Customer segmentation for products marketing

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2023-01-17

```
# set working directory ------
setwd("D:/Ph.D_materials/Programming/R_programming/mdsr/customer-segmentation_analysis")
# Load functions and packages ------
source("pkg.R")
```

DATA VISUALIZATION

```
# Import the Mall customers data -----
customers <- vroom::vroom("Mall_Customers.csv", col_names = T)</pre>
customers_old <- customers</pre>
# Take a glimpse of the data sets
customers %>%
   glimpse()
## Rows: 400
## Columns: 5
## $ CustomerID
                            <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14~
## $ Gender
                            <chr> "Male", "Male", "Female", "Female", "Female",~
## $ Age
                            <dbl> 19, 21, 20, 23, 31, 22, 35, 23, 64, 30, 67, 3~
## $ 'Annual Income (k$)'
                            <dbl> 15, 15, 16, 16, 17, 17, 18, 18, 19, 19, 19, 1~
## $ 'Spending Score (1-100)' <dbl> 39, 81, 6, 77, 40, 76, 6, 94, 3, 72, 14, 99, ~
# Change gender to factor -----
customers <- customers %>%
   mutate(Gender = factor(Gender))
# rename income and spending variables -----
customers <- customers %>%
   rename(annual_income = "Annual Income (k$)", spending_score = "Spending Score (1-100)")
```

There are 400 observations and 5 variables in the movies data. Additionally, all variables were numerical. However, we convert the class variables to factors.

```
# check the five number summary and other measures of Amount
# ------
d <- favstats(Age ~ Gender, data = customers)
knitr::kable(d, digits = 3, format.args = list(scientific = FALSE), caption = "Descriptive summary of agents.")</pre>
```

EXPLORATORY DATA ANAYSIS

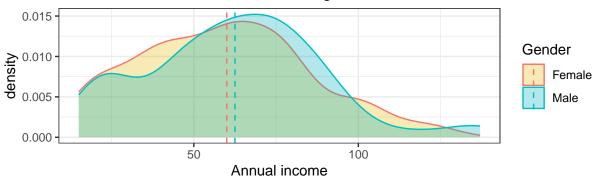
Table 1: Descriptive summary of age by gender.

Gender	min	Q1	median	Q3	max	mean	sd	n	missing
Female	18	29.0	35	47.5	68	38.1	12.6	224	0
Male	18	27.8	37	50.5	70	39.8	15.5	176	0

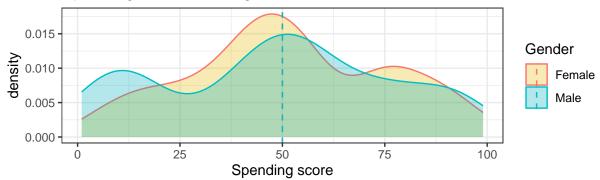
```
tt <- ggplot(data = customers, aes(x = Gender)) + geom_bar(aes(fill = Gender)) +
    labs(y = "Number of values in class", title = "Bar graph of the target variable class") +
    theme_bw()</pre>
```

Clearly, this shows a highly imbalanced classification problem.

Annual income distribution across gender

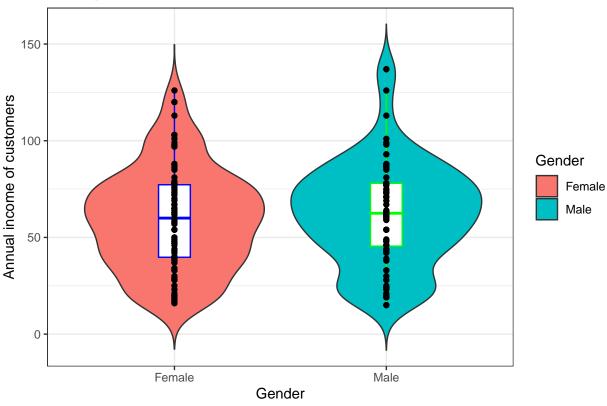


Spending score across gender



```
# Change violin plot colors by gender ------
p <- ggplot(data = customers, aes(x = Gender, y = annual_income)) + geom_violin(trim = FALSE,
    aes(fill = Gender)) + geom_boxplot(width = 0.15, color = c("blue", "green"),
    fill = c("white", "white")) + geom_point() + labs(y = "Annual income of customers",
    title = "Violin plot of income distribution") + theme_bw()
p</pre>
```

Violin plot of income distribution



```
customers %>%
    select(Gender) %>%
    unique()

## # A tibble: 2 x 1

## Gender

## <fct>
## 1 Male

## 2 Female

# scale spending and income variable -----

customers <- customers %>%
```

The descriptive statistics show that the amount values are highly variable. This suggests the we scale the data as it helps with most machine learning algorithms.

mutate(annual_income = scale(annual_income), spending_score = scale(spending_score))

```
# Elbow Method for finding the optimal number of clusters
set.seed(123)
# Compute and plot wss for k = 2 to k = 15.
k.max <- 10
kk = customers %>%
    select(annual_income, spending_score)
data <- kk
wcss <- sapply(1:k.max, function(k) {</pre>
```

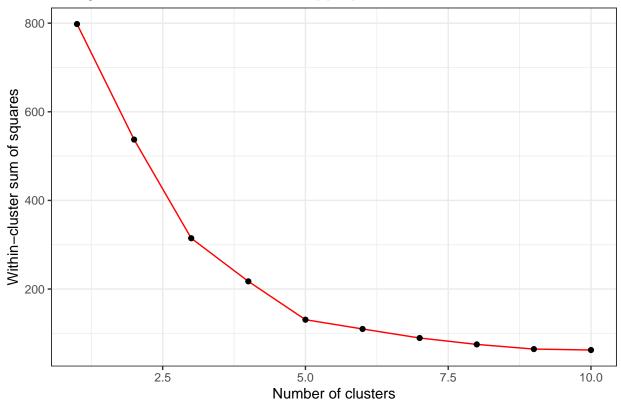
```
kmeans(data, k, nstart = 10, iter.max = 350)$tot.withinss
})
wcss
```

[1] 798.0 537.3 314.6 217.3 130.8 109.8 89.5 75.0 64.5 62.3

```
kt <- data.frame(k.max = 1:k.max, wcss = wcss)

# plot graph
ggplot(kt, aes(x = k.max, y = wcss)) + geom_line(color = "red") + geom_point() +
    labs(y = "Within-cluster sum of squares", x = "Number of clusters", title = "Using \"Elbow method\"
    theme_bw()</pre>
```

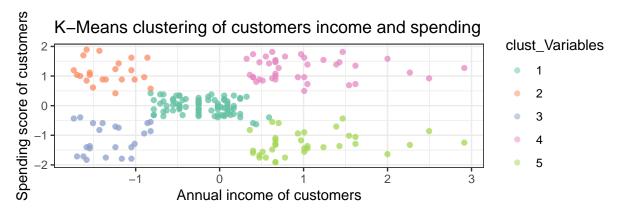
Using "Elbow method" to choose appropriate K

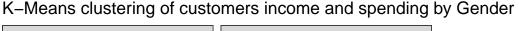


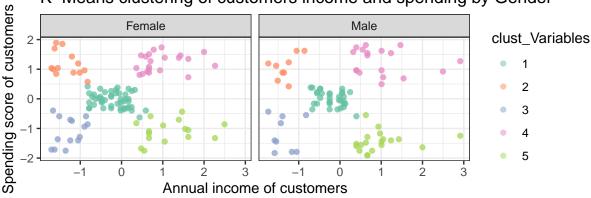
```
set.seed(6)
library(cluster)

clust_Variables <- customers %>%
    select(annual_income, spending_score) %>%
    kmeans(5, iter.max = 300, nstart = 2) %>%
    fitted("classes") %>%
    as.factor()
customers <- customers %>%
```

```
mutate(clust_Variables = clust_Variables)
p3 <- customers %>%
    ggplot(aes(x = annual_income, y = spending_score)) + geom_point(aes(color = clust_Variables),
    alpha = 0.5) + scale_color_brewer(palette = "Set2") + labs(y = "Spending score of customers",
    x = "Annual income of customers", title = "K-Means clustering of customers income and spending") +
    theme bw()
p4 <- customers %>%
    ggplot(aes(x = annual_income, y = spending_score)) + geom_point(aes(color = clust_Variables),
    alpha = 0.5) + scale_color_brewer(palette = "Set2") + labs(y = "Spending score of customers",
    x = "Annual income of customers", title = "K-Means clustering of customers income and spending by G
    facet_wrap(~Gender, nrow = 1) + theme_bw()
p3/p4
```







```
# selecting cluster 4
customers %>%
   select(CustomerID) %>%
   filter(clust Variables == "4") %>%
   as.vector()
```

```
## $CustomerID
```

[1] 124 126 128 130 132 134 136 138 140 142 144 146 148 150 152 154 156 158 160

```
## [20] 162 164 166 168 170 172 174 176 178 180 182 184 186 188 190 192 194 196 198 
## [39] 200 324 326 328 330 332 334 336 338 340 342 344 346 348 350 352 354 356 358 
## [58] 360 362 364 366 368 370 372 374 376 378 380 382 384 386 388 390 392 394 396 
## [77] 398 400
```