Analysis of Customer Data using K-means Clustering

Application Area Project

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Introduction

Data has recently become one of the most important driving forces behind running a successful business. There is an unfathomable amount of big data available from various sources, including web databases and social media. Marketing professionals could benefit greatly from this massive amount of data if it can be properly processed and analyzed. They can use this processed data as a tool in their business venture by using it to gain valuable insights into their target customers.

The practice of data science is employing cutting-edge technologies to explore and analyze a vast quantity of data. It gathers data in a more sophisticated and organized manner, and it organizes that data. Data science is used in business to pinpoint external factors that might directly or indirectly affect company's operations and income. Data science and digital marketing work hand in hand because it is such a crucial aspect in operating a firm. We may utilize data analytics and data science to create marketing plans that will work for the business

since they can anticipate market trends and, in general, make practical future predictions about how the firm will perform in the future.

Motivation

Faster service and personalization appear to be valued by most e-commerce customers. In addition, marketers must, as always, compete with rivals for the attention of their target clients if they are to succeed in the commercial world. And for this reason, sales and marketing need data science. Technology has advanced significantly in the previous ten to fifteen years and particularly in the area of data science. With such a vast quantity of data at our fingertips, using it for marketing initiatives is only logical. Businesses won't require many data scientists and analysts now to produce knowledge on their target market.

A lot of automation and machine learning algorithms make it possible to examine a lot of data in a very short amount of time. The use of data analytics in marketing is no longer a distant possibility. These techniques are already being used by many large businesses to increase sales. Businesses will fall far behind those that seize this chance if they do not start doing so right away. Businesses may use strong marketing techniques and data science to better understand the wants and desires of their consumers and draw in new ones.

Problem statement

Business want to understand the customer behaviors to perform the campaigns and advertising to increase the customer base and to check the loyal customers.

1. Which age group has the highest earnings and spendings?
2. Is there any correlation between income earned and spending?

Design and Implementation

Data Preparation

Data is fetched from a kaggle to github and read the data in R by using the github link. Data opted is related to perform customer segmentation with two hundred rows and five columns with two categorical columns(Age, Gender) and three numerical columns(CustomerID, Annual Income, Spending Score) with CustomerID as primary key.

```
The downloaded binary packages are in
    /var/folders/16/qnwjsjfn5011fpzs33fhppqw0000gn/T//RtmprgEvRp/downloaded_packages
```

```
The downloaded binary packages are in
    /var/folders/16/qnwjsjfn5011fpzs33fhppqw0000gn/T//RtmprgEvRp/downloaded_packages
```

```
Attaching package: 'dplyr'
```

```
The following objects are masked from 'package:stats':

    filter, lag
```

```
The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union
```

```
# reading the data from github
customer_data=read.csv("https://raw.githubusercontent.com/sriram8113/Data-Science-as-field
```

```
#sample Represntation of Data
head(customer_data)
```

```
  CustomerID Gender Age Annual.Income..k.. Spending.Score..1.100.
1          1   Male  19                 15                      39
2          2   Male  21                 15                      81
3          3 Female  20                 16                       6
4          4 Female  23                 16                      77
5          5 Female  31                 17                      40
6          6 Female  22                 17                      76
```

```
#structure of the data

str(customer_data)
```

```
'data.frame':   200 obs. of  5 variables:
 $ CustomerID            : int  1 2 3 4 5 6 7 8 9 10 ...
 $ Gender                : chr  "Male" "Male" "Female" "Female" ...
 $ Age                   : int  19 21 20 23 31 22 35 23 64 30 ...
 $ Annual.Income..k..    : int  15 15 16 16 17 17 18 18 19 19 ...
 $ Spending.Score..1.100.: int  39 81 6 77 40 76 6 94 3 72 ...
```

```r
#Displaying names of the columns

names(customer_data)
```

```
[1] "CustomerID"             "Gender"                 "Age"
[4] "Annual.Income..k.."     "Spending.Score..1.100."
```

```r
#selcting required columns for further analysis

numerical_customer_columns_data = customer_data%>%select('Age','Annual.Income..k..','Spend
```

```r
#sample representation of numerical data
head(numerical_customer_columns_data)
```

```
  Age Annual.Income..k.. Spending.Score..1.100.
1  19                15                     39
2  21                15                     81
3  20                16                      6
4  23                16                     77
5  31                17                     40
6  22                17                     76
```

```r
#summary of numerical data
summary_numerical = apply(numerical_customer_columns_data, 2, summary)
summary_numerical
```

```
          Age Annual.Income..k.. Spending.Score..1.100.
Min.    18.00              15.00                   1.00
1st Qu. 28.75              41.50                  34.75
Median  36.00              61.50                  50.00
Mean    38.85              60.56                  50.20
3rd Qu. 49.00              78.00                  73.00
Max.    70.00             137.00                  99.00
```

```r
#standard Deviation of numerical columns
apply(numerical_customer_columns_data, 2, sd)
```

```
                Age     Annual.Income..k.. Spending.Score..1.100.
           13.96901               26.26472               25.82352
```

```r
#summary of total data
summary(customer_data)
```

```
  CustomerID        Gender              Age        Annual.Income..k..
Min.   :  1.00   Length:200         Min.   :18.00   Min.   : 15.00
1st Qu.: 50.75   Class :character   1st Qu.:28.75   1st Qu.: 41.50
Median :100.50   Mode  :character   Median :36.00   Median : 61.50
Mean   :100.50                      Mean   :38.85   Mean   : 60.56
3rd Qu.:150.25                      3rd Qu.:49.00   3rd Qu.: 78.00
Max.   :200.00                      Max.   :70.00   Max.   :137.00
Spending.Score..1.100.
Min.   : 1.00
1st Qu.:34.75
Median :50.00
Mean   :50.20
3rd Qu.:73.00
Max.   :99.00
```

Data Pre-Processing

Pre-processing of data is a mandatory process after getting any data. In this report, data cleansing techniques such as finding the missing, NA values, outlier verification are performed. One outlier could be found in the numerical data and removed the outlier in the data and plotted the charts to verify the difference.

Data Cleansing

```r
#checking for Na values

which(is.na(customer_data))
```

```
integer(0)
```

we can see that there are no Na values in the data.

```r
sum(is.na(customer_data))
```

```
[1] 0
```

```r
#Dimensions of the data

dim(customer_data)
```

```
[1] 200   5
```

```r
#Selecting unique rows

customer_data1<- customer_data%>% distinct()
dim(customer_data1)
```

```
[1] 200   5
```

we can see that there are no duplicated values

Outlier validation

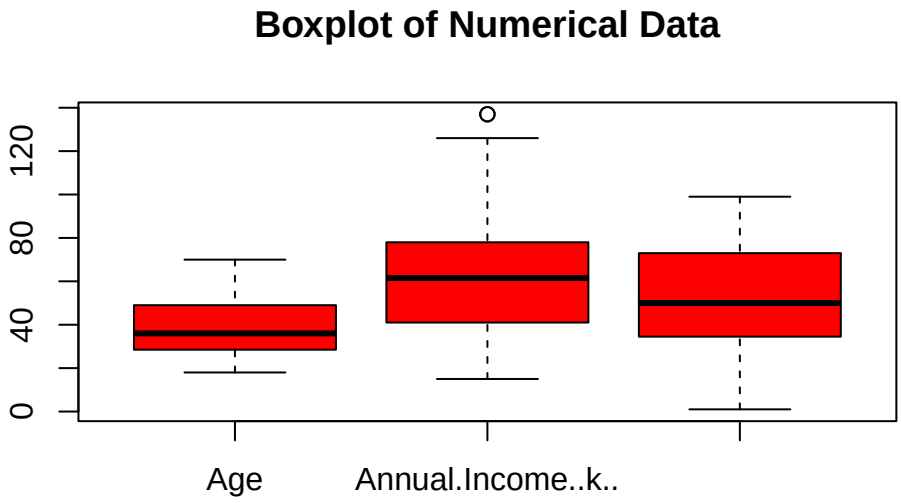
```r
dim(customer_data)
```

```
[1] 200   5
```

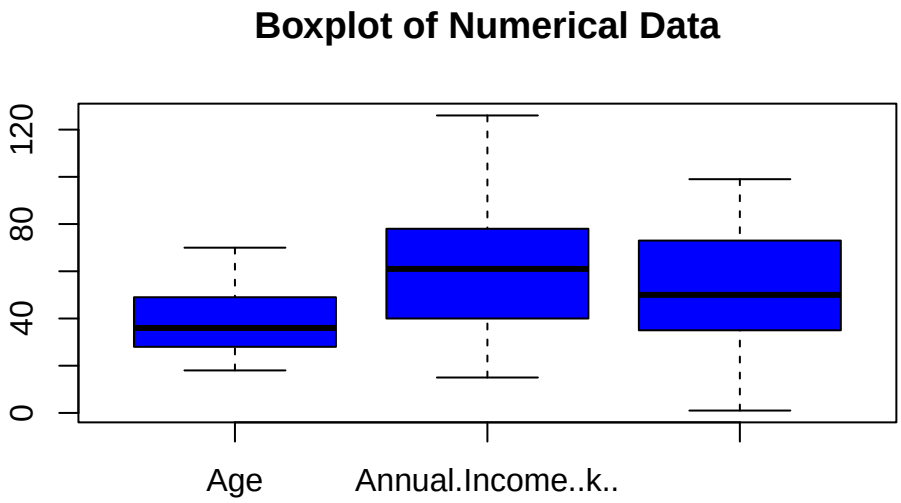
```r
quartiles <- quantile(customer_data$Annual.Income..k.., probs=c(.25, .75), na.rm = FALSE)
IQR <- IQR(customer_data$Annual.Income..k..)

Lower <- quartiles[1] - 1.5*IQR
Upper <- quartiles[2] + 1.5*IQR

customer_data <- subset(customer_data, customer_data$Annual.Income..k.. > Lower & customer

dim(customer_data)
```

```
[1] 198   5
```

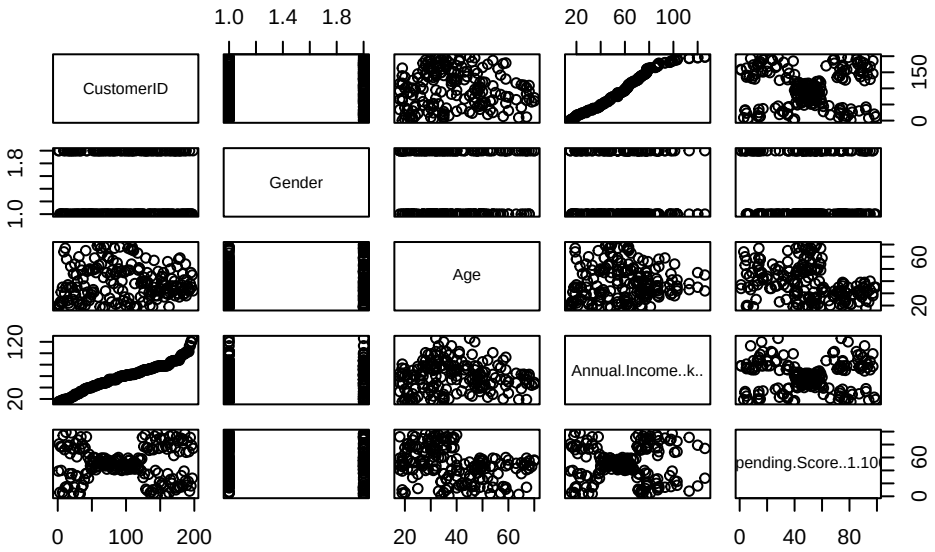
```r
#Boxplot

boxplot(numerical_customer_columns_data, col = "red", main  = 'Boxplot of Numerical Data')
```




```r
#Boxplot
boxplot(customer_data[,3:5], main = "Boxplot of Numerical Data", col = 'Blue')
```



```
#plotting all the data together.
plot(customer_data)
```



Data Transformation

Transformation of data plays a vital role in structuring the data by using few techniques such as such as normalization, attribute selection, and feature selection.

```
#mean
means = apply(numerical_customer_columns_data, 2, mean)
```

```
#standard deviation
sds = apply(numerical_customer_columns_data, 2, sd)
```

```
#sample representation of normalised data

normalised_numerical_customer_data  =  scale(numerical_customer_columns_data,center=means,
head(normalised_numerical_customer_data)
```

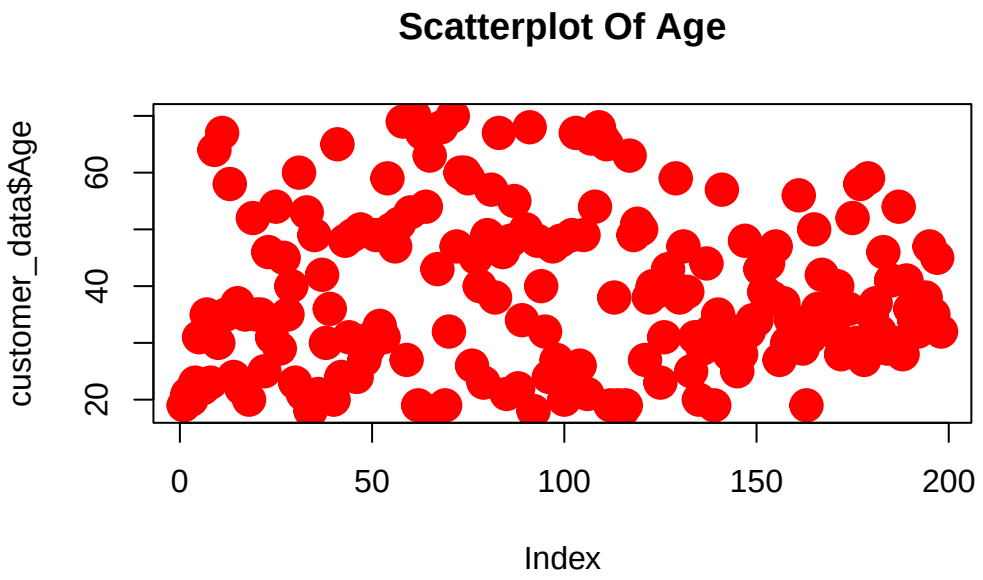
```
        Age Annual.Income..k.. Spending.Score..1.100.
```

```
[1,] -1.4210029          -1.734646            -0.4337131
[2,] -1.2778288          -1.734646             1.1927111
[3,] -1.3494159          -1.696572            -1.7116178
[4,] -1.1346547          -1.696572             1.0378135
[5,] -0.5619583          -1.658498            -0.3949887
[6,] -1.2062418          -1.658498             0.9990891
```

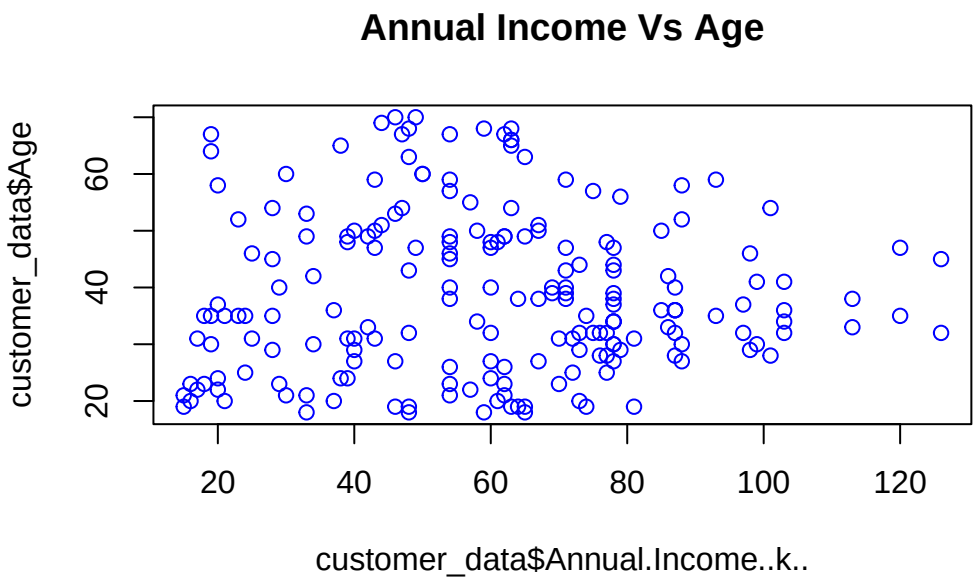
Analysis of Data using Visualizations

The below code represents the various scatter plots with the combination of multiple numerical columns. Exploratory data analysis such as uni-variate analysis for the Age, Gender and bivariate analysis for the annual income, spending score versus age

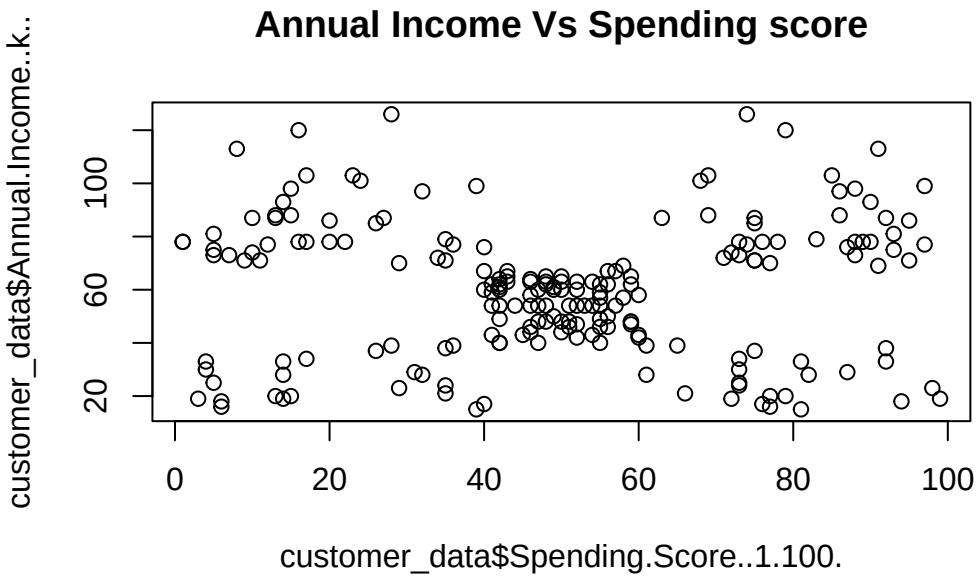
```r
#scatter plot
plot(customer_data$Age, col = "red", lwd = 10,main = "Scatterplot Of Age")
```




```r
#Scatter plot
plot(customer_data$Age~customer_data$Annual.Income..k.., col = 'blue')
title(main ='Annual Income Vs Age')
```

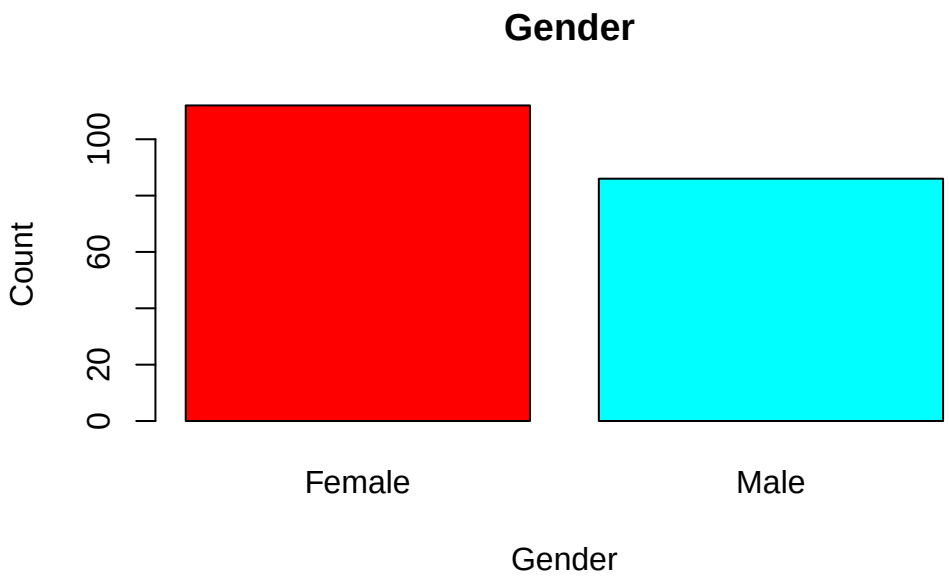



```
#Scatter plot

plot(customer_data$Annual.Income..k..~customer_data$Spending.Score..1.100.)
title(main ='Annual Income Vs Spending score')
```



Below code shows the charts of the individual columns spread and distribution. Bar plot shows the number of customers in each gender in the data set.

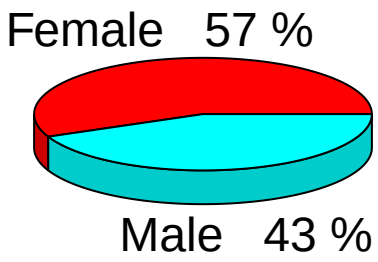
```
#Barplot reprenting gender

barplot(table(customer_data$Gender),main=" Gender",
        ylab="Count",
        xlab="Gender",
        col=rainbow(2),
        legend=rownames(customer_data$Gender))
```




```
#Pie chart
install.packages('plotrix', repos = "http://cran.us.r-project.org")
```

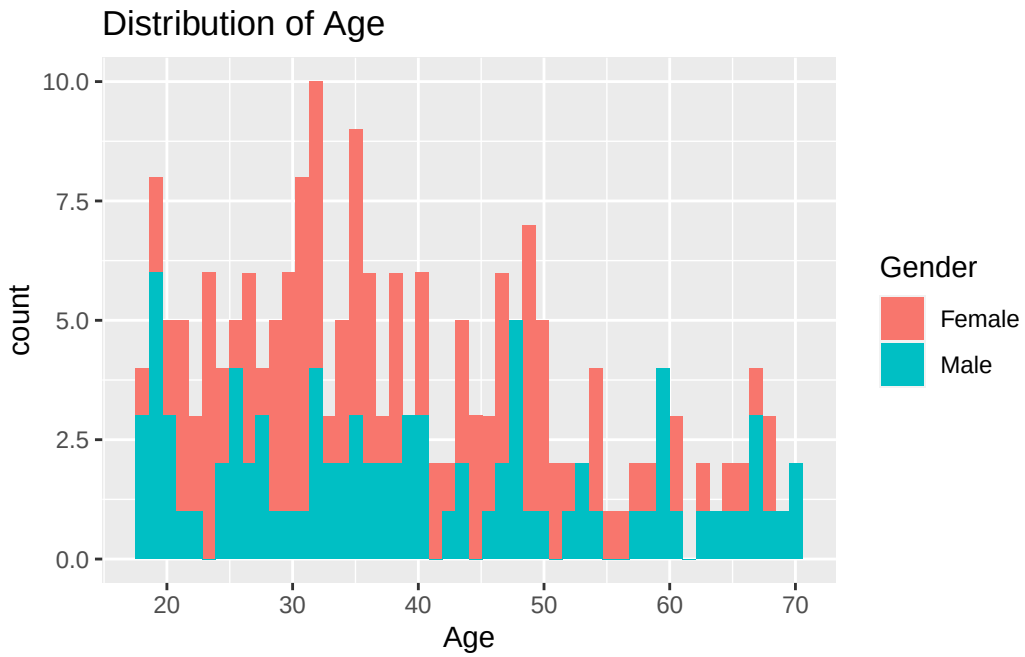
```
The downloaded binary packages are in
    /var/folders/16/qnwjsjfn5011fpzs33fhppqw0000gn/T//RtmprgEvRp/downloaded_packages
```

```
percentage=round(table(customer_data$Gender)/sum(table(customer_data$Gender))*100)
labels_gender=paste(c("Female","Male")," ",percentage,"%",sep=" ")
library(plotrix)
pie3D(table(customer_data$Gender), main="Pie Chart  of Female and Male", labels = labels_g
```



From the above two charts, it can be concluded that female customers are more in number than the male customers.

```
#Histogram of Age

ggplot(customer_data,aes(x= Age, fill=Gender))+geom_histogram(bins = 50)+ggtitle('Distribu
```



From the above histogram,

1. with increase in the age number of customers decreased.
2. Maximum number of customers are in the age between 30 and 40years.

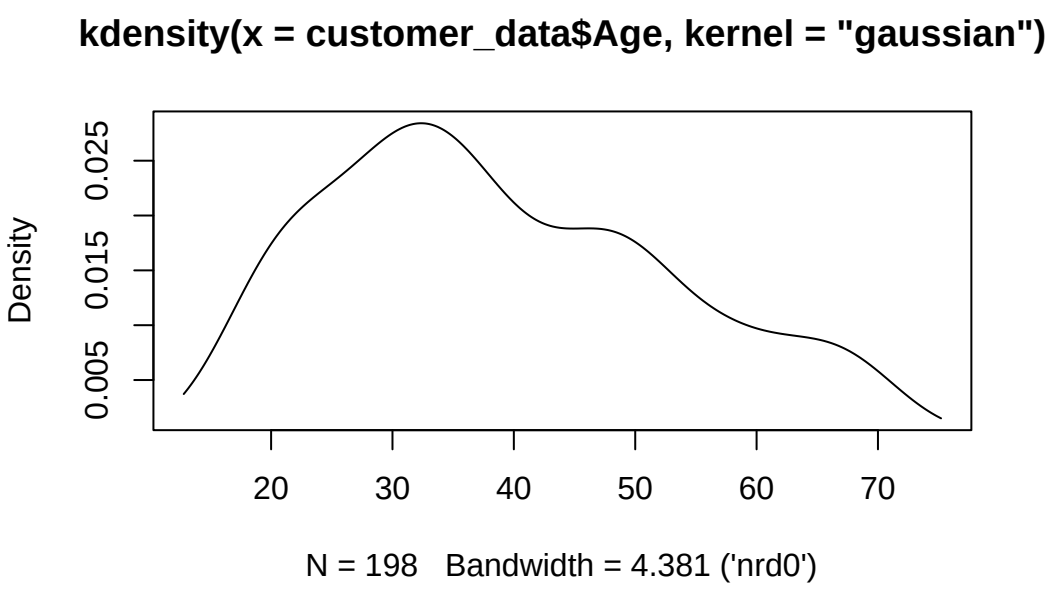
```
ggplot(customer_data,aes(x= `Spending.Score..1.100.`, col=Gender)) + geom_freqpoly(bins=50
```

From the above chart, it can be seen spending of women are higher than the male.

```
# Kernal Density Plot
install.packages('kdensity', repos = "http://cran.us.r-project.org")
```

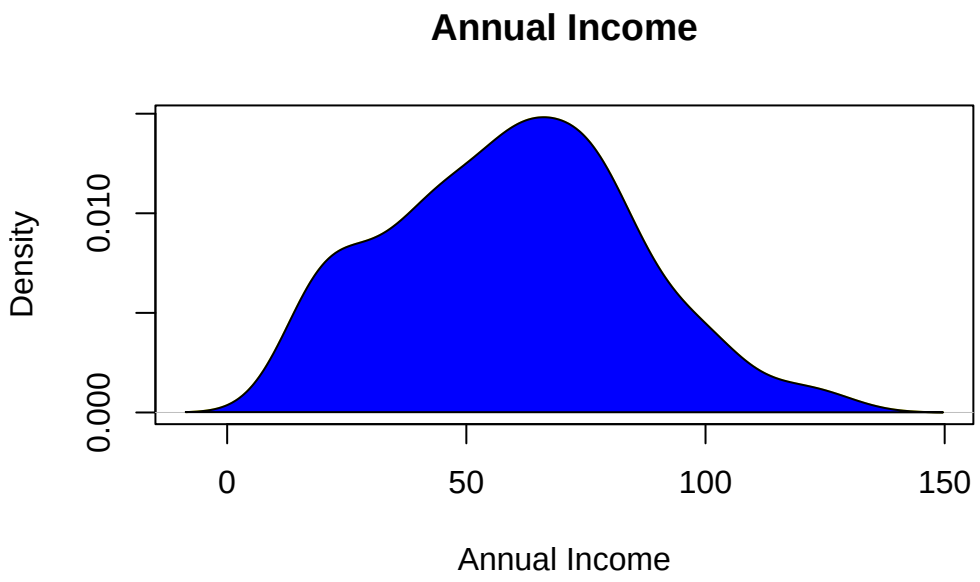
```
The downloaded binary packages are in
    /var/folders/16/qnwjsjfn5011fpzs33fhppqw0000gn/T//RtmprgEvRp/downloaded_packages
```

```
library(kdensity)
KDE_age <- kdensity(x=customer_data$Age, kernel = 'gaussian')
plot(KDE_age)
```



From the above Gaussian distribution, highest density is in the range of 30 to 40 so we can say that there are more number of customers in the same age range.

```
#Density plot

plot(density(customer_data$Annual.Income..k..),
     col="yellow",
     main="Annual Income",
     xlab="Annual Income",
     )
polygon(density(customer_data$Annual.Income..k..),
        col="blue")
```



from the above density graph, it shows the maximum customers annual income ranges between $50K - $100K.

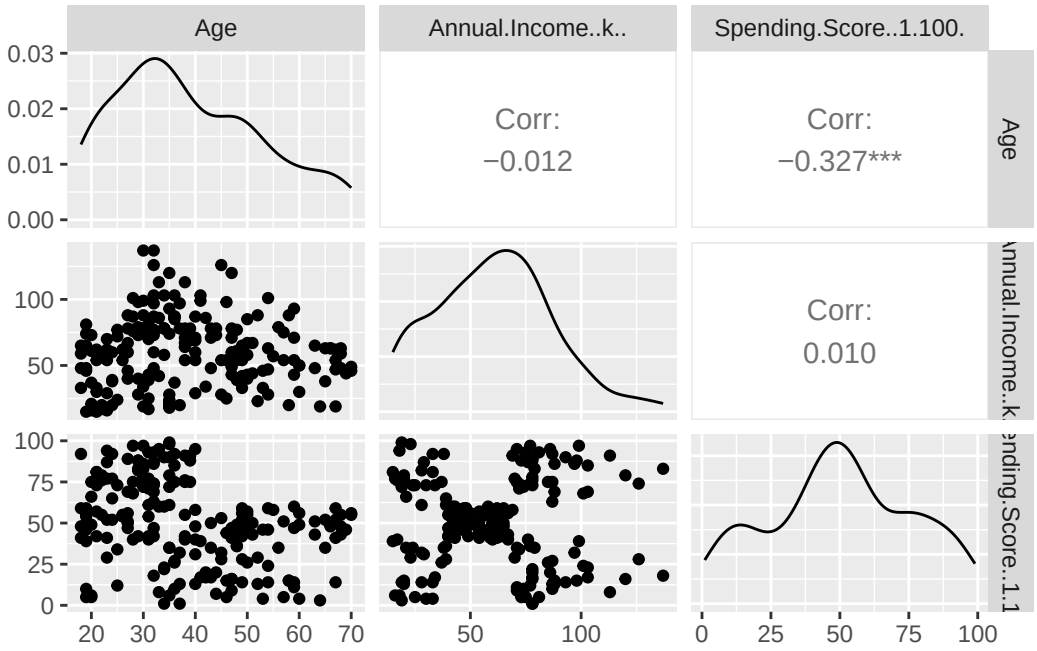
```
install.packages('GGally', repos ="http://cran.us.r-project.org")
```

```
The downloaded binary packages are in
    /var/folders/16/qnwjsjfn5011fpzs33fhppqw0000gn/T//RtmprgEvRp/downloaded_packages
```

```
library(GGally)
```

```
Registered S3 method overwritten by 'GGally':
  method from
  +.gg   ggplot2
```

```
ggpairs(numerical_customer_columns_data)
```



from the above graph, we can conclude:

1. correlation between annual income and Age: Negative
2. correlation between spending scores and Age: Negative
3. correlation between spending scores and annual income: Positive

```
new_data <- data.frame(customer_data)
new_data$Age1 <-cut(new_data$Age, seq(10,70,10))
head(new_data)
```

```
  CustomerID Gender Age Annual.Income..k.. Spending.Score..1.100.    Age1
1          1   Male  19                 15                     39 (10,20]
2          2   Male  21                 15                     81 (20,30]
3          3 Female  20                 16                      6 (10,20]
4          4 Female  23                 16                     77 (20,30]
5          5 Female  31                 17                     40 (30,40]
6          6 Female  22                 17                     76 (20,30]
```

Created a new column named Age1 for further analysis.

```
Groupby_age_data <- new_data %>% group_by(Age1)%>%summarise(total_spendings = sum(Spending
Groupby_age_data
```

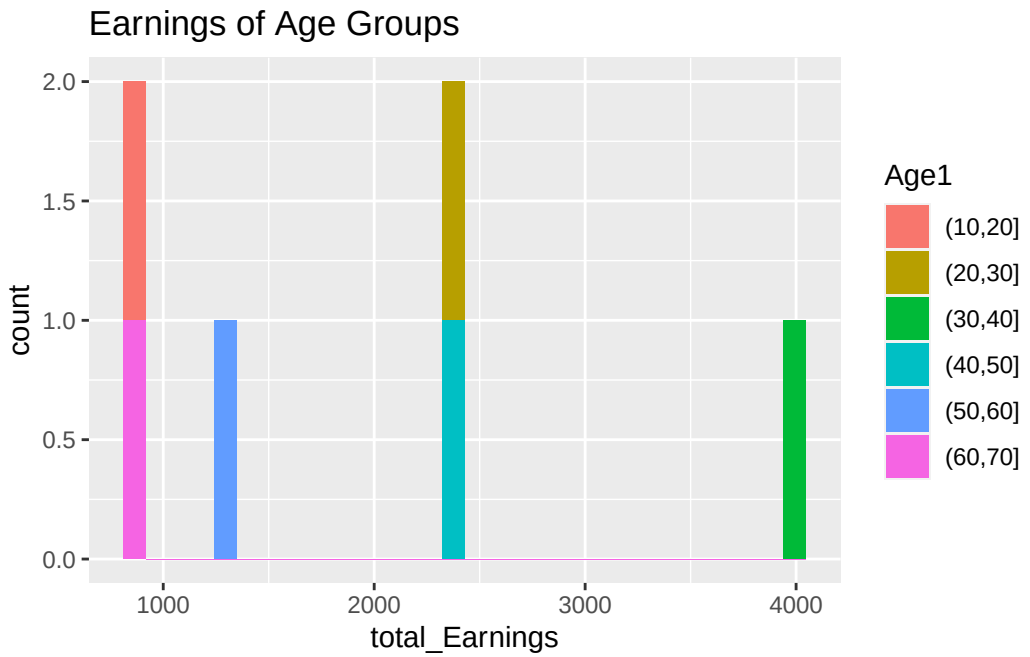
```
# A tibble: 6 x 3
  Age1    total_spendings total_Earnings
  <fct>             <int>          <int>
1 (10,20]             759            869
2 (20,30]            2942           2417
3 (30,40]            3432           3981
4 (40,50]            1307           2417
5 (50,60]             748           1304
6 (60,70]             751            850
```

Above table clearly shows that:

1. Age group between 30,40 has the highest spending and earnings.
2. Age group between 60,70 has the lowest spending and earnings.

```
ggplot(Groupby_age_data,aes(x= total_Earnings, fill=
Age1))+geom_histogram()+ggtitle('Earnings of Age Groups')
```

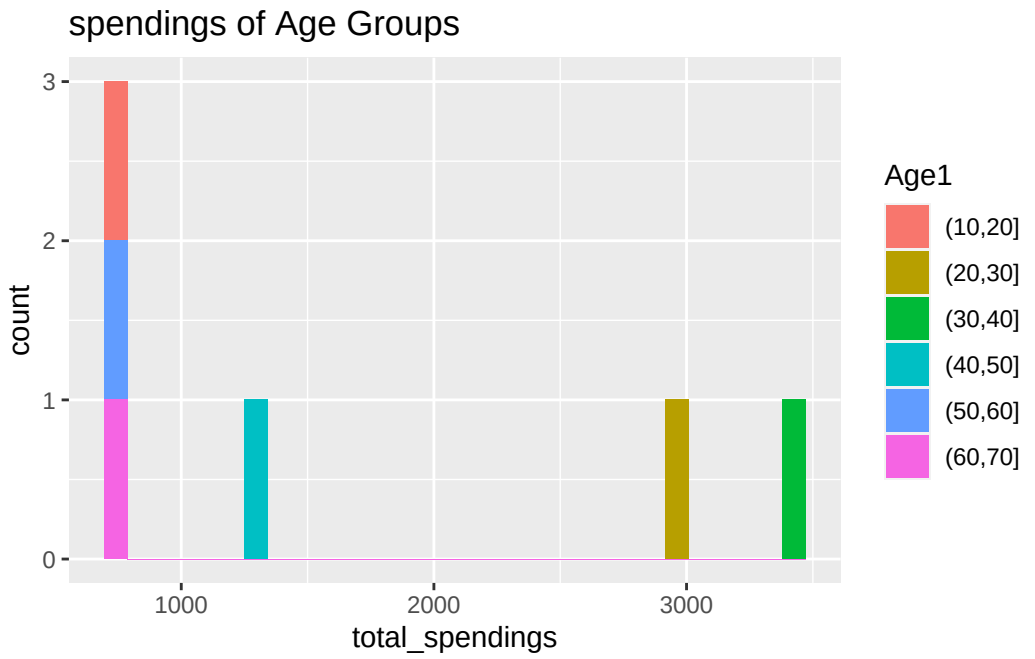
```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



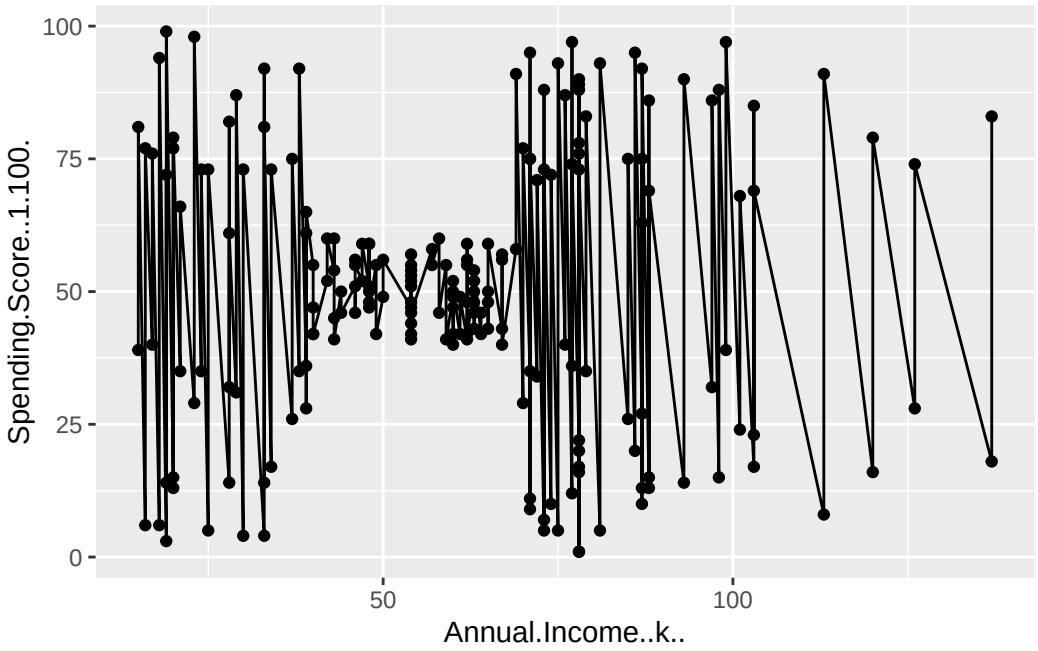
Above chart shows that with with age 30 to 40(green color bar) shows the total highest earnings.

```
ggplot(Groupby_age_data,aes(x= total_spendings, fill=
Age1))+geom_histogram()+ggtitle('spendings of Age Groups')
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
ggplot(numerical_customer_columns_data, aes(x =Annual.Income..k..)) +
geom_point(aes(y = Spending.Score..1.100.))+geom_line(aes(y = Spending.Score..1.100.))
```



Data Modelling

K-means Clustering

When an unlabeled data is available its always suggestible to go ahead with the unsupervised ML model. K-means clustering is one of the models opted here in order to generate the different clusters. Silhouette method, is used here to find the number of clusters and found that K=6.

Finding optimal no of clusters

```
install.packages('NbClust',repos = "http://cran.us.r-project.org")
```

```
The downloaded binary packages are in
    /var/folders/16/qnwjsjfn5011fpzs33fhppqw0000gn/T//RtmprgEvRp/downloaded_packages
```

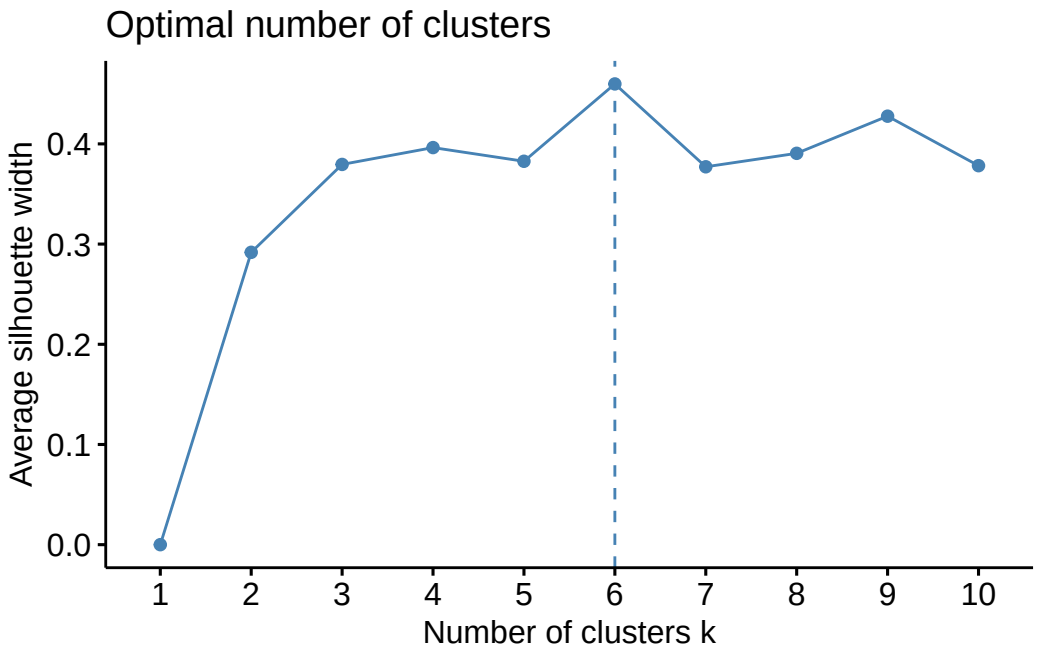
```
install.packages('factoextra',repos = "http://cran.us.r-project.org")
```

```
The downloaded binary packages are in
    /var/folders/16/qnwjsjfn5011fpzs33fhppqw0000gn/T//RtmprgEvRp/downloaded_packages
```

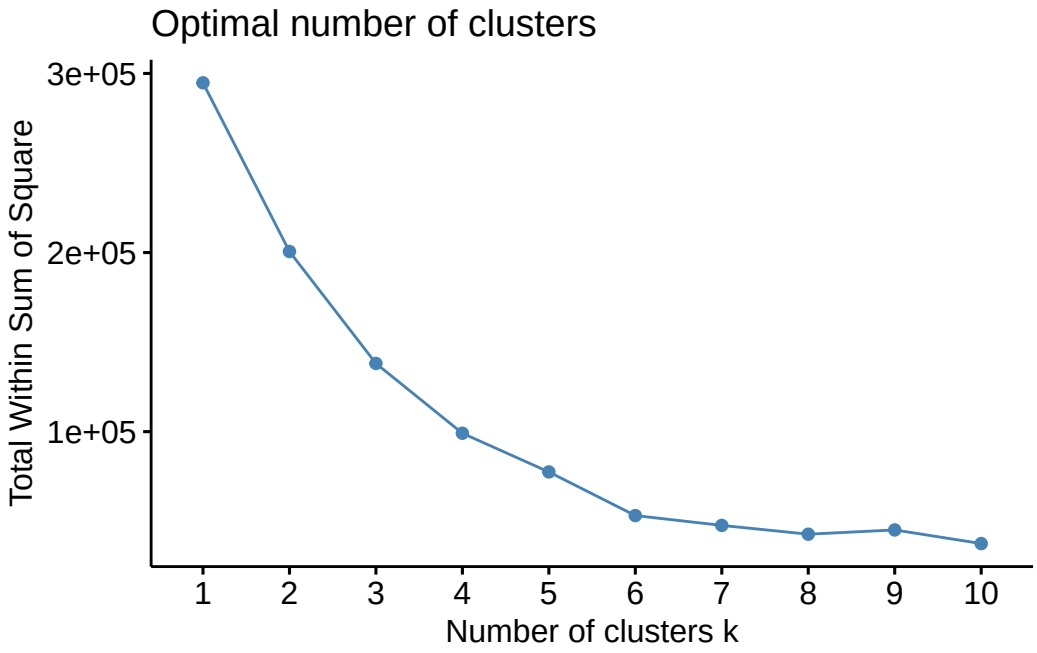
```
library(NbClust)
library(factoextra)
```

```
Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

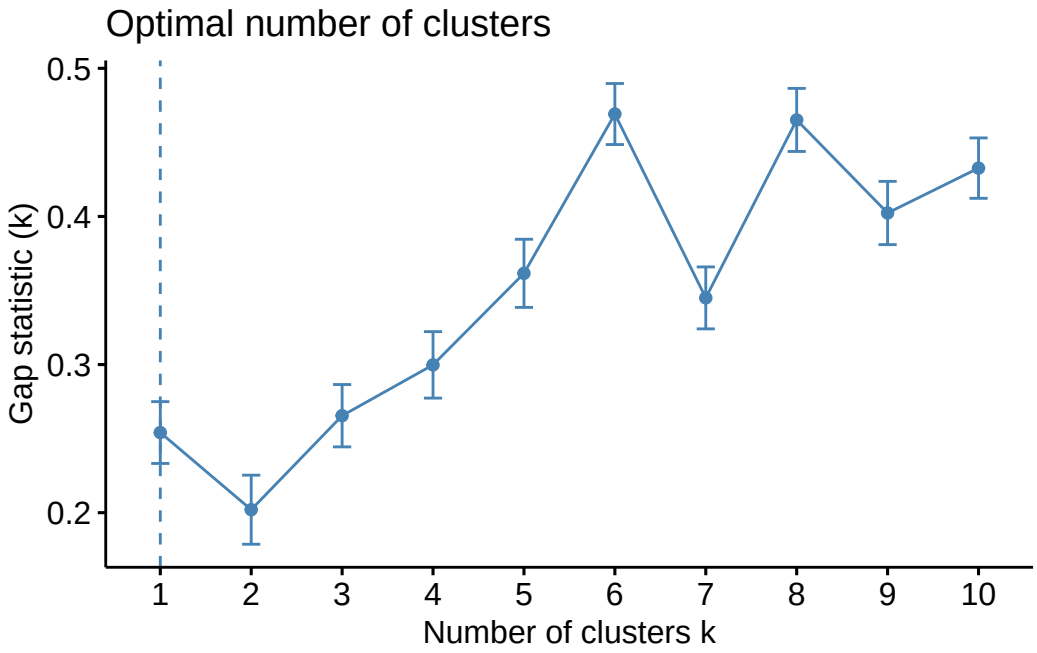
```
fviz_nbclust(customer_data[,3:5], kmeans, method = "silhouette")
```




```
fviz_nbclust(customer_data[,3:5], kmeans, method = "wss")
```



```
fviz_nbclust(customer_data[,3:5], kmeans, method = "gap_stat")
```



From these 3 methods we can see that the optimal no of clusters are 6.

```
#Applying kmeans to the data with 6 clusters

kmeans_6cluters <- kmeans(customer_data[,3:5],6)
kmeans_6cluters
```

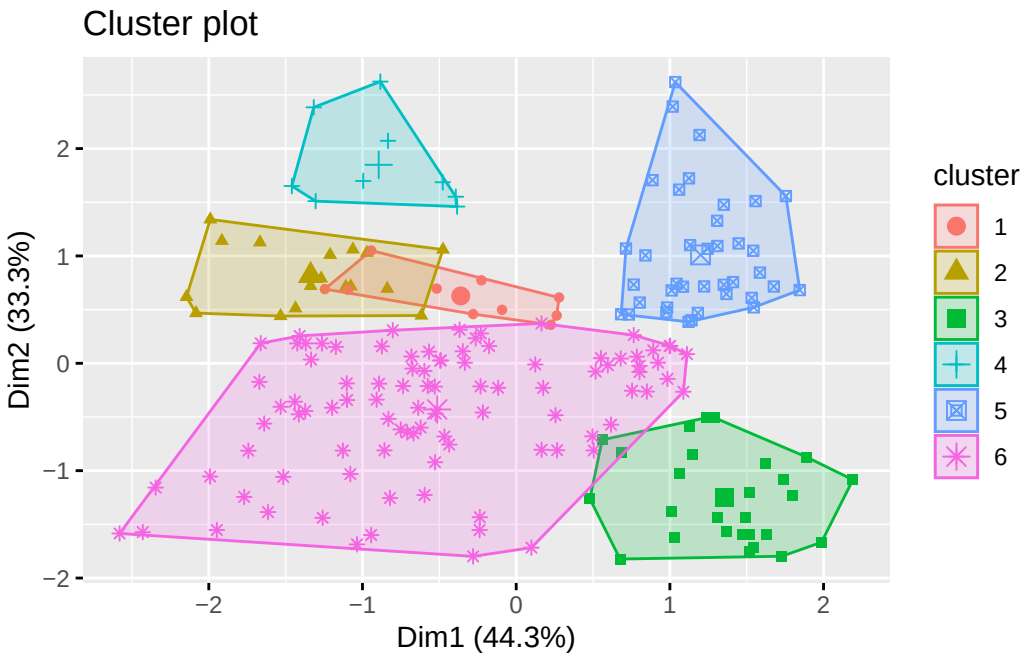
```
K-means clustering with 6 clusters of sizes 11, 17, 28, 9, 38, 95

Cluster means:
       Age Annual.Income..k.. Spending.Score..1.100.
1 27.27273           76.72727                15.36364
2 48.52941           80.29412                18.76471
3 24.82143           28.71429                74.25000
4 42.00000          106.66667                22.44444
5 32.76316           85.21053                82.10526
6 44.89474           48.70526                42.63158

Clustering vector:
```

```
  1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17  18  19  20
  3   3   6   3   6   3   6   3   6   3   6   3   6   3   6   3   6   3   6   3
 21  22  23  24  25  26  27  28  29  30  31  32  33  34  35  36  37  38  39  40
  6   3   6   3   6   3   6   3   6   3   6   3   6   3   6   3   6   3   6   3
 41  42  43  44  45  46  47  48  49  50  51  52  53  54  55  56  57  58  59  60
  6   3   6   3   6   3   6   6   6   6   6   3   6   6   6   6   6   6   6   6
 61  62  63  64  65  66  67  68  69  70  71  72  73  74  75  76  77  78  79  80
  6   3   6   6   6   3   6   6   3   6   6   6   6   6   6   6   6   6   6   6
 81  82  83  84  85  86  87  88  89  90  91  92  93  94  95  96  97  98  99 100
  6   6   6   6   6   6   6   6   6   6   6   6   6   6   6   6   6   6   6   6
101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120
  6   6   6   6   6   6   6   6   6   6   6   6   6   6   6   6   6   6   6   6
121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140
  6   6   6   5   1   5   2   5   2   5   2   5   1   5   1   5   2   5   1   5
141 142 143 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160
  2   5   1   5   1   5   2   5   1   5   2   5   2   5   2   5   1   5   1   5
161 162 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180
  2   5   1   5   2   5   2   5   2   5   2   5   1   5   2   5   2   5   2   5
181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197 198
  4   5   4   5   4   5   4   5   4   5   4   5   4   5   4   5   4   5

Within cluster sum of squares by cluster:
[1]  2578.909  3168.824  9099.071  1978.222 11350.763 62300.800
 (between_SS / total_SS =  69.3 %)

Available components:

[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
[6] "betweenss"    "size"         "iter"         "ifault"
```

```
install.packages("ggpubr", repos = "https://cloud.r-project.org/", dependencies = TRUE)
```

```
The downloaded binary packages are in
    /var/folders/16/qnwjsjfn5011fpzs33fhppqw0000gn/T//RtmprgEvRp/downloaded_packages
```

```
library(ggpubr)
fviz_cluster(kmeans_6cluters, data = customer_data[,3:5],geom = "point")
```



Here we can see the formation of 6 clusters.

```
kmeans_cluster_data <- data.frame(Cluster = kmeans_6cluters$cluster, customer_data[,3:5])
head(kmeans_cluster_data)
```

```
  Cluster Age Annual.Income..k.. Spending.Score..1.100.
1       3  19                 15                     39
2       3  21                 15                     81
3       6  20                 16                      6
4       3  23                 16                     77
5       6  31                 17                     40
6       3  22                 17                     76
```

```
#Sizes of the clusters
kmeans_6cluters$size
```

```
[1] 11 17 28  9 38 95
```

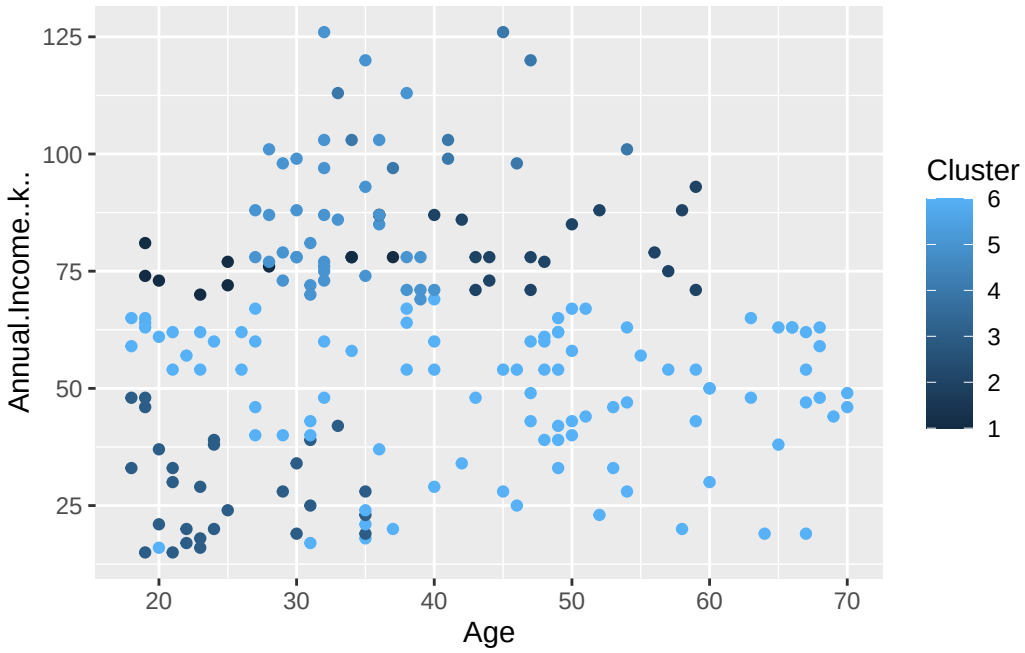
```
#Centres of the clusters
kmeans_6cluters$centers
```

```
       Age Annual.Income..k.. Spending.Score..1.100.
1 27.27273           76.72727                15.36364
2 48.52941           80.29412                18.76471
3 24.82143           28.71429                74.25000
4 42.00000          106.66667                22.44444
5 32.76316           85.21053                82.10526
6 44.89474           48.70526                42.63158
```

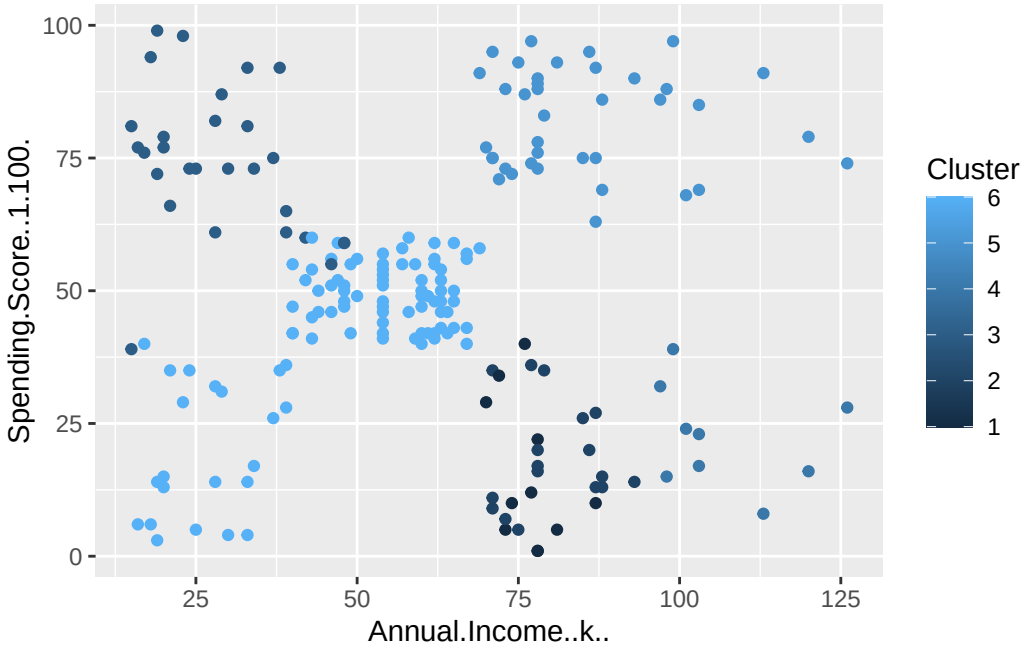
```
names(kmeans_cluster_data)
```

```
[1] "Cluster"                "Age"                    "Annual.Income..k.."
[4] "Spending.Score..1.100."
```

```
ggplot() +
  geom_point(data = kmeans_cluster_data,mapping = aes(x = Age, y = Annual.Income..k.., col
```




```
ggplot() +
  geom_point(data = kmeans_cluster_data,mapping = aes( x = Annual.Income..k.., y = Spendin
```



The `echo: false` option disables the printing of code (only output is displayed).

Bias

In general case scenarios, it is assumed that people with highest income will have the highest spending, but from the above analysis it shows that there is no such correlation between income earnings and spending.

Conclusion

It is clearly proved that customer segmentation in marketing domain can be easily performed by the unsupervised learning to personalize marketing campaigns and advertisements more effectively. This report gives the step-by-step process of cleaning, transforming and analyzing the data in targeting and prioritizing the best customer segments. It also depends on what kind of data is being used.

By performing the best customer segmentation process, the impact on various domains of the organisation such as marketing, advertising and customer services is immense. By executing the customer segmentation, the organizations focuses on segments rather every customer individuals.

```r
sessionInfo()
```

```
R version 4.2.1 (2022-06-23)
Platform: aarch64-apple-darwin20 (64-bit)
Running under: macOS Monterey 12.3

Matrix products: default
BLAS:   /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/lib/libRblas.0.dylib
LAPACK: /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/lib/libRlapack.dylib

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
[1] ggpubr_0.5.0     factoextra_1.0.7 NbClust_3.0.1    GGally_2.1.2
[5] kdensity_1.1.0   plotrix_3.8-2    ggplot2_3.4.0    dplyr_1.0.10

loaded via a namespace (and not attached):
 [1] ggrepel_0.9.2       Rcpp_1.0.9          lattice_0.20-45
 [4] tidyr_1.2.1         cvar_0.5            gbutils_0.5
 [7] assertthat_0.2.1    digest_0.6.30       utf8_1.2.2
[10] R6_2.5.1            plyr_1.8.8          backports_1.4.1
[13] fBasics_4021.93     fGarch_4022.89      logitnorm_0.8.38
[16] evaluate_0.18       pillar_1.8.1        Rdpack_2.4
[19] rlang_1.0.6         spatial_7.3-15      rstudioapi_0.14
[22] car_3.1-1           Matrix_1.5-3        rmarkdown_2.18
[25] labeling_0.4.2      nakagami_1.1.0      stringr_1.5.0
[28] munsell_0.5.0       univariateML_1.1.1  broom_1.0.1
[31] compiler_4.2.1      xfun_0.35           pkgconfig_2.0.3
[34] htmltools_0.5.3     tidyselect_1.2.0    tibble_3.1.8
[37] reshape_0.8.9       fansi_1.0.3         withr_2.5.0
[40] rbibutils_2.2.10    grid_4.2.1          jsonlite_1.8.3
[43] gtable_0.3.1        lifecycle_1.0.3     DBI_1.1.3
[46] magrittr_2.0.3      scales_1.2.1        carData_3.0-5
[49] cli_3.4.1           stringi_1.7.8       ggsignif_0.6.4
[52] farver_2.1.1        timeDate_4021.106   generics_0.1.3
[55] vctrs_0.5.1         expint_0.1-8        actuar_3.3-1
[58] RColorBrewer_1.1-3  tools_4.2.1         glue_1.6.2
[61] purrr_0.3.5         abind_1.4-5         fastmap_1.1.0
```

```
[64] yaml_2.3.6          colorspace_2.0-3    extraDistr_1.9.1
[67] cluster_2.1.4       timeSeries_4021.105 rstatix_0.7.1
[70] knitr_1.41
```