.395 11.377 19 59
## Annual.Income..k.. 38 87.000 16.271 70 137
## Spending.Score..1.100. 38 18.632 10.916 1 40
## -----
stargazer(cluster2[, variables], type = "text", title = "Cluster 2 Descriptive Stats")

##
## Cluster 2 Descriptive Stats
## =====
## Statistic      N   Mean   St. Dev. Min Max
## -----
## Age           39 32.692 3.729 27 40
## Annual.Income..k.. 39 86.538 16.312 69 137
## Spending.Score..1.100. 39 82.128 9.364 63 97
## -----
stargazer(cluster3[, variables], type = "text", title = "Cluster 3 Descriptive Stats")

##
## Cluster 3 Descriptive Stats
## =====
## Statistic      N   Mean   St. Dev. Min Max
## -----
## Age           123 40.325 16.114 18 70
## Annual.Income..k.. 123 44.154 16.038 15 69
## Spending.Score..1.100. 123 49.829 19.694 3 99
## -----



#How to do multiple linear regression in R

MallData <- read.csv("Mall_Customers_extended.csv", header=TRUE)

names(MallData)

```

```

## [1] "Unnamed..0"           "CustomerID"          "Genre"
## [4] "Age"                  "Annual.Income..k.."   "Spending.Score..1.100."
## [7] "IncomePerAge"         "SpendingEfficiency" "AgeCategory"
## [10] "HighSpender"          "IncomeTier"           "OnlineShopFreq"
## [13] "LoyaltyScore"          "Satisfaction"        "CreditUtilization"

y <- MallData$y.LoyaltyScore

x1 <- MallData$Age

x2 <- MallData$Annual.Income..k..

x3 <-MallData$Spending.Score..1.100.

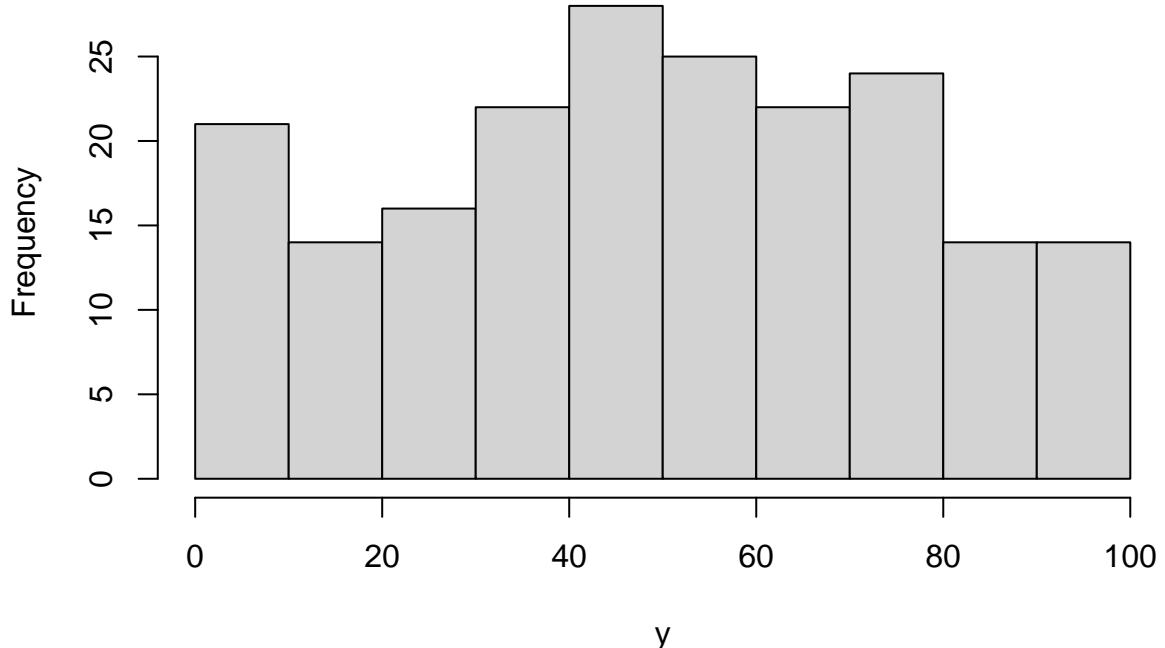
str(MallData$LoyaltyScore)

## num [1:200] 46 75 28 83.9 39.9 ...
y <- as.numeric(as.character(MallData$LoyaltyScore))

hist(y)

```

**Histogram of y**



```

model2 <- lm(y ~ x1 + x2 + x3, data=MallData)
model2

##
## Call:
## lm(formula = y ~ x1 + x2 + x3, data = MallData)
##
## Coefficients:
## (Intercept)          x1          x2          x3

```

```

##      4.40942   -0.08975   -0.01474    0.98109
attach(MallData)

summary(model2)

##
## Call:
## lm(formula = y ~ x1 + x2 + x3, data = MallData)
##
## Residuals:
##       Min     1Q Median     3Q    Max
## -22.0324 -6.4708 -0.5225  5.9657 31.4818
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 4.40942   3.02939   1.456   0.1471
## x1          -0.08975   0.04761  -1.885   0.0609 .
## x2          -0.01474   0.02393  -0.616   0.5385
## x3           0.98109   0.02575  38.099 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.864 on 196 degrees of freedom
## Multiple R-squared:  0.8956, Adjusted R-squared:  0.894
## F-statistic: 560.7 on 3 and 196 DF,  p-value: < 2.2e-16

#Intercepts: There are 3 x-values that are independent: these are x1 is the
#intercept for Age. x2 is the intercept for Annual Income K and x3 is the
#intercept for Spending Score. The estimated Beta for x1 is -0.08975, x2 is
#-0.01474 and x3 is 0.98109. There are 3 different variables with different
#outcomes. Age, Annual Income K and Spending Score are all continuous variables.
#For every unit in x1 (Age), there is a decrease of -0.0875 for the outcome
#(LoyaltyScore). Applies for x2, there is a decrease of -0.01474 for the outcome
#and for x3, there is an increase of 0.98108 for the outcome.

#Based on the summary, x1 and x2 are not significant. They do not contain the
#asterick. In this multiple Linear Regression ,x3 significantly predicts the
#outcome. For every unit in x3, the expected outcome increases by 0.98109
#which is adjusting for x1 and x2.

#Multiple R-Squared: This is used for Multiple Linear Regression to avoid bias
#when trying to find associations of x variables with outcome. When adding more
#variables R, usually increases, therefore we avoid using Multiple R-squared in
#this situation. Thus, they both provide the proportion of variability that
#the x's will explain on the variance of the outcome. It is ideal for it to be
#high, it should be close to 1. This would mean that all of systematic
#variances are being accounted for, in this model, it is high of 0.894.

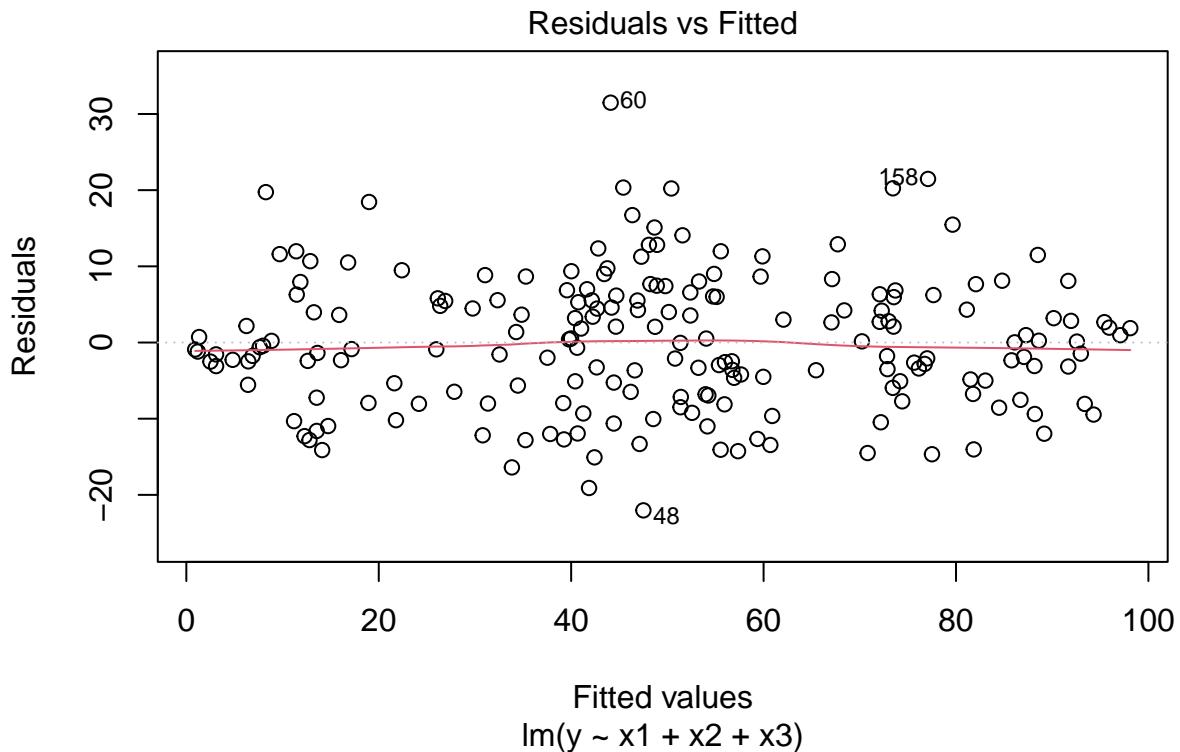
#F-Statistics: The F-statistics is more than 1, it is 560.7, this means that
#p-value is significant as well. When F-statistics is more than 1, it means that
#the systematic variances are being accounted by these x variables and they
#outweigh the unsystematic variances.

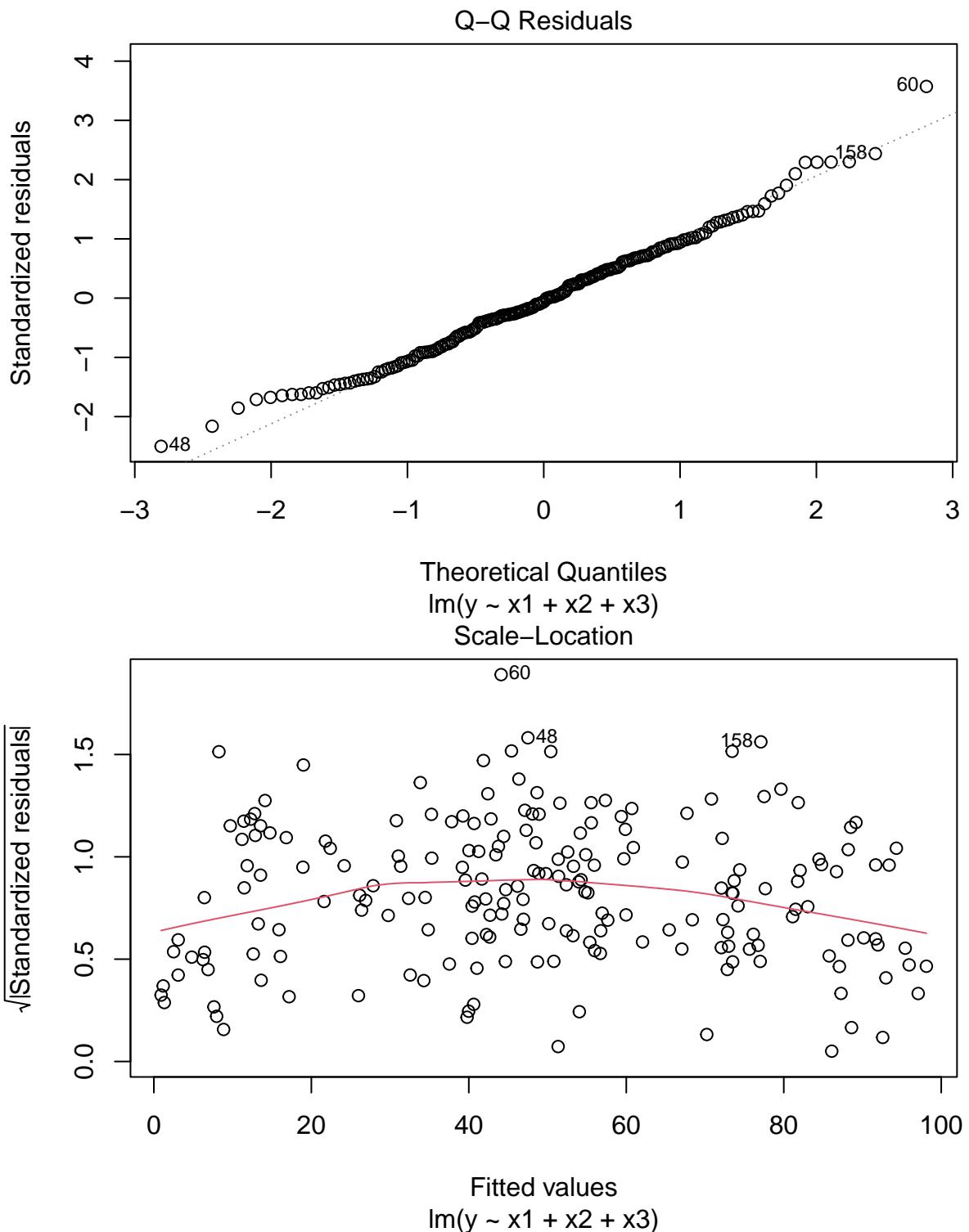
```

#*p*-Value: This would be considered a good model because it is less than 0.05,  
#shows that it is statistically significant.

#Income does not predict more Loyalty stronger than other clusters. The cluster  
#that show to have a stronger Loyalty is x3 (Spending Score) with a positive  
#beta of 0.98109. The other betas for x1 and x2 variable show decrease with  
#association of outcome.

#Assessing fit of model  
plot(model2)





Residuals vs Leverage

